BORDER SECURITY AS A LABOR SCREENING DEVICE:

A NEW MODEL OF IMMIGRATION ECONOMICS

by

Jesse D. Melvin

A dissertation submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics

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A NEW MODEL OF IMMIGRATION ECONOMICS

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Jesse D. Melvin

Approved: ____

Michael A. Arnold, Ph.D.
Chair of the Department of Economics

Approved: ____

Bruce W. Weber, Ph.D.
Dean of the Alfred Lerner College of Business and Economics

Approved: ____

Douglas J. Doren, Ph.D.
Interim Vice Provost for the Office of Graduate and Professional Education

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed:

Michael A. Arnold, Ph.D.
Professor in charge of dissertation

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed:

Desmond J. Toohey, Ph.D.
Member of dissertation committee

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed:

Saul D. Hoffman, Ph.D.
Member of dissertation committee

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed:

Breck L. Robinson, Ph.D.
Member of dissertation committee

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ABSTRACT

I present a new model of immigration that describes the migration-decision process on an individual level, based on Spence's (1973) signaling model. The model allows for an explanation of phenomena such as chain migration and the positive selectivity of migrants, and specifically examines the positive relationship between a nation's immigration control policy and the productivity of the migrants entering that nation. The logic is straightforward: the personal cost of migrating into a nation rises as that nation's border security becomes stricter and more strongly enforced, which deters individuals who are less motivated and/or capable to migrate. I develop two distinct models based on the assumption of exogenous wage-setting (e.g. minimum wage markets) or endogenous wage-setting. Once these models have been developed, I proceed to model for optimal government behavior under the particular conditions. Using data from the Current Population Survey (CPS), I present empirical evidence of the direct relationship between border strictness and migrant productivity by using the implementation of the Homeland Security Act of 2002 as a natural experiment. The passage of the Act exogenously initiated a dramatic increase in the efficacy and strictness of immigration control policy in the United States, causing the personal cost of migrating to rise significantly. Difference-in-difference regression results for the entire U.S. market reveal that migrants who entered the nation after 2002 have a wage rate that is approximately 3.0 – 4.5% higher relative to their counterparts, and work 0.6 – 1.0 additional hours per week, ceteris paribus. Afterward, I perform this analysis on subsamples of the data relating to exogenous and endogenous-wage markets. Through difference-in-difference as well as difference-in-difference-in-indifference analysis, I find that migrants working in minimum wage sectors (e.g. exogenous-wage) experienced an even stronger screening effect, whereas those working in migrant-intensive sectors (endogenous-wage) were less impacted by the screening effect of the Homeland Security Act, in concordance with the models presented in this paper. Lastly, I find that migrants who entered the U.S. before coming of age – such as DREAMers – tended to have a larger productivity premium than other migrants.

Chapter 1

INTRODUCTION

The migration of individuals to new communities and geographic areas has always been an important element of society. Along with immigrants come new ideas, different skill sets, and a larger pool of laborers. All of these have a powerful impact on the lives of the domestic population as well as the migrants themselves, and governments have implemented international immigration control policies as a result. These measures include physical border security to prevent illegal entry, obstacles to legal immigration (e.g. financial, bureaucratic, etc.), and deportation practices targeting undocumented residents.

Within the field of economics, researchers have focused mainly on the question of how migration and immigration control policies affect the welfare and wages of the host population and laborers. This has been accomplished through the application of simple supply and demand models, with the assumption that migrant labor is a close substitute to native labor with the same type of skills. Therefore, when these researchers examine the economic effects of changes in international immigration control policies they do so solely through the lens of labor supply expansion/restriction. One issue with this type of analysis is that it automatically assumes that there is no differentiation amongst individuals within a particular skill category (as determined by education, work experience at home, work experience abroad, etc.). The migrants are all assumed to have identical productivity, motivation, and ability and therefore have identical reactions to immigration control policies.

By introducing laborer heterogeneity, my research aims to investigate the effect of international immigration control policies on the *composition* of the migrant labor force, rather than just the *size* of the migrant labor force. This is be accomplished by adopting Spence's labor screening model and applying it to a modified version of Everett Lee's classic push-pull migration model (Spence 1973, Lee 1966). Then, I empirically test for the existence of a labor screening effect using CPS data and the passage of the Homeland Security Act as a natural experiment.

I begin this paper with a review of the academic literature on immigration and labor screening in Chapter 2. I start with a discussion of the fundamental and most recent papers in the field of immigration economics, with a focus on the impact of immigrants on the native labor force and economy, as well as migrants' economic assimilation over time. I follow this with a brief review of Spence's labor signaling article, upon which the framework of the model in this paper is founded. Then, I discuss the article by Everett Lee that provided the framework for the fundamental Push-Pull demographic model of immigration.

In Chapter 3, I present a new model of international immigration economics. I begin developing the model by laying out the migration-decision utility function, which is populated by variables and relationships laid out in the classic Push-Pull model of immigration. Then I present a simple two-nation example of immigration control as a labor screening device with specifically-valued exogenous variables. I go on to complete the model more generally by defining the distribution of the centerpiece variable - motivation/ability - and then solving for the steady state equilibrium of the model under the assumption of exogenous wage-setting in Section 3.4 and endogenous wage-setting in Section 3.5.

Table 1.1 Summary of Model

	Response		
	Exogenous-Wage	*Endogenous-Wage*	
Shock (increase)	Migrant Quality	Migrant Quality	Migrant Wage Rate
Immigration Control Policy	+	+	+
Overall Productivity in Receiving Country	0	-	+
Migrant Wage Rate in Receiving Country	-	n/a	n/a
Migrant Homeland Conditions	+	+	+
Distance and/or Ethnic Costs	+	+	+

For each of the models, I interpret the differential impacts of changes to immigration control policy, technological productivity shocks, homeland conditions, and so on. A summary of these effects can be found in Table 1.1 above. The model implies that the labor screening effect exists: there should be a positive relationship between the amount or strictness of a nation's immigration control policy and the conditional quality of migrants entering that nation. I also find that, in endogenous-wage markets, a nation with higher level of overall productivity should attract a migrant pool that has – on average – a lower level of motivation/ability. Conversely, both models indicate that there is a direct relationship between the living conditions of the migrants' sending country and the quality of the individuals who decide to relocate to another country. In other words, migrants arriving from nations with a relatively higher standard of living will tend to be relatively more productive individuals. And finally, migrants who find themselves at a greater distance from their destination nation – either physically or culturally – tend to be more motivated and capable individuals.

I conclude Sections 3.4 and 3.5 by expanding the model to incorporate a social welfare equation that is a function of the size of the migrant population, the average productivity of the migrants, and natives' attitudes toward these factors. After making reasonable assumptions of the form of the function (e.g.

Table 1.2 Summary of Government Response

	Optimal Government Response (in terms of immigration control)	
Shock (increase)	*Exogenous-Wage*	*Endogenous-Wage*
Overall Productivity in Receiving Country	0	+
Per-unit Cost of Border Security	-	-
Migrant Wage Rate in Receiving Country	+	n/a
Migrant Homeland Conditions	-	-
Distance and/or Ethnic Costs	-	-

native citizens desire a migrant pool of labors that are relatively more productive), I go on to solve for the optimal level of immigration control policy that maximizes the social welfare function. Then, I investigate the differential impacts on the optimal level of border security that are caused by shocks to important exogenous variables and parameters; a summary of these relationships can be found in Table 1.2 above. The models imply that the government of the receiving nation should increase its immigration control policy in response to a more productive economy (endogenous-wage market) or migrants earning a higher wage rate in the receiving nation (exogenous-wage market). Both models agree that border security follows the Law of Demand: there is an inverse relationship between price of border control and optimal quantity demanded of border control. Interestingly, based on the assumptions and economic principles laid out in this paper, both models imply that a nation should be expected to loosen its border control for individuals from economically/politically healthy countries, and make its immigration control policy stricter for migrants hailing from nations experiencing significant hardship.

I finish Chapter 3 with a discussion of two expansions of the exogenous-wage model, presented in Section 3.6. I begin by examining the labor screening effect of an active deportation mechanism in the receiving country. Earlier in the chapter, it was assumed that a migrant would always be able to circumvent border security if they paid the associated costs. In Sub-section 3.6.1, I introduce a Von-Neumann Morgenstern migration-decision utility function, in which there is now the possibility that a migrant's relocation "investment" is wasted as they are returned to their home country. I also assume that the likelihood of successfully entering the receiving nation is positively correlated with an individual's motivation/ability characteristic. After these additional effects have been introduced to the model, I find that the labor screening effect is even more pronounced, indicating that an active find-and-remove deportation program may be more effective as a screening measure than inert measures (such as building a wall).

For the second part of Section 3.6, I expand the framework of the model to include a variety of potential migrant-receiving nations, which more accurately represents the situation in other continents such as Europe. After solving for the steady state equilibrium, I find that the model implies that the nation with the highest wage rate offered to migrants (denoted as Nation 0) experiences a positive labor screening effect, as witnessed with the two-nation model. However, this screening effect is more pronounced: the direct relationship between immigration control policy and migrant productivity is of a greater magnitude for Nation 0 than it is for the receiving nation in the two-nation model. Conversely, if there are any other receiving nations other than Nation 0 in the multi-nation model, the model implies that the labor screening effect is indeterminate/negligible for these countries.

In Chapter 4, I provide a background discussion on immigration in the United States. I begin the chapter with a detailed history of migration, starting with Native Americans travelling over the Asiatic footbridge and the Europeans that crossed the Atlantic, and ending with the large wave of undocumented migrants that characterized American migration in the second half of the twentieth century. Afterward, I provide an overview of contemporary immigration in the 21st century by looking at a profile of the migrants that live here, as well as going over the legal paths available for foreigners to become lawful residents of the United States. I finish the chapter by discussing the various federal agencies responsible for enforcing the myriad of immigration laws, and their effectiveness in the past fifteen years.

In Chapter 5, I conduct a comprehensive empirical analysis in order to show that immigration control policy has a significant and positive labor screening effect on the productivity of incoming migrants. The centerpiece of this analysis is the passage of the Homeland Security Act of 2002, which was put into legislation following the September 11 attacks in order to protect the national security of the United States. The Act had a huge impact on the federal government's attitude, strategy, and funding toward the closing of the nation's porous borders, which were seen as a security threat. Therefore, there was a concerted (and successful) attempt to make illegal migration into the U.S. a more difficult endeavor. In addition to this, the Act made the vetting and bureaucratic process much longer and costlier for legal migrants and travelers, in the name of public safety. Therefore, the passage of the Homeland Security Act of 2002 significantly and exogenously increased the cost of migrating into the U.S., thereby providing the framework for a difference-in-difference natural experiment analysis.

Using Current Population Survey data from the U.S. Census between the years of 1998 and 2015, I begin the empirical analysis by examining the entire U.S. labor market as a whole, thereby avoiding any potential issues of market "closedness." After controlling for a host of demographic, geographic, and temporal variables, the difference-in-difference regression results revealed that migrants that entered the United States after 2002 earned a wage rate that is approximately 3.0-4.5% higher than migrants who entered on or before that year. I also find that those post-2002 migrants also tended to work a longer workweek: to the magnitude of two-thirds to one additional hour per week.

Then, for Section 5.5, I conduct the labor screening analysis for a more narrowly selected subset of the population: individuals working in an exogenous-wage market, as defined by those earning a wage determined by a binding price floor (i.e. minimum wage). I use four different methods to determine who belongs to this subset. The first and most direct method identified individuals earning within 50 cents of their particular state's effective minimum wage rate, in their year of observation, as minimum wage workers. The full sample difference-in-difference-indifference estimation produced the exact results expected from the model presented in this paper: a positive screening effect (as measured in hours worked per week) exists for everyone, and it is more pronounced for workers earning close to minimum wage. The restricted sample difference-in-difference estimation produced insignificant results, which could be a result of out-selection by successful workers (i.e. getting a raise may remove worker from sample) or a much smaller sample size. The second method identified minimum wage workers as those belonging to the common demographic group: uneducated, under 26 years old, and working part-time. The restricted-sample DID and full-sample DIDID regressions revealed that, while the general labor market experienced a labor screening effect, the effect was negligible on those belonging to this particular demographic. Just as with the prior method, this could be attributable to the removal of capable/successful workers from the subsample (i.e. a worker moving from part-time to full-time status is removed from the sample).

For the next two approaches of determining which workers belong to a minimum wage market, I use the industrial sector that a worker belongs to (Method 3), and the classification of an individual's particular occupation (Method 4), as the defining characteristics. Since two-thirds of all minimum wage workers belong to the Leisure and Hospitality sector, I define laborers in that particular sector as belonging to an exogenous-wage market in Method 3. For Method 4, individuals that work in an occupation that is substantially populated by minimum wage workers belong to the exogenous-wage subset of the population. The DID and DIDID estimations using both two methods all produced results that are congruent with each other, as well as the implications of the model: individuals working in an exogenous-wage (minimum wage) market experienced a positive post-2002 screening effect on hours worked per week, and this screening effect was of a larger magnitude than for the entire labor market.

For Section 5.6, I conduct the labor screening analysis for migrants who work in a market with endogenous wage-setting, in which there is a stable information feedback loop between the migrant workers and their employers such that wages are determined by previous migrants' performance. Thus, I define migrants as belonging to endogenous-wage market if they are working in a sector or occupation that has a history of employing a high fraction of migrant workers. For Method 1, I denote an individual as belong to an endogenous-wage market if they are Hispanic individual working in the agricultural sector. For Method 2, a laborer belongs to the subset if they are working in one of the eight occupations employs the highest share of migrant workers. For both methods, the wage rate regression results for the DID and DIDID analyses were congruent with each other as well as the model in this paper: migrants belonging to endogenous-wage markets experienced a significant and positive post-2002 screening effect, but this wage premium was smaller than for migrant laborers in general. The estimations for hours worked per week produced somewhat similar results: endogenous-wage migrants experienced a positive labor screening effect, but the magnitude of the weekly-hours premium was not significantly different from the average laborer.

Overall, the empirical results presented in Chapter 5 support the labor screening effect that is implied by the model presented in Chapter 3. The exogenous increase in immigration control policy appears to have caused a significant increase in migrants' productivity, as measured by their wage rate and weekly hours worked. As predicted by the model, this labor screening effect was more pronounced for individuals working in an exogenous-wage market, and less pronounced for those working in an endogenous-wage market. Also, the fact that a host of statistically significant results were obtained for migrants working in a variety of sectors and occupations indicates that the measured labor screening effect occurred within-class. In other words, the wage and weekly-hours premiums observed for the entire U.S. labor market were not driven by cross-sectoral shifts (e.g. employment growth in high-wage positions held by migrants), but rather by a change in the quality of migrants themselves.

And finally, I find that the labor screening impact of the HSA Act of 2002 was much stronger for individuals who moved to U.S. before they were old enough to enter the labor force. This has important political ramifications: the United States has been embroiled in an intense debate over Deferred Action for Childhood Arrivals (DACA). The executive order signed by President Obama determined that migrants who entered the U.S. before their 16^{th} birthday may have a two-year deferment from deportation and may apply for a work visa. President Trump ordered that the program stop receiving applications by March 2018, however migrants are still able to apply due to a federal court order. The estimation results presented in this paper would indicate that these DREAMers have not only been screened by U.S. immigration control policy, but the screening effect was even more pronounced for these individuals, resulting in a more productive class of workers.

Chapter 2

LITERATURE REVIEW

2.1. Economics Literature Regarding Immigration

2.1.1 Effect on Native Employment and Wages

One of the most widely debated aspects of immigration is its effect on the employment opportunities of the native population. There is a particularly strong political interest in the topic, as there is a commonly held belief that immigrant workers “steal” job opportunities from native workers. This phenomenon is tentatively supported by factor-demand and supply economic theory. Employers consider migrant labor and native labor, within a skill group, to be close substitutes. Therefore, when an influx of immigrants causes the wage rate of migrant labor to decrease, we expect employers to substitute some of their native laborers for migrant laborers.

This has led to research in which economists measure the impact of migrant workers on the employment (or the unemployment rate) of the domestic labor force. This has typically been accomplished by calculating the correlation between native employment and the relative number of immigrants in a particular geographic area, which researchers assume to be a closed labor market. Since immigrants tend to cluster in metropolitan areas, the trend is to examine this correlation in major cities.

The results of these studies vary, but there is a general consensus: an increase in immigrant labor negatively impacts the employment of domestic labor, but the relationship is very weak. A metadata review conducted by Friedberg and Hunt (1995) found that there is no evidence that immigration causes an "economically significant" reduction in native employment. More recently, Kerr and Kerr (2011) collected a survey of North American and European studies conducted since 1991 that examined the correlation between the immigrants' share of population and native employment. Out of 16 total studies, nine of them found evidence of a negative correlation. Four of the studies found no statistically significant correlation and, surprisingly, three studies found evidence of a positive employment effect. Out of the studies that found a negative correlation, five of them calculated and reported an employment elasticity (the percentage change in employment in response to a 1% increase in immigrants' share of population). Of these five studies, the average employment elasticity is approximately -0.13, implying that immigration has a relatively small effect.

Economists have also examined the impact of immigration on the wages of the domestic labor force. The theory is simple: an increase in the number of immigrants within a closed labor market leads to an increase in the labor supply in that market, which causes wages to decrease. Therefore, we expect to see a negative correlation between migrant labor supply and natives' wage rate.

Many studies have examined this relationship, typically by using a spatial fixed-effects model regressing logged wage rate on the share of immigrant population and a set of controls. The overall results of these wage studies are very similar to that of employment: there is a general consensus of a negative, but small, correlation. A survey of the literature conducted by Borjas (1994) found that there is "only a weak negative correlation." A summary of several UK studies (Dustmann 2008) reports that there is no evidence for negative average wage impacts. More recently, Kerr and Kerr (2011) collected and reported the wage elasticities that were calculated in 29 different studies. Out of these, only 11 studies reported a wage elasticity that was statistically significantly negative, while 5 studies reported a significantly positive elasticity.

There are several empirical concerns regarding the validity of these spatial correlation results. One of these issues is in regard to the endogeneity of the choice of location for immigrants. When deciding on their destination, new migrants are naturally attracted to areas with higher wages, leading to a spurious positive correlation between immigrant share of population and wages in a labor market.

Researchers have utilized several methods in an attempt to avoid the endogeneity issue. The most prevalent is the application of a natural experiment, in which there is an exogenous influx of immigrants into a particular labor market. Perhaps the most famous of these studies is the one conducted by Card (1990), wherein he examined the effect of the 1980 Mariel boatlift. The politically inspired exodus of Cubans caused Miami's population to rapidly rise by 7%, and this sudden rise in the low-skill labor supply had almost no impact on the market. Low-skill non-Cuban laborers experienced virtually no change in their wage rate or unemployment rate, and even native Cuban laborers were not "substantially effected." The Hunt study (1992) reviewed the 1962 repatriation of Algerians into France following Algerian Independence, and the Friedberg (2001) study examined the mass migration of Jews into Israel following the breakup of the Soviet Union. Both of these studies also concluded that immigration had a very weak adverse impact on natives' wages and employment. In addition to these natural experiment studies, researchers perform analyses that use past immigrant populations and migration trends as an instrumental variable (e.g. Altonji and Card 1991, Card 2001, Peri 2007). The results of these "chain migration" studies also support the finding of immigration having a weak negative impact on similar-skill native workers.

The other major empirical issue with these spatial correlation studies is the assumption that the labor markets being observed are actually “closed.” Borjas, Freeman, and Katz (1996) found that the magnitude of the wage elasticity grows significantly larger as the geographic area under examination grew larger. This indicated that there is a significant flow of labor between regions in response to economic conditions, and these flows can create a severe bias in locality-specific studies. Researchers have directly investigated how “open” spatial labor markets actually are by examining how native laborers reacted to a change in immigration population/share, in terms of geographic location. Studies by Card and DiNardo (2000) and Card (2001) showed that metropolitan natives did not emigrate in response to increased immigration, and research by Peri (2007) revealed the same lack of response in a cross-state analysis. However, an analysis of U.S. rural counties (Partridge et al. 2008) found a significant out-migration response by native laborers, a rare and important find, considering that the recent growth rate of the immigrant population ratio is significantly higher in rural counties than in metropolitan counties. Despite the recent research by Partridge, the general consensus is that native laborers (particularly urban) do not geographically respond to changes in immigration.

In terms of capital mobility, economists originally looked to changes in cross-industry composition to explain the “absorption” of new migrant laborers. The general argument is that as the share of immigrant workers increases, there will be an expansion in the sectors of industry that are more likely to hire immigrants (or individuals or the same skill composition). For example, if new immigrants are highly likely to be high school dropouts, than an increase in immigrant population should cause an expansion in sectors such as agriculture and textile manufacturing. However, research by Card (2005) and Card and Lewis (2007) found “limited evidence” that increased immigration causes changes in industry composition; claiming that most of the response that occurs is within-industry. In a study utilizing detailed plant-level data, Lewis (2004) tracked the adoption of numerous manufacturing technologies between 1988 and 1993. He found that plants located in geographic regions with a relatively high share of low-skill population had significantly slower adoption of automating technologies. In other words, his results confirmed that of the other researchers: industries will change their in-house composition of capital and technology in response to changes in migrant labor supply such that wages remain relatively constant.

In response to the trend of case studies in the literature, Borjas (2003) introduced a new structural approach to the problem of assessing the wage impact of migrants, by using a nested CES production function to determine the impact of a supply shock (caused by immigration) to wages in the U.S. labor market as a whole. Using data from the U.S. Census PUMS and the CPS from 1970 to 2001, he classified workers into distinct education-experience groups.

He then used variation in the supply of these worker groups to determine the differential wage impact on groups with similar education but different experience. His analysis found a wage elasticity around -0.3 to -0.4: a 10% increase in immigration in a particular class (as defined by education and experience) of labor will cause a 3-4% decrease in wages for that particular group.

All of the studies in the economics literature until the mid-1990's had operated under the assumption that native and migrant labor were perfect substitutes. Jaeger (1996) was the first to test this assumption, using 1980/1990 PUMS data on a national scale to calculate substitutability between broad skill categories in which native and migrant labor is disaggregated. His analysis supported the assumption: native and migrant labor were virtually perfect substitutes.

Using a multi-city model of production and consumption, Ottaviano and Peri (2006) studied the issue from a different angle, examining whether there are complementarities among similarly skilled ethnic groups. As they describe it: "Who can deny that Italian restaurants, French beauty shops, German breweries, Belgian chocolate stores, Russian ballets, Chinese markets, and Indian tea houses all constitute valuable consumption amenities that would be inaccessible to Americans were it not for their foreign-born residents? Similarly the skills and abilities of foreign-born workers and thinkers may complement those of native workers and thus boost problem solving and efficiency in the workplace." Analyzing 1970/1980/1990 PUMS data using reduced-form regressions, they found that native citizens living in cities with an increasing share of foreign-born residents experienced higher wages.[1]

Ottaviano and Peri (2012) re-estimated the substitutable/complimentary nature of migrant and native labor, this time using a general equilibrium approach of the nested-CES methodology introduced by Borjas (2003). They found that the substantial increase in U.S. immigration during the 1990-2004 period caused a significant increase in the real wage earned by skill groups that comprise 90% of the labor force, and this wage increase was in the range of 0.7 to 3.4%. High school dropouts were the only group of workers that experienced a negative wage effect, which was fairly negligible.

2.1.2 Economic Assimilation of Immigrants

For political as well as economic reasons, there has been interest in how immigrants fare upon arrival in a new country. The two elements of particular interest are the earnings and labor market status of the migrants. Virtually all of

[1] In order to deal with endogeneity issues, the authors also employ instrumental variables on which they successfully conduct exogeneity tests.

the research around the world agrees: newly arrived immigrants have lower employment ratios and lower earnings/wages than their labor market counterparts.[2] This could be explained by a lack of local labor market information, imperfectly transferable human capital, language barriers, and other cultural differences. However, the negative gap in employment and earnings appears to diminish over time as immigrants begin to assimilate into their new environment. The foundational cross-sectional analysis by Chiswick (1978) found that, after 10 to 15 years of residence, U.S. male migrant earnings matched that of American-born men with similar education and age. After those 15 years, average migrant earnings surpassed that of their American counterparts.

Subsequent research seemed to bolster these findings, until Borjas (1985) pointed out that a cross-sectional analysis like the one performed by Chiswick cannot control for cohort effects. He argues that a decline in the "quality" of cohorts since the mid-20th century is causing an overstatement of the effect of residence duration on earnings. In his longitudinal study, he finds that there is a

[2] Out of a survey of 29 American and European studies collected by Kerr and Kerr (2011), 19 of the studies found a significant negative wage gap. Only 5 found significant positive results. In terms of labor market status, Angrist and Kugler (2003) report that immigrants into the EU have lower participation and employment rates than natives. Research by Nekby (2002), Vilhelmsson (2000), and Ekberg (1999) on Nordic labor markets has revealed that non-Nordic immigrants have significantly lower participation and employment rates, while Nordic-based immigrants had employment outcomes comparable to natives. Recent American studies have found comparable results (e.g. Chiswick et al. 2007, Card 2001, Borjas 1995).

positive years-since-migration effect, but of a significantly smaller magnitude. Beyond cohort effects, other researchers argue that there is another econometric issue, this time in the form of sample selection. Over time, a significant fraction of migrants decide to permanently re-migrate, thusly removing themselves from the samples of these assimilation studies. Studies have shown that these out-migrants tend to have significantly lower earnings than "permanent" immigrants (e.g. Edin et al. 2000, Bellamare 2003). This negative selectivity of out-migration causes an overstatement of the effect of residence duration on earnings in analyses that do not account for this. When accounting for the negative selectivity of outmigration Lubotsky (2007) found, using confidential longitudinal Social Security data, that the actual rate of earnings growth is only half as large as reported in similar repeated-cross-sectional studies.

In his paper, "Self-Selection and the Earnings of Immigrants," Borjas (1987) set out to model the migration-decision and assimilation process using the earnings framework laid out by Roy (1951). In some ways the model he presents is similar to the model I present in this paper: it pays attention to the characteristics of the origin-country, host-country, and personal characteristics of the potential migrants. However, he stresses that the quality of incoming immigrants "depends entirely" on the ratio of variances in the incomes between the two nations. He argues that it is possible for migrants to positively self-select or negatively self-select, and that this determination is mostly governed by conditions in the sending nation. Using data from the 1970/1980 U.S. Census, Borjas compares the earnings of working age male immigrants from 41 different origin-nations to the earnings of natives (i.e. white, non-Hispanic, non-Asian men). He constructed a country-specific set of variables by using socio-economics measures such as “party legitimacy,” gross national product per person, income distribution variance, and distance from the United States. He found that migrants with equal skillsets coming from different nations tended to have significant earnings differentials that are mostly attributable to variations in economic and political conditions in the origin-nation. Further research by Grogger and Hanson (2011) confirmed these findings, and found evidence that migrants tend to exhibit positive selectivity in general.

Researchers have also examined the economic assimilation of migrants through the lens of investment in human capital that is specific to the host nation, with particular interest in migrants learning the primary language of their new home. Lazaer (1997) argued that when a society is predominantly comprised of individuals from one culture, individuals belonging to minority groups will assimilate more quickly out of necessity. Using U.S. Census data, he showed that the likelihood of an immigrant learning English decreased with the percentage of the local community that spoke his or her native language. Researchers went on develop a formal language model that they empirically tested using 1990 PUMS U.S. Census data and found that language proficiency rates were higher for those who live in areas with few origin-language speakers, as well as for migrants with a low chance of return migration and with less access to origin-language media (Chiswick and Miller 1998). In their international study using survey data from the U.S. Census, the German Socio-Economic Panel, and the National Immigrant Survey of Spain, Isphording and Otten (2013) they find that there is an inverse relationship between migrants' host-nation language skills and the 'linguistic distance' between the migrant's native language and the language of the host-nation. Applying this to international trade flow panel data using a gravity model, they find that linguistic distance actually has an inverse relationship with bilateral trade volume.

There is also interest in the intergenerational economic assimilation of immigrant families. Researchers first tackled the problem by analyzing cross-sections of the 1970 U.S. Census, and found that 'second-generation' American men had significantly higher wages than first-generation immigrants or third-generation[3] Americans (Chiswick 1977, Carliner 1980). In other words, the children of immigrants tended to earn a higher wage than their children or their parents, even after controlling for the wage effects of age and education. The reasoning: while an arriving immigrant has the motivation/ability to face the

[3] The category of 'third-generation' Americans included grandchildren of immigrants, great-grandchildren of immigrants, and so on.

difficult challenges of migration, they do not possess human capital assets specific to their host-nation (e.g. language fluency). However, those immigrants pass on that 'lift yourself by your bootstraps' attitude to their children. Therefore, the second generation has the advantage of growing up in the host-nation and developing nation-specific human capital, while also carrying the work ethic imparted by their parents. However, since the third generation did not personally witness the challenges overcome by their grandparents and instead grew up comfortably, they do not have the same enthusiasm and motivation in the labor market, resulting in a lower wage rate.

Subsequent research focused on the persistence of intergenerational income persistence through the lens of family endowments, particularly through education and other human capital assets. These researchers developed a quantitative measure in order to determine income mobility among families: intergenerational wage correlation ρ. The intergenerational wage correlation measures the relationship between the conditional wage differential (relative to the average) of one family's generation to the generation that precedes it. In other words, if the n^{th} generation worker in a family earns a wage that is 1% higher than the average worker of the same age and education, the $(n+1)^{th}$ generation worker can be expected to earn a wage that is ρ% higher than average. Using data from the NAS-NRC Twin sample, Behrman and Taubman (1985) found that the 'third generation' does not suffer from the problem described above,[4] and that the intergenerational wage correlation coefficient was approximately 0.2. Subsequent research seemed to bolster these findings, with the results implying an intergenerational wage correlation that is small enough that “almost all the earnings advantages or disadvantages of ancestors are wiped out in three generations.” (Becker and Tomes 1986) Overall, it appeared that there was significant income mobility among U.S. families.

Further research into the matter revealed that these intergenerational wage correlation computations were significantly biased downward due to measurement error and unrepresentative samples. By using longitudinal data from the Panel Study of Income Dynamics, rather than performing a cross-section analysis, Solon (1992) computed an intergenerational correlation coefficient exceed 0.4, at least double the previous estimates. Researchers conducted more studies with U.S. longitudinal data, and they also computed a ρ coefficient of 0.4 or higher (Mazumder 2006, Zimmerman 1992). International researchers computed this measure of intergenerational income for German families, and found that there was significant income persistence in the European nation as well, although the issue is more pronounced in the U.S. (Couch and Dunn 1997). In an attempt to determine why this intergenerational income persistence exists, Swedish researchers employed an innovative dataset

[4] They determined that grandparents’ education does not affect educational attainment, which was previously believed to have a negative effect.

with information regarding respondent's biological parents *and* their adopted parents. They discovered that pre-birth factors (i.e. nature) and post-birth factors (i.e. nurture) both play a significant role in the human capital asset endowment process (Bjorkland et al 2007).

Along this line of reasoning, Borjas (1992) explains that intergenerational skill endowment among immigrants depends on parental inputs *as well as* the quality of the ethnic environment in which parents invest in their children, which he deemed 'ethnic capital.' In other words, an individual's skillset is not only determined by their parents' skills, but also by the average skills of their parents' ethnic group. Using data from the National Longitudinal Surveys of Youth, Borjas determined that ethnic capital does have a significant effect on skillset acquisition and wages. Taking it a step further, he found that this ethnic capital externality had an impact even when comparing individuals belonging to the same local neighborhood (Borjas 1995). Overall, Borjas argues convincingly that ethnic capital should be recognized as a substantial component of intergenerational skill/income persistence. Since immigrants have a very strong tendency to congregate in ethnic communities, this ethnic capital externality is an important determinant in migrants' intergenerational economic assimilation.

Another body of literature has focused on the consequences of high skill immigration. Modern growth theory states that when an economy receives individuals possessing relatively high human capital, they tend to generate large and positive externalities through innovation, to the benefit of everyone in their market. Using data from the 2003 National Survey of College Graduates, Hunt and Gauthier-Loiselle (2010) investigated the issue by examining patent issuances. They found that migrant college graduates patent at double the rate of natives, therefore a 1% increase in foreign-born college graduates should result in a 6% increase in patents per capita. However, using 1940-2000 panel data on U.S. states from the U.S. Patent and Trademarks Office and other sources, they revealed that a 1% increase resulted in 15% more patents overall, indicating that there were positive externalities to those in their particular labor market. A study by Kerr and Lincoln (2010) found that cities with higher H-1B admissions for science and engineer employment led to a significantly higher number of patents filed by inventors with Indian or Chinese surnames. For most of their specifications, there was a negligible effect on native employment within science and engineering occupations.

2.2 Economics Literature Regarding Labor Signaling/Screening

The concept of labor signaling and screening was introduced by Michael Spence (1973) in the article "Job Market Signaling." He first describes a world of information asymmetry in which firms cannot directly observe a potential employee's productivity (which varies), yet the individuals know all information about themselves. In the absence of any sort of screening/signaling strategy, we expect to see a pooled equilibrium in which firms hire all workers at the same wage rate, despite the fact that they have varying productivities. Assuming that the firms are risk-neutral, this wage rate is equal to the unconditional expected marginal productivity of the worker pool.

Firms and potential employees can avoid this "blind" hiring by utilizing a labor signaling strategy. A signal is an observable characteristic that an individual has the power to change. In order for a person to alter this attribute, they must incur *signaling costs*, which differ from person to person. While Spence notes that there are many different types of signals, educational attainment is the most widely recognized (and the one he uses in the article for purposes of illustration). Formal education is an easily observed trait; a firm can simply request to see an applicant's diploma or school transcript. In order to obtain further education, an individual must pay the associated costs. These include explicit monetary costs (e.g. tuition, academic supplies), implicit monetary costs such as foregone wages, and psychic costs. It is an important assumption of the model that these signaling costs are negatively correlated with a worker's productivity. In other words, the costs of successfully obtaining further education are lower for individuals with high capability and motivation.

Due to the existence of this negative correlation, firms are able to separate the high-productivity workers from the low-productivity workers and offer them two different wage schedules (equal to their marginal productivity). They accomplish this by offering the high-wage positions only to those who have obtained a particular level of education, and the low-wage offer to the rest. Therefore, the high productivity individuals will pursue an education to send a signal to employers, and achieve a higher wage as a result. If the required education level is set high enough, low-productivity individuals will observe a wage differential that is smaller than the cost of obtaining the education. Therefore, these workers will choose not to incur the costs of signaling and will accept the lower wage offer.

2.3 Demographic Literature Regarding Immigration

Within the demographic literature, the dominant framework regarding immigration is the Push-Pull model that was popularized by Lee (1966). The model establishes a dichotomy of motivating influences: positive factors that *pull* migrants into a new location, and negative factors that *push* migrants out of their current location. Acting as the connection between the place of origin and the destination are the *intervening obstacles*, which must be overcome by the migrant if he or she wishes to relocate. And lastly, Lee recognizes that potential migrants have varying *personal factors* that influence – or even make possible – the choice of migration.

The various "push" factors include religious strife, an oppressive political environment, and military action (such as civil war). Out of the total volume of international migration, a minority is principally caused by push factors. These refugees are moving out of necessity rather than opportunity. Therefore, these imperiled individuals tend to move to the nearest or safest location, regardless of their individual characteristics or the economic opportunities in their new home. (Ul-Haq and Ul-Haq 1979) Thus, we expect immigrants who are primarily influenced by "push" factors to have lower productivity, since they do not exhibit the properties pertaining to a labor screening process. This "push" factor effect has interesting ramifications when it comes to interpreting the results of various studies. Studies such as Card's Mariel Boatlift examine situations in which immigrants have been "pushed." Therefore, those results may be biased since these individuals were not screened by immigration control policy.

There are several types of "pull" factors as well, including religious freedom and family reunification. However, the "pull" factor of paramount importance is the pursuit of an advanced standard of living. This typically means moving to a location where one can obtain a higher likelihood of employment, better upward mobility, and/or significantly higher wages. (e.g. Bade 2003, Borjas 1990) This has led to, in most cases, individuals leaving less-developed regions and gravitating toward those that are more economically advanced (Doerschler 2006). In addition to being the most prevalent form of migration, this type of migration is relevant to the analysis in this paper because the individuals are *deliberating* relocation, not being *forced* into relocation. Therefore, a potential migrant is taking the costs of migration into consideration. This allows for the labor screening process I have described, since low motivation/ability individuals are less likely to suffer the higher costs of migration.

A person who has decided to migrate faces a myriad of "intervening obstacles." In the framework of the analysis in this paper, these "intervening obstacles" are the source of the costs of migration that potential migrants face when relocating. These obstacles include any physical barriers to movement, such as overall distance and the intervening terrain (e.g. mountains, oceans, rivers, etc.). There are often monetary costs, such as payments to smugglers (for illegal immigration) or bureaucratic processing fees (for legal immigration). There are also the psychological costs that arise from familial separation, cultural displacement, and the uncertainty associated with international immigration. To bring the thesis of this paper into focus, it is important to realize that the primary goal of immigration control policy is to create additional intervening obstacles. Border walls and immigration checkpoints are obvious examples of creating physical barriers to illegal immigration. These supplementary obstacles lead to even higher costs of migration.

Central to this analysis is the existence of varying "personal factors" that potential migrants possess. Examples include marriage status, parental status, land-owning status, age, physical build, intelligence, education, work experience, personal wealth, etc. While many of these characteristics will be accounted for in the empirical analysis, I will focus on one broad characteristic for the theoretical framework of this paper: motivation/ability. This attribute describes an individual's desire to improve their lot in life, and their capability to actually do so. As stated before, I assume that an individual with a high degree of motivation/ability will have relatively high workplace productivity and relatively low personal costs of migration.

Chapter 3

MODEL

I begin this section by developing the foundations of the model: the migration-decision utility function and migrants' marginal productivity function, with the "motivation/ability" attribute as the centerpiece. I then demonstrate the labor screening effect of immigration control policy through a discrete and specific example. In order to solve the model more generally, I establish the motivation/ability variable along a uniform distribution. With this done, I first solve the model under the assumption of exogenous wage-setting, like we would expect to see in sectors where migrants are earning minimum wage, or where the wage rate is virtually determined by external factors (e.g. the native labor force). I then solve the model under endogenous wage-setting, in which there is a feedback loop between average migrant productivity and the wage rate offered to migrants. With both models, I find a positive labor screening effect: there is a direct relationship between average migrant productivity and the level of immigration control policy. I go on to discuss the effects of shocks to "push" and “pull” factors, such deteriorating homeland conditions or improvements productivity in productivity.

After establishing a linear welfare function for nation j, I model optimal government behavior in response to changes in various conditions, such as the cost of implementing immigration control policy, social attitudes regarding migrants, or a widening wage-gap. Afterward, I examine and discuss three possible expansions of the model, beginning with rejection and deportation of illegal immigrants. I show that an active deportation mechanism has an even greater effect on migrant productivity than inert immigration control measures (such as building a wall) through its state-contingent impact on the migration-decision utility function, as well as its differential screening impact on low vs. high motivation/ability individuals. Next, I expand the original model to include more than one destination-nation and solve for the general form, as well as illustrate through a simple discrete example. Finally, I discuss the implications of introducing error terms into the utility and productivity functions.

3.1 Migration-Decision Utility Function

In order to develop the model, I begin by constructing a utility function for an individual who is considering migrating to another nation. We assume that the individual calculates an expected utility for every possible location choice, and subsequently chooses the nation destination that affords the best outcome. For the purposes of illustration, we will imagine a Mexican laborer making this decision. Potential migrant i chooses country j that maximizes

$$U_i = max(U_{MEX,i}\ , U_{US,i}\ , U_{CAN,i}\ , \dots\ , U_{Ji})$$

For the sake of simplicity, I assume that the expected utility of each nation-choice, U_{ji} is a function of two elements. The first is the migrant's expected real wage rate that he or she could earn in nation j's labor market, W_{ij}. It is very important to note that this wage rate is *conditional* on the individual's personal characteristics (e.g. educational attainment, work experience, gender), and is adjusted for the cost-of-living in that nation. The second element of the potential migrant's nation-choice utility function is the expected cost of migration, C_{ji}. The expected cost of migration is different for each destination-nation, as well as for each individual under consideration. Continuing with the example, our Mexican laborer observes the following:

$$U_{MEX,i} = f(W_{MEX,i})$$

$$U_{US,i} = f\left(W_{US,i}\right) - C_{US,i}(P_{US}\ , D_{US,i}\ , E_{US,i}\ , M_i)$$

$$U_{CAN,i} = f\left(W_{CAN,i}\right) - C_{CAN,i}(P_{CAN}\ , D_{CAN,i}\ , E_{CAN,i}\ , M_i)$$

…

$$U_{Ji} = f\left(W_{Ji}\right) - C_{Ji}(P_J\ , D_{Ji}\ , E_{Ji}\ , M_i)$$

The costs of migration take multiple factors into account, and it is important to note that these costs are monetary, physical, and emotional.

The variable P_j represents the strictness of nation j's immigration control policy, and is pivotal to the analysis in this paper. The costs that are incurred through immigration control policy manifest both in legal and illegal immigration. When obtaining legal residency documentation, there is a myriad of bureaucratic obstacles that require time, energy, and money to overcome. Illegal migration comes with an even greater variety of costs. In order to cross protected borders undetected, some migrants are forced to cross dangerous terrain such as desert or ocean, and these migrants face a significant chance of serious injury or death. In 2009 alone, the United States Border Patrol reported that 417 migrants perished while crossing the U.S.-Mexican border. In order to avoid the difficulties of making the trip alone, some migrants pay "coyotes" (i.e. people-smugglers) a significant monetary fee in order to circumvent border security. Regardless of the method used to relocate, we assume that the costs of migration rise as immigration control policy becomes stricter. In addition to all this, as the effectiveness/strictness of immigration agencies increases, the risk of deportation increases. Not only does this render an unsuccessful migrant's "investment" wasted, but they also incur the physical and emotional costs that are inherent in the arrest and detainment process.

The variable D_{jh} represents the distance between nation j and the potential migrant's home location, h. As the distance between the two nation increases, the cost of migrating increases due to several factors. The most obvious is the monetary/temporal/physical cost of actually transporting the migrant's person to the new nation. Other factors include significant temperature or climate change and the toll of long-distance familial separation.

The variable E_{ji} represents "ethnic differences." This variable captures all of the culture-shock effects of relocating to a new country. Perhaps the most significant of these is the struggle of dealing with international language barriers. Combined with a lack of knowledge of local institutions and customs, migrants can find it very difficult to adapt to a new labor market. This is very costly for an individual, especially when factoring in the emotional discomfort associated with an uncertain economic future. In addition to this, belonging to a minority or "foreign" ethnic group potentially leaves a migrant vulnerable to the actions of xenophobic natives. Therefore, the greater the difference between migrant i's ethnic/cultural/lingual characteristics and that of the population of nation j, the greater the costs of migrating to that particular nation.

The last variable, M_i, represents the motivation/ability of the individual making this decision. This catch-all variable encompasses an individual's personal drive and enthusiasm for a better life, as well as their ability to complete demanding tasks. Therefore, I assume that this motivation/ability attribute is positively correlated with the migrants' marginal productivity, θ_{ij}. I model marginal productivity as:

$$\theta_{ji} = f(M_i) + K_j$$

where $\partial\theta_i/\partial M_i > 0$ and $K_j > 0$.

In addition to this, I also assume that M_i is negatively correlated with the expected costs of migration. This is in accordance with Spence's labor screening model, I am simply substituting the "cost of education" with the "cost of migration". In order to illustrate this inverse relationship, consider a migrant that is relatively more physically and mentally capable than others. This individual is less likely to incur serious injury during a border crossing, or suffer setbacks in the process of legal immigration. Therefore, that migrant's expected costs of migration are going to be lower than other potential migrants.

There are many forms that the utility and marginal productivity functions could take. For the sake of simplicity, I will assume that the functions are strictly linear for the rest of this analysis. The utility and marginal productivity functions are written as:

$$U_{ji} = W_{ji} - (\alpha P_j + \beta D_{jh} + \gamma E_{ji})(1 - M_i)$$

$$\theta_{ji} = \delta M_i + K_j$$

3.2 Immigration Control Policy as Labor Screening Device: A Simple Example

Now that I have established the foundation of the model, I will demonstrate the ability of a nation to screen potential migrants by utilizing stricter immigration control policies. I will do so through a specific example. Suppose there are three equally large groups of potential migrants that are all of the same nation (Mexico) and ethnicity. The groups vary by the motivation/ability attribute, such that Group 1 laborers have $M_i = -0.5$, Group 2 laborers have $M_i = 0$, and Group 3 laborers have $M_i = 0.5$. For the sake of simplicity, all of these individuals have identified the U.S. as the best relocation choice; thus the ultimate decision is whether to stay in Mexico or migrate to the United States. I will assume that $D_{j/MEX}$ and $E_{j,I}$ are the same for all individuals, and will standardize their values to 1. I will also arbitrarily assign a value of 1 to the parameters α, β, γ, δ and K_{US}. And finally, we observe wages rates for the two countries such that $W_{MEX} = 1.5$ and $W_{US} = 4$.

Let's begin the analysis by assuming the United States has immigration policy such that $P_{US} = 0$. If this is the case, then for Group 1 individuals, the utility of migrating to the United States is $U_{US} = 4 – (0 + 1 + 1)(1 + 0.5) = 1$. Therefore, the laborers of Group 1 will choose not to migrate, since doing so yields a lower utility than staying in Mexico, where $U_{MEX} = 1.5$. For the workers of Group 2, migrating to the U.S. yields a utility of $U_{US} = 4 – (0 + 1 + 1)(1) = 2$. For group 3 individuals, migration confers a utility of $U_{US} = 4 - (0 + 1 + 1)(1 - 0.5) = 3$. Thus, the members of both Group 2 and Group 3 will decide to move to the United States.

Keep in mind that all three groups are equally sized, and that $\theta_i = M_i + 1$. Therefore, the average marginal productivity of the migrants entering the United States is $E(\theta) = 0.5(0 + 1) + 0.5(0.5 + 1) = 1.25$. This is higher than the average marginal productivity of all the potential migrants, $E(\theta) = 1$. This is a basic demonstration of the positive selectivity of migrants in general. Even without any immigration control policy, the expected "distance" and "ethnic differences" costs incurred by the Group 1 individuals were too high to justify the wage increase. These migration costs are smaller for Group 2 and 3 individuals, thus leading these higher productivity individuals to migrate into the U.S.

Table 3.1 Summary of Discrete Example

	$P_j = 0$				$P_j = 1$		
	Group 1	**Group 2**	**Group 3**		**Group 1**	**Group 2**	**Group 3**
Motivation	-0.5	0	0.5	Motivation	-0.5	0	0.5
Migration Cost	3	2	1	Migration Cost	4.5	2	1.5
U_{US}	1	2	3	U_{US}	-0.5	1	2.5
U_{MEX}	1.5	1.5	1.5	U_{MEX}	1.5	1.5	1.5
Decision	Stay	Migrate	Migrate	Decision	Stay	Stay	Migrate
Productivity	0.5	1	1.5	Productivity	0.5	1	1.5
Average Migrant Productivity = 1.25				Average Migrant Productivity = 1.5			

In order to illustrate the impact of a change in immigration control policy in this example, we now assume that the United States has implemented new immigration policy such that $P_{US} = 1$. Group 1 individuals are now even more disinterested in migrating, with an expected utility of $U_{US} = 4 – (1 + 1 + 1)(1 + 0.5) = -0.5$. With the new policy, Group 2 workers now expect a utility of $U_{US} = 4 – (1 + 1 + 1)(1) = 1$, and Group 3 observes an expected utility of $U_{US} = 4 – (1 + 1 + 1)(1 – 0.5) = 2.5$. Therefore, the implementation of stricter immigration control policy has caused Group 2 to stay in Mexico, while Group 3 will still migrate to the United States. Now that Group 2 has been “screened” by the increase in immigration control policy; the average productivity of the migrant labor force in the United States has risen from 1.25 to 1.5. This is a demonstration of the positive correlation between a nation’s immigration control policy and the average productivity of its incoming migrants.

3.3 Distribution of Motivation/Ability Attribute

In the “simple example” of labor screening that I just provided, I grouped the laborers into three discrete groups, differentiated by the motivation/ability characteristic. This allowed for an easy demonstration, but is not representative of reality. One can safely assume that the motivation/ability attribute follows a continuous distribution. For the purpose of this analysis, I establish that the motivation/ability variable follows a continuous and uniform distribution bounded between M_L and M_H:

$$M_i \sim [M_L, M_H]$$

I assume that $M_H \leq 1$, since a motivation/ability attribute exceeding 1 would lead to the highly improbable situation in which individuals migrate to nation j despite receiving any benefits for doing so (recall that the motivation/ability modifier is $(1 - M_i)$. This supposition also allows for the assumption that the wage rate in nation j is higher than the utility of the next best alternative, $W_{ij} > U_{ALT}$, as long as any individuals are migrating to nation j.

3.4 Equilibrium Model: Exogenous Wage-Setting

3.4.1 Exogenous Immigration Control Policy

The example of labor screening that I just described makes two assumptions. The first assumption is that a nation's immigration control policy is exogenously determined. In other words, the government of a nation does not consider labor market information when making legislative decisions regarding border security or legal paths to residency/citizenship. Based on historical evidence in the U.S., this assumption is rather weak. Over the past century, the United States Congress has passed three Acts which significantly reformed the nation's immigration control policy (refer to section on History of Immigration for more details). The first Act was passed with the purpose of maintaining ethnic homogeneity, the second was ratified in order to promote multiculturalism and family reunification, and the third Act was passed in response to the security threat of the September 11 terrorist attacks. Therefore, it is relatively safe to assume that a nation's immigration control policy is set exogenously.

3.4.2 Exogenous Wage-Setting

The second assumption that I am making is that the wage rate offered by firms in this market is exogenously determined. This is a rather strong assumption. It is assumed that firms will offer a wage rate that is equal to average marginal productivity, and the average marginal productivity of incoming migrants is determined by the wage rate being offered (among other things). The existence of this feedback loop weakens the validity of the assumption of exogeneity.

That being said, there are several reasonable arguments to be made in defense of the assertion of exogeneity of wage setting for migrants. The first argument requires the assumption that firms are unable to discern migrant laborers from native laborers. If we assume that employers cannot tell the laborers apart, then they will pay both groups the same wage rate, ceteris paribus. Keep in mind that incoming migrants often make up an insignificant share of the overall labor force. In 2009, just over 1.1 million immigrants entered the United States (source: OECD), which was less than 1% of the total labor force. Therefore, the wage rate offered to these incoming migrants would be virtually decided by the average productivity of the overall labor force. Since the domestic labor force and its attributes are external to this particular immigration model, it is safe to say that, under the given assumptions, the wage rate is set exogenously.

Another potential argument to be made in favor of exogenous wage setting, particularly for low-skill laborers, is that the wage is set through wage floor legislation. If the natural equilibrium price is below the minimum wage for a particular set of laborers, firms will be forced to pay the legislated wage rate rather than set their wages according to the marginal productivity of those laborers. Many urban immigrants tend to be clustered in these low-wage labor markets, such as food service and preparation industry. Therefore, this model is an especially good fit for laborers in this sector.

3.4.3 Solving the Equilibrium Model

Under the assumptions that every variable in the model except M_i is exogenously determined, finding the equilibrium results is fairly straightforward.

In order to do so, I must first identify which migrants will actually migrate. We know that the individual will migrate to country j if doing so confers a higher utility then the next best alternative nation: $U_{ji} > U_{ALT}$.[5] After substituting equation (1) in for U_{ji}, we say that an individual migrates if:

$$W_{ji} - \left(\alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)(1 - M_i) > U_{ALT}$$

I rearrange this inequality so that we can determine what level of the motivation/ability attribute is necessary in order for an individual to actually migrate to country j:

$$-\left(\alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)(1 - M_i) > U_{ALT} - W_{ji}$$

$$\alpha P_j M_i + \beta D_{jh} M_i + \gamma E_{ji} M_i > U_{ALT} - W_{ji} + \alpha P_j + \beta D_{jh} + \gamma E_{ji}$$

$$M_i > \frac{U_{ALT} - W_{ji} + \alpha P_j + \beta D_{jh} + \gamma E_{ji}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}}$$

Now we know the exact range of the motivation/ability attribute that is necessary for an individual's utility to be higher in country j than the individual's best alternative location. Using this information, I identify the minimum level of the motivation/ability attribute of incoming migrants as:

$$(3) \quad M_{min} = 1 - \frac{W_{ji} - U_{ALT}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}}$$

[5] Initially, I simplify the model by assuming that there are only two nations. Thus, U_{ALT} represents the utility derived by remaining in one's home country. I will expand the model to include more than just two nations in a later section.

Now that the minimum level of motivation/ability has been determined for incoming migrants, I define the number of incoming immigrants, I, as the range of the motivation/ability distribution that lies above this. Therefore:

$$I_j = 0 \qquad \text{if } M_{min} > M_H$$

$$I_j = M_H - M_{min} \qquad \text{if } M_H > M_{min} > M_L$$

$$I_j = M_H - M_L \qquad \text{if } M_{min} < M_L$$

I now proceed to calculating average migrant marginal productivity. According to equation (2), average migrant productivity is equal to:

$$E(\theta_{ji}) = \delta E(M_i) + K_j$$

Keeping in mind that M_i follows a uniform distribution, average migrant marginal productivity is equal to:

$$E(\theta_{ji}) = 0.5\delta(M_{min} + M_{max}) + K_j$$

We can automatically infer that $M_{max} = M_H$, since all individuals with $M_i > M_{min}$ migrate. Therefore, average migrant productivity is defined as:

$$(4) \quad E(\theta_{ji}) = 0.5\delta(M_{min} + M_H) + K_j$$

In the instance in which the minimum level of the motivation/ability attribute that is necessary in order for an individual to migrate, M_{min}, is below the entire distribution of M_i

($M_{min} < M_L$), all of the potential migrants in the model will decide to move to nation j. Therefore, M_L can be substituted in for M_{min} and average migrant productivity is:

$$E(\theta_{ji}) = 0.5\delta(M_L + M_H) + K_j \qquad \text{if } M_{min} < M_L$$

Next, let's examine the instance in which the minimum level of the motivation/ability attribute is necessary in order for an individual to migrate falls within the distribution of M_i ($M_H > M_{min} > M_L$). In this case, I substitute equation (3) in for M_{min} and find that average migrant productivity is:

$$(5) \quad E(\theta_{ji}) = 0.5\delta\left(1 - \frac{W_{ji} - U_{ALT}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}} + M_H\right) + K_j \qquad \text{if } M_H > M_{min} > M_L$$

In the instance in which M_{min} is higher than the entire distribution of motivation/ability distribution ($M_{min} < M_l$), nobody migrates to nation j. Therefore:

$$E(\theta_{ji}) \; is \; undefined \qquad \text{if } M_{min} > M_H$$

Since every other variable in this equation is externally chosen, this model (operating under the assumptions of exogenous wage-setting and immigration control policy) has now been completely solved.

3.4.4 Interpreting the Model

Now that the model has been solved, we can examine the relationships between the variables in this model, such as the impact of immigration control policy on the productivity of incoming migrants. In order to conduct this comparative statics analysis, I do so through the three different sets of initial conditions described above: (1) some individuals are migrating and some are staying, (2) nobody is migrating, and (3) everybody is migrating.

Scenario 1: Some Initial Migration

Necessary Conditions $[M_H > M_{min}^* > M_L]$

Let's begin with the first scenario, in which some laborers initially decide to migrate to nation j and some decide to remain in their home country. In order for this to be the case, there needs to be some individuals with a motivation/ability attribute level that is high enough to grant them a relatively higher utility in nation j. Conversely, there needs to be some individuals with a low enough motivation/ability such that the adjusted costs of migration are too high to justify moving to a new country. In other words, those at the top of the motivation/ability distribution are migrating and those at the bottom are not migrating.

In terms of the mathematical model I have developed, I say that some people will migrate to country j if the initial minimum level of the motivation/ability attribute necessary to migrate is less than the upper limit of the motivation distribution, yet greater than the lower limit of the distribution: $M_H > M_{min}^* > M_L$. After substituting for M_{min} using equation (3), we find that some laborers initially migrate to country j if:

$$M_H > 1 - \frac{W_{ji} - U_{ALT}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}} > M_L$$

Comparative Statics: Impact of Immigration Control Policy on Number of Migrants

With Scenario 1, the initial minimum level of the motivation/ability attribute that is necessary for an individual to choose to migrate falls between the lower and upper bound of the distribution. Recalling that the initial number of incoming immigrants is: $I_j = M_H - M_{min}$, and substituting equation (3) in for M_{min}:

$$(6) \quad I_j = M_H - 1 + \frac{W_{ji} - U_{ALT}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}}$$

By taking the partial derivative of equation (6), I find the differential impact of immigration control policy on the number of incoming migrants:

$$\frac{\partial I_j}{\partial P_j} = -\alpha \frac{W_{ji} - U_{ALT}}{(\alpha P_j + \beta D_{jh} + \gamma E_{ji})^2}$$

Since it is assumed that $\alpha > 0$, $W_{ji} > U_{ALT}$, and the costs of migration are positive ($\alpha P_j + \beta D_{jh} + \gamma E_{ji} > 0$), there is an inverse relationship between the number of migrants and the level of immigration control policy: $\partial I/\partial P_j < 0$. This is not a surprising result at all, given that the purpose of immigration control policy is to prevent, deter, or filter immigrants. An increase in P_j causes migration to be more costly, thus reducing overall migration.

Comparative Statics: Impact of Immigration Control Policy on Migrant Productivity

With Scenario 1, the initial minimum level of the motivation/ability attribute that is necessary for an individual to choose to migrate falls below the upper bound of that variable's distribution. Therefore, some immigration occurs ($M_H - M_L > I_j^* > 0$) and, recalling equation (5), average migrant marginal productivity is:

$$E(\theta_{ji}) = 0.5\delta \left(1 - \frac{W_{ji} - U_{ALT}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}} + M_H\right) + K_j$$

In order to find the differential impact of immigration control policy on average migrant productivity, I take the partial derivative of this equation with respect to P_j:

$$(7) \quad \frac{\partial E(\theta_{ji})}{\partial P_j} = 0.5\alpha\delta \frac{W_{ji} - U_{ALT}}{\left(\alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)^2}$$

With equation (7), we observe direct evidence of the labor screening effect of immigration control policy in this model, since there is a positive relationship between immigration policy and migrant productivity: $\partial E(\theta_{ij})/\partial P_j > 0$. We know this to be true because there is a direct relationship between the costs of migration and immigration policy ($\alpha > 0$), we have assumed that the wage offered in nation j is higher than at home ($W_{ji} - U_{ALT} > 0$), the costs of migration are positive ($\alpha P_j + \beta D_{jh} + \gamma E_{ji} > 0$), and the relationship between motivation/ability and productivity is positive ($\delta > 0$).

Since it is the centerpiece of this analysis, let's examine how the variables and parameters in this model impact the magnitude of this labor screening effect, beginning with P_j itself. Taking the partial derivative of equation (7) with respect to P_j yields:

$$\frac{\partial^2 E(\theta_{ji})}{\partial P_j^2} = -\alpha^2\delta \frac{W_{ji} - U_{ALT}}{\left(\alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)^3}$$

Thus, we find that there is an inverse relationship between the magnitude of the labor screening effect and the level of immigration control policy: $\partial^2 E(\theta_{ij})/\partial P_j^2 < 0$. In other words, a nation with a relatively strict immigration policy will see a relatively smaller productivity impact from an incremental change to its policy. One could say that, in terms of its labor screening properties, immigration control policy exhibits diminishing marginal returns.

Nearly the same exact relationship[6] applies to all but one of the other parameters and variables that comprise the costs of migration: β, D_{jh}, γ, and E_{ji}. This is due to the fact that these factors impact a potential migrant in the same way that a change in P_j would. An individual is going to consider the dangers of traveling a long distance (D_{jh}) in the same way that they will consider the dangers of border security (P_j), and thus their differential impact on the labor screening effect will match.

The exception to this is the migrants' cost multiplier to immigration policy: α. Suppose there is a shock to this parameter, perhaps due to a stronger "coyote" network between the origin-nation and nation j, improved forgery

[6] $\partial^2 E(\theta_i)/\partial P_j \partial\beta = -\alpha D_{jh} (W_{ji} - U_{ALT}) (\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-3} > 0$

$\partial^2 E(\theta_i)/\partial P_j \partial D_{jh} = -\alpha\beta (W_{ji} - U_{ALT}) (\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-3} > 0$

$\partial^2 E(\theta_i)/\partial P_j \partial\gamma = -\alpha E_{ji} (W_{ji} - U_{ALT}) (\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-3} > 0$

$\partial^2 E(\theta_i)/\partial P_j \partial E_{ji} = -\alpha\gamma (W_{ji} - U_{ALT}) (\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-3} > 0$

techniques, and so on. Taking the partial derivative of the labor screening effect with respect to α, I find:

$$\frac{\partial^2 E(\theta_{ji})}{\partial P_j \partial \alpha} = 0.5\delta \frac{W_{ji} - U_{ALT}}{\left(\alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)^2} - \alpha\delta \frac{P_j(W_{ji} - U_{ALT})}{\left(\alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)^3}$$

$$\frac{\partial^2 E(\theta_{ji})}{\partial P_j \partial \alpha} = \delta\left(W_{ji} - U_{ALT}\right) \frac{0.5\left(\alpha P_j + \beta D_{jh} + \gamma E_{ji}\right) - \alpha P_j}{\left(\alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)^3}$$

Since $W_{ji} - U_{ALT} > 0$, and all of the other parameters are positive, we cannot ascertain the sign of this relationship. In the case that immigration control policy costs composes the majority of migration costs, such that $\alpha P_j > \beta D_{jh} + \gamma E_{ji}$, there is an inverse relationship between the labor screening effect and the policy cost multiplier: $\partial^2 E(\theta_{ij})/\partial P_j \partial\alpha < 0$. Otherwise, there is a direct relationship between the two. The reason for the conflicting results: the parameter α determines the differential impact of P_j (positive substitution effect), as well as being a component of overall costs of migration (negative income effect).

Lastly, let's examine how a shock to δ, the relationship between motivation/ability and migrant productivity, impacts the magnitude of the labor screening effect. As we can see in equation (4), if the two attributes are independent of one another (δ = 0), then average migrant productivity reduces to $E(\theta_{ij}) = K_j$. Therefore, when δ = 0, there is no labor screening effect in this model: $\partial E(\theta_{ij})/\partial P_j = 0$. In order to find the exact impact, I derive equation (7) with respect to δ:

$$\frac{\partial^2 E(\theta_{ji})}{\partial P_j \partial \delta} = 0.5\alpha \frac{W_{ji} - U_{ALT}}{\left(\alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)^2}$$

Unlike the other variables, the relationship between $\partial E(\theta_{ij})/\partial P_j$ and δ is linear as well as direct. In other words, the stronger the relationship between motivation/ability and productivity, the stronger the labor screening effect of P_j will be, at a constant rate. Due to this fact, and the fact that $\partial E(\theta_{ij})/\partial P_j = 0$ when $\delta = 0$, it is obvious that this parameter is very important in the labor screening process. This is because it is the connection between a migrants' decision-making process (M_i) and his or her workplace productivity (θ_i), which is the conceptual foundation of the labor screening process.

Comparative Statics: Impact of Other Parameters and Variables

Let's begin by analyzing the impact of a shock to the utility that an individual derives by remaining in their home country, U_{ALT}. In order to determine the relationship between origin-nation conditions and the number of immigrants, I take the partial derivative of equation (6) with respect to U_{ALT}:

$$\frac{\partial I_j}{\partial U_{ALT}} = -\frac{1}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}}$$

Since the costs of migration are positive, we can clearly see that there is an inverse relationship between U_{ALT} and I_j. This makes perfect sense: if conditions are worse at home, then there is greater incentive to move elsewhere (and vice versa). Thus, we can identify U_{ALT} as the "push" factor in this model.

In order to find the relationship between origin-nation conditions and the productivity of the workers that actually migrate, I take the partial derivative of equation (5) with respect to U_{ALT} and find:

$$\frac{\partial E(\theta_{ji})}{\partial U_{ALT}} = -\frac{0.5\delta}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}}$$

Since $\delta > 0$ and the costs of migration are also positive, we find that there is a direct relationship between the utility derived at home and average migrant productivity: $\partial E(\theta_{ij})/\partial U_{ALT} > 0$. This result is due to the fact that an increase in wages at home leads to a smaller wage premium for migrating to nation j. This smaller wage premium causes the individuals who were barely better off by migrating to no longer migrate. Since these individuals were the ones with a relatively lower level of motivation/ability, the average productivity of those who do actually migrate increases.[7]

[7] This inverse relationship between homeland conditions and the productivity of those who leave was identified by Anwar-ul-Huq (1979), who argued that a significant decrease in conditions at home would push out all kinds of individuals as a matter of necessity. Otherwise, the migrant pool consists mostly of those who seek economic opportunity, and these tend to be more capable and motivated people.

Next, let's examine the impact of a shock to the wage offered to migrants in nation j, W_{ij}. When we take the partial derivatives of average migrant productivity and the immigrant population and with respect to W_{ij}, I find that the relationships between these variables exactly mirrors that for U_{ALT}, but with a reverse sign:

$$\frac{\partial I_j}{\partial W_{ji}} = \frac{1}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}}$$

$$\frac{\partial E(\theta_{ji})}{\partial W_{ji}} = \frac{0.5\delta}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}}$$

This is the case because the only importance that U_{ALT} and W_{ij} serve in this model is the difference of the two: the wage premium ($W_{ji} - U_{ALT}$). Therefore, a one unit decrease in one variable has exactly the same impact as a one unit increase in the other variable. Also, notice that there is a positive relationship between the number of immigrants and the wage being offered: $\partial I_j/\partial W_{ij} > 0$. Thus, we can identify W_{ij} as the "pull" factor in this model.

When we examine the impact of a shock to one of the parameters or variables comprising the costs of migration, we find a result that is virtually identical to the impact of P_j.[8] An increase in any of the migration cost factors will

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[8] $\partial E(\theta_{ij})/\partial \alpha = 0.5\delta P_j (W_{ji} - U_{ALT}) (\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-2}$

$\partial E(\theta_{ij})/\partial D_{jh} = 0.5\delta\beta (W_{ji} - U_{ALT}) (\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-2}$

$\partial E(\theta_{ij})/\partial \beta = 0.5\delta D_{jh} (W_{ji} - U_{ALT}) (\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-2}$

cause an increase in immigrant productivity and a decrease in the number of incoming migrants. This is due to the fact that the costs of migration are linear in this model, so that there is effectively no difference between the various components.

Next, let's examine the impact of labor productivity shocks, beginning with the correlation between motivation/ability and productivity, δ. The parameter only has an impact on $E(\theta_{ij})$, since there is no connection between migrant productivity and wage rate under the assumption of exogenous wage-setting. Individuals make their migratory decisions based on the wage premium and adjusted costs of motivation, and these remain unaffected. Therefore, the parameter has zero impact on the number (or composition) of incoming migrants: $\partial I_j/\partial\delta = 0$. However, it does have an influence on migrant productivity. Taking the partial derivative of equation (2) yields:

$$\frac{\partial E(\theta_{ji})}{\partial \delta} = 0.5(M_{min} + M_H)$$

Therefore, we know that:

$$\frac{\partial E(\theta_{ji})}{\partial \delta} > 0 \qquad if \quad M_{min} + M_H > 0$$

$\partial E(\theta_{ij})/\partial E_{ji} = 0.5\delta\gamma\,(W_{ji} - U_{ALT})\,(\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-2}$

$\partial E(\theta_{ij})/\partial\gamma = 0.5\delta\gamma\,(W_{ji} - U_{ALT})\,(\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-2}$

$$\frac{\partial E(\theta_{ji})}{\partial \delta} = 0 \qquad if \quad M_{min} + M_H = 0$$

$$\frac{\partial E(\theta_{ji})}{\partial \delta} < 0 \qquad if \quad M_{min} + M_H < 0$$

Put another way, if the average migrant has a positive motivation/ability, then an increase in δ will lead to an increase in average productivity. However, if the majority of the motivation/ability distribution of those who migrate is falls below zero, then there is an inverse relationship between the two.

Under the current assumption of exogenous wage-setting, a shock to K_j will have no impact on migration decisions: $\partial I_j/\partial K_j = 0$. This is due to the disconnect between $E(\theta_{ij})$ and W_{ij}, that I described earlier for the δ parameter. In terms of its impact on average marginal migrant productivity, I derive equation (4) with respect to K_j and find that $\partial E(\theta_{ij})/\partial K_j = 1$. This is due to the fact that K_j is merely a constant in the productivity function, which bears no link to the migration decisions made by individuals under the current assumptions.

Scenario 2: Zero Initial Migration

Necessary Conditions [$M_{min}* > M_H$]

Let's move onto the second scenario, in which nobody decides to migrate initially. In order for this to be the case, all of the potential migrants have a motivation/ability attribute level that is too low to grant them a relatively higher utility in the new nation. Let's put this in terms of the mathematical model I have developed. Nobody will migrate to country j if the initial minimum level of the motivation/ability attribute necessary to migrate is equal to or surpasses the upper limit of the motivation distribution: $M_{min}* > M_H$. After substituting for M_{min} using equation (3), I find that nobody migrates to country j if:

$$1 - \frac{W_{ji} - U_{ALT}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}} > M_H$$

Solving for the initial level of immigration control policy, P_j, I find that nobody migrates to country j if:

$$P_j^* > \frac{W_{ji} - U_{ALT}}{\alpha(1 - M_H)} - \frac{\beta D_{jh} + \gamma E_{ji}}{\alpha}$$

Thus, I have identified the necessary conditions for the initial level of immigration control policy for Scenario 2. If nation j's government decides to lower P_j beyond this point, then individuals at the top of the motivation/ability distribution will begin to migrate to the nation. Therefore, for the rest of this section, I denote the minimum level of immigration control policy at which zero individuals will migrate as:

$$P_j^H = \frac{W_{ji} - U_{ALT}}{\alpha(1 - M_H)} - \frac{\beta D_{jh} + \gamma E_{ji}}{\alpha}$$

Comparative Statics: Impact of Immigration Control Policy on Number of Migrants

With Scenario 2, the initial level of immigration control policy is so high that there are no individuals migrating to nation j: $I_j^* = 0$. Therefore, any differential change in P_j will have no impact on the number of incoming migrants: $\partial I_j/\partial P_j = 0$.

However, a nation with a significant enough drop in P_j can entice potential migrants to make the journey. Let's suppose that the initial M_{min}^* is exactly λ_H higher than M_H, such that:

$$M_{min}^* - \lambda_H = M_H$$

Substituting for M_{min}^*, we get:

$$\big(U_{ALT} - W_{ji}\big)\big(\alpha P_j^* + \beta D_{jh} + \gamma E_{ji}\big)^{-1} + 1 - \lambda_H = M_H$$

where P_j^* is the initial level of immigration control policy. When we solve for P_j^* we find:

$$P_j^* = \alpha^{-1}\left(\big(U_{ALT} - W_{ji}\big)(M_H - 1 + \lambda_H)^{-1} - \beta D_{jh} - \gamma E_{ji}\right)$$

Recall that the maximum level of immigration control policy at which individuals will migrate is:

$$P_j^H = \alpha^{-1}\left(\big(U_{ALT} - W_{ji}\big)(M_H - 1)^{-1} - \beta D_{jh} - \gamma E_{ji}\right)$$

Taking the difference of the between P_H and the initial level of P^* yields the change in immigration control policy that is necessary to entice individuals to begin migrating to country j:

$$P_j^H - P_j^* = \alpha^{-1}\left(\left(U_{ALT} - W_{ji}\right)(M_H - 1)^{-1} - \beta D_{jh} - \gamma E_{ji}\right) - \alpha^{-1}\left(\left(U_{ALT} - W_{ji}\right)(M_H - 1 + \lambda_H)^{-1} - \beta D_{jh} - \gamma E_{ji}\right)$$

$$P_j^H - P_j^* = \alpha^{-1}\left(\left(U_{ALT} - W_{ji}\right)(M_H - 1)^{-1} - (M_H - 1 + \lambda_H)^{-1}\right)$$

$$P_j^H - P_j^* = -\alpha^{-1}\lambda_H\left(\left(W_{ji} - U_{ALT}\right)(M_H^2 - 2M_H + M_H\lambda_H - \lambda_H + 1\,)^{-1}\right)$$

Therefore, if $\Delta P_j > -\alpha^{-1}\lambda_H (W_{ji} - U_{ALT}) (M_H^2 - 2M_H + M_H\lambda_H - \lambda_H + 1)^{-1}$, then M_{min} still exceeds M_H and no migration occurs. However, if $\Delta P_j \leq -\alpha^{-1}\lambda_H (W_{ji} - U_{ALT}) (M_H^2 - 2M_H + M_H\lambda_H - \lambda_H + 1)^{-1}$, nation j successfully begins enticing individuals to migrate.

In order to measure the total effect on migration, ΔI_j, one simply needs to compute the number of incoming migrants since this scenario begins with $I_j^* = 0$. Recall that the number of immigrants (when migration occurs) is:

$$I_j = M_H - M_{min}$$

After substituting for M_{min}, I find that the number of migrants is equal to:

$$I_j = M_H - \left(U_{ALT} - W_{ji}\right)\left(\alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)^{-1} - 1$$

Therefore, for scenario 2 (where initial migration is zero), when P_j has been lowered enough to prompt migration:

$$\Delta I_j = M_H - (U_{ALT} - W_{ji})(\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-1} - 1$$

Since the current level of immigration control policy as the initial level plus the shock, it is defined as:

$$P_j = P_j^* + \Delta P_j$$

Substituting for P_j yields:

$$\Delta I_j = I_j = M_H - (U_{ALT} - W_{ji})(\alpha P_j^* + \alpha \Delta P_j + \beta D_{jh} + \gamma E_{ji})^{-1} - 1$$

Since $U_{ALT} - W_{ji} < 0$, there is an inverse relationship between the number of migrants and the change in immigration control policy. This is exactly what is expected: looser/easier border security and legal migration processes are going to lead to more individuals willing to overcome the hurdles of immigration. We also find that there is an inverse relationship between our initial level of immigration control policy and the number of migrants. This is due to the fact that the gap between P_j* and P_H must be "covered" before any laborers consider migrating. The higher the initial level of immigration control policy, the larger that this gap is. When the gap is larger, it means that a larger amount of the change in policy, ΔP_j, is dedicated to overcoming this gap and therefore has a smaller impact on the number of migrants.

Comparative Statics: Impact of Immigration Control Policy on Migrant Productivity

Let's move onto the impact that a change in immigration control policy has on average migrant productivity. Differentially speaking, a shock to P_j will not cause a change in the average productivity of incoming migrants, since it is undefined (there are no migrants). This is because an infinitesimal change in P_j leads to an infinitesimal change in M_{min}, after which M_{min} will still exceed M_H (and there is zero migration). The same impact is observed for the all of the other variables and parameters in the model. Since average migrant productivity starts as undefined in Scenario 2, it is also impossible to calculate the total impact of a shock to P_j.

Comparative Statics: Impact of Other Parameters and Variables

In Scenario 2, infinitesimal changes in any of the parameters and variables result in the same impact as a change in P_j. In terms of the impact on the number of incoming migrants, the differential effect is equal to zero. This is because the scenario begins with $I_j^* = 0$. Since marginal productivity starts as undefined in Scenario 2 (as there are no migrants), we say that the differential impact of any of the parameters/variables is also undefined.

However, there can be a change in I_j with a significant finite change in the other variables and parameters. For example, suppose that the costs of migration fell significantly (due to decreasing distance or ethnic differences), or that conditions at home worsened considerably, or that the wage offered in nation j skyrocketed. In all three of these cases, some individuals will start to see nation j as the better choice and migration to that nation will begin.

Scenario 3: Complete Initial Migration

Necessary Conditions [$M_{min}* < M_L$]

In the third scenario, we have a situation in which all potential migrants are initially moving to nation j, because doing so grants them a higher utility. In other words, the minimum level of motivation/ability that a person would need to have in order to migrate is lower than the entire distribution of that characteristic: $M_{min}* < M_L$. After substituting equation (3) in for M_{min}, I find that all potential migrants initially migrate if:

$$1 - \frac{W_{ji} - U_{ALT}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}} < M_L$$

Solving for P, I find that everybody migrates if:

$$P_j < \frac{W_{ji} - U_{ALT}}{\alpha(1 - M_L)} - \frac{\beta D_{jh} + \gamma E_{ji}}{\alpha}$$

Therefore, I denote the maximum level of immigration control policy at which all individuals will migrate as:

$$P_L = \frac{W_{ji} - U_{ALT}}{\alpha(1 - M_L)} - \frac{\beta D_{jh} + \gamma E_{ji}}{\alpha}$$

Comparative Statics: Impact of Immigration Control Policy on Number of Migrants

In Scenario 3, the entire distribution of individuals is migrating to nation j. Therefore, the number of immigrants in scenario 3 is:

$$\mathrm{I}_j = M_H - M_L$$

Differentially, a shock to P_j will have no impact on the number of migrants: $\partial I_j/\partial P_j = 0$. An infinitesimal change will still result in the entire distribution migrating.

It is possible for a nation to increase its immigration control policy significantly enough such that some migrants start to become screened. Let's suppose that the initial M_{min}* is exactly λ_L lower than M_L, such that:

$$M_{min}^{*} + \lambda_L = M_L$$

After substituting for M_{min}*, and solving for P_j*:

$$P_j^* = \frac{(U_{ALT} - W_{ji})}{\alpha(M_L - 1 - \lambda_L)} - \frac{\beta D_{jh} - \gamma E_{ji}}{\alpha}$$

Recall the maximum level of immigration control policy at which all individuals will migrate:

$$P_j^L = \frac{(U_{ALT} - W_{ji})}{\alpha(M_L - 1)} - \frac{\beta D_{jh} - \gamma E_{ji}}{\alpha}$$

Taking the difference of the two yields the change in policy that is necessary for screening to take place:

$$P_j^L - P_j^* = \frac{(U_{ALT} - W_{ji})}{\alpha(M_L - 1)} - \frac{\beta D_{jh} - \gamma E_{ji}}{\alpha} - \frac{(U_{ALT} - W_{ji})}{\alpha(M_L - 1 - \lambda_L)} + \frac{\beta D_{jh} - \gamma E_{ji}}{\alpha}$$

$$P_j^L - P_j^* = \frac{\lambda_L(U_{ALT} - W_{ji})}{\alpha(M_L^2 - 2M_L - 2M_L\lambda_L + \lambda_L + 1)}$$

Therefore, if $\Delta P_j < \alpha^{-1}\lambda_L (U_{ALT} - W_{ji}) (M_L^2 - 2M_L - M_L\lambda_L + \lambda_L + 1)^{-1}$, then M_L still exceeds M_{min} and all potential migrants will continue to move to nation j. However, if

$\Delta P_j \geq \alpha^{-1}\lambda_L ((U_{ALT} - W_{ji}) ((M_L^2 - 2M_L - M_L\lambda_L + \lambda_L + 1)^{-1}$, nation j successfully begins screening migrants.

In order to measure the total effect on migration in the latter case, I take the difference between the I_j* and I_j:

$$\Delta I_j = I_j - I_j^* = (M_H - M_{min}) - (M_H - M_L)$$

$$\Delta I_j = M_L - M_{min}$$

After substituting for M_{min}, I find that the change in the number of migrants is equal to:

$$\Delta I_j = M_L - \frac{U_{ALT} - W_{ji}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}} - 1$$

After substituting for P_j:

$$\Delta I_j = M_L - \frac{U_{ALT} - W_{ji}}{\alpha P_j^* + \alpha \Delta P_j + \beta D_{jh} + \gamma E_{ji}} - 1$$

Just as expected, there is an inverse relationship between the change in the number of migrants and the change in immigration control policy. We also find this same relationship with the initial level of immigration control policy and change in migration. This is due to the fact that the gap between P_j* and P^L must be "covered" before any laborers consider migrating. The higher the initial level of immigration control policy, the smaller that this gap is. Therefore, a smaller amount of the change in policy, ΔP_j, is dedicated to overcoming this gap and more screening (decrease in I_j) occurs.

Comparative Statics: Impact of Immigration Control Policy on Migrant Productivity

For Scenario 3, the entire distribution of potential migrants is initially migrating to nation j. Therefore, we know that $M_{min} = M_L$. Substituting this into equation (4) yields an average migrant marginal productivity of:

$$E(\theta_{ji}) = 0.5\delta(M_L + M_H) + K_j$$

Differentially, a change in the level of immigration control policy will have no impact on the average productivity of the migrants: $\partial E(\theta_{ij})/\partial P_j = 0$. This is because M_{min} initially is not being decided by the level of immigration control policy in Scenario 3, but rather is defined as the lower bound of the motivation distribution. An infinitesimal change in P_j will not change this in any way; the entire distribution of individuals will continue to migrate, and average migrant productivity remains constant.

However, as discussed earlier, it is possible that a significant enough increase in P_j,
$\Delta P_j \geq \alpha^{-1}\lambda_L (U_{ALT} - W_{ji}) (M_L^2 - 2M_L - M_L\lambda_L + \lambda_L + 1)^{-1}$, can cause some migrants to become screened. In order to find the impact on average migrant productivity, I take the difference between initial and the new migrant productivity (recall equation (5)):

$$\Delta E(\theta_{ji}) = E(\theta_{ji}) - E(\theta_{ji})^*$$

$$\Delta E(\theta_{ji}) = 0.5\delta\left(\frac{U_{ALT} - W_{ji}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}} + 1 + M_H\right) + K_j - 0.5\delta(M_L + M_H) - K_j$$

$$\Delta E(\theta_{ji}) = 0.5\delta\left(\frac{U_{ALT} - W_{ji}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}} + 1 - M_L\right)$$

After substituting for P_j:

$$\Delta E(\theta_{ji}) = 0.5\delta\left(\frac{U_{ALT} - W_{ji}}{\alpha P_j^* + \alpha \Delta P_j + \beta D_{jh} + \gamma E_{ji}} + 1 - M_L\right)$$

Since $W_{ji} > U_{ALT}$, there is a direct relationship between the change in immigration control policy and change in average migrant productivity. The same exists for the initial level of immigration control policy. This is due to the fact that the migrants at the bottom end of the distribution now find migration to be too costly to justify moving. There is a direct relationship for the initial level as well. A higher initial P_j* leads to a smaller gap with P^L, meaning that the change in immigration control policy would have a greater impact on the actual screening process.

Comparative Statics: Impact of Other Parameters and Variables

In Scenario 3, infinitesimal changes in any of the parameters or variables result in the same impact as a change in P_j. In terms of the impact on the number of incoming migrants, the differential effect is equal to zero. This is because the scenario begins with $I_j^* = M_H - M_L$; a constant in which none of the parameters/variables have an impact. We observe the same differential impact with average migrant productivity, which has a constant value of $E(\theta_{ij}) = 0.5\delta(M_L + M_H) + K_j$.

However, there can be a change in I_j and $E(\theta_{ij})$ with a significant finite change in the other variables and parameters. For example, suppose that the costs of migration rose significantly (due to increasing ethnic differences), or that nation j's wage premium falls dramatically. In these instances, some individuals at the bottom of the motivation will choose not to migrate.

3.4.5 Optimal Government Behavior

Let's suppose that the government of nation j is aware of the labor screening process, has full information, and wishes to determine the optimal level of immigration control policy. In order to model this behavior, I first need to establish a linear welfare function for the government of nation j. I establish social welfare as a linear function of the number of immigrants, average migrant productivity, and the level of immigration control policy:

$$(8) \quad \dot{G}_j = \psi \dot{I}_j + \varphi \dot{E}(\theta_{ji}) - \Omega P_j$$

The parameter ψ determines the valuation that the citizens/government of nation j place on new migrants. The sign of this factor is uncertain and entirely circumstantial. For example, following World War 2, the commonwealth of Australia wanted to boost its population for strategic as well as economic purposes. In that case, we would expect ψ to have a positive value. However, this is an extremely rare occurrence. Throughout history, many nations have viewed migrants through an isolationist lens, and wish to maintain a homogenous ethnic culture or an insulated economy. Here we would see ψ take a negative value. And then, there are countries with mixed or neutral attitudes toward migrants, such as the United States, where we might consider the parameter to be insignificant (zero).

We can be certain of the sign of ϕ, which indicates the valuation that nation j places on the average productivity of its migrant population. Across the board, we expect this to have a positive value; nations always prefer to have individuals with a higher productivity. Having high productivity laborers simply leads to a relatively higher economic output for nation j, thus raising the standard of living. There are other elements as well. For example, lower productivity individuals tend to have higher unemployment rates (a real problem for migrants in the European Union), which leads to higher rates of impoverishment and crime. Therefore, we can be sure that $\phi > 0$.

The parameter Ω is the cost multiplier for the level of immigration control policy for nation j. This obviously has a positive value; the government must pay more money if it wishes to have stricter border security and legal migration processes. I have modeled this cost function as linear for the sake of simplicity, but it may be more accurate if this process exhibited some form of diseconomy of scale (e.g. $c(P_j) = P_j^{\Omega}$ where $\Omega > 1$). Since I have placed no resource restrictions on the government in this model, this immigration control policy cost will as the constraining factor in this optimization problem. Also, I will assume a lower bound of zero for the immigration control policy variable, thereby disallowing the illogical case in which a nation sets a negative P_j in an effort to increase its welfare through negative costs.

Now that I have established the social welfare function for nation j, let's determine exactly what the optimal level of immigration control policy is for government to choose. Let's begin with scenario 1, in which there are some individuals initially migrating. I begin by recalling equation (8) and substituting in for I_j and $E(\theta_{ij})$ with the equations for scenario 1:

$$G_j = \psi\left(M_H - 1 + \frac{W_{ji} - U_{ALT}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}}\right) + \Phi\left(0.5\delta\left(M_H + 1 - \frac{W_{ji} - U_{ALT}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}}\right) + K_j\right) - \Omega P_j$$

In order to find the level of immigration control policy that maximizes G_j, I derive with respect to P_j and set equal to zero:

$$\frac{\partial G_j}{\partial P_j} = 0.5\Phi\alpha\delta \frac{W_{ji} - U_{ALT}}{\left(\alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)^2} - \psi\alpha \frac{W_{ji} - U_{ALT}}{\left(\alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)^2} - \Omega = 0$$

After some rearrangement, I find that the optimal (see Appendix B for proof of maximum) level of immigration control policy is set at:

$$(9) \quad P_j^0 = \hat{P}_j^0 = \sqrt{\frac{(W_{ji} - U_{ALT})(0.5\Phi\delta - \psi)}{\alpha\Omega}} - \frac{\beta D_{jh} + \gamma E_{ji}}{\alpha} \qquad if\ P_L > \hat{P}_j^0 > 0$$

$$P_j^0 = 0 \qquad if\ \hat{P}_j^0 \leq 0$$

$$P_j^0 = P_H \qquad if\ \hat{P}_j^0 \geq P_H$$

Notice that there are two possible corner solutions to this optimization problem. The first, $P_j^o = 0$, occurs due to the constraining assumption that a nation cannot have negative immigration control policy, and the fact that nation j has no incentive to have a positive P_j level below P_L. Recall that P_L is the maximum level of immigration control policy at which all individual migrate. If $\acute{P}_j^o$ is less than P_L, nation j can reduce its costs with no change in migration by setting $P_j = 0$.

The second corner solution, $P_j^o = P_H$, is due to the fact that nation j has no incentive to raise its policy beyond P_H. Recall that P_H is the minimum level of immigration control policy in which zero individuals migrate. Raising P_j beyond this point would yield no difference in migration behavior, but costs Ω per additional unit.

Let's take a look at how the various variables and parameters differentially impact the optimal level of immigration control policy, assuming we are not at a corner solution. I begin with the term ($0.5\phi\delta - \psi$) in equation (9). This term indicates the relative valuations that nation j places on the size of the migrant population and the average screened productivity of that population. Keep in mind that we expect all the terms in this equation to be positive (see footnote on previous page). I derive equation (9) with respect to the variables/parameters in this term:

$$\frac{\partial P_j^0}{\partial \Phi} = 0.5\delta \sqrt{\frac{W_{ji} - U_{ALT}}{\alpha\Omega(0.5\Phi\delta - \psi)}}$$

$$\frac{\partial P_j^0}{\partial \delta} = 0.5\Phi \sqrt{\frac{W_{ji} - U_{ALT}}{\alpha\Omega(0.5\Phi\delta - \psi)}}$$

$$\frac{\partial P_j^0}{\partial \psi} = -\sqrt{\frac{W_{ji} - U_{ALT}}{\alpha\Omega(0.5\Phi\delta - \psi)}}$$

Whenever nation j has a relatively high ϕ (strongly values average productivity) and/or a high δ (strong correlation between productivity/motivation), this term becomes larger and nation j is better off by engaging in more screening by having stricter immigration control policy: $\partial P_j^o/\partial\phi > 0$ and $\partial P_j^o/\partial\delta > 0$. Conversely, if nation j has a relatively high value of ψ (strongly values large immigrant population), we expect the government to entice potential migrants by lowering their immigration control policy: $\partial P_j^o/\partial\psi <$

0. The magnitude of these effects are directly correlated with the wage premium, and inversely correlated with α and Ω.

Next, let's examine the impact of a change in the per-unit cost of immigration policy, Ω, on the optimal level of immigration policy, P_j^o. I derive equation (9) with respect to this parameter and find:

$$\frac{\partial P_j^0}{\partial \Omega} = -\sqrt{\frac{(W_{ji} - U_{ALT})(0.5\Phi\delta - \psi)}{\alpha\Omega^3}} - \alpha^{-1}\left(\beta D_{jh} + \gamma E_{ji}\right)$$

As we would expect to see, there is an inverse relationship between the per-unit cost of P_j, and the optimal level of P_j. The intuition behind this is simple: when the "marginal cost" of immigration control policy rises, the government needs "marginal benefit" to rise in order to achieve optimality.[9] Since P_j exhibits diminishing marginal returns, this means that nation j responds optimally by decreasing its immigration control policy. Therefore, if technological/productivity advances or changes in input prices lead to a decrease in Ω, we would expect to see nation j impose more costs on migrants through stricter immigration control policy.

What should the government of nation j do if there is an increase in the wage rate offered to migrants, or if conditions in the migrants' homeland

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[9] Through the perspective of marginal analysis of immigration control policy:
Marginal Benefit = $\alpha\,(0.5\phi\delta - \psi)\,(W_{ji} - U_{ALT})\,(\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-2}$
Marginal Cost = Ω

significantly worsen? In other words, what is the optimal policy response when there is a change in the wage premium? I derive equation (9) with respect to the two variables in question:

$$\frac{\partial P_j^0}{\partial W_{ji}} = 0.5\sqrt{\frac{0.5\Phi\delta - \psi}{\alpha\Omega(W_{ji} - U_{ALT})}}$$

$$\frac{\partial P_j^0}{\partial U_{ALT}} = -0.5\sqrt{\frac{0.5\Phi\delta - \psi}{\alpha\Omega(W_{ji} - U_{ALT})}}$$

Under the weak assumption that nation j places relatively more value on migrant productivity, $0.5\phi\delta > \psi$, I find that there is a direct relationship between optimal immigration policy and the wage premium in nation j. In other words, P_j^o has a positive correlation with the migrants' wage rate, and a negative relationship with their homeland conditions. The reason for this: when the wage premium increases, more migrants with relatively lower motivation/ability decide to enter nation j. The government of nation j optimally responds by tightening its immigration control policy in order to partially screen these new migrants. Through a marginal perspective, a hike in the wage premium causes the marginal benefit of immigration control policy to rise. It follows that that stronger immigration policy would be enacted.

Now, let's discuss the relationship between the non-policy costs of migration ($\beta D_{jh} + \gamma E_{ji}$) and P_j^o. In order to do so, I take the derivative of equation (9) with respect to this term:

$$\frac{\partial P_j^0}{\partial(\beta \mathrm{D}_{jh}\ +\ \gamma \mathrm{E}_{ji})} = -\frac{1}{\alpha}$$

A one unit increase in the non-policy costs of migration will cause the government of nation j to decrease its optimal immigration policy by a factor of $1/\alpha$. This inverse linear relationship exists because individuals treat policy costs the same as distance and ethnic costs, since the costs of migration are modelled linearly. So, in effect, the government is really setting the optimal level of total migration costs, but can only achieve this through its utilization of P_j. Recall that the costs of migration are: $\alpha P_j + \beta D_{jh} + \gamma E_{ji}$. Rearranging, we find that $P_j = \alpha^{-1}(\beta D_{jh} + \gamma E_{ji})$. Thus, for every unit of non-policy migration costs being incurred by migrants, the government can forgo enacting $1/\alpha$ units of P_j. In other words, these non-policy costs act as a negative income effect for optimal immigration control policy.

Next, let's move onto the impact of the individual's policy cost multiplier, α. I derive equation (9) with respect to α and find:

$$\frac{\partial P_j^0}{\partial \alpha} = 0.5\sqrt{\frac{(0.5\Phi\delta - \psi)(W_{ji} - U_{ALT})}{\alpha^3 \Omega}} + \frac{\beta \mathrm{D}_{jh}\ +\ \gamma \mathrm{E}_{ji}}{\alpha^2}$$

Unlike the other parameters and variables, we cannot be certain whether there is a direct or inverse relationship here. The first overall term represents the decision-making being made on the margin. This term is inversely correlated because an increase in α means that the impact of P_j is more pronounced on migrants (this can be seen as a negative substitution effect of sorts). Therefore, nation j does not need to set such strict immigration policy in order to achieve optimality. The second term is the income effect discussed in the previous paragraph, and this term is positively correlated with α. The reason: if α rises, the non-policy costs of migration ($\beta D_{jh} + \gamma E_{ji}$) will "replace" a relatively smaller amount of P_j when the government is setting the optimal level.

Let's move onto the impact of productivity shocks, beginning with the relationship between the parameter δ, and the optimal level of immigration control policy, P_j^o. I derive equation (9) with respect to δ:

$$\frac{\partial P_j^0}{\partial \delta} = \frac{0.25\Phi}{\sqrt{\frac{(0.5\Phi\delta - \psi)(W_{ji} - U_{ALT})}{\alpha\Omega}}}$$

I find that there is a direct relationship between the two, under the assumptions that have been made. Since nation j values higher migrant productivity, the marginal benefit of immigration control policy increases whenever there is a stronger connection between motivation/ability and productivity. In other words, there is a stronger connection between migrant productivity and the costs of migration, which is the mechanism through with nation j “screens” its migrants.

A shock to the constant in the productivity function, K_j, has zero impact on the optimal level of immigration control policy: $\partial P_j^o/\partial K_j = 0$. This is due to the fact that migrant productivity is not a factor in the decision-making of whether to migrate in the exogenous wage-setting model. A change in K_j results only in a change in $E(\theta_{ij})$ and has zero impact on the costs of migration, the wage premium, or any other migration-determining factors.

3.5 Equilibrium Model: Endogenous Wage-Setting

3.5.1 Endogenous Wage-Setting

In the previous model, I assumed that the wage rate being offered to incoming migrants was decided by a process external to the model. Now, I model this wage rate as being determined by the hiring firms using their current information regarding the migrant population. This means that this phenomenon must now be modeled as a multi-stage game with a feedback loop between the decisions of potential migrants and the wage being offered to those who migrate. Firms offer a particular wage rate, which causes some migrants to enter nation j. After hiring the migrants for one period, the firms learn their average marginal productivity, and offer a new wage rate to the incoming migrants based on this information. This new wage rate causes a different group of individuals to migrate, and the process continues until a steady-state equilibrium is reached.

I believe that the assumption of endogenous wage-setting is a very valid one and that this model is a better fit to reality than the previous model for some labor sectors. Firms use information about laborers when making payroll decisions, so we should model them as doing so. One of the arguments in favor of exogenous wage-setting was that firms cannot tell migrants apart from other workers, thus the domestic workforce virtually determines the migrants' wage rate. This is a very strong assumption for labor markets where a significant portion of the workers are migrants. Even in sectors that are dominated by domestic laborers, employers can use various physical, personal, and legal characteristics (e.g. ethnicity, primary language, residency or citizenship status, etc.), to discern whether a person is an immigrant or a native, and offer a wage rate accordingly.

The other argument in favor of exogenous wage-setting was the existence of a binding price floor. While this may definitely be the case in certain industries, e.g. food service and preparation, the majority of immigrants work in sectors that earn higher than minimum wage. (Orrenius and Zavodny 2007) Thus, it is safe to assume that, for most industries, firms will offer immigrants a wage rate based on their average marginal productivity rather than one that is mandated by the government.

3.5.2 Solving the Equilibrium Model

I begin by defining firms' wage-setting behavior. Firms choose wage rate W_{ij} that is equal to the expected marginal productivity of the migrants:

$$W_{ji} = E(\theta_{ji})$$

Recalling equation (4), we say that firms set:

$$W_{ji} = 0.5\delta(M_{min} + M_H) + K_j$$

In order to begin solving the steady state equilibrium of this model, I substitute this wage equation in for W_{ij} in equation (3), the minimum level of motivation/ability attribute necessary to choose to migrate to nation j:

$$M_{min} = 1 - \frac{0.5\delta(M_{min} + M_H) + K_j - U_{ALT}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}}$$

I rearrange and solve to determine the steady-state minimum level of the attribute necessary to migrate:

$$(10) \quad \overline{M}_{min} = \frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j + \beta D_{jh} + \gamma E_{ji}}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}}$$

Notice the change when we switch from exogenous to endogenous wage-setting. The decision to migrate is now impacted by the parameters and variables involved in migrants' productivity: δ, K_j, and M_H.

Now that I have determined the steady-state level of M_{min}, I calculate expected migrant marginal productivity in order to solve the model. I do so by substituting the above equation for $\dot{M}_{min}$ into the firm's wage-setting equation:

$$\overline{W}_{ji} = 0.5\delta\left(\frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j + \beta D_{jh} + \gamma E_{ji}}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}} + M_H\right) + K_j$$

We know that firms set the wage rate equal to expected marginal productivity. Therefore, when assuming an interior solution, the steady-state expected marginal productivity in this model is:

$$(11)\ \ \bar{E}(\theta_{ji}) = 0.5\delta\left(\frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j + \beta D_{jh} + \gamma E_{ji}}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}} + M_H\right) + K_j$$

$$if\ M_H >$$

$$\overline{M}_{min} > M_L$$

And then, just like the previous model, there are the two corner solutions for scenarios 2 and 3:

$$\bar{E}(\theta_{ji}) = 0.5\delta(M_L + M_H) \qquad\qquad if\ \overline{M}_{min} < M_L$$

$$\bar{E}(\theta_{ji})\ is\ undefined \qquad\qquad if\ \overline{M}_{min} > M_H$$

In order to determine the steady-state population of incoming migrants, I substitute equation (10) in for $\dot{M}_{min}$:

$$(12)\quad I_j = M_H - \frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j + \beta D_{jh} + \gamma E_{ji}}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}} \qquad if\ M_H > \bar{M}_{min} > M_L$$

And the two corner solutions:

$$I_j = 0 \qquad if\ \bar{M}_{min} < M_L$$

$$I_j = M_H - M_L \qquad if\ \bar{M}_{min} > M_H$$

3.5.3 Interpreting the Model

Now that the endogenous wage-setting model has been solved, we can examine the relationships between the variables and parameters in this model. In order to conduct this comparative statics analysis, I do so through the three different sets of initial conditions described in the previous section: (1) some individuals are migrating and some are staying, (2) nobody is migrating, and (3) everybody is migrating.

Scenario 1: Some Initial Migration

Necessary Conditions [$M_H > M_{min} > M_L$]

In the first scenario, we have a situation in which some migrants are initially moving to nation j, and some are staying in their home country. This occurs because the minimum level of the motivation/ability attribute needed to migrate falls between the upper and lower bounds of that attribute's distribution: $M_H > M_{min}^* > M_L$. Assuming that we are initially in long-run equilibrium, I substitute in for the steady state value of M_{min} and find that there is some initial migration if:

$$M_H > \frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j + \beta D_{jh} + \gamma E_{ji}}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}} > M_L$$

Comparative Statics: Impact of Immigration Control Policy on Number of Migrants

In the fully exogenous model, we found that an increase in immigration control policy causes a decrease in the number of migrants, as expected. To see if this is also the case under endogenous wage-setting, I derive equation (12) with respect to P_j and find:

$$\frac{\partial \bar{I}_j}{\partial P_j} = -\alpha \frac{0.5\delta + 0.5M_H + K_j - U_{ALT}}{\left(0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)^2}$$

In order to determine the nature of this relationship, recall that α, δ, and the costs of migration are positively valued. Under these assumptions, I find that there is an inverse relationship between immigration control policy and the size of the immigrant population: $\partial \dot{I}_j / \partial P_j < 0$. The proof of this can be found in Appendix A.

When comparing the magnitude of this relationship to the exogenous wage-setting model, I find that the immigration control policy has a smaller impact under the endogenous model. Under the exogenous model, a rise in P_j simply causes M_{min} to rise and migrant population to fall, and that's it. Under the endogenous model, the rise in M_{min} causes expected migrant productivity to rise, thereby leading the wage rate to rise. This wage rate increase entices more individuals to migrate to nation j, causing M_{min} to actually decrease. This counter-effect leads to P_j having a smaller labor-screening impact on the steady-state (equilibrium) $\dot{M}_{min}$ than it would have under exogenous wage-setting.

Comparative Statics: Impact of Immigration Control Policy on Migrant Productivity

Let's move onto the relationship between nation j's immigration control policy and the productivity of that nation's migrants. In order to do so, I derive equation (11) with respect to P_j and find:

$$(13) \quad \frac{\partial \bar{E}(\theta_{ji})}{\partial P_j} = 0.5\delta\alpha \frac{0.5\delta + 0.5M_H + K_j - U_{ALT}}{\left(0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)^2}$$

We observe a positive labor screening effect in this model: $\partial\bar{E}(\theta_{ij})/\partial P_j > 0$, since there is a positive correlation between the two variables because $0.5\delta + 0.5\delta M_H + K_j - U_{ALT} > 0$ (refer to Appendix A for proof), and the rest of the parameters/variables are positively valued. *Relative to the exogenous wage-setting model, this effect is of a lesser magnitude* due to the fact that responsive wage-setting counters some of the initial screening effect.[10]

Let's move onto an examination of the magnitude of this labor screening effect and how the various variables and parameters impact this, beginning with immigration control policy itself. Does the labor screening impact of immigration control policy fall as P_j rises, as with the exogenous model? I derive equation (13) with respect to P_j:

$$\frac{\partial^2 \bar{E}(\theta_{ji})}{\partial P_j^2} = -\delta\alpha^2 \frac{0.5\delta + 0.5M_H + K_j - U_{ALT}}{\left(0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)^3}$$

Since all of the terms in this equation are positive, immigration control policy exhibits diminishing marginal returns in terms of labor screening impact: $\partial^2\bar{E}(\theta_{ij})/\partial P_j^2 < 0$. As a nation expands its immigration control policy, the ability of

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[10] Recall the labor screening effect under exogenous wages: $\partial E(\theta_{ij})/\partial P_j = 0.5\delta\alpha\,(W_{ji} - U_{ALT})\,(\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-2}$
And the effect under endogenous wages: $\partial\dot{E}(\theta_{ij})/\partial P_j = 0.5\delta\alpha\,(0.5\delta + 0.5\delta M_H + K_j - U_{ALT})\,(0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-2}$

We know that the labor screening effect has a smaller magnitude under the endogenous model due to the addition of 0.5δ in the denominator, and the fact that $0.5\delta + 0.5\delta M_H + K_j \geq W_{ij} = 0.5\delta M_{min} + 0.5\delta M_H + K_j$.

incremental changes to policy to filter out immigrants lessens. Relative to the exogenous wage-setting model, immigration control policy has diminishing returns of a lower magnitude.

The same relationship applies to all but one of the other parameters and variables that comprise the costs of migration: β, D_{jh}, γ, and E_{ji}. An increase in any of the factors of the costs of migration will cause a decrease in the magnitude of the labor screening effect, due to the diminishing impact of migration costs. The relationship is identical because these costs impact a potential migrant in the same way that a change in P_j would, based on the linear nature of these costs.

Unlike the other migration cost parameters and variables, a change in the parameter α has an uncertain impact on the magnitude of the labor screening impact. Taking the partial derivative of equation (13) with respect to α:

$$\frac{\partial^2 \bar{E}(\theta_{ji})}{\partial P_j \partial \alpha} = 0.5\delta \frac{0.5\delta + 0.5M_H + K_j - U_{ALT}}{\left(0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)^2}$$

$$- \delta\alpha P_j \frac{0.5\delta + 0.5M_H + K_j - U_{ALT}}{\left(0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)^3}$$

$$\frac{\partial^2 \bar{E}(\theta_{ji})}{\partial P_j \partial \alpha} = \delta(0.5\delta + 0.5M_H + K_j$$

$$- U_{ALT}) \frac{0.5\left(0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}\right) - \alpha P_j}{\left(0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)^3}$$

Since all of the parameters and variables in this equation are positive, we cannot determine the nature of this relationship. If the costs of migration or δ are relatively high, such that

$\alpha P_j(0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-1} > 0.5$, then there is an inverse relationship between the magnitude of the labor screening effect and the parameter α: $\partial^2\bar{E}(\theta_{ij})/\partial P_j\partial\alpha < 0$. Otherwise, there is a direct relationship between the two. The reason for the conflicting results: the parameter α determines the differential impact of P_j (positive substitution effect), as well as being a component of overall costs of migration (negative income effect).

Finally, let's determine the impact of a shock to δ on the magnitude of the labor screening effect. As explained in the exogenous wage-setting model, this parameter is extremely important. When there is no connection between motivation/ability and marginal productivity (δ = 0), the labor screening effect collapses to zero. In order to determine the differential impact, I derive equation (13) with respect to δ:

$$\frac{\partial^2\bar{E}(\theta_{ji})}{\partial P_j\partial\alpha} = 0.5\alpha\frac{0.5\delta + 0.5M_H + K_j - U_{ALT}}{\left(0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)^2}$$

Based on the proof found in Appendix A, we find that there is always a direct relationship between $\partial\bar{E}(\theta_{ij})/\partial P_j$ and δ. In other words, the stronger the relationship between migrants' motivation/ability and productivity, the larger the magnitude of the labor screening effect.

Comparative Statics: Impact of Other Parameters and Variables

I begin by examining the impact of a change to the utility afforded to a potential migrant by remaining in their home country. In order to do so, I derive equations (11) and (12) with respect to U_{ALT}:

$$\frac{\partial \bar{I}}{\partial U_{ALT}} = -\frac{1}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}}$$

$$\frac{\partial \bar{E}(\theta_{ji})}{\partial U_{ALT}} = \frac{0.5\delta}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}}$$

As we would expect to see, when conditions in the next best alternative country worsen, there is an increase in the number of people migrating to nation j. Thus, this variable remains an effective "push" factor in the endogenous wage-setting model. This increase in migration is due to relatively lower motivation individuals now finding it worthwhile to make the move. Thus, poorer conditions at home will cause average migrant productivity in nation j to drop. When compared to the exogenous wage-setting model, we see that the impact of a shock to U_{ALT} is smaller under the endogenous wage-setting. This is because firms will respond to the initial shock to M_{min} by changing W_{ij}, which will have a partially reversing effect on M_{min}. Ergo, when equilibrium is achieved, the impact will be smaller.

When we examine the impact of a shock to one of the parameters or variables comprising the costs of migration, we find a result that is virtually identical to the impact of P_j.[11] An increase in any of the migration cost factors will cause an increase in immigrant productivity and a decrease in the number of incoming migrants. This is due to the fact that the costs of migration are linear in this model, so that there is effectively no difference between the various components.

Let's move onto the impact of a shock to the parameter linking an individual's motivation/ability and their marginal productivity, δ. In the exogenous wage-setting model, this only impacted average productivity. In this model, the population size of immigrants is also affected. This is due to the fact that there is now a link between migrant's decision-making and their productivity: the offered wage rate. I derive equations (11) and (12) with respect to δ:

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[11] $\partial E(\theta_{ij})/\partial\alpha = 0.5\delta P_j (W_{ji} - U_{ALT}) (\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-2}$
$\partial E(\theta_{ij})/\partial D_{jh} = 0.5\delta\beta (W_{ji} - U_{ALT}) (\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-2}$
$\partial E(\theta_{ij})/\partial\beta = 0.5\delta D_{jh} (W_{ji} - U_{ALT}) (\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-2}$
$\partial E(\theta_{ij})/\partial E_{ji} = 0.5\delta\gamma (W_{ji} - U_{ALT}) (\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-2}$
$\partial E(\theta_{ij})/\partial\gamma = 0.5\delta\gamma (W_{ji} - U_{ALT}) (\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-2}$

$$\frac{\partial \bar{I}}{\partial \delta} = \frac{0.5}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}} \left(M_H - \frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j + \beta D_{jh} + \gamma E_{ji}}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}} \right)$$

$$\frac{\partial \bar{E}(\theta_{ji})}{\partial \delta} = \frac{0.5\left(U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}} + 0.5M_H - \frac{0.25\delta}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}} \left(M_H + \frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j + \beta D_{jh} + \gamma E_{ji}}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}} \right)$$

I find that there is an inverse relationship between the number of immigrants and δ, if:

$$\frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j + \beta D_{jh} + \gamma E_{ji}}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}} > M_H$$

Recalling that $M_H = 1$, this simplifies to:

$$U_{ALT} - K_j > \delta$$

Therefore, the impact of a shock to δ on the number of immigrants is uncertain.

In terms of average migrant productivity, I find that there is an inverse relationship if:

$$U_{ALT} - K_j > \delta \qquad if\ 0.5 > \frac{0.25\delta}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}}$$

$$U_{ALT} - K_j < \delta \qquad if\ 0.5 < \frac{0.25\delta}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}}$$

We can be more certain of the impact of a shock to the migrants' productivity modifier in country j, the constant K_j. I take the derivative of equations (11) and (12) with respect to this variable:

$$\frac{\partial \bar{I}_j}{\partial K_j} = \frac{1}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}}$$

$$\frac{\partial \bar{E}(\theta_{ji})}{\partial K_j} = 1 - \frac{0.5\delta}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}}$$

There is a direct relationship between migrants' productivity in nation j and the number of migrants entering that country: $\partial \dot{I}/\partial K_j > 0$. The logic behind this is straightforward: an increase in K_j causes expected marginal productivity of migrants to rise, which causes firms in nation j to offer a higher wage rate, thereby enticing more migrants to pursue a higher utility in nation j. We can also see that there is a direct correlation between K_j and steady-state $\bar{E}(\theta_{ij})$, although this is a little less obvious due to two opposing forces.[12] When K_j increases, it has the obvious one-to-one impact on the productivity of migrants in nation j. However, as described above, this incentivizes more migrants to enter the nation. Since these individuals are coming from the lower end of the motivation/ability distribution, this results in the migrant pool having a lower

[12] In order for $\partial \dot{E}(\theta_{ij})/\partial K_j > 0$, the positive impact of the one-to-one relationship with the productivity function must outweigh the negative impact of the lower motivation migrants: $1 > 0.5\delta\ (0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-1}$
Since the costs of migration are positive, the ratio on the right must be less than unitary, thus confirming that there is a direct relationship.

motivation/ability on average, which has a negative effect on average productivity. Therefore, a one-unit increase in K_j will always result in a positive, but less than one-unit, change in steady-state average productivity: $0 < \partial\bar{E}(\theta_{ij})/\partial K_j < 1$.

<u>Scenario 2: Zero Initial Migration</u>

Necessary Conditions [M_{min} > M_H]*

Let's move onto the second scenario, in which nobody decides to migrate initially. In order for this to be the case, all of the potential migrants have a motivation/ability attribute level that is too low to grant them a relatively higher utility in the new nation: $M_{min}^* > M_H$. Assuming that we are initially in long-run equilibrium, I substitute in for the steady state value of M_{min} and find that there is zero initial migration if:

$$\frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j + \beta D_{jh} + \gamma E_{ji}}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji}} > M_H$$

Solving for the initial level of immigration control policy, P_j^*, I find that nobody migrates to country j if:

$$P_j^* > \frac{\dfrac{0.5\delta}{M_H\big(U_{ALT} + 1 - 0.5M_H - K_j\big) - 1} - \beta D_{jh} - \gamma E_{ji}}{\alpha}$$

For the rest of this analysis, I denote the minimum level of immigration control policy at which zero individuals will migrate as:

$$P_j^H > \frac{\frac{0.5\delta}{M_H\left(U_{ALT} + 1 - 0.5M_H - K_j\right) - 1} - \beta D_{jh} - \gamma E_{ji}}{\alpha}$$

Comparative Statics: Impact of Immigration Control Policy on Number of Migrants

With Scenario 2, the initial level of immigration control policy is so high that there are no individuals migrating to nation j: $I_j^* = 0$. Therefore, any differential change in P_j will have no impact on the number of incoming migrants: $\partial I_j/\partial P_j = 0$.

However, a nation with a significant enough drop in P_j can entice potential migrants to make the journey. In order to find what change is needed, let's suppose that the initial M_{min}^* is exactly λ_H higher than M_H, such that:

$$M_{min}^* - \lambda_H = M_H$$

Substituting in for long-run equilibrium M_{min}^*:

$$\frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j^* + \beta D_{jh} + \gamma E_{ji}}{0.5\delta + \alpha P_j^* + \beta D_{jh} + \gamma E_{ji}} - \lambda_H = M_H$$

where P_j^* is the initial level of immigration control policy. Solving for P_j^*:

$$P_j^* = \frac{U_{ALT} - 0.5\delta M_H - K_j - \alpha P_j^* - \beta D_{jh} - \gamma E_{ji} - (M_H + \lambda_H)\big(0.5\delta + \beta D_{jh} + \gamma E_{ji}\big)}{\alpha(M_H + \lambda_H - 1)}$$

Recall that the maximum level of immigration control policy at which individuals will migrate is:

$$P_j^H > \frac{\frac{0.5\delta}{M_H\big(U_{ALT} + 1 - 0.5M_H - K_j\big) - 1} - \beta D_{jh} - \gamma E_{ji}}{\alpha}$$

Taking the difference of the between P_H and the initial level of P* yields the change in immigration control policy that is necessary to entice individuals to begin migrating to country j:

$$P_j^H - P_j^* = \frac{\frac{0.5\delta}{M_H\big(U_{ALT} + 1 - 0.5M_H - K_j\big) - 1} - \beta D_{jh} - \gamma E_{ji}}{\alpha} - \frac{U_{ALT} - 0.5\delta M_H - K_j - \alpha P_j^* - \beta D_{jh} - \gamma E_{ji} - (M_H + \lambda_H)\big(0.5\delta + \beta D_{jh} + \gamma E_{ji}\big)}{\alpha(M_H + \lambda_H - 1)}$$

Therefore, if $\Delta P_j > \alpha^{-1}(((0.5\delta M_H^{-1}(U_{ALT} + 1 - 0.5\delta M_H - K_j) - 1)^{-1} - \beta D_{jh} - \gamma E_{ji}) - (U_{ALT} - 0.5\delta M_H - K_j - \beta D_{jh} - \gamma E_{ji} - (M_H + \lambda_H)(0.5\delta + \beta D_{jh} + \gamma E_{ji}))\,(M_H + \lambda_H - 1)^{-1})$, then M_{min} still exceeds M_H and no migration occurs. Otherwise, nation j successfully begins enticing individuals to migrate.

In order to measure the total effect on migration, ΔI_j, I compute the total number of incoming migrants since this scenario begins with $I_j^* = 0$. After substituting for M_{min} in the migrant size equation, I find that the change in the number of migrants is:

$$\Delta I_j = M_H - \frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j + \beta D_{jh} + \gamma E_{ji}}{0.5\delta + \alpha P_j^* + \alpha \Delta P_j + \beta D_{jh} + \gamma E_{ji}}$$

Comparative Statics: Impact of Immigration Control Policy on Migrant Productivity

Since average migrant productivity is initially undefined in Scenario 2, a change in P_j, of any magnitude, will result in an indeterminate change in $E(\theta_{ij})$. The same is observed for the all of the other variables and parameters in the model.

Comparative Statics: Impact of Other Parameters and Variables

In Scenario 2, infinitesimal changes in any of the parameters and variables result in the same impact as a change in P_j. In terms of the impact on the number of incoming migrants, the differential effect is equal to zero. This is because the scenario begins with $I_j^* = 0$. Since marginal productivity starts as undefined in Scenario 2 (as there are no migrants), we say that the differential impact of any of the parameters/variables is also undefined.

However, with a significant enough change in the other variables and parameters, there can be a change in I_j. For example, suppose that the costs of migration fell significantly (due to decreasing distance or ethnic differences), or that conditions at home worsened considerably, or that the wage offered in nation j skyrocketed. In all three of these cases, some individuals will start to see nation j as the better choice and migration to that nation will begin.

<u>Scenario 3: Complete Initial Migration</u>

Necessary Conditions $[M_{min}^* < M^L]$

In the third scenario, we have a situation in which all potential migrants are initially moving to nation j, because doing so grants them a higher utility. In other words, the minimum level of motivation/ability that a person would need to have in order to migrate is lower than the entire distribution of that characteristic: $M_{min}^* < M^L$. After substituting equation (3) in for M_{min}, I find that all potential migrants initially migrate if:

$$\bar{M}_{min} = \frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j^* + \beta D_{jh} + \gamma E_{ji}}{0.5\delta + \alpha P_j^* + \beta D_{jh} + \gamma E_{ji}} < M_j^L$$

Solving for P*, I find that everybody migrates if:

$$P_j^* > \frac{U_{ALT} - 0.5\delta(M_H + M_L) - K_j + (1 - M_L)\big(\beta D_{jh} + \gamma E_{ji}\big)}{\alpha(M_L - 1)}$$

For the rest of this analysis, I denote the maximum level of immigration control policy at which all individuals migrate as:

$$P_j^L = \frac{U_{ALT} - 0.5\delta(M_H + M_L) - K_j + (1 - M_L)\big(\beta D_{jh} + \gamma E_{ji}\big)}{\alpha(M_L - 1)}$$

Comparative Statics: Impact of Immigration Control Policy on Number of Migrants

In Scenario 3, the entire distribution of individuals is migrating to nation j. Therefore, the number of immigrants in scenario 3 is:

$$I_j = M_H - M_L$$

Since M_H and M_L are given constants, shock to P_j will have no differential impact on the number of migrants: $\partial I_j/\partial P_j = 0$.

It is possible for a nation to increase its immigration control policy significantly enough such that some migrants start to become screened. Let's suppose that the initial M_{min}* is exactly λ_L lower than M_L, such that:

$$M^*_{min} + \lambda_L = M_L$$

I substitute for long run-equilibrium M_{min}*, and solve for P_j*:

$$\frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j^* + \beta D_{jh} + \gamma E_{ji}}{0.5\delta + \alpha P_j^* + \beta D_{jh} + \gamma E_{ji}} + \lambda_L = M_L$$

$$P_j^* = \frac{U_{ALT} - 0.5\delta(M_H + M_L) - K_j + (1 - M_L)\big(\beta D_{jh} + \gamma E_{ji}\big) + \lambda_L(0.5\delta + \alpha P_j^* + \beta D_{jh} + \gamma E_{ji})}{\alpha(M_L - 1)}$$

Recall that the maximum level of immigration control policy at which all individuals will migrate is:

$$P_j^L = \frac{U_{ALT} - 0.5\delta(M_H + M_L) - K_j + (1 - M_L)\big(\beta D_{jh} + \gamma E_{ji}\big)}{\alpha(M_L - 1)}$$

Taking the difference of the two yields the change in policy that is necessary for screening to take place:

$$P_j^L - P_j^* = \frac{-\lambda_L(0.5\delta + \alpha P_j^* + \beta D_{jh} + \gamma E_{ji})}{\alpha(M_L - 1)}$$

Therefore, if $\Delta P_j < -\lambda_L(0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ji})\alpha^{-1}(M_L - 1)^{-1}$, then M_L still exceeds M_{min} and all potential migrants will continue to move to nation j. Otherwise, the significant rise in P_j successfully allows nation j to begin screening migrants.

In order to calculate the total impact on the number of migrants, I recall that the initial migrant population is $I_j = M_H - M_L$, and subtract the new formula, after substituting for M_{min} and P_j:

$$\Delta I_j = (M_H - M_L) - \left(M_H - \frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j^* + \beta D_{jh} + \gamma E_{ji}}{0.5\delta + \alpha P_j^* + \beta D_{jh} + \gamma E_{ji}}\right)$$

$$\Delta I_j = \frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j^* + \beta D_{jh} + \gamma E_{ji}}{0.5\delta + \alpha P_j^* + \beta D_{jh} + \gamma E_{ji}} - M_L$$

Comparative Statics: Impact of Immigration Control Policy on Migrant Productivity

For Scenario 3, the entire distribution of potential migrants is initially migrating to nation j. Therefore, we know that $M_{min} = M_L$, and $E(\theta_{ij}) = 0.5\delta(M_L + M_H) + K_j$. This means that a infinitesimal change in the level of immigration control policy will have zero impact on the average marginal productivity of the migrants: $\partial E(\theta_{ij})/\partial P_j = 0$. This is because M_{min} initially is not being decided by the level of immigration control policy in Scenario 3, but rather is defined as the lower bound of the motivation/ability distribution.

However, we know that a significant enough increase in P_j can cause some migrants to become screened. In order to find the impact on average migrant productivity, I take the difference between initial and new steady-state migrant productivity:

$$\Delta\bar{E}(\theta_{ji}) = \bar{E}(\theta_{ji}) - \bar{E}(\theta_{ji}^{*})$$

I substitute equation (11) for $\dot{E}(\theta_{ij})$ and $0.5\delta(M_L + M_H)$ in for $E(\theta_{ij})^*$:

$$\Delta\bar{E}(\theta_{ji}) = 0.5\delta\left(\frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j^{*} + \beta D_{jh} + \gamma E_{ji}}{0.5\delta + \alpha P_j^{*} + \beta D_{jh} + \gamma E_{ji}} + M_H\right) - 0.5\delta(M_L + M_H)$$

After substituting for P_j:

$$\Delta\bar{E}(\theta_{ji}) = 0.5\delta\left(\frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha\Delta P_j + \alpha P_j^{*} + \beta D_{jh} + \gamma E_{ji}}{0.5\delta + \alpha\Delta P_j + \alpha P_j^{*} + \beta D_{jh} + \gamma E_{ji}} + M_H\right) - 0.5\delta(M_L + M_H)$$

There is a direct relationship between the change in immigration control policy and change in average migrant productivity. The same exists for the initial level of immigration control policy. This is due to the fact that the migrants at the bottom end of the distribution now find migration to be too costly to justify moving. There is a direct relationship for the initial level as well. A higher initial P_j* leads to a smaller gap with P_L, meaning that the change in immigration control policy would have a greater impact on the actual screening process.

Comparative Statics: Impact of Other Parameters and Variables

In Scenario 3, infinitesimal changes in any of the parameters or variables result in the same impact as a change in P_j. In terms of the impact on the number of incoming migrants, there is no differential impact. This is because the scenario begins with $I_j^* = M_H – M_L$; a constant in which none of the parameters/variables have an impact. Except for a change in the productivity constant, we observe the same differential impact with average migrant productivity, which has a constant value of $E(\theta_{ij}) = 0.5\delta(M_L + M_H) + K_j$.

However, there can be a change in I_j and $E(\theta_{ij})$ with a significant finite change in the other variables and parameters. For example, suppose that the costs of migration rose significantly (due to increasing ethnic differences), or that nation j's wage premium falls dramatically. In these instances, some individuals at the bottom of the motivation will choose not to migrate.

3.5.4 Optimal Government Behavior

Now that I have discussed the impact of a change in one of the variables and parameters in this model on $\dot{I}_j$ and $\dot{E}(\theta_{ij})$, it is time to examine their impact on the optimal immigration policy implemented by nation j. Just like the other endogenous variables in this model, this level of P_j^o changes from period to period until long-run equilibrium is achieved. For the remainder of this section, I investigate the impact of a shock to one of the exogenous variables/parameters on this steady-state optimal level of immigration control policy: $\acute{P}_j^{o}$.

I begin by recalling equation (8), to find the steady-state welfare function for nation j:

$$\dot{G}_j = \psi\dot{I}_j + \varphi\dot{E}(\theta_{ji}) - \Omega P_j$$

I then substitute equations (11) and (12) in for $\dot{E}(\theta_{ij})$ and $\dot{I}_j$, respectively:

$$\dot{G}_j = \psi\left(M_H - \frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j + \beta D_{jh} + \gamma E_{ij}}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ij}}\right) +$$

$$\varphi\left(0.5\delta\left(\frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j + \beta D_{jh} + \gamma E_{ij}}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ij}} + M_H\right) + K_j\right) - \Omega P_j$$

I find the optimal level of immigration control policy for nation j by deriving this welfare function with respect to P_j, setting it equal to zero, and solving for P_j:

$$\partial\dot{G}_j \big/ \partial P_j = \psi\left(\alpha\frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j + \beta D_{jh} + \gamma E_{ij}}{(0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ij})^2} - \alpha\frac{1}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ij}}\right) +$$

$$0.5\delta\varphi\left(\frac{\alpha}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ij}} - \alpha\frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j + \beta D_{jh} + \gamma E_{ij}}{(0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ij})^2}\right) - \Omega = 0$$

$$\partial\dot{G}_j \big/ \partial P_j = \alpha\frac{0.5\delta\varphi - \psi}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ij}}\left(1 - \frac{U_{ALT} - 0.5\delta M_H - K_j + \alpha P_j + \beta D_{jh} + \gamma E_{ij}}{0.5\delta + \alpha P_j + \beta D_{jh} + \gamma E_{ij}}\right) -$$

$$\Omega = 0$$

$$P_j = \mp\frac{\sqrt{\alpha^3\Omega(\delta\varphi - 2\psi)\left(2K_j - 2U_{ALT} - \delta M_H + \delta\right)} + \alpha\Omega(2\beta D_{jh} + 2\gamma E_{ij} + \delta)}{2\Omega\alpha^2}$$

Therefore, the optimal level of immigration control policy under the assumptions of endogenous wage-setting and non-negative P_j:[13]

(10) P_j^o

$$= \frac{\sqrt{\alpha^3\Omega(\delta\varphi - 2\psi)(2K_j - 2U_{ALT})} + \alpha\Omega(2\beta D_{jh} + 2\gamma E_{ij} + \delta)}{2\Omega\alpha^2} \quad if\ P_L > \hat{P}_j^0 > 0$$

$$P_j^0 = 0 \qquad if\ \hat{P}_j^0 \leq 0$$

$$P_j^0 = P_H \qquad if\ \hat{P}_j^0 \geq P_H$$

Just as with the exogenous-wage model, there are two possible corner solutions to this optimization problem. The first, $P_j^o = 0$, occurs due to the constraining assumption that a nation cannot have negative immigration control policy, and the fact that nation j has no incentive to have a positive P_j level below P_L. Recall that P_L is the maximum level of immigration control policy at which all individuals migrate. If $\acute{P}_j^o$ is less than P_L, nation j can reduce its costs with no change in migration by setting $P_j = 0$. The second corner solution, $P_j^o = P_H$, is due to the fact that nation j has no incentive to raise its policy beyond P_H. Recall that P_H is the minimum level of immigration control policy in which zero individuals migrate. Raising P_j beyond this point would yield no difference in migration behavior, but costs Ω per additional unit.

[13] Note: This requires the assumption that δϕ - 2ψ > 0 and Kj - Ualt > 0.

First, let's determine the impact of a shock to productivity on the optimal level of immigration control policy, beginning with K_j. Recall that a rise in K_j represents an increase in the productivity of all migrants moving to nation j, potentially spurned through technological advance or improving market conditions. I derive equation (10) with respect to K_j:

$$\frac{\partial P_j^0}{\partial K_j} = \frac{\alpha(\delta\varphi - 2\psi)}{2\sqrt{\alpha^3\Omega(2K_j - 2U_{ALT})(\delta\varphi - 2\psi)}}$$

Since all of the terms and parameters are positively valued, I find that there is a direct relationship between the productivity of workers in nation j and the optimal level of immigration control policy set by nation j: $\partial P_j^o / \partial\delta < 0$. In other words, we would expect to see a nation with technological advances (that cause the value of migrant labor to rise) to more strictly enforce their border and customs protection.

Next, I examine the impact of an increase in the parameter δ, which is the correlation between a migrants' productivity and their level of motivation/ability. To do so, I derive (10) with respect to δ:

$$\frac{\partial P_j^0}{\partial \delta} = \frac{\alpha\delta(2K_j - 2U_{ALT})}{4\sqrt{\alpha^3\Omega(2K_j - 2U_{ALT})(\delta\varphi - 2\psi)}} + \frac{1}{2\alpha}$$

Just as observed with the exogenous-wage setting model, there is a positive relationship between the parameter δ and the optimal level of immigration control policy: $\partial P_j^o / \partial \delta < 0$.

Now, let's examine how a shock to one of the variables or parameters in the model impacts the optimal level of immigration control policy for nation j. I begin with ψ, the valuation that the members of nation j place on the presence of migrants. To do so, I derive (10) with respect to ψ:

$$\frac{\partial P_j^0}{\partial \psi} = \frac{\alpha(U_{ALT} - K_j)}{\sqrt{2}\sqrt{-\alpha^3\Omega(U_{ALT} - K_j)(\delta\varphi - 2\psi)}}$$

Since $K_j > U_{ALT}$, $\delta\varphi > 2\psi$, and all parameters are positively valued, I find that there is the expected inverse relationship between the society's valuation of the size of the migrant population and the strictness of immigration control policy: $\partial P_j^o / \partial \psi < 0$.

Next, I determine the effect on P_j^o of a change in society's valuation of the productivity of migrants. I derive equation (10) with respect to φ:

$$\frac{\partial P_j^0}{\partial \varphi} = \frac{\alpha\delta(2K_j - 2U_{ALT})}{4\sqrt{\alpha^3\Omega(2K_j - 2U_{ALT})(\delta\varphi - 2\psi)}}$$

As expected, there is a direct relationship between the optimal level of immigration control policy and society's desire for high-productivity migrants: $\partial P_j^o / \partial \phi < 0$.

Next, let's examine the impact of a change in the per-unit cost of immigration policy, Ω, on the optimal level of immigration policy, P_j^o. I derive equation (10) with respect to this parameter and find:

$$\frac{\partial P_j^0}{\partial \Omega} = \frac{\sqrt{\alpha^3 \Omega (K_j - U_{ALT})}\,(\delta\varphi - 2\psi)}{2\sqrt{2}\alpha^2 \Omega}$$

Under the assumptions that we have made for this model, optimal policy follows the Law of Demand; there is an inverse relationship between the cost of immigration control and the optimal amount of immigration control: $\partial P_j^o / \partial \Omega < 0$.

Oftentimes, immigration is driven by changing conditions in a potential migrant's native country. In order to determine nation j's optimal government policy in response to a shock in the migrants' homeland utility, I derive (10) with respect to U_{ALT}:

$$\frac{\partial P_j^0}{\partial U_{ALT}} = \frac{\alpha(\delta\varphi - 2\psi)}{2\sqrt{\alpha\Omega(2K_j - 2U_{ALT})(\delta\varphi - 2\psi)}}$$

Under the assumptions made for this model, there is a direct relationship between the optimal level immigration control policy for nation j and living conditions in the sending country: $\partial P_j^o / \partial U_{ALT} < 0$. In other words, according to this model we expect to see a nation tighten up its borders and more strictly enforce its legal migration practices in response to a neighboring country experiencing significant hardship, since the drop in U_{ALT} drives less productive people to nation j. On the converse side, if the sending nation experiences political stability and economic growth, we would expect nation j to loosen up its borders and spend fewer resources to screen migrants.

Finally, let's discuss the relationship between the non-policy costs of migration ($\beta D_{jh} + \gamma E_{ji}$) and P_j^o. In order to do so, I take the derivative of equation (9) with respect to this term:

$$\frac{\partial P_j^0}{\partial(\beta D_{jh} + \gamma E_{ji})} = -\frac{1}{\alpha}$$

A one unit increase in the non-policy costs of migration will cause the government of nation j to decrease its optimal immigration policy by a factor of $1/\alpha$, exactly like the exogenous wage-setting model. This negative linear relationship exists because individuals in this model treat policy costs the same as distance and ethnic costs. The government of nation j is determining the optimal level of total migration costs, but achieves this through its utilization of P_j. Recall that the costs of migration are: $\alpha P_j + \beta D_{jh} + \gamma E_{ji}$. Since the optimal total migration cost does not change with a shock to non-policy costs, the government can forgo enacting $1/\alpha$ units of P_j for every unit of non-policy migration costs being incurred by migrants. In other words, these distance and ethnic costs act as a negative income effect for the optimal level of immigration control policy for nation j.

3.6 Expansions of the Model

3.6.1 Deportation Risk

So far in this model, there is no mechanism to account for the fact that the government of nation j may engage in the rejection or deportation of a portion of the incoming migrants. We could assume that potential migrants take this risk into consideration when calculating their costs of migration. An increase in P_j leads to a higher risk of rejection/deportation, which causes the incurred policy costs of migration (αP_j) to rise. However, this is a naïve way to model for deportation risk since we are dealing with a multiple-outcome situation.

In order to properly model for deportation risk, I begin by transforming the migrants' utility function into a Von Neumann – Morgenstern expected utility function. For the sake of simplicity, I use the exogenous wage-setting model. Therefore, If migrant i chooses to migrate to nation j, he or she has an expected utility of:

$$E(U_{ji}) = (1 - R_{ji})W_{ji} + R_{ji}U_{ALT} - (\alpha P_j + \beta D_{jh} + \gamma E_{ji})(1 - M_i)$$

where R is the risk of rejection/deportation that the individual faces when he or she tries to migrate to nation j. In other words, it is the percentage chance that the person will be forced to return home after making the attempt to relocate.

The value of R should be inversely related to the potential migrant's motivation/ability, and directly related to the level of immigration control policy implemented by nation j (with diminishing returns). I model this as:

$$(14) \quad R_{ji} = \frac{(1 - M_i)P_j}{P_j + 1}$$

For this section I assume that the distribution of the motivation/ability attribute is between zero and one: M_i~[0,1]. Therefore, the value of R will never be negative, never exceed one, and those at the very top end of the motivation distribution will always have a chance to enter the nation. It also will simplify calculations later in this section.

Now that I have detailed the expected utility function and the risk of rejection function, I move onto solving the expanded model. Migrant i will only relocate to nation j if the expected utility of doing so exceeds that which can be obtained at home, $E(U_{ji}) > U_{ALT}$:

$$(1 - R_{ji})W_{ji} + R_{ji}U_{ALT} - (\alpha P_j + \beta D_{jh} + \gamma E_{ji})(1 - M_i) > U_{ALT}$$

$$\left(1 - \frac{(1 - M_i)P_j}{P_j + 1}\right)W_{ji} + \frac{(1 - M_i)P_j}{P_j + 1}U_{ALT} - (\alpha P_j + \beta D_{jh} + \gamma E_{ji})(1 - M_i) > U_{ALT}$$

$$M_i > \frac{(U_{ALT} - W_{ji})}{\alpha P_j + \beta D_{jh} + \gamma E_{ij} + \frac{P_j(W_{ji} - U_{ALT})}{P_j + 1}} + 1$$

Thus, I have identified the minimum level of motivation/ability needed to migrate to nation j:

$$(15) \quad M_{min} = 1 - \frac{(W_{ji} - U_{ALT})}{\alpha P_j + \beta D_{jh} + \gamma E_{ij} + \frac{P_j(W_{ji} - U_{ALT})}{P_j + 1}}$$

Comparing this solution to the one calculated in the original exogenous wage-setting model,[14] we see that nothing has fundamentally changed. All of the relationships between the variables have changed slightly in magnitude but still maintain the same orientation. As we might expect to see, the direct relationship between M_{min} and P_j is more pronounced with the addition of deportation risk. Thus, the labor screening impact has a higher magnitude. Also, due to an inflated denominator (for the negatively valued term) we observe a higher M_{min} under the expanded model, which we also expect to see. This means that there will be fewer immigrants, and the workers that do decide to migrate will have a higher average marginal productivity. Thus, we observe that the risk of deportation acts as an effective labor screening device, even for our risk-neutral migrants. If the individuals in this model are risk averse, this effect would be even more pronounced.

[14] Original minimum level of motivation/ability attribute: $M_{min} = 1 - \frac{W_{ji} - U_{ALT}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji}}$

The alteration to the nation-decision utility function is not the only impact that an active deportation system will have on the migration process. It is important to also model for the effect of the actual deportation/rejection mechanism that is forcefully preventing migrants from entering the labor force of nation j and returning them home.

Lets' begin with a simple discrete example. Suppose there are 4 laborers each that belong to Groups 1, 2, and 3, with a motivation of $M_i = 0$, $M_i = 0.5$, and $M_i = 1$, respectively. I assign unitary value to P_j, δ, and K_j, and I suppose that $M_{min} = 0$ so that the entire distribution of individuals decides to migrate. Recalling equation (14), the risk of rejection/deportation under these circumstances is $R = 0.5(1 - M_i)$. Therefore, two out of the four Group 1 individuals would be deported, one individual would be rejected from Group 2, and all of Group 3 successfully enters nation j. Thus, the deportation mechanism causes the immigrant population to fall from 12 to 9, and causes the average productivity of the migrants to rise from 1.5 to 1.6. This is a particularly interesting result, since we are observing a labor screening process that is entirely separated from M_{min}, which was the *sole* determining factor for I_j and $E(\theta_{ij})$ in the basic model.

Now that I have exhibited the basic properties of the deportation/rejection mechanism, I will solve for the generalized model in which M_i is uniformly distributed between 0 and 1. In order to do so, I can no longer take the difference between M_{min} and M_H. Instead, I aggregate the density of "successful" migrations between M_{min} and M_H. Recalling that the probability of a successful migration is 1-R, the size of the migrant population is:

$$I_j = \int_{M_{min}}^{M_H} (1 - R_{ji}) dM_i \quad = \int_{M_{min}}^{1} (1 - \frac{(1 - M_i)P_j}{P_j + 1}) dM_i$$

$$= F_I(1) - F_I(M_{min})$$

$$I_j = 1 + \frac{P_j(-0.5)}{P_j + 1} - M_{min} - \frac{M_{min}P_j(0.5M_{min} - 1)}{P_j + 1}$$

$$I_j = 1 + \frac{P_j(-0.5)}{P_j + 1} - M_{min}\left(1 + \frac{P_j(0.5M_{min} - 1)}{P_j + 1}\right)$$

To illustrate, let's continue with the situation in which $M_{min} = 0$, and that $P_j = 1$. The entire distribution of individuals chooses to migrate; those at the bottom end have a success rate of 50% and those at the top have a 100% success rate. Therefore, the migrant population size would be F(1) - F(0) = 1 – 0.25 = 0.75. In other words, a quarter of the incoming migrants would be deported, with the majority of the rejectees belonging to the lower end of the motivation/ability distribution.

I now move onto generally solving for I_j by substituting equation (15) in for M_{min}:

$$I_j = 1 + \frac{P_j(-0.5)}{P_j + 1} - \left(\frac{(U_{ALT} - W_{ji})}{\alpha P_j + \beta D_{jh} + \gamma E_{ij} + \frac{P_j(W_{ji} - U_{ALT})}{P_j + 1}} + 1 \right)$$

$$\left(1 + \frac{P_j \left(0.5 \left(\frac{(U_{ALT} - W_{ji})}{\alpha P_j + \beta D_{jh} + \gamma E_{ij} + \frac{P_j(W_{ji} - U_{ALT})}{P_j + 1}} + 1 \right) - 1 \right)}{P_j + 1} \right)$$

When we compare this result to that found in the basic model,[15] we find that I_j is smaller with the deportation mechanism, and is more severely impacted by a change in P_j. This is due to the combined effects of fewer individuals choosing to migrate, as well as the physical rejection of some of those who do decide to relocate.

This deportation process does not happen uniformly, as individuals with lower motivation/ability have a higher rejection rate. In order to calculate for the actual labor screening impact of the deportation mechanism, I move onto solving for the average productivity of the migrants who successfully relocate to nation

[15] Under the exogenous wage-setting model, where $M_H = 1$:

$I_j = (W_{ji} - U_{ALT}) (\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-1}$

j. In order to calculate this, I take the “total” marginal productivity of all successful migrants and divide it by the number of migrants:

$$\mathrm{E}\left(\theta_{ji}\right) = \frac{\int_{M_{min}}^{1}\left(1 - R_{ji}\right)\theta_{ji}dM_i}{\int_{M_{min}}^{1}\left(1 - R_{ji}\right)dM_i} = \frac{\int_{M_{min}}^{1}\left(1 - \frac{(1 - M_i)P_j}{P_j + 1}\right)\theta_{ji}dM_i}{\int_{M_{min}}^{1}\left(1 - \frac{(1 - M_i)P_j}{P_j + 1}\right)dM_i}$$

Recall from equation (2) that $\theta_{ij} = \delta M_i + K_j$:

$$\mathrm{E}\left(\theta_{ji}\right) = \frac{\int_{M_{min}}^{1}\left(1 - \frac{(1 - M_i)P_j}{P_j + 1}\right)(\delta M_i + K_j)dM_i}{\int_{M_{min}}^{1}\left(1 - \frac{(1 - M_i)P_j}{P_j + 1}\right)dM_i} = \frac{F_\theta(1) - F_\theta(M_{min})}{F_I(1) - F_I(M_{min})}$$

$$\mathrm{E}\left(\theta_{ji}\right) = \frac{F_\theta(1) - F_\theta(M_{min})}{F_I(1) - F_I(M_{min})} = \frac{F_\theta(1)}{F_I(1) - F_I(M_{min})} - \frac{F_\theta(M_{min})}{F_I(1) - F_I(M_{min})}$$

$$= \frac{\left(0.5\delta + K_j + \frac{P_j}{P_j + 1}\left(0.33\delta + 0.5(K_j - 1\right) - K_j\right)}{1 + \frac{P_j(-0.5)}{P_j + 1} - M_{min}\left(1 + \frac{P_j(0.5M_{min} - 1)}{P_j + 1}\right)}$$

$$- \frac{M_{min}\left(0.5\delta M_{min} + K_j + \frac{P_j}{P_j + 1}\left(0.33\delta M_{min}^2 + 0.5M_{min}(K_j - \delta\right) - K_j\right)}{1 + \frac{P_j(-0.5)}{P_j + 1} - M_{min}\left(1 + \frac{P_j(0.5M_{min} - 1)}{P_j + 1}\right)}$$

Now that I have solved for average migrant productivity, let’s continue with the example of $M_{min} = 0$ and $P_j = 1$, in which the size of the migrant population is 0.75. We will also assume unitary value for δ and K_j. Plugging in these values, I find that the average marginal productivity of the “successful” migrants is $E\left(\theta_{ji}\right) = \frac{0.5 + 1 + 0.5(0.33 - 1)}{0.75} = 1.56$. Keep in mind that the entire distribution of potential migrants attempted to relocate, and these individuals have an average productivity of $E(\theta_{ji}) = E(M_i) + 1 = 1.5$. Therefore, even in the absence of any effect from M_{min}, we observe that an active deportation mechanism is an effective labor screening device and leads to higher average productivity in migrants who successfully integrate into the labor market of nation j.

3.6.2 Multiple-Nation Model

When I established the nation-decision utility function in the beginning of this model, I allowed migrant i the option to choose from many nations. However, for the rest of the analysis I assumed that U_{ALT} was solely provided by the migrants' wages/conditions at home. Effectively, the migrants in the model had two choices: either migrate to nation j, or stay at home. While that assumption may hold validity in some circumstances (e.g. Mexico and United States), in other cases (such as the recent E.U. migration) it is not well supported; potential migrants often have several options to choose from. For this reason, I wish to expand the model by introducing more than one nation receiving migrants. In other words, I wish to explore the possibility of U_{ALT} being provided by a nation other than the migrants' homeland. For the sake of simplicity, I assume that motivation/ability is distributed M_i~[0,1] for this section.

Solving the Model

Recall that, in order for migrant i to migrate to nation j, the following inequality must hold:

$$W_{ji} - \left(\alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)(1 - M_i) > U_{ALT}$$

In this expansion, I replace U_{ALT} with the utility function for the next best alternative nation-choice:

$$W_{ji} - \left(\alpha P_j + \beta D_{jh} + \gamma E_{ji}\right)(1 - M_i)$$
$$> W_{ALT,i} - (\alpha P_{ALT} + \beta D_{ALT,h} + \gamma E_{ALT,i})(1 - M_i)$$

$$W_{ji} - W_{ALT,i} > (\alpha P_j + \beta D_{jh} + \gamma E_{ji} - \alpha P_{ALT} + \beta D_{ALT,h} + \gamma E_{ALT,i})(1 - M_i)$$

$$M_i > 1 - \frac{W_{ji} - W_{ALT,i}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji} - \alpha P_{ALT} + \beta D_{ALT,h} + \gamma E_{ALT,i}}$$

Thus, I identify the lower bound of the motivation/ability distribution of the migrants moving to nation j as:

$$M_{min,j} = 1 - \frac{W_{ji} - W_{ALT,i}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji} - \alpha P_{ALT,i} - \beta D_{ALT,h} - \gamma E_{ALT,i}}$$

In order to determine what nation is the "next best alternative," I work sequentially, beginning with the nation that offers the highest wage (which I will denote as nation 0). We know for certain that the individuals at the top of the distribution, with M_i virtually equal to one, will choose nation 0 as their destination. This is because the adjusted costs of migration are virtually zero, making the wage rate the only important component of utility. Therefore, the upper bound for nation 0 is $M_H = 1$. To find the "next best alternative," I calculate $M_{min,0}$ using each of the other nations as the alternative. The nation with the highest M_{min} within the "available" range of M_i~[0,1] is the next best alternative, which I now denote as nation 1. Thus, we can solve for nation 0:

$$(16)\quad I_0 = 1 - M_{min,0} = \frac{W_{0i} - W_{1i}}{\alpha P_0 + \beta D_{0h} + \gamma E_{0i} - \alpha P_{1i} - \beta D_{1h} - \gamma E_{1i}}$$

$$(17)\quad E(\theta_{0i}) = 0.5\frac{W_{0i} - W_{1i}}{\alpha P_0 + \beta D_{0h} + \gamma E_{0i} - \alpha P_{1i} - \beta D_{1h} - \gamma E_{1i}} + 1 + K_0$$

We know that the upper bound of the distribution that is migrating to nation 1 is the lower bound of nation 0: $M_{max,1} = M_{min,0}$. To find the lower bound for nation 1, I repeat the same process as before. I begin by calculating $M_{min,1}$ for each possible nation, except nation 0. Then, I pick the highest $M_{min,1}$ within the available range of M_i~[0, $M_{min,0}$] to find the "next best alternative," nation 2. At this point, we can solve for nation 1:

$$I_1 = M_{max,1} - M_{min,1} = M_{min,0} - M_{min,1}$$

$$I_1 = \frac{W_{1i} - W_{2i}}{\alpha P_1 + \beta D_{1h} + \gamma E_{1i} - \alpha P_{2i} - \beta D_{2h} - \gamma E_{2i}} - \frac{W_{0i} - W_{1i}}{\alpha P_0 + \beta D_{0h} + \gamma E_{0i} - \alpha P_{1i} - \beta D_{1h} - \gamma E_{1i}}$$

$$E(\theta_{1i}) = 0.5\delta\left(2 - \frac{W_{0,i} - W_{1i}}{\alpha P_0 + \beta D_{0h} + \gamma E_{0i} - \alpha P_1 - \beta D_{1h} - \gamma E_{1i}} - \frac{W_{1i} - W_{2,i}}{\alpha P_1 + \beta D_{1h} + \gamma E_{1i} - \alpha P_{2i} - \beta D_{2h} - \gamma E_{2i}}\right) + K_1$$

Once I have solved for nation 1, I continue the exact same process for nation 2 and so on until I reach the final "viable" location, nation J. We know that we have reached nation J when all of the $M_{min,J}$ calculations fall outside of the available range of the M_i distribution: M_i~$[0, M_{min,J-1}]$. This means that the rest of the nations can be ignored as none of the individuals in the model have an incentive to relocate there. At this point, nation J has a lower bound of zero.

Now that I have defined nations 1 through J, I can solve for the general form of the "center-of-distribution" nation j where 0 < j < J, as well as the bottom-of-distribution nation J:

$$(18) \quad I_j = \frac{W_{ji} - W_{j+1,i}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji} - \alpha P_{j+1,i} - \beta D_{j+1,h} - \gamma E_{j+1,i}} - \frac{W_{j-1,i} - W_{ji}}{\alpha P_{j-1} + \beta D_{j-1,h} + \gamma E_{j-1,i} - \alpha P_j - \beta D_{jh} - \gamma E_{ji}}$$

$$(19) \quad E(\theta_{ji}) = 0.5\delta\left(2 - \frac{W_{j-1,i} - W_{ji}}{\alpha P_{j-1} + \beta D_{j-1,h} + \gamma E_{j-1,i} - \alpha P_j - \beta D_{jh} - \gamma E_{ji}} - \frac{W_{ji} - W_{j+1,i}}{\alpha P_j + \beta D_{jh} + \gamma E_{ji} - \alpha P_{j+1,i} - \beta D_{j+1,h} - \gamma E_{j+1,i}}\right) + K_j$$

$$where\ j \neq 0$$

$$j \neq J$$

$$(20) \quad I_J = 1 - \frac{W_{Ji} - W_{J-1,i}}{\alpha P_J + \beta D_{Jh} + \gamma E_{Ji} - \alpha P_{J-1} - \beta D_{J-1,h} - \gamma E_{J-1,i}}$$

$$(21) \quad E(\theta_{Ji}) = 0.5\delta\left(2 - \frac{W_{J+1,i} - W_{Ji}}{\alpha P_{J+1} + \beta D_{J+1,h} + \gamma E_{J+1,i} - \alpha P_J - \beta D_{Jh} - \gamma E_{Ji}}\right) + K_J$$

Solving the Model: A Simple Example

I illustrate with a simple example, in which the exogenous variables and parameters have unitary value. For a more detailed 26-nation simulation of the process, refer to Appendix A.5. Let's suppose that a group of Syrian individuals have been displaced by war, are considering migration, and face the following nation-choice utility functions:

$$U_{SYR,i} = -1$$

$$U_{TURK,i} = 1 - (1 + 1 + 1)(1 - M_i)$$

$$U_{GER,i} = 3 - (1 + 4 + 2)(1 - M_i)$$

$$U_{ITA,i} = 2 - (1 + 2.5 + 2)(1 - M_i)$$

… and so on (we'll assume these are the four best options) …

Let's start with the individuals at the top of the motivation distribution. Since these migrants have adjusted costs of migration of virtually zero, they will always pursue the option in which they achieve the highest wage rate: Germany. The next order of business is determining the bottom end of the range of German-bound migrants. In order for a migrant to wish to migrate to Germany, the utility in doing so must be higher than the next best alternative: Turkey.[16] I set this up and solve for M_i:

$$U_{GER,i} > \mathrm{U}_{\mathrm{TURK,i}}$$

$$3 - (1 + 4 + 2)(1 - \mathrm{M_i}) > 1 - (1 + 1 + 1)(1 - \mathrm{M_i})$$

$$M_i > 0.5$$

Therefore, the German-bound migrants have a motivation/ability attribute between 0.5 and 1. Thus, the population size is $I_{GER} = 0.5$ and, assuming unitary value for parameters and variables, $E(\theta_{GER,j}) = 1.75$.

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[16] I know that this is the next best alternative through direct comparison. When I compare $U_{GER,I}$ to $U_{ITA,I}$, I find that individuals will choose Germany over Italy if:
$3 - (1 + 4 + 2)(1 - M_i) > 2 - (1 + 2.5 + 2)(1 - M_i)$
$M_i > 0.33$

And I find that individuals choose Germany over remaining in Syria if:
$3 - (1 + 4 + 2)(1 - M_i) > -1$
$M_i > 0.33$

When we compare this to the motivation/ability required to choose Germany over Turkey ($M_i > 0.5$), we find that there are individuals (M_i~[0.33,0.5]) who would choose to live in Turkey, but not in Italy or Syria. In other words, Turkey has the "highest" M_{min} and is revealed to be the "next best alternative."

Since Turkey is the next best alternative, we know that those with M_i that is just below 0.5 consider Turkey to be the best option. Thus, this is the upper bound of the Turkey-bound migrants. In order to calculate the low end of this range, I compare to the next best alternative, Syria,[17] and solve for M_i:

$$U_{TURK,i} > U_{SYR,i}$$

$$1 - (1 + 1 + 1)(1 - \mathrm{M_i}) > -1$$

$$M_i > 0.33$$

Therefore, the population of migrants relocating to Turkey is M_i~[0.33,0.5]. Thus, the population size is $I_{TURK} = 0.17$ and $E(\theta_{TURK,j}) = 1.41$.

The remainder of the potential migrant population, M_i~[0,0.33], will decide to remain in Syria despite the poor conditions there. We know that 0 is the lower bound for Syria, thus excluding Italy from the final solution, by comparing the utility functions of Syria and Italy. Migrants will choose to live in Italy over Syria if:

$$U_{ITA,i} > U_{SYR,i}$$

$$2 - (1 + 2.5 + 2)(1 - \mathrm{M_i}) > -1$$

$$M_i > 0.45$$

[17] In order to determine that Syria is the next best alternative, I compare the utility derived in Turkey to that of Italy and find that individuals choose Italy over Turkey if:

$2 – 5.5(1 - M_i) > 1 – 3(1 – M_i)$

$M_i > 0.6$

Since migrants with motivation/ability above 0.5 are migrating to Germany, we know that Italy is the inferior choice, and Syria is the next best alternative.

We know that individuals in this range are already migrating to Turkey and Germany, thus none decide to move to Italy. Therefore, the population size for Syria in this example is I_{SYR} = 0.33 and the average productivity of these individuals is $E(\theta_{SYR,j})$ = 1.17.

Interpreting the Results

I will begin by analyzing the impact of a change in immigration control policy on migrant population and productivity on nation 0, the highest-wage nation. I take equations (16) and (17) and derive by P_0:

$$\frac{\partial I_0}{\partial P_0} = \frac{-\alpha(W_{0i} - W_{1i})}{(\alpha P_0 + \beta D_{0h} + \gamma E_{0i} - \alpha P_1 - \beta D_{1h} - \gamma E_{1i})^2}$$

$$\frac{\partial E(\theta_0)}{\partial P_0} = \frac{0.5\delta\alpha(W_{0i} - W_{1i})}{(\alpha P_0 + \beta D_{0h} + \gamma E_{0i} - \alpha P_1 - \beta D_{1h} - \gamma E_{1i})^2}$$

Just as with the simple model, we find an inverse correlation between migrant population and immigration control policy, and a direct one with average migrant productivity. We know this is true because the wage gap has to be positive by definition (nation 0 is highest-wage), and the costs of migration to nation 1 must be lower than nation 0 in order for lower M_i individuals to choose nation 1 (see first part of Appendix A.3 for proof). If only one nation (the migrants' homeland) has lower costs of migration than nation 0, the situation effectively reverts to the 2-nation model.

The magnitude of the labor screening effect is a different story. When we compare to the 2-nation model[18], we see that the labor screening effect is more pronounced for nation 0 in the multi-nation model. This is due to the subtraction of nation 1's costs of migration in the denominator, thus inflating the fraction. Migrants are now comparing nation 0 to another nation with migration costs, as opposed to their home country (with zero migration costs). This means that, when making the comparison to nation 1, migrants in the multi-nation model experience a smaller "cost-of-migration differential." Since the labor screening effect exhibits diminishing marginal returns (from Section 1.3), a decrease in the cost-of-migration differential effectively increases the screening power of nation 0's immigration control policy. Conceptually speaking, it is because the migrants that are on the margin of $M_{min,0}$ are more easily swayed to pursue the next best alternative nation. These migrants on the margin are interested in a high-wage, high-cost location, and with the multi-nation model, they can "shop around" between nations 0 and 1.

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[18] Labor screening under the 2-Nation Model (recall that $U_{ALT} = W_{1i}$ in the 2-nation model):
$\partial I_j/\partial P_j = -\alpha (W_{ji} - W_{1i}) (\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-2}$
$\partial E(\theta_{ij})/\partial P_j = 0.5\delta\alpha (W_{ji} - W_{1i}) (\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-2}$

All of the other relationships between the various variables and parameters and I_0 and $E(\Theta_{0i})$ maintain the same orientation as they do under the 2-nation model. The magnitudes of these effects are different, for the same reason as described above.

I move onto the analysis of labor screening effect for the general nation j. I derive equations (18) and (19) with respect to P_j:

$$\frac{\partial I_j}{\partial P_j} = \frac{-\alpha(\mathrm{W_{ji}} - \mathrm{W_{j+1,i}})}{\left(\alpha\mathrm{P_j} + \beta\mathrm{D_{jh}} + \gamma\mathrm{E_{ji}} - \alpha\mathrm{P_{j+1,i}} - \beta\mathrm{D_{j+1,h}} - \gamma\mathrm{E_{j+1,i}}\right)^2} - \frac{\alpha\left(\mathrm{W_{j-1,i}} - \mathrm{W_{ji}}\right)}{\left(\alpha\mathrm{P_{j-1}} + \beta\mathrm{D_{j-1,h}} + \gamma\mathrm{E_{j-1,i}} - \alpha\mathrm{P_j} - \beta\mathrm{D_{jh}} - \gamma\mathrm{E_{ji}}\right)^2}$$

$$\frac{\partial E(\theta_j)}{\partial P_j} = 0.5\alpha\delta\left(\frac{\mathrm{W_{ji}} - \mathrm{W_{j+1,i}}}{\left(\mathrm{P_j} + \beta\mathrm{D_{jh}} + \gamma\mathrm{E_{ji}} - \alpha\mathrm{P_{j+1,i}} - \beta\mathrm{D_{j+1,h}} - \gamma\mathrm{E_{j+1,i}}\right)^2} - \frac{\mathrm{W_{j-1,i}} - \mathrm{W_{ji}}}{\left(\alpha\mathrm{P_{j-1}} + \beta\mathrm{D_{j-1,h}} + \gamma\mathrm{E_{j-1,i}} - \alpha\mathrm{P_j} - \beta\mathrm{D_{jh}} - \gamma\mathrm{E_{ji}}\right)^2}\right)$$

The correlation between the size of the immigrant population and P_j remains inverted for nation j, solidifying its effect as a “push” factor. We know this is true because α and the two wage gaps are all positively valued (see Appendix A.4 for proof). The magnitude of this relationship appears to be significantly higher under the multi-nation model relative to the two-nation model. This is due to the fact that an increase in P_j causes migrants on the margin of $M_{min,j}$ to relocate to nation j-1, *as well as* influencing migrants on the margin of $M_{max,j}$ to move to nation j+1. This effect on the migrants at the margin of $M_{max,j}$ is absent from the two-nation model.

Unlike the 2-nation model, the relationship between the immigration control policy and average migrant productivity is uncertain. An increase in P_j causes $M_{min,j}$ to rise, with a positive impact on $E(\Theta_{ji})$. However, it also causes $M_{max,j}$ to fall, which has a negative impact on average productivity. The magnitudes of these opposing forces are determined by the size of wage and cost gaps between nation j and its "neighbors," j-1 and j+1. Suppose that we assume that the wage and cost gaps with nations j-1 and j+1 are identical: $W_{j-1,i} - W_{ji} = W_{ji} - W_{j+1,i}$ and $\alpha P_{j-1} + \beta D_{j-1,h} + \gamma E_{j-1,i} - \alpha P_j - \beta D_{jh} - \gamma E_{ji} = \alpha P_j + \beta D_{jh} + \gamma E_{ji} - \alpha P_{j+1,i} - \beta D_{j+1,h} - \gamma E_{j+1,i}$. In this case, a differential change in P_j would have zero impact on average migrant productivity. If the wage/cost gap is higher for nation j+1 than j-1, there is a direct relationship between the two variables. The converse is true when the wage/cost gap is higher for j-1.

I now move onto the analysis of the labor screening effect for the low-wage, low-cost nation J. I take the derivative of equations (20) and (21) with respect to P_J;

$$\frac{\partial I_J}{\partial P_J} = \frac{-\alpha(W_{J-1,i} - W_{Ji})}{\left(\alpha P_J + \beta D_{Jh} + \gamma E_{Ji} - \alpha P_{J-1} - \beta D_{J-1,h} - \gamma E_{J-1,i}\right)^2}$$

$$\frac{\partial E(\theta_J)}{\partial P_J} = 0.5\delta \frac{-\alpha(W_{J-1,i} - W_{Ji})}{\alpha P_J + \beta D_{Jh} + \gamma E_{Ji} - \alpha P_{J-1} - \beta D_{J-1,h} - \gamma E_{J-1,i}}$$

The correlation between migrant population and immigrant control policy remains negative, as we would expect to see. However, differentially speaking, there is now an inverse relationship between average migrant productivity and P_J, as opposed to the direct relationship that we have normally seen. This is due to the fact that the lower bound of the motivation/ability range of individuals locating in nation J is zero: $M_{min,J} = 0$. An incremental change in P_J will have no impact on this boundary; there are no migrants "on the margin" between nation J and J+1, thus no change in migration between the two nations: $\partial M_{min,J}/\partial P_J = 0$. An increase in P_J will, however, cause a decrease in $M_{max,J}$ as individuals on the margin with nation J-1 decide to relocate to that nation: $\partial M_{max,J}/\partial P_J < 0$. Therefore, an increase in P_J causes both migrant population and average productivity to decline.

<u>Interpreting the Results: A Simple Example</u>

Continuing with the example from earlier, let's examine the impact of a shock to P_j for each of the three nations in question, beginning with nation 0: Germany. Let's suppose that the nation of Germany decides to lower P_j in response to the Syrian crisis, such that P_j falls from 1 to 0.5. Now, when migrants are considering moving to Germany or Turkey, they will relocate to Germany if:

$$U_{GER} > U_{TURK}$$

$$3 - (1 + 4 + 2)(1 - M_i) > 1 - (1 + 1 + 1)(1 - M_i)$$

$$M_i > 0.43$$

Therefore, the German-bound migrants have a motivation/ability attribute between 0.43 and 1. Thus, the decrease in immigration control policy has caused migrant population size to grow significantly to $I_{GER} = 0.57$, while average productivity has fallen to $E(\theta_{GER,j}) = 1.71$. Therefore, we observe a significant inverse relationship between I_0 and P_0, and a significant direct relationship between $E(\theta_{0i})$ and P_0.

Now, let's observe the impact of an incremental increase in P_j for nation 1: Turkey. Suppose Turkey raises its level of immigration control policy from 1 to 1.2. In this case, when migrants are considering whether they want to live in Germany or Turkey, they will live in Turkey if:

$$U_{TURK} > U_{GER}$$

$$1 - (1.2 + 1 + 1)(1 - M_i) > 3 - (1 + 4 + 2)(1 - M_i)$$

$$M_i < 0.475$$

Thus, the upper bound of Turkey-bound migrants falls to $M_{max,1} = 0.475$. To find the lower bound, I compare the utility earned by relocating to Turkey to that of remaining in Syria:

$U_{TURK} > U_{SYR}$

$$1 - (1.2 + 1 + 1)(1 - M_i) > -1$$

$$M_i > 0.375$$

Therefore, the Turkey-bound immigrants now have motivation/ability of M_i~[0.375,0.475]. Thus, the small increase in P_1 has caused the migrant population to fall significantly from 0.17 to 0.1. On the other hand, average migrant productivity increased very slightly from 1.41 to 1.425. This goes to show that for "middle-of-distribution" nation j, there is a strong negative relationship between immigration control policy and the migrant population size, while the correlation between P_j and $E(\theta_{ji})$ is rather weak.

Now let's move onto Nation J in this example: Syria. Since I have assumed a lower bound of zero for P_j, the nation is unable to lower its level of immigration control policy to entice more (higher-productivity) individuals to remain in the country. However, let's suppose that the government imposes costs on them if they choose to remain (e.g. costly documentation process, bombing campaigns, routine military checkpoints, etc.) so there is an increase in P_J from 0 to 0.5. In that case, migrants will choose to remain in Syria if:

$U_{SYR} > U_{TURK}$

$$-1 - (0.5)(1 - M_i) > 1 - (1.2 + 1 + 1)(1 - M_i)$$

$M_i < 0.2$

Thus, the individuals who remain in Syria have a motivation/ability attribute that is between 0 and 0.2. The increase in P_J caused the "migrant" population size to fall from 0.33 to 0.2, and average marginal productivity fell from 1.17 to 1.1. Here we observe a significant inverse relationship between P_J and both I_J and $E(\theta_{Ji})$.

Chapter 4

BACKGROUND

4.1 History of U.S. Immigration (16^{th} – 20^{th} century)

From the beginning, the United States has had a history of migration. The original inhabitants, the Native Americans, travelled across a land bridge that had once connected North America and northeast Asia. In the 16^{th} century, European explorers (mostly French and Spanish) had discovered the vast resources of the United States and began establishing trading posts. By the early 17th century, European settlers (mostly British) had begun forming permanent settlements in Virginia, Massachusetts, and Maryland in pursuit of religious freedom and economic opportunity. Most of the families moving to the colonies became farmers due to the availability of cheap and productive farmland. A significant fraction of these immigrants could not afford the high monetary costs of the voyage, and voluntarily indentured themselves for a number of years in order to pay for the relocation. In addition to these European migrants, there were African slaves who were imported against their will. Through these migrant

Table 4.1 U.S. Population, by Place of Origin (1790)

England[1]	Africa	Ireland[2]	Germany[3]	Scotland	Netherlands	Other[4]
2,110,000	757,000	300,000	270,000	150,000	100,000	219,000

Source: Ann Arbor, Michigan: Inter-University Consortium for Political and Social Research

[1] Estimate includes Wales

[2] Comprised mostly of Ulster Scotch-Irish

[3] Comprised of Prussia and other small independent nations

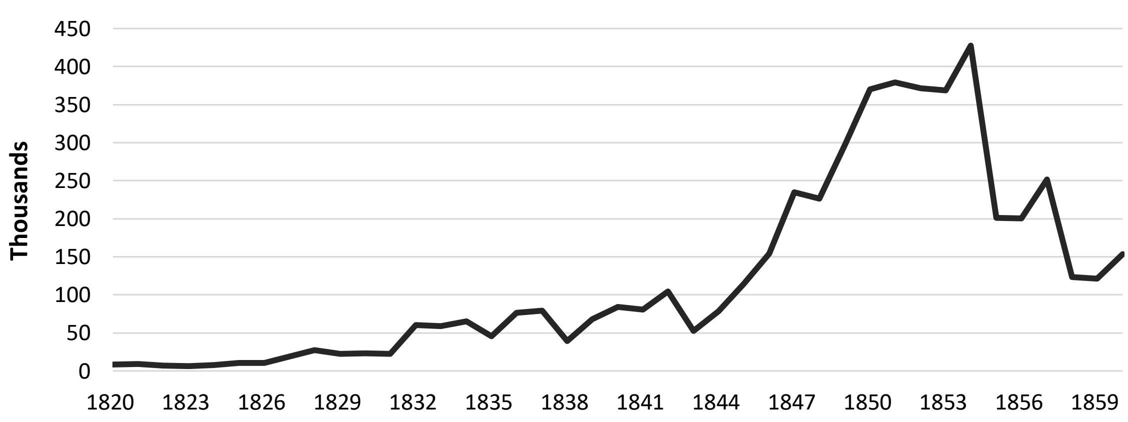
[4] Comprised of French, Swedish, Jewish and unknown nationalities

influxes and internal increases, the official population of the colonies rose from roughly 50,000 to 250,000 between the years of 1650 and 1700 (U.S. Census Bureau 2004). The wave of migration into the colonies continued until the onset of the American Revolution, by which time the population had risen to approximately two and half million people.

Following the conflict, the newly formed United States did not see another significant influx of migrants for several more decades. Table 4.1 above shows the breakdown of the nation of origin for the United States' estimated population in 1790. As we can see, the nation was mostly inhabited by those with English ancestry, followed by the African slave population and other Northern European nations. Around this time, Congress began enacting the first immigration laws of the United States. Between 1790 and 1798, they passed three versions of the Naturalization Act, which ultimately determined that non-whites cannot become naturalized citizens, the president was given deportation powers, and citizenship required 14 years of residence (instead of 5). With the Naturalization Law of 1802, the fourteen year residency requirement was abolished, and citizenship rights were broadened (for white people) and better defined.[19] Several years later, Congress passed the Act Prohibiting Importation of Slaves of 1807, which effectively ended the international importation of slaves.

Immigrant inflows remained relatively low for the United States until around 1830. Figure 4.1 below presents the annual numbers of individuals who obtained legal residency status, perhaps the reliable indicator of the number of incoming migrants for this period of time, between 1820 and 1860. As we can see, immigration started to pick up in the 1830's and was in full swing by 1850. The potato famine of 1845-1849 caused widespread poverty and malnutrition, which caused millions of Irish people to either emigrate or perish from starvation. The potato blight also affected continental Europe, helping to fuel

Figure 4.1 Persons Obtaining Legal U.S. Permanent Resident Status (1820 -



Source: Yearbook of Immigration Statistics 2010, by U.S. Department of Homeland Security

[19] Children of naturalized citizens were deemed citizens, and children birthed in a foreign nation by U.S. citizens were deemed citizens. The Law also mandated better record-keeping for incoming migrants.

widespread political turmoil culminating in the Revolutions of 1848. These push factors helped to drive hundreds of thousands of German (particularly liberals and intellectuals), British, and French individuals to the resource-abundant United States. Table 4.2 below displays the national origins of the American immigrant population in 1850.

Some of these migrants moved west to claim their own farmland, but many remained in the cities to make use of their artisanal skills or to be employed as a factory worker. Also, the conclusion of the Mexican War in 1848 and the California Gold Rush of 1949 led to significant migration to the west coast, resulting in California's statehood in the year 1850. Following the Civil War, several states (California, Louisiana, and New York) individually began passing legislation that affected immigration practices. The matter was brought to the U.S. Supreme Court in the case of *Chy Lung v. Freeman*, which ruled that the power to determine immigration laws rested with the federal government, rather than the individual states.

This power was exercised with the passage of the Page Act of 1875,

Table 4.2 U.S. Immigrant Population, by Nation of Origin (1850)

Ireland	Germany[1]	England[2]	Canada	France	Scotland	Other
1,611,304	1,276,075	477,455	249,970	109,870	108,518	305,505

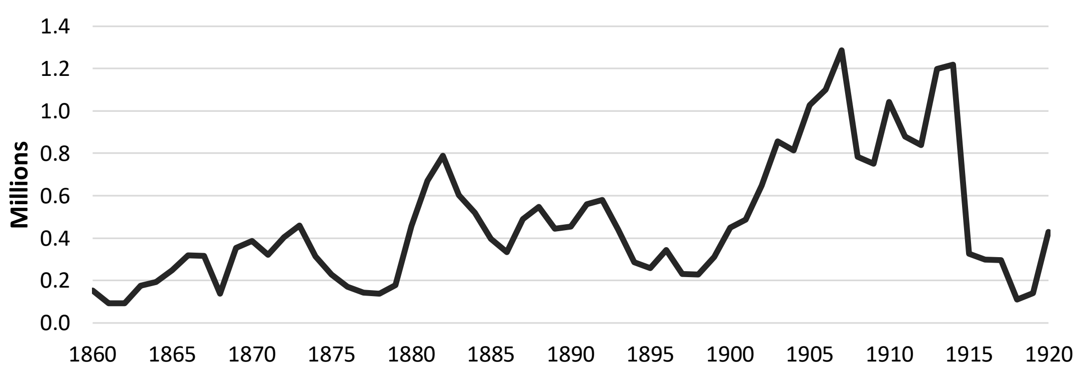
Source: U.S. Census Bureau
[1] Comprised of Prussia and other small independent nations
[2] Includes Wales

which was passed in response to increasing Asian migration into California, whose residents argued that the new wave of immigration was depressing their wages. The legislation banned the importation of contract laborers from Asia, as well as any individuals considered to be criminals in their native country. Congress took it a step further in 1882 by passing the Chinese Exclusion Act, which outright outlawed any migrant laborers from China for the next thirty years. In order to better execute these new immigration practices, the federal government established Ellis Island as a national immigration station in 1890, and Angel Island a couple decades later.

Beginning in the 1880's a new form of technology was radically changing the phenomenon of global immigration: the advent of the steam-powered ocean liner. These ships significantly lowered the monetary cost of travelling abroad, while also reducing the amount of travel time and the risk of perishing at sea. At the same time, improved agricultural practices in Southern and Eastern Europe led to a significant surplus of labor in the region. In parts of Scandinavia and Northern Europe, economic conditions had plummeted and unemployment was rampant. All across the European continent, millions of Jews (and other minority religions) were suffering from religious persecution. Meanwhile, the U.S. economy was growing at an incredible pace and gainful employment was nearly guaranteed upon arrival. There was also the promise of religious and political freedom, and the existence of ethnic urban communities ensured that one could find a home among their own people.

All of these factors led to the United States experiencing the largest wave of migration to date, with tens of millions of individuals entering between 1880 and 1915. Figure 4.2 below shows the annual number of migrants filing for residency status between 1860 and 1920. As we can see, there was a large influx of migrants in the 1880's, a brief lull in the 90's, and then migration skyrocketed in the early 20th century. Table 4.3 on the next page displays the breakdown of the U.S. migrant population by region of origin in the according to the 1920 Census, and gives us a snapshot of where this new wave of migrants came from. Unlike the previous wave of migration (which was composed almost entirely of Protestants from Northern Europe and African slaves), there was a large degree

Figure 4.2 Persons Obtaining Legal U.S. Permanent Resident Status (1860



Source: Yearbook of Immigration Statistics by U.S. Department of Homeland Security

Table 4.3 U.S. Immigrant Population, by Region of Origin (1920)

Eastern Europe[1]	Western Europe[2]	British Isles	Southern Europe[3]	Scandinavia
3,731,327	2,740,767	2,172,723	1,939,600	1,328,426
Canada	Latin America	Asia[4]	Africa	Other
1,138,174	588,843	237,950	16,126	26,756

Source: U.S. Census Bureau

[1] Comprised mostly of migrants from Poland and the Russian Empire.

[2] Roughly 80% of these migrants hailed from Germany and Austria.

[3] Nearly 1.8 million of these migrants hailed from Italy alone.

[4] This is a significant underestimation, since Asian laborers were not legally permitted to enter the United States between 1882 and 1912.

of heterogeneity in the composition of the incoming migrants.

Dubbed by some as the "New Immigrants," most of these migrants were Catholic or Jewish. And, unlike the previous wave of migrants, these new arrivals tended to be poor, unskilled, and uneducated[20] individuals. They also tended to behave differently when they arrived in the United States. Whereas the previous wave of migrants typically sought new farmland and established rural communities, these "new immigrants" tended to stay in or near whatever port city they arrived in (usually New York City) and obtained employment in a manufacturing plant. The United States was a land of abundant resources, and had developed significant physical capital by the turn of the century. An influx of unskilled workers was the missing component that the U.S. industrial sectors needed to expand, and the massive wave of "New Immigration" supplied them.

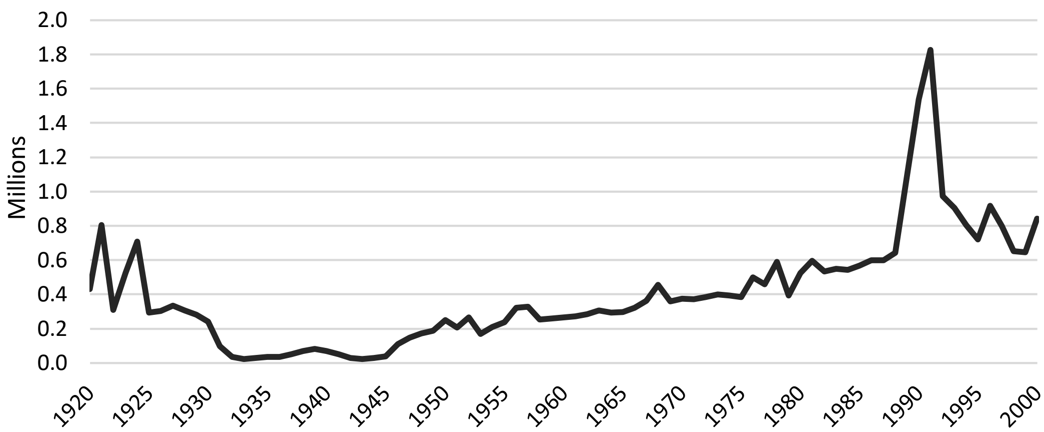
[20] Many of these new arrivals were illiterate in their own language.

By the beginning of the 20th century, the United States economy had become the largest in the world.

Tensions mounted between the various ethnic groups in the "melting pot." The established Anglo-Saxon Protestant communities resented the new arrivals, who often practiced a different religion, spoke a different language, and were blamed for lower wage rates being offered to workers. These attitudes led to the institution of mandatory literacy tests for newly arriving migrants over the age of 16, which would exclude many of the uneducated individuals arriving from Southern and Eastern Europe. Several years later, Congress passed the Immigration Act of 1924, which set annual quotas for European migrants according to their nation of origin. The legislation set the quota for each nation at 2% of the U.S. immigrant population from that nation in 1890. This significantly reduced the amount of migrants allowed to enter from Southern and Eastern Europe, while favoring nations with an Anglo-Saxon Protestant heritage. The law also prevented all Asians and Arabs from legally migrating into the country, and severely restricted the entry of Africans.

Figure 4.3 on the next page displays the number of migrants seeking legal residency status after WW1 through the 20th century. With the onset of the Great Depression and World War Two, immigration into the United States dropped to nearly zero. After WW2, many American soldiers legally brought

Figure 4.3 Persons Obtaining Legal U.S. Permanent Resident Status



Source: Yearbook of Immigration Statistics by U.S. Department of Homeland Security

back European "war wives" with the passage of the War Brides Act of 1945. The United States also accepted a significant number of refugees, orphans, and families that had been displaced by the war. The Displaced Persons Act of 1948 opened the doors for approximately half a million of these individuals to obtain residency status. Outside of these two channels, many migrants entered the United States through the national quota system established by the Immigration Act of 1924. Most of these incoming migrants easily found employment upon arrival, since many factory positions had become vacant when their female laborers returned to the homestead after the war. As we can see in the graph above, there remained a slow and steady growth in this legal migration over the next couple decades. These migrant inflows were determined by the national origins quota system, and so they were primarily composed of Caucasian individuals. According the 1960 U.S. Census, approximately 85% of all foreign-born U.S. residents hailed from Europe or Canada.

There was a substantial shift in these legal migration practices with the passage of the Hart-Celler Act of 1965. The legislation abolished the discriminatory practice of national origin quotas and replaced it with a "category" system. First priority was given to relatives of U.S. citizens and legal permanent residents, and immediate family members were accepted without a numerical restriction. The Act also established the "work visa" system, which was the first immigration control policy that focused on the skill-sets of incoming migrants in order improve the economic well-being of the nation by bridging the gap in any labor shortages recognized by the Secretary of Labor. The landmark piece of legislation also limited immigration from the Americas for the first time in history, while opening the (previously closed) door for migrants from Asia and the Middle East. Also, for the first time in U.S. history, the Hart-Cellar Act placed numerical restrictions on incoming migrants from the western hemisphere.

As expected, the Hart-Cellar Act had several substantial long-term impacts on immigration into the United States. The abolishment of the national

Table 4.4 U.S. Immigrant Population, by Region of Origin (1990)

Latin America[1]	Asia	Eastern Europe	Western Europe	Southern Europe
8,407,837	4,979,037	1,231,372	1,090,582	1,054,141
British Isles	Canada	Africa	Scandinavia	Other
809,972	744,830	363,819	158,299	119,269

Source: U.S. Census Bureau

[1] The majority (4.3 million) of these migrants hail from Mexico.

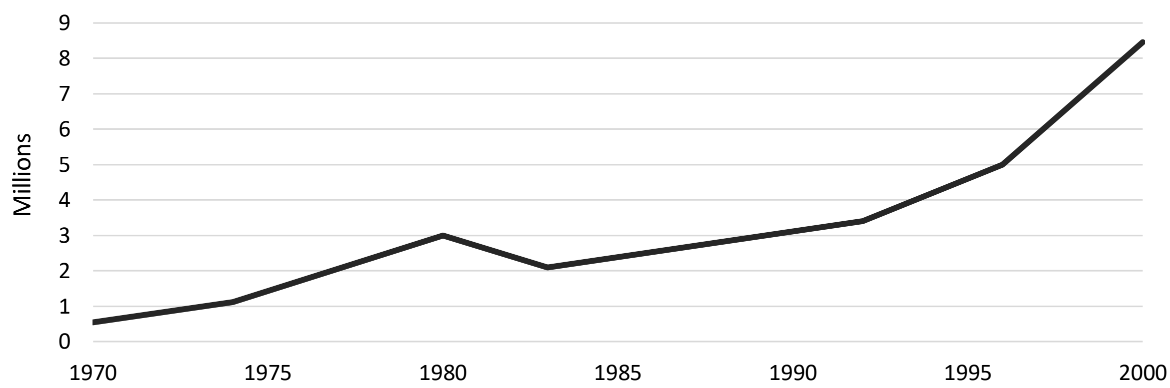
quotas system led to a significant diversification in the ethnic composition of legal migrants. Table 4.4 above displays the breakdown of U.S. immigrant population in 1990, by region. As we can see, millions of Europeans continued to migrate to the nation, albeit at a significantly lower rate compared to the pre-WW2 period. The numbers of individuals migrating from Canada, Scandinavia, and the British Isles also experienced a significant decline. Overall, the Act caused a significant drop in migration from nations that are predominantly Caucasian.

In the second half of the 20th century, the most significant sources of migration were Latin American countries. More than 4 million of these migrants travelled from Mexico in particular, a populous nation that shares a long border with the United States. This trend in Mexican migration began with the Bracero Program, in which the U.S. federal government imported Mexican laborers to assist in agricultural production during World War Two. The program remained in operation until 1964, by which time millions of contracts had been awarded.

Although the labor-contracts were short-term, the Bracero Program had a long-lasting impact by developing Mexican communities north of the border. Once strong communication networks were established, migrants in the United States could relay information about labor market conditions and optimal migration routes back to their friends and family in Mexico. Since there was an enormous discrepancy in wages between the two nations, this sparked a decades-long trend in northward migration from Mexico. Staying true to their historic origins, most of these Hispanic migrants were relatively uneducated laborers and sought employment in the agricultural sectors.

Recall that the Hart-Cellar Act of 1965 placed numerical restrictions on the number of migrants legally allowed to enter from Latin American countries. This coincided with the growing influx of individuals wanted to relocate from these nations, and by the 1970's, those numerical legal limits were reached. As one might expect, migrants reacted by entering the U.S. without legal authorization. Figure 4.4 on the next page presents the annual number of migrants who entered the nation illegally for the last three decades of the 20th century. The population of undocumented migrants rose to approximately 3 million by 1980, levelled out after the 1980's recession, and then rapidly rose during the 90's to exceed 8 million individuals. The U.S. federal government reacted by implementing the Immigration Reform and Control Act (IRCA) of 1986, which instituted two major policies. First, it granted legal amnesty to

Figure 4.4 Population of Immigrants who Entered U.S. Illegally (1969 - 2000)



Sources:
- Robert Warren and Jeffrey S. Passel, "A Count of the Uncountable: Estimates of Undocumented Aliens Counted in the 1980 United States Census," Demography, Aug. 1987
- U.S. Census Bureau
- U.S. Immigration and Naturalization Service
- U.S. Department of Homeland Security

nearly 3 million undocumented migrants who had been residing in the United States for five years. Second, the law required employers to attest to their workers' immigration status and made it illegal for firms to knowingly hire unauthorized migrants. While the amnesty portion of the IRCA of 1986 may have reduced crime levels among migrants (Baker 2015), there was no discernable impact on migration trends.

The second biggest source of American migrants in the second half of the 20th century came from across the Pacific Ocean. Before the Hart-Cellar Act, Asian migration had been severely suppressed by United States legislation, starting with the Page Act of 1875, which prohibited Chinese laborers from bringing their family with them. Subsequently, the Chinese Exclusion Act of 1882 and the Geary Act 1892 virtually outlawed any migration from China. Migrants started pouring in from other Asian countries until Congress passed The Immigration Act of 1924, which effectively banned all Asian immigration for the next thirty years.[21]

Following the Hart-Cellar Act, a large amount of Japanese and Taiwanese migrants and a smaller amount of Hong Kong students joined the wave of Post-Korea/Vietnam 'war brides' moving to the United States. Incidentally, there were very few Chinese migrants taking advantage of the new legislation until 1978, because the People's Republic of China had banned emigration to the United States. Once these restrictions were lifted, an exponentially growing tide of individuals, many of them university students and skilled professionals swept into the United States. The Chinese-born population of the U.S. grew from 286,120 in 1980 to 529,837 in 1990, to nearly 1 million at the turn of the century. Unlike the Asian migrants of the 19th century, many of these laborers were well educated and technically skilled, and entered the nation through the family reunification or work visa channels. Therefore, while Latin American migrants tended to work in rural areas, these Asian immigrants typically worked and settled in urban communities.

[21] This does not include the Philippines, who had become U.S. nationals in 1898 after the conclusion of the Spanish-American War. Therefore, they were not subject to exclusion laws.

4.2 Contemporary U.S. Immigration (21st century)

4.2.1 The Migrants

The number of foreign-born individuals residing within the United States has continued to grow into the 21st century, with a migrant population exceeding 43 million - or 13.4% of the total population - in 2015 (U.S. Census Bureau). Nearly one-half of them have attained U.S. citizenship status, while approximately 11 million of these migrants – roughly a quarter of the total migrant population – are residents who do not have legal authorization. Around two thirds of the migrant population are labor force participants, and 16.5% live below the poverty line. Following historic trends of 'chain migration,' most new arrivals tend to settle in communities whose members share the same national origins, ethnicity, and language.

Table 4.5 on the next page presents the makeup of these migrants in 2015, according to their region of birth. While a significant fraction of immigrants hail from Europe, they no longer dominate the demographic landscape as they did in the early 20th century. Latin America is now the largest sender, with border-sharing Mexico providing 11.5 million alone. Asian migrants make up the second largest demographic group, with millions of individuals who hail from China. Compared to the migration numbers from the 20th century, there has been a marked increase in migrants entering the United States from the

Table 4.5 U.S. Immigrant Population, by Region of Origin (2015)

Asia[1]	Mexico	Europe/Canada	Carribean	Central America[2]
11,615,903	11,576,253	5,012,135	4,153,579	3,393,853
South America	Middle East[3]	Africa[4]	Canada	Other
2,892,436	1,743,272	1,704,261	829,623	236,795

Source: Pew Research Center, using 2015 American Community Survey (1% IPUMS) data

[1] Three largest sources are China (2.7 million), India (2.4 million), and the Philippines (2 million)

[2] This figure does not include Mexico

[3] This includes the nations of Afghanistan, Iran, Iraq, Israel, Palestine, Jordan, Kuwait, Lebanon, Saudi Arabia, Syrua, Turkey, Yemen, Algeria, Egypt, Morocco, and Sudan

[4] Specifically, Sub-Saharan Africa

Caribbean islands, the Middle East, and sub-Saharan Africa.

In the past, the migrant stereotype has been a young, usually uneducated, male leaving his country in search for economic opportunity. However, in 2016, a slight majority (52%) of the migrants in the United States were female (Migration Policy Institute). The average migrant in 2016 was 44.4 years old, which is actually higher than the average 36.1 years of age for U.S. born individuals. The ideal of the uneducated migrant does have some factual backing: nearly 30% of immigrant adults do not have a high school diploma or its equivalent (GED), compared to the 9% of U.S. citizens without one. However, between the years of 2012 and 2016, almost half (47%) of all new migrants were college-educated. This is significantly higher than U.S. citizens educational attainment, in which only 32% obtained a college degree. Certain countries, especially nations from South and East Asia have an even higher sending rate for college educated (e.g. 78% of Indian migrants have a college degree.)

According to the Migration Policy Institute, approximately 22% of households in the United States speak a primary language at home that is not English. Spanish is certainly the most prevalent, comprising 62% of these households, followed by Mandarin and Cantonese Chinese (5%) and a smattering of dozens of other languages. Despite the fact that over a fifth of American households speak a non-English primary language, only nine percent of American residents are classified as Limited English Proficient (LEP). An individual was classified as LEP if they spoke English "well", "not well," or "not at all." This indicates a significant degree of linguistic assimilation on the part of foreigners in the United States.

Table 4.6 below presents the shares of civilian labor force working in broad occupational categories in 2016, separated by nativity. While the most migrants belong to the first category (Management, Business, Science,

Table 4.6 Employed Workers in United States, by Occupation (2016)

Occupation	*Foreign-Born*	*Native-Born*
Management, Business, Science, and Arts	31.6%	38.8%
Service	24.1%	16.8%
Sales and Office	16.6%	24.7%
Natural Resources, Construction, and Maintenance	12.9%	8.0%
Production, Transportation, and Material Moving	14.9%	11.6%

Source: Migration Policy Institute, using numbers tabulated from the American Community Survey of the U.S. Census Bureau and Arts), they are underrepresented in this occupation-type relative to U.S. citizens (31.6% compared to 38.8%). They also comprise a relatively smaller share of Sales and Office jobs as well. Compared to the native population, migrants hold a significant larger share of service positions, especially within the restaurant and hospitality industries. There is a positive differential for migrants in the last two categories, indicating that jobs that require physical labor (e.g. resource extraction, construction, manufacturing, transportation) also tend to be more migrant-intensive.

4.2.2 Legal Paths of Migration

The current legislation governing immigration practices in the United States provides foreigners several different paths to legal residency. These individuals are deemed 'lawful permanent residents' (LPR) and are issued a 'green card' indicating their legal migration status. Each category of legal migration serves a different purpose, whether it be economic, humanitarian, or political in nature. Several of these paths offer migrants the opportunity for a long-term residency. In order to maintain diversity in the immigrant population, no single country can send more than 7% of the total incoming migrants in a single year.

Lawful permanent resident may apply for U.S. citizenship after a five year tenure in the country. Applicants for naturalized U.S. citizenship need to be 18 years or older, demonstrate "good moral character," pass a battery of language (speaking, reading, and writing) and civics tests, and pay an administrative fee. A lawful permanent resident may apply for citizenship after three years if they are the spouse of a U.S. citizen or a victim of violence against women. Foreign-born persons who serve in the U.S. military during wartime are instantly eligible to become a citizen, and are not subject to the same set of restrictions.

Family Unification

Obtaining a family unification visa is the path to permanent residency that has benefitted the most migrants in recent years, with over half a million individuals – just under two thirds of all incoming lawful permanent residents – joining their families in the United States each year. There is a multi-tiered system to the family unification process, and some components of the mechanism are costly (both temporally and monetarily). In order for an individual to move to the U.S., they must have a sponsor that will petition for the individual's relocation, confirm the legitimacy of the relationship, meet minimum income standards, and sign paperwork stating that the sponsor is financially responsible for the migrant upon arrival.

The top tier of the system grants lawful permanent residency to any 'immediate relatives' of a U.S. citizen. In order to be considered an 'immediate relative,' the foreign-born individual must either be a parent, unmarried minor child, or spouse to an American citizen. The interesting aspect of this particular category of family unification is that there is no numerical limit to the number of immediate relatives that can relocate to the United States, as long as their sponsor is an American citizen.

The system gets a little more complicated as we move to potential migrants who are not immediate relatives, or sponsors that are not U.S. citizens. These individuals fall under the 'family preference system,' which technically has

Table 4.7 Family Preference System of U.S. Legal Migration (FY 2014)

Category	*Sponsor*	*Relationship*	*Quota*
1	U.S. citizen	Unmarried adult children	23,400[1]
2A	LPR	Spouses and minor children	87,900
2B	LPR	Unmarried adult children	26,300
3	U.S. citizen	Married adult children	23,400[2]
4	U.S. citizen	Brothers and Sisters	65,000[3]

Source: William A. Kandel, Permanent Legal Migration to the United States, (CRS Report No. R42866) (Washington, DC: Congressional Research Service, 2014)

[1] Plus any unused visas from the 4th preference.

[2] Plus any unused visas from 1st and 2nd preference.

[3] Plus any unused visas from the all other family-based preferences.

an annual numerical limit equal to 480,000 minus the number of 'immediate relatives' that moved to the United States. However, the Immigration and Naturalization Act has a clause that sets an overall floor of 226,000 'family preference' migrants, and in recent years this floor has been binding due to the high amount (exceeding 254,000) of 'immediate relatives' that have been relocating. The breakdown of the five 'family preference categories are summarized in Table 4.7 on the previous page.

Employment-Based Immigration

The second most used channel of legal migration into the United States is the "work visa" program. Much like the family unification system, there are a multitude of visa categories available to employment-based migrants, and the potential migrant requires a sponsor. However, the sponsor in this case is a prospective U.S. employer that has already offered the individual a job.[22] Depending on the visa category, some foreign nationals are granted a temporary stay, whereas others are granted lawful permanent resident status and eventually the opportunity to become a citizen.

Overall, the employment-based permanent immigration system admits 140,000 individuals per year. The law allows lawful permanent residents

[22] There are a few specific situations in which no sponsor is necessary.

obtaining a work visa to bring their spouse and children under 18 years with them to the United States, and these immediate family members are counted toward the quota of 140,000. The five categories of permanent work visas are displayed in Table 4.8 on the next page. The first two categories specifically target individuals with "extraordinary" or "exceptional" ability in the arts, sciences, academia, or business. The third category is much more accessible: a potential migrant either needs a bachelor's degree or two years of work experience, with a very small (5,000) allotment to "other" workers with no defined skillset. According to the United States Citizenship and Immigration Services, there is a very long backlog of individuals applying through the third category system. The fourth and fifth categories are not targeted toward bringing in high-skill laborers, but instead allow foreigners working with the State Department or high-capital investors whose business activity will increase employment by at least ten workers. The second and third category of permanent work visas (EB-2 and EB-3) have a special requirement: it is mandatory for the sponsoring employer to obtain an approved Labor Certification from the United States Department of Labor (DOL). In order for the Labor Certification to be issued for a position, the US DOL must testimony from employers in the sector that verifies that there is an insufficient number of qualified native U.S. laborers available. The Department of Labor also must determine that the hiring of the new migrant workers will not adversely affect

Table 4.8 Permanent Worker Visa Preference Categories

Category	*Description*	*Quota*	*Labor Certification Required*
EB-1	Persons of extraordinary ability in the sciences, arts, education, business, or athletics; outstanding professors or researchers; and multinational executives and managers.	40,000[1]	No
EB-2	Persons who are members of the professions holding advanced degrees or for persons with exceptional ability in the arts, sciences, or business.	40,000[2]	Yes[3]
EB-3	Skilled workers with at least two years of training or experience, professionals with college degrees, or "other" workers for unskilled labor that is not temporary or seasonal.	40,000[4]	Yes
EB-4	"Special immigrants," which includes certain religious workers, employees of U.S. foreign service posts, retired employees of international organizations, alien minors who are wards of courts in the United States, and other classes of aliens.	10,000	No
EB-5	Business investors who invest $1 million or $500,000 (if the investment is made in a targeted employment area) in a new commercial enterprise that employs at least 10 full-time U.S. workers.	10,000	No

Sources:
-William A. Kandel, Permanent Legal Migration to the United States, (CRS Report No. R42866) (Washington, DC: Congressional Research Service, 2014)
-United States Immigration and Citizenship Services

[1] Plus any unused visas from the 4th and 5th preferences.

[2] Plus any unused visas from the 1st preference.

[3] Labor certification not required if applicant can obtain a national interest waiver.

[4] Plus any unused visas from the 1st and 2nd preference. "Other" unskilled laborers restricted to 5,000

the wages and working conditions of U.S. citizens that are “similarly employed.” This certification is also required for several categories of the temporary work visa program.

The temporary work visa program for “non-immigrant workers” has over twenty different categorizations. These categorizations fulfill a broad variety of national interests, such as bringing in individuals working with the Department of Defense, artists of exceptional ability, teachers of foreign culture, laborers willing to relocate for seasonal work, etc. I present a table of many of these visa-types in Appendix A.6. Temporary employment-based visa holders must work for the firm that sponsored them, and are restricted in their ability to work for a different employer. These “non-immigrant workers” are in the country for a fixed period of time (usually between 3 and 6 months), and must leave the country if their employment is terminated or their visa expires. According to the Center for Migration Studies, approximately two-thirds of all unauthorized migrants in the United States are expired visa-holders.

Diversity Visa

The United States Immigration and Citizenship Services accepts 50,000 migrants each year from selected countries, in the name of cultural diversification. The countries are selected because they have a historical record of sending a small amount of migrants (thus countries like China and Mexico are excluded). The requirements for a diversity green card are pretty basic: one must have a high school education *or* have a couple years' experience working in an occupation with two years of training. Since the application carries no monetary costs, millions of individuals apply to the program. The winners are chosen by a randomized selection system, also known as the 'green card lottery.' Since only 50,000 people are chosen out of the millions that apply, the odds of being accepted are very small.

Refugees and Asylum-Seekers

Refugees are admitted into the United States if they are unable to return to their home nation because there is a reasonable fear that they would face persecution on the basis of race, religion, political opinion, et cetera. Other factors also come into play: such as whether the potential refugee has family in the U.S., or whether they belong to a group of special interest (as determined by the President and Congress). In 2016, the President of the United States set the maximum limit on incoming refugees at 85,000. Table 4.9 on the next page displays the numerical limits on refugee acceptance, according to their region of origin. Oftentimes, a refugee will file with U.S. Citizenship and Immigration Services in a transition country that is willing to host the individual until they are

Table 4.9 U.S. Refugee Admissions (FY 2016)

Near East / South Asia 34,000	Africa 25,000	East Asia 13,000
Europe / Centra Asia 4,000	Latin America/Caribbean 3,000	Unallocated Reserve 6,000

Source: U.S. Departments of State, Homeland Security, and Health and Human Services, Proposed Refugee Admissions for Fiscal Year 2016: Report to the Congress, (Washington, DC, 2015).

transferred to the United States. After staying in the country for twelve months, refugees may apply for a green card.

Individuals who are already residing within the United States for less than a year – and face reasonable fears of persecution in their home country – may seek asylum with the U.S. Citizenship and Immigration Services, with the same qualifying rules as those seeking refugee status. After one year of asylum status of residency, an individual may apply for a green card. In 2014, asylum status was granted to 23,533 individuals.

Deferred Action for Childhood Arrivals (DACA)

In June 2012, the Obama administration signed an executive order known as Deferred Action for Childhood Arrivals (DACA). The immigration control policy targeted individuals who either entered or remained in the country without authorization when they were under 16 years of age. The reasoning was that these individuals did not make the decision to break the law and they have already been assimilated into U.S. culture, since they were immersed throughout their childhood. The immigration policy established that these migrants, commonly known as DREAMers, could receive a two-year period of 'deferred action' from deportation and were eligible to apply for work visa permits. At the end of the two-year period, a person is eligible to reapply for DACA status. According to the Pew Research Center, approximately 800,000 individuals have received legal protection through DACA since its inception. In September 2017, President Trump began to phase the program out of existence, and the fate of many DREAMers hangs in the balance as Congress works to institute replacement legislation.

4.2.3 Immigration Enforcement

Immigration control policy in the United States has grown explosively over the past century, expanding beyond Ellis and Angel Island into a conglomerate of federal agencies with multi-billion dollar budgets that employ tens of thousands of administrative and law enforcement individuals. According to the Migration Policy Institute (Meissner et al. 2013), the immigration agencies in the United States have a de facto 'enforcement first' policy, with six main 'pillars' of enforcement:

1. Border enforcement
2. Visa controls and travel screening
3. Information and interoperability of data systems
4. Workplace enforcement
5. Intersection of criminal justice system and immigration enforcement
6. Detention and removal on noncitizens

The first two 'pillars,' border enforcement and visa controls and travel screening, are handled by the United States Customs and Border Protection Agency (CBP). The agency has seen an enormous amount of growth in resources and manpower in the 21st century. From 2005 to 2013, the agency's annual budget rose from $6.3 billion to $11.7 billion and staffing grew from 41,001 to 61,354 personnel, mostly through the hiring of additional border patrol agents. In order to stem the flow of unlawful border crossings, specifically land-crossings from Mexico into the United States, the CBP adopted a multi-faceted plan that employed resources in high-traffic border areas and points of entry, such as airports. Through a combination of physical construction of barriers (e.g. fencing), employment of advanced surveillance technology, and simply more boots on the ground,[23] the efficacy of U.S. border protection increased significantly, making illegal entry much more difficult for migrants (Amuedo-Dorantes and Pozo 2014). This, combined with a relatively improving Mexican

[23] The number of Border Patrol agents more than doubled from 2004 through 2012. In addition to this, the U.S. National Guard was activated through Operation Phalanx to work alongside Border Patrol on the Southwest border with Mexico.

economy, led to a net negative flow from Mexico for the first time in 40 years (U.S. Department of Homeland Security).

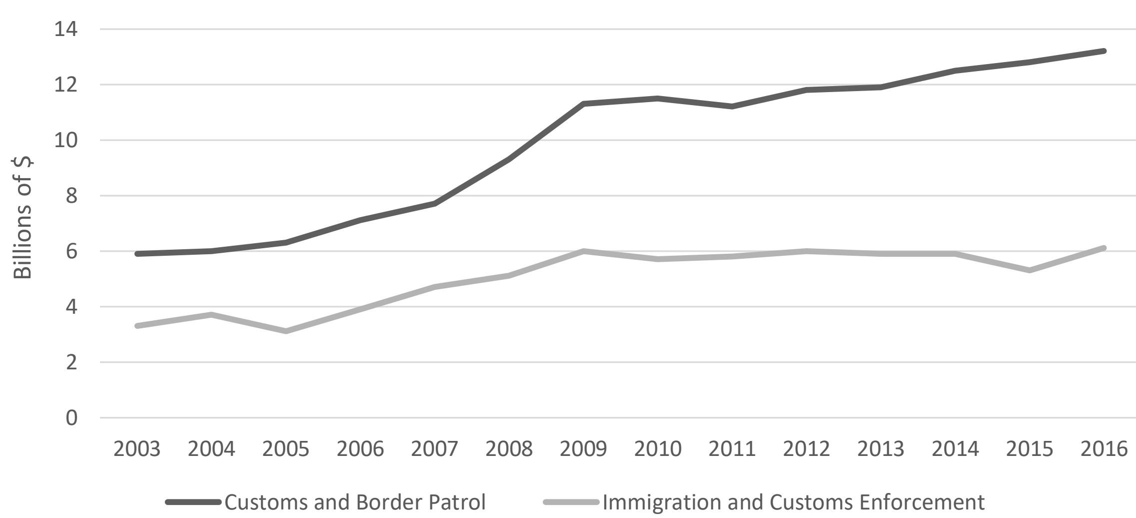
According to the Pew Hispanic Center, approximately 40 to 50% of unauthorized migrants residing in the United States entered the country lawfully but remained in the U.S. after their visa had expired. Once a migrant has gained entry to the United States, they fall under the jurisdiction of the United States Immigration and Customs Enforcement Agency (ICE). ICE is responsible for the handling of interior enforcement function represented by the last three 'pillars:' workplace enforcement, immigrant criminal justice, and detention/removal of noncitizens.

ICE's role in workplace enforcement is mostly defined by the Immigration Reform and Control Act of 1986, which mandates that firms must verify the work eligibility / lawful residency status of its employees. Initially the law was mostly ineffective, as employers realized that there was virtually zero risk in hiring undocumented workers, and the required documents were easy to counterfeit. The federal government responded by instituting E-Verify, a voluntary and much more effective employment verification system that is now being required by a substantial number of U.S. states. In the past several years, ICE has also instituted a shift in who they target in workplace enforcement. Instead of conducting massive raids and arrests, they are focusing on employers: since

2009, ICE has audited thousands of companies, debarred hundreds of companies and persons, and imposed tens of millions of dollars in fines for breaking ‘employer sanction’ laws (Meissner et al. 2013).

Ever since 9/11, immigration enforcement agencies have become increasingly interconnected with the U.S. criminal justice system. In 2005, the Department of Homeland Security and the Department of Justice enacted Operation Streamline. With this new directive, migrants caught entering the country unlawfully would now be arrested, charged, and prosecuted, rather than the previous policy of granting voluntary return. By 2011, the majority of all

Figure 4.5 Annual FY Budgets for CBP and ICE (2003 - 2016)



federal criminal prosecutions were based on immigration-related charges[24] (Transactional Records Access Clearinghouse 2013). In addition to this initiative, there has also been an increased effort in the removal of undocumented residents that have committed a criminal offense (other than unlawful residency).

ICE has instituted a host of programs to this effect, which now have an annual budget exceeding a half billion. One of these, Section 287(g), allows the Department of Homeland Security to deputize local law enforcement officers. These officers received four weeks of specialized training and the authorization to identify and detain immigrant criminals, leading to the deportation of nearly half a million migrants since 2006 (U.S. Department of Homeland Security). Other programs such as the National Fugitives Operation and the Criminal Alien Program, focus on identifying violent migrant criminals and deporting them. According to ICE, these programs have led to the removal of hundreds of thousands of dangerous individuals.

Following the September 11th attacks and the decentralization of the immigration control system in 2003, the Department of Homeland Security recognized that its agencies needed to connect its databases in order to effectively carry out its mission. Thus, in 2004, a third agency

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[24] The two most common charges are 'illegal entry' (misdemeanor) and 'illegal entry following removal' (felony).

was created under the purview of DHS: the United States Visitor Immigration Status and Information Technology (US-VISIT). The primary objective of this agency was the formation of the Automated Biometric Identification System (IDENT), which collected biological data on every single migrant that enters the nation legally, as well as migrants who have been processed by a law enforcement agency. According to the DHS, the IDENT system currently has more than 200 million fingerprints on file, making it one of the largest criminal databases in the world. This information is being integrated with the FBI and DOD biometric datasets (and the Secure Communities program), making the information available to virtually every law enforcement officer and social analyst in the federal government.

Chapter 5

EMPIRICAL ANALYSIS

In order to test whether or not immigration control policy acts as an effective labor screening device, I examine the relationship between migrants' wages and weekly hours worked and the amount of funding and effort that goes into establishing obstacles for incoming migrants. I do so by analyzing the impact of the implementation of the Homeland Security Act of 2002 on migrants who moved to the United States after the legislation had passed. This event serves as a natural experiment, since the inception of the legislation was completely unrelated to migrants' economic conditions. Therefore, this analysis does not suffer bias due to endogeneity. By examining the national labor market as a whole, this study also avoids the "closedness" issue that plagues other spatial correlation analyses in the field.

I will be conducting this analysis on three different subsets of the population, beginning with the entire U.S. labor market before moving onto the exogenous-wage labor market and the endogenous-wage labor market.

According to the model presented in this paper, the labor market in which wages are set exogenously should exhibit a stronger labor screening effect than the endogenous wage market.[25] Before continuing, it is important to note that there is the potential for omitted variable bias, as other conditions may have changed after 2002, such as the recession that followed the Sept. 11 attacks. However, I attempt to control for these changes by employing various demographic, geographic, and temporal variables.

5.1 Homeland Security Act of 2002

The terrorist attacks on the September 11, 2001 had many far-reaching implications on the American people, including a significant shift in public attitude toward national security. Suddenly, all potential avenues of terroristic activity were under close scrutiny. By the start of 2002, politicians and their constituents began making claims that the United States border with Mexico was too porous. People feared that terrorists could easily cross the largely unprotected border. The avenue of legal migration was also viewed as a potential source of danger, and government agencies responded by increasing airport security, tightening vetting practices and even engaging in racial profiling.

[25] This is due to the fact that the feedback loop in the endogenous-wage market causes firms to offer migrants a wage rate that is relatively higher, which subsequently draws in relatively less productive migrants and lowers the average productivity of the migrant pool.

When the Homeland Security Act was passed in November of 2002, it included many immigration control measures that strengthened security measures – especially along the border with Mexico – and mandated harsher punishment for those caught illegally crossing into the country. The implementation of these stricter immigration control policies caused the human costs of illegal migration to increase significantly (Amuedo-Dorantes and Pozo 2014). Examples of these costs include a “significant increase” in migrants’ perceived risks of death and familial separation. These migrants also faced a higher risk of deportation after successfully crossing the border, as the Homeland Security Act contained state-level legislation that allowed local and state law enforcement to act as de facto immigration agents. In fact, the number of immigrants that were returned and removed from the United States more than doubled from 2002 to 2008 (U.S. Department of Homeland Security).

5.2 Data

The data for this analysis come from the CEPR Uniform Extract of the March Current Population Survey (CPS). The CPS is a monthly survey conducted by the U.S. Census Bureau that collects extensive demographic information for non-institutionalized adults at the household level. This information includes variables of interest such as age, race, ethnicity, gender, citizenship status, and language, as well as the year of arrival and nation of origin for immigrants. The interviews for the CPS are conducted on a 4/8/4 rotation schedule in which a household is surveyed for 4 months, ignored for 8, and surveyed another 4 months before leaving the rotation. The sample size is approximately 60,000 households selected at random. In March, the survey includes questions from the Annual Social and Economic Supplement, which asks respondents about information on their annual earnings among other socio-economic conditions. The data for this analysis stretches from 2015 back to 1998, which was the first year that the March supplement was instituted, for a total of 1.37 million observations.

5.3 Method

Using difference-in-difference techniques, I compare the wages of migrants who arrived in the U.S. before the passage of the Homeland Security Act with those who arrived afterward, relative to non-migrants. According to the model I present in this paper, immigrants arriving after 2002 should have a higher wage rate than their pre-2002 counterparts, after controlling for all other variables. In addition to this, I also investigate the impact of the increase in immigration control policy on the average number of hours worked per week.

For the entire U.S. labor market, exogenous-wage markets, and endogenous-wage markets, I perform least-square regressions with a difference-in-difference specification of:

$$(13)\quad y_i = \alpha + \beta(Migrant|Post\_2002\_entry_i) + \delta Migrant_i + \varphi Post\_2002\_entry_i + \gamma X_i + \varepsilon_i$$

where y_i is the market outcome variable of interest (log wage rate or hours worked), β is the coefficient of interest, and X_i is a set of controls including demographic characteristics (i.e. age, race, ethnicity, gender, rural/urban status), educational attainment, year of observation, and migrant interaction effects. Simply being a migrant, or entering the labor force after 2002, may influence a laborer's market outcome, thus I include the third and fourth terms in order to control for this variation.

For the exogenous and endogenous-wage markets, I perform difference-in-difference-in-difference regression analyses in order to isolate the differential screening effect that the Homeland Security Act of 2002 had on the different types of markets. These unrestricted regressions had the following specification:

$$
\begin{aligned}
(14)\quad y_i = \alpha &+ \omega(Migrant|Exog\_Endog\_Market|Post\_2002\_entry_i) \\
&+ \beta(Migrant|Post\_2002\_entry_i) \\
&+ \vartheta(Migrant|Exog\_Endog\_Market_i) \\
&+ \mu(Exog\_Endog\_Market|Post\_2002\_entry_i) + \delta Migrant_i \\
&+ \varphi Post\_2002\_entry_i + \pi Exog\_Endog\_Market_i + \gamma X_i + \varepsilon_i
\end{aligned}
$$

Based on the implications of the model, we expect to see that the increase in immigration control policy had a stronger effect on the exogenous-wage market ($\omega>0$) and a weaker effect on the endogenous-wage market ($\omega<0$), since the feedback loop in the endogenous wage market causes more low-productivity migrants to enter in response to the increased wage rate.

5.4 Entire U.S. Labor Market

5.4.1 Comparative Statistics

Summary statistics of several key market and demographic characteristics are displayed separately for migrants and non-migrants in Table 5.1 on the next page. Native laborers have an average hourly wage rate that exceeds migrants' by $2.60, a small but significant difference that could partially be explained by the fact that native laborers have an additional year and a half of educational attainment, on average. There is virtually no difference between the two populations in hours worked per week and the rate of unemployment.

Citizens and migrants are also approximately the same age, on average. In terms of race and ethnicity, there is a wide degree of separation: only a small minority of migrants are non-Hispanic Caucasian. Nearly half of all migrants identify as Hispanic, and almost a quarter are Asian. There is also a significant gender differential; males make up 8% more of the migrant labor population relative to the native laborer population.

Table 5.2 displays market and demographic characteristics for migrant

Table 5.1 Characteristics of Workers in the United States, by Origin of Birth (1998-2015)

	Native Citizens	Migrants
Average Hourly Wage	$24.62	$22.02
Average Hours per Week	39.7	39.7
% Unemployed	4.9%	4.9%
Average Age	39.7	39.5
Average Years of Education	14.0	12.5
% Residing in Rural Area	17.2%	4.3%
% Male	50.9%	58.9%
% White	77.1%	18.0%
% Hispanic	7.8%	49.6%
% Black	12.4%	8.5%
% Asian	1.7%	23.7%
% Other	1.1%	0.2%
Sample Size	1,163,655	212,679

Any individuals below the age of 18 or above the age of 65, belonging to the armed services, self-employed, or with an hourly real wage exceeding $10,000 were removed from the sample. All values estimated using CEPR Uniform Extract March CPS sampling weights.

laborers, sorted by whether they arrived in the United States before or after January 1, 2002. Migrants who arrived after 2002 have a lower real wage rate by $2.67, work an hour less per week, and have a higher unemployment rate. These market condition differentials can be explained by the fact that pre-2002 migrants are roughly 6 years older and have been residing in the country nearly

Table 5.2 Migrant Workers in the United States, by Year of Arrival (1998-2015)

	Entered before 2002	Entered after 2002
Average Hourly Wage	$22.41	$19.74
Average Hours per Week	39.8	38.8
% Unemployed	4.8%	5.5%
Average Age	40.4	34.4
Average Years of Education	12.5	12.5
Years Since Arrival	19.9	6.1
% Residing in Rural Area	4.2%	5.0%
% Male	58.1%	63.5%
% White	18.5%	15.6%
% Hispanic	49.7%	49.2%
% Black	8.2%	9.8%
% Asian	23.4%	25.2%
% Other	0.2%	0.2%
Sample Size	181,668	31,011

Any individuals below the age of 18 or above the age of 65, belonging to the armed services, self-employed, or with an hourly real wage exceeding $10,000 were removed from the sample. All values estimated using CEPR Uniform Extract March CPS sampling weights.

14 years longer, on average. The two groups have very similar educational attainment and racial/ethnic characteristics, although the new migrants tend to be slightly more male and non-white, with increases in the shares of black and Asian individuals.

5.4.2 Results

I begin this section with a naïve comparison of the hourly wage earned by the four subsets of American laborers, separated by migrant status and the year of entry into the labor force. These values are displayed in Table 5.3 below, along with the differences between the temporally separated groups, and the final difference-in-difference. Workers who entered the labor force after 2002

Table 5.3 Comparison of Average Hourly Wages, 1998-2015

	Entered Labor Force		
	Before 2002	**After 2002**	**Difference**
Native Citizen	$25.80	$17.40	-$8.40
Migrant	$22.41	$19.74	-$2.67
		Difference-in-Difference:	$5.73

Any individuals below the age of 18 or above the age of 65, belonging to the armed services, self-employed, or with an hourly real wage exceeding $10,000 were removed from the sample. All values estimated using CEPR Uniform Extract March CPS sampling weights.

make significantly less than those who entered beforehand, for both migrants and non-migrants. However, the difference between the migrant subsamples is much smaller than for native citizens. In fact, migrants entering the workforce before/during 2002 had a considerably lower wage rate than their native counterparts, whereas migrants entering after 2002 had a relatively higher wage rate than non-migrants, resulting in a large difference-in-difference calculation of $5.73.

This evidence suggests that the screening effect exists, but there are many underlying factors that could be driving these results. When native citizens enter the workforce, they are typically doing so between the ages of 16 and 26. In contrast, when migrants enter the labor force, they are doing so at whatever age they migrate to the new country, resulting in a higher average age and thus a higher experience level and wage rate. Other confounding factors include educational attainment, racial/ethnic makeup, geographic differentiation, and the impact of the subset of migrants who entered the country as a child. In order to control for these influences, I estimate equation (8), allowing for a more accurate calculation of the impact of the Homeland Security Act on migrants' market condition outcomes.

The results of these regression analyses are presented in Table 5.4 below. For the sake of completeness, I conducted OLS regressions on two variables of interest – migrants' wage rate and the usual number of hours worked in a week – with six different specifications. The table shows only the key coefficient (i.e. the effect on migrants entering the United States after the passage of the HSA of 2002) and its respective p-value for each specification. I begin with a "naïve"

Table 5.4 Regression Results: Impact of Post-2002 Entry on Migrants

		(1)	(2)	(3)	(4)	(5)	(6)
Log Real Hourly Wage	*Coefficient estimate*	0.244	0.060	0.030	0.034	0.045	0.031
	P-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Hours Worked	*Coefficient estimate*	4.020	1.112	0.650	1.043	0.966	0.664
	P-value	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Demographic characteristics		No	Yes	Yes	Yes	Yes	Yes
Years of education - linear		No	Yes	No	Yes	No	No
Diploma attainment		No	No	Yes	No	Yes	Yes
Year of observation - linear and squared		No	Yes	No	No	No	No
Year of observation - fixed effects		No	No	Yes	Yes	Yes	Yes
Migrant interaction effects		No	No	No	Yes	Yes	Yes
Year of arrival - linear and squared		No	Yes	No	No	Yes	No
"Young migrants" excluded		No	No	No	No	No	Yes

Any individuals below the age of 18 or above the age of 65, belonging to the armed services, self-employed, or with an hourly real wage exceeding $10,000 were removed from the sample. All parameters are estimated using CEPR Uniform Extract March CPS sampling weights, and errors are clustered by current state of residence. Demographic characteristics include experience, experience squared, and years since arrival, with dummy indicators for race/ethnicity, gender, and urban/rural status. For migrant interaction effects, new explanatory variables are introduced in which each independent variable is multiplied by a dummy indicator for whether the individual is a migrant. "Young migrants" are defined as individuals who relocated to the United States before having the chance to enter the labor force.

specification with only the DID terms, and move onto specifications that include demographic control variables, education controls (linear or indicators), temporal controls (trend or fixed effects), and migrant interaction effects.

In the second and fifth specifications, I include trend variables (linear and squared) for migrants' year of arrival. It is possible that there has been a continuous and significant relationship between migrants' year of arrival and productivity. Without the aforementioned trend variables, a binary before/after 2002 analysis would register a significant difference, even if there was not a discrete jump in productivity after 2002. In the sixth specification, migrants who were too young to work when they entered the United States before 2002 were removed from the sample, since these individuals could potentially bias the difference-in-difference results (they are migrants who entered the labor force post-2002, but were not "screened" by the Homeland Security Act).

For all six specifications, I obtain positive and statistically significant estimations of the parameter β for the hourly real wage rate and hours worked per week. With the naïve and the linear/squared time control specifications, the percentage wage differential is quite high: 24.4% and 6.0%, respectively. However, according to specifications (3) through (6) in which I employ annual fixed effects, migrants arriving after 2002 had a wage rate (or marginal productivity) that is approximately 3.0-4.5% higher relative to their counterparts, ceteris paribus. For the same set of specifications, migrants who arrived after the passing of the Act work approximately 0.65-1.04 more hours per week than those who arrived beforehand, after controlling for outside factors. This is compelling evidence that the increase in immigration control policy through the Homeland Security Act of 2002 had a "screening" effect on incoming migrants, resulting in a significantly more productive class of migrants.

5.5 Exogenous-Wage U.S. Labor Market

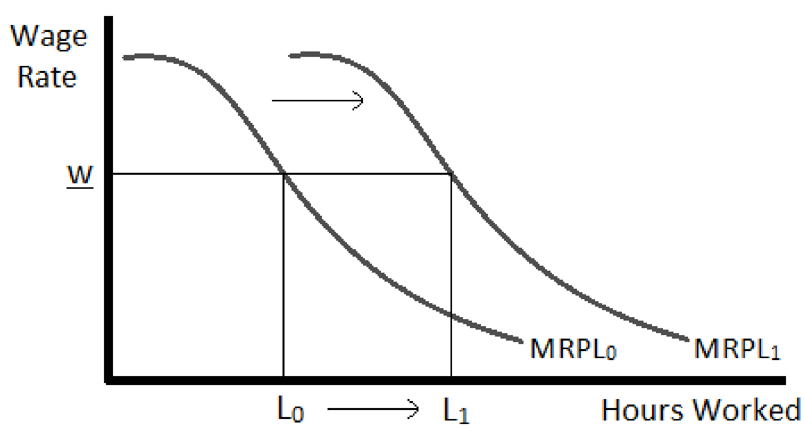
5.5.1 Defining the Market

For the purposes of this paper, the exogenous wage-setting market is one in which the wage rate that is offered to migrants in a particular market/sector is unaffected by the decision-making of potential incoming migrants. In other words, the offered wage rate is determined by a process that is external to the migration model such that there is no feedback loop between the two variables. There is only one type of labor market that truly satisfies this condition: markets in which a binding wage floor is established by the government (i.e. minimum wage legislation).

Enacted at the federal, state, and municipal levels of government, minimum wage legislation determines a minimum hourly wage rate that employers must offer their employees. These price floors are established with the goal of ensuring a basic standard of living for all workers. According to the U.S. Bureau of Labor Statistics, a small percentage of American workers actually earn minimum wage, and these (typically young and uneducated) individuals tend to be clustered in sectors that do not require skilled labor. Since there is no question on the CPS that asks respondents if they earn minimum wage, I will use four different methods to approximately determine which subset of the population works in a labor market with binding wage floor.

For the purposes of the minimum wage analyses, the only independent variable that is analyzed is the 'hours worked per week' variable. The reason here is obvious: a worker's hourly wage rate is fixed in the minimum wage market. Any variation in a laborer's productivity cannot impact that wage rate

Figure 5.1 Increase in Marginal Productivity of Minimum Wage Laborer



that they earn. However, according to basic microeconomic theory, an increase in a worker's marginal (revenue) product of labor will incentivize a profit-maximizing employer to hire that laborer for more time per market period (see Figure 5.1 above). Keeping in mind that the model predicts a stronger screening effect for exogenous wage markets, we would expect that the passage of the Homeland Security Act of 2002 would have a relatively larger impact on weekly hours worked for migrant workers earning minimum wage.

Method 1

The first method that I employ in order to define the market is also the most straightforward: I define a worker as "minimum wage" if they have an hourly earning rate that is roughly equal to their state's effective minimum wage for their given year of observation. Using data from the United States Department of Labor, I present these minimum wage rates by year for all 50 states (plus the District of Columbia) in Table 5.5 on the next page. There are several states who have not passed any minimum wage legislation, or have a price floor that is set below the federal level. According to the Fair Labor Standards Act, any workers in these states are entitled to receive hourly compensation as determined by the U.S. Congress. In other words, those states'

Table 5.5 Effective Minimum Wage Rates by State and Year (1998-2015)

	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Federal	**$5.15**	**$5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.85**	**6.55**	**7.25**	**7.25**	**7.25**	**7.25**	**7.25**	**7.25**
Alabama	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.85**	**6.55**	**7.25**	**7.25**	**7.25**	**7.25**	**7.25**	**7.25**
Alaska	5.65	5.65	5.65	5.65	5.65	7.15	7.15	7.15	7.15	7.15	7.15	7.15	7.75	7.75	7.75	7.75	7.75	8.75
Arizona	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	6.75	6.90	7.25	7.25	7.35	7.65	7.80	7.90	8.05
Arkansas	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	6.25	6.25	**6.55**	**7.25**	**7.25**	**7.25**	**7.25**	**7.25**	7.50
California	5.15	5.75	5.75	6.25	6.75	6.75	6.75	6.75	6.75	7.50	8.00	8.00	8.00	8.00	8.00	8.00	9.00	9.00
Colorado	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	6.85	7.02	7.28	**7.25**	7.36	7.64	7.78	8.00	8.23
Connecticut	5.18	5.65	6.15	6.40	6.70	6.90	7.10	7.10	7.40	7.65	7.65	8.00	8.25	8.25	8.25	8.25	8.70	9.15
Delaware	5.15	5.65	5.65	6.15	6.15	6.15	6.15	6.15	6.15	6.65	7.15	7.15	7.25	7.25	7.25	7.25	7.75	8.25
Dist. of Columbia	6.15	6.15	6.15	6.15	6.15	6.15	6.15	6.60	7.00	7.00	7.00	7.55	8.25	8.25	8.25	8.25	9.50	10.50
Florida	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	6.40	6.67	6.79	7.21	7.25	7.25	7.67	7.79	7.93	8.05
Georgia	**5.15**	**5.15**	**5.15**	**5.15**	5.15	5.15	5.15	5.15	5.15	5.15	**5.85**	**6.55**	**7.25**	**7.25**	**7.25**	**7.25**	**7.25**	**7.25**
Hawaii	5.25	5.25	5.25	5.25	5.75	6.25	6.25	6.25	6.75	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.75
Idaho	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.85	6.55	7.25	7.25	7.25	7.25	7.25	7.25
Illinois	5.15	5.15	5.15	5.15	5.15	5.15	5.50	6.50	6.50	6.50	7.50	7.75	8.00	8.25	8.25	8.25	8.25	8.25
Indiana	**5.15**	**5.15**	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.85	6.55	7.25	7.25	7.25	7.25	7.25	7.25
Iowa	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	7.25	7.25	7.25	7.25	7.25	7.25	7.25	7.25
Kansas	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.85**	**6.55**	7.25	7.25	7.25	7.25	7.25	7.25
Kentucky	**5.15**	**5.15**	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.85	6.55	7.25	7.25	7.25	7.25	7.25	7.25
Louisiana	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.85**	**6.55**	**7.25**	**7.25**	**7.25**	**7.25**	**7.25**	**7.25**
Maine	5.15	5.15	5.15	5.15	5.75	6.25	6.25	6.35	6.50	6.75	7.00	7.25	7.50	7.50	7.50	7.50	7.50	7.50
Maryland	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	6.15	6.15	6.55	7.25	7.25	7.25	7.25	7.25	8.25
Massachusetts	5.25	5.25	6.00	6.75	6.75	6.75	6.75	6.75	6.75	7.50	8.00	8.00	8.00	8.00	8.00	8.00	8.00	9.00
Michigan	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	6.95	7.15	7.40	7.40	7.40	7.40	7.40	8.15	8.15
Minnesota[1]	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	6.15	6.15	6.15	**6.55**	**7.25**	**7.25**	**7.25**	**7.25**	8.00	9.00
Mississippi	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.85**	**6.55**	**7.25**	**7.25**	**7.25**	**7.25**	**7.25**	**7.25**
Missouri	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	6.50	6.65	7.05	7.25	7.25	7.25	7.35	7.50	7.65
Montana	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	6.15	6.25	6.90	7.25	7.35	7.65	7.80	7.90	8.05
Nebraska	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.85	6.55	7.25	7.25	7.25	7.25	7.25	8.00
Nevada	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	6.15	6.33	6.55	**7.25**	7.25	7.25	7.25	7.25	7.25
New Hampshire	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	6.50	7.25	7.25	7.25	7.25	7.25	7.25	7.25
New Jersey	**5.15**	**5.15**	5.15	5.15	5.15	5.15	5.15	5.15	6.15	7.15	7.15	7.15	7.25	7.25	7.25	7.25	8.25	8.38
New Mexico	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	5.15	5.15	5.15	5.15	6.50	7.50	7.50	7.50	7.50	7.50	7.50	7.50
New York	**5.15**	**5.15**	**5.15**	5.15	5.15	5.15	5.15	6.00	6.75	7.15	7.15	7.15	7.25	7.25	7.25	7.25	8.00	8.75
North Carolina	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	6.15	6.15	6.55	7.25	7.25	7.25	7.25	7.25	7.25
North Dakota	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.85	6.55	7.25	7.25	7.25	7.25	7.25	7.25
Ohio	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	6.85	7.00	7.30	7.30	7.40	7.70	7.85	7.95	8.10
Oklahoma	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.85	6.55	7.25	7.25	7.25	7.25	7.25	7.25
Oregon	6.00	6.00	6.50	6.50	6.50	6.90	7.05	7.25	7.50	7.80	7.95	8.40	8.40	8.50	8.80	8.95	9.10	9.25
Pennsylvania	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	6.25	7.15	7.15	7.25	7.25	7.25	7.25	7.25	7.25
Rhode Island	5.15	5.65	5.65	6.15	6.15	6.15	6.75	6.75	6.75	7.40	7.40	7.40	7.40	7.40	7.40	7.75	8.00	9.00
South Carolina	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.85**	**6.55**	**7.25**	**7.25**	**7.25**	**7.25**	**7.25**	**7.25**
South Dakota	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.85	6.55	7.25	7.25	7.25	7.25	7.25	8.50
Tennessee	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.15**	**5.85**	**6.55**	**7.25**	**7.25**	**7.25**	**7.25**	**7.25**	**7.25**
Texas	**5.15**	**5.15**	**5.15**	**5.15**	5.15	5.15	5.15	5.15	5.15	5.15	5.85	6.55	7.25	7.25	7.25	7.25	7.25	7.25
Utah	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.85	6.55	7.25	7.25	7.25	7.25	7.25	7.25
Vermont	5.25	5.25	5.75	6.25	6.25	6.25	6.75	7.00	7.25	7.53	7.68	8.06	8.06	8.15	8.46	8.60	8.73	9.15
Virginia	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.85	6.55	7.25	7.25	7.25	7.25	7.25	7.25
Washington	**5.15**	5.75	6.50	6.72	6.90	7.01	7.16	7.35	7.63	7.93	8.07	8.55	8.55	8.67	9.04	9.19	9.32	9.47
West Virginia	**5.15**	**5.15**	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.85	6.55	7.25	7.25	7.25	7.25	7.25	7.25	8.00
Wisconsin	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.15	5.70	6.50	6.50	**6.55**	7.25	7.25	7.25	7.25	7.25	7.25
Wyoming	**5.15**	**5.15**	**5.15**	**5.15**	5.15	5.15	5.15	5.15	5.15	5.15	**5.85**	**6.55**	**7.25**	**7.25**	**7.25**	**7.25**	**7.25**	**7.25**

Sources: United States Department of Labor, California Department of Industrial Relations, Connecticut Department of Labor, Delaware Laws: 140th General Assembly, Massachusetts Department of Workforce Development, Washington State Department of Labor & Industries, Tax Policy Center.

Bolded entries indicate that the state has no mimum wage legislation, or a minimum wage rate set below the federal standard.

[1] Minnesota sets a lower rate for enterprises with annual receipts of less than $500,000. For the purposes of this analysis, I encode observations reporting either wage rate values as "minimum wage." This effective alternative minimum wage was $5.25 in 2006 and 2007, and the federal minimum wage rate between 2008 and 2015.

effective minimum wage are equal to the federal minimum wage (and appear bolded in Table 5.5).

According to the CPS data that I have collected from 1998 to 2015, a very small fraction (<1%) of workers actually earn exactly the minimum wage. It is fairly common for an employee to be working in a minimum wage sector whilst earning a rate slightly below or above the actual price floor. There are several potential reasons for this variance, such as employers' non-compliance to the law, inaccuracies in data collection (e.g. inaccurate reporting), and the fact that many firms in these sectors offer a small wage premium just above minimum wage. Because of this variance in minimum, I encode an observation as belonging to a minimum wage market if the wage rate that the individual is earning is within $0.50 of their state's effective minimum wage. By establishing a minimum wage range, rather than using a single price point, the subsample of "minimum wage workers" consists of 31,180 laborers, or 2.3% of the total labor pool in the dataset.

Method 2

The prevalence of minimum wage workers is not homogenous across the United States labor pool; certain demographics and geographic areas tend to have a higher incidence than others. The most important characteristic is age: as a worker grows older they continue to develop their skillset. This makes that worker more productive over time, and in turn they command a higher wage rate. Thus, young workers tend to have an undeveloped skillset and a marginal productivity that is exceeded by the minimum wage rate, causing the price floor to be binding in their case. According to the US BLS in 2015, nearly half (45%) of all minimum wage workers are under the age of 26, although that age group only comprises 19% of all hourly paid workers.[26]

The education level of a laborer is another important determinant as to whether they will earn a minimum wage: more education leads to higher workplace productivity and wages. In 2015, high school dropouts were twice as likely to earn minimum wage compared those with a high school diploma (3% vs. 6%), whereas only 2% of college graduates earned minimum wage. Marital status also plays a significant role, with 5% of never-married workers earning minimum wage, compared to the 2% of married workers. The length of an individual's workweek is another important indicator as to whether an individual works in a minimum wage position. Only 2% of all full-time workers at their state's effective wage price floor, compared to 7% of workers who were classified as part-time.[27]

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[26] Source: 2015 BLS Minimum Wage Report, https://www.bls.gov/opub/reports/minimum-wage/2015/home.htm

[27] A laborer is considered "full-time" if they work at least 35 hours per week at their primary job.

There are other sources of variation, but the differentials are rather small and thus they are not included in this analysis.[28] Therefore, for Method 2, I identify the following subset of the labor pool as a minimum wage worker: individuals that are younger than 26 years old, do not have a high school diploma, and hold a part-time position. Once these restrictions have been enforced, the subsample has 18,961 observations, comprising approximately 1.3% of the entire U.S. labor market.

Method 3

The prevalence of minimum wage positions is not heterogeneous across the various industries of the United States economy. In other words, there are particular industries in which the proportion of workers earning minimum wage in much higher than most. These types of jobs tend to hire individuals who do not have any particular work skills or a high level of education (thus the low wage).

Table 5.6 on the next page presents the number of minimum wage workers that were employed in various sectors of the U.S. economy, as well as the fraction of hourly workers in that sector being paid a minimum wage rate

[28] Gender: Women (4%) vs. Men (3%)
Ethnicity: Black (4%) vs White/Asian/Hispanic (3%)

according to the U.S. Bureau of Labor Statistics. The table specifically displays these numbers for the five industries that employed the most minimum wage workers. As we can see, the leisure and hospitality sectors employs - by far - the most of these laborers: with nearly one and a half million workers earning at/below minimum wage, or 14.5% of the laborers in the entire sector. These numbers drop off significantly as we move on to second highest sector: retail trade (with 322,000 laborers, or 2.8% of the industry). The U.S. BLS 2015 report identified that *over* two-thirds of all minimum wage workers work in the leisure/hospitality sector. Therefore, for the Method 3 analysis, I identify laborers working in that sector as belonging to an exogenously-determined wage-rate labor market. This subsample has 63,913 observations, or 4.6% of the entire U.S. labor market.

Table 5.6 U.S. Minimum Wage Laborers, by Sector (2015)

Leisure/Hospitality 1,459,000 (14.5%)	Retail trade 322,000 (2.8%)	Education/Health 213,000 (1.6%)
Public Sector 121,000 (1.3%)	Professional Services 91,000 (1.4%)	Other 117,000

Source: U.S. Bureau of Labor Statistics 2015 Minimum Wage Report, https://www.bls.gov/opub/reports/minimum-wage/2015/home.htm
Note: The US BLS reports figures for laborers who earn at or below the minimum wage. The figure in parenthesis displays the percentage of hourly workers in the sector that earn at/below minimum wage.

Method 4

In addition to questions regarding a worker's industry/sector, the March CPS survey also asks respondents to describe their occupation type. The survey has an exhaustive numerically-coded list of virtually every type of worker: with hundreds of professions and occupations to choose from. There are certain types of jobs that are much more likely to hire a laborer at minimum wage, and as mentioned before, these occupations are those that require no special skills or education. As the 2015 U.S. BLS report has recognized, most of these minimum wage positions are clustered within the food service industry, with a sizable portion also working in the hospitality industry.

Table 5.7 below presents the various job-types that have been deemed minimum wage occupations for the purposes of this analysis. The majority of these occupations belong to the food service industry, with a couple occupations representing the unskilled laborers of the hospitality industry. Due to the evolving nature of the CPS survey over the decades, there have been changes to the categories that respondents can choose from. For instance, observations from the years 1998-2002 have fewer and broader occupation categories, compared to those of later years. Categories such as 'waiter's/waitresses' assistant' were broken down into more specific groupings like 'hosts/hostesses' and 'dining room attendants.' Therefore, for Method 4 analysis, I identify

Table 5.7 Occupations Included in Minimum Wage Analysis

Food Service Occupations		
1998-2002	**2003-2012**	**2013-2015**
Waiters/waitresses	Waiters/waitresses Food servers, non-restaurant	Waiters/waitresses Food servers, non-restaurant
Waiter's/waitresses' assistant	Hosts/hostesses Dining room attendants[1]	Hosts/hostesses Dining room attendants[1]
Cooks	Cooks	Cooks
Misc. food preparation	Food preparation workers Food prep/service, inc. fast food Food prep/service, all other	Food preparation workers Food prep/service, inc. fast food
Food counter, fountain, etc.	Counter attendants[2]	Counter attendants[2]
Kitchen workers	Dishwashers	Dishwashers
Hospitality Occupations		
1998-2015		
Baggage porters, bellhops, and concierges		
Laundry and dry-cleaning workers		

[1] Category includes cafeteria attendants and bartender helpers

[2] Category includes food concession, coffee shop, and cafeteria counter

laborers working in those all of those occupations (according to the year of observation) as belonging to a minimum wage labor market. This subsample of workers has 64,196 observations, representing 4.7% of the entire U.S. labor market.

5.5.2 Results

Method 1

The regression results for minimum wage workers, as defined by individuals earning an hourly wage rate that is within $0.50 of their state's effective minimum wage, are displayed in Table 5.8 below. For the restricted

Table 5.8 Impact of Post-2002 Entry by Migrants Earning Approximately Minimum Wage

		(1)	(2)	(3)	(4)	(5)	(6)
Hours Worked	*Coefficient estimate*	3.826	-0.365	-0.342	0.026	-0.048	-0.436
(restricted sample)	*P-value*	*0.000*	*0.435*	*0.467*	*0.957*	*0.930*	*0.375*
Hours Worked	*Coefficient estimate*	3.848	0.670	0.671	0.928	0.890	0.602
(full sample)	*P-value*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Minwage Migrant	*Coefficient estimate*	*2.556*	*2.463*	*2.307*	*1.970*	*1.991*	*1.962*
(full sample)	*P-value*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Demographic characteristics		No	Yes	Yes	Yes	Yes	Yes
Years of education - linear		No	Yes	No	Yes	No	No
Diploma attainment		No	No	Yes	No	Yes	Yes
Year of observation - linear and squared		No	Yes	No	No	No	No
Year of observation - fixed effects		No	No	Yes	Yes	Yes	Yes
Migrant interaction effects		No	No	No	Yes	Yes	Yes
Year of arrival - linear and squared		No	No	No	No	Yes	No
"Young migrants" excluded		No	No	No	No	No	Yes

Source: Center for Economic and Policy Research. 2016. March CPS Uniform Extracts, Version 1.0. Washington, DC.
Note: Any individuals below the age of 18 or above the age of 65, belonging to the armed services, self-employed, or with an hourly real wage exceeding $10,000 were removed from the sample. All parameters estimated using CEPR Uniform Extract March CPS sampling weights, and errors are clustered by current state of residence. Demographic characteristics include experience, experience squared, and years since arrival, with dummy indicators for race/ethnicity, gender, and urban/rural status. For migrant interaction effects, new explanatory variables are introduced in which each independent variable is multiplied by a dummy indicator for whether the individual is a migrant. "Young migrants" are defined as individuals who relocated to the United States before having the chance to enter the labor force.

sample, with the DID specification of equation (13), I find that the number of weekly hours worked by minimum wage migrants were not significantly impacted by the passage of the Homeland Security Act of 2002 (presented in the first two rows of table 5.8). Two of the estimations produced a positive coefficient β, and the other four produced a negative coefficient β. Except for the 'naïve' specification, none of the estimated coefficients were statistically significant. This is an unexpected result, since the models presented in this paper implied that there would be a screening effect of a larger magnitude for the exogenous-wage market relative to the endogenous-wage market. However, it is possible that it could be due to the fact that the restricted sample size is very small (2.3%).

The results for the full sample, difference-in-difference-in-difference regression using specification (14) are more in line with what is expected. As we can see by the 'hours worked' coefficient β (presented in the third and fourth rows), there is a significant post-2002 screening effect on the general migrant labor market of approximately 0.6 – 0.9 additional hours worked per week. The coefficient measuring the differential screening effect experienced by minimum wage workers, ω, was also positive for all six specifications (found in the fifth and sixth rows). Since this coefficient was statistically significant (p-value≈0.00), these results indicate that the Homeland Security Act had a stronger screening effect for migrants earning minimum wage than the general migrant population.

This implication is in concordance with the migration-decision model presented in this paper, but conflicts with the inference of the restricted sample estimations.

Method 2

The difference-in-difference regression results for minimum wage workers, as defined by individuals that are younger than 26 years old, do not have a high school diploma, and hold a part-time position, are displayed in Table 5.9 on the next page. For the restricted sample, we observe results that are somewhat similar to what I obtained using Method 1 subsample selection process: mixed and mostly insignificant coefficient estimates. I obtained positive estimations for the first four specifications, although the "naïve" specification was the only one to yield a statistically significant result. Specifications 5 and 6 yielded insignificant negative coefficients, indicating that individuals belonging to the minimum wage demographic were not differentially impacted by the border security screening effect.

The results obtained through the full sample difference-in-difference-in-difference estimation are congruent with the findings of the restricted sample

Table 5.9 Impact of Post-2002 Entry by Migrants in Minimum Wage Demographic

		(1)	(2)	(3)	(4)	(5)	(6)
Hours Worked	*Coefficient estimate*	3.445	0.422	0.457	0.044	-0.130	-0.006
(restricted sample)	*P-value*	*0.000*	*0.393*	*0.355*	*0.923*	*0.829*	*0.991*
Hours Worked	*Coefficient estimate*	3.564	0.783	0.784	1.020	0.983	0.653
(full sample)	*P-value*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Minwage Demographic	*Coefficient estimate*	*-1.953*	*0.260*	*-0.235*	*0.477*	*0.196*	*-0.021*
(full sample)	*P-value*	*0.001*	*0.665*	*0.703*	*0.420*	*0.737*	*0.973*
Demographic characteristics		No	Yes	Yes	Yes	Yes	Yes
Years of education - linear		No	Yes	Yes	Yes	Yes	Yes
Diploma attainment		No	No	No	No	No	No
Year of observation - linear and squared		No	Yes	No	No	No	No
Year of observation - fixed effects		No	No	Yes	Yes	Yes	Yes
Migrant interaction effects		No	No	No	Yes	Yes	Yes
Year of arrival - linear and squared		No	No	No	No	Yes	No
"Young migrants" excluded		No	No	No	No	No	Yes

Source: Center for Economic and Policy Research. 2016. March CPS Uniform Extracts, Version 1.0. Washington, DC.
Note: Any individuals below the age of 18 or above the age of 65, belonging to the armed services, self-employed, or with an hourly real wage exceeding $10,000 were removed from the sample. All parameters estimated using CEPR Uniform Extract March CPS sampling weights, and errors are clustered by current state of residence. Demographic characteristics include experience, experience squared, and years since arrival, with dummy indicators for race/ethnicity, gender, and urban/rural status. For migrant interaction effects, new explanatory variables are introduced in which each independent variable is multiplied by a dummy indicator for whether the individual is a migrant. "Young migrants" are defined as individuals who relocated to the United States before having the chance to enter the labor force.

analysis. While I still obtain a significantly positive estimate of β, the coefficient estimates for ω were all statistically insignificant. This indicates that the screening effect exists for the migrant labor population in general, but there is no differential impact on young, uneducated migrants who are working part-time. It is possible that the subsample requirement of 'must work less than 35 hours per week' is having a restrictive effect on the screening effect of these individuals. For example, suppose that a post-2002-entry migrant is working 36 hours per week instead 34 hours due to the screening effect. This person would be excluded from the 'minimum wage demographic,' potentially causing a downward-bias in the estimation of the screening effect for his group.

Method 3

The regression results for minimum wage workers, as defined by individuals who were classified as working in the 'Leisure' industry, are presented in Table 5.10 on the next page. When the sample has been reduced to only these laborers, we observe that migrants who entered the nation after 2002 work at least an additional hour relative to the pre-2002 migrants, for five out of the six specifications (with an extremely low p-value). This is a stronger screening effect than estimated when looking at the entire U.S. labor market. The sixth specification, in which migrants who entered the United States after 2002 as a minor are excluded, produced a positive but screening coefficient that is smaller in magnitude, but still statistically significant. I obtain similar results when estimating the full sample DIDID regression. The passage of the HSA of 2002 had a positive screening effect of 0.3 – 0.7 hours per week for the general migrant labor pool. However, for migrants working in the leisure industry, the

Table 5.10 Impact of Post-2002 Entry by Migrants in Leisure Industry

		(1)	(2)	(3)	(4)	(5)	(6)
Hours Worked	*Coefficient estimate*	6.033	1.145	1.197	1.247	1.137	0.705
(restricted sample)	*P-value*	*0.000*	*0.000*	*0.000*	*0.000*	*0.001*	*0.047*
Hours Worked	*Coefficient estimate*	3.444	0.364	0.376	0.661	0.638	0.384
(full sample)	*P-value*	*0.000*	*0.019*	*0.019*	*0.000*	*0.000*	*0.013*
Lesiure Migrant	*Coefficient estimate*	*2.589*	*2.664*	*2.567*	*2.454*	*2.359*	*1.952*
(full sample)	*P-value*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Demographic characteristics		No	Yes	Yes	Yes	Yes	Yes
Years of education - linear		No	Yes	No	Yes	No	No
Diploma attainment		No	No	Yes	No	Yes	Yes
Year of observation - linear and squared		No	Yes	No	No	No	No
Year of observation - fixed effects		No	No	Yes	Yes	Yes	Yes
Migrant interaction effects		No	No	No	Yes	Yes	Yes
Year of arrival - linear and squared		No	No	No	No	Yes	No
"Young migrants" excluded		No	No	No	No	No	Yes

Source: Center for Economic and Policy Research. 2016. March CPS Uniform Extracts, Version 1.0. Washington, DC.
Note: Any individuals below the age of 18 or above the age of 65, belonging to the armed services, self-employed, or with an hourly real wage exceeding $10,000 were removed from the sample. All parameters estimated using CEPR Uniform Extract March CPS sampling weights, and errors are clustered by current state of residence. Demographic characteristics include experience, experience squared, and years since arrival, with dummy indicators for race/ethnicity, gender, and urban/rural status. For migrant interaction effects, new explanatory variables are introduced in which each independent variable is multiplied by a dummy indicator for whether the individual is a migrant. "Young migrants" are defined as individuals who relocated to the United States before having the chance to enter the labor force.

screening effect is much more pronounced: I estimate a ω coefficient exceeding two hours per week for five of the specifications. For the specification for which 'young migrants' are excluded, I estimated a smaller screening effect, but still with a p-value ≈ 0.000. Thus, both estimation methods imply the same conclusion: there was a stronger post-2002 screening effect on migrants working in the leisure industry.

Method 4

The regression results for minimum wage workers, as defined by individuals who work in occupations that typically pay their workers minimum wage, are presented in Table 5.11 on the next page. For the restricted sample estimation, I obtain positive and statistically significant results across the board with a level of significance never exceeding 10%. It is worth noting that these estimations produced numbers that look very similar to the entire U.S. labor market estimation, with a screening effect of approximately 0.5 – 1.1 additional hours worked per week.

For the full sample estimations, we observe positive β and ω coefficients, all with a p-value that is less than 0.001 with the exception of the naïve DIDID specification. The estimates of β look very similar to that of the restricted sample regression, with the average migrant working an additional 0.5 to 0.8 weekly hours. The positive ω coefficient estimates suggest that this screening effect was even more pronounced for individuals working in minimum wage occupations, to the tune of 1.2 – 1.5 additional hours per week. These findings support the implications of the models presented in this paper: exogenous-wage workers experience a stronger screening effect than individuals in a market with endogenously set wages.

Table 5.11 Impact of Post-2002 Entry by Migrants in Minimum Wage Occupations

		(1)	(2)	(3)	(4)	(5)	(6)
Hours Worked	*Coefficient estimate*	4.123	0.555	0.597	1.106	0.706	0.650
(restricted sample)	*P-value*	*0.000*	*0.068*	*0.052*	*0.000*	*0.025*	*0.033*
Hours Worked	*Coefficient estimate*	3.548	0.523	0.528	0.809	0.767	0.514
(full sample)	*P-value*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Minwage Occupation	*Coefficient estimate*	*0.574*	*1.461*	*1.388*	*1.543*	*1.439*	*1.194*
(full sample)	*P-value*	*0.050*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Demographic characteristics		No	Yes	Yes	Yes	Yes	Yes
Years of education - linear		No	Yes	No	Yes	No	No
Diploma attainment		No	No	Yes	No	Yes	Yes
Year of observation - linear and squared		No	Yes	No	No	No	No
Year of observation - fixed effects		No	No	Yes	Yes	Yes	Yes
Migrant interaction effects		No	No	No	Yes	Yes	Yes
Year of arrival - linear and squared		No	No	No	No	Yes	No
"Young migrants" excluded		No	No	No	No	No	Yes

Source: Center for Economic and Policy Research. 2016. March CPS Uniform Extracts, Version 1.0. Washington, DC.
Note: Any individuals below the age of 18 or above the age of 65, belonging to the armed services, self-employed, or with an hourly real wage exceeding $10,000 were removed from the sample. All parameters estimated using CEPR Uniform Extract March CPS sampling weights, and errors are clustered by current state of residence. Demographic characteristics include experience, experience squared, and years since arrival, with dummy indicators for race/ethnicity, gender, and urban/rural status. For migrant interaction effects, new explanatory variables are introduced in which each independent variable is multiplied by a dummy indicator for whether the individual is a migrant. "Young migrants" are defined as individuals who relocated to the United States before having the chance to enter the labor force.

5.6 Endogenous-Wage U.S. Labor Market

5.6.1 Defining the Market

For the purposes of this paper, the endogenous wage-setting market is one in which the wage rate that is offered to migrants in a particular market/sector is partially determined by the decisions of potential incoming migrants. In other words, the offered wage rate is determined by a process that is internal to the migration model, such that there is a feedback loop between the two variables. While I could define the endogenous-wage labor market as the U.S. economy less the minimum wage market, that analysis would not produce significantly different results from the "overall" analysis in Section 5.4. Instead, I define a labor market as endogenous-wage if the sector has a historically strong presence of migrants, *and* the workers do not typically earn minimum wage. In these types of markets, firms have a lot of information about the characteristics (and productivity) of migrants, and respond to changes in the composition of the immigrant labor pool by subsequently offering a different wage rate and work schedule.

Method 1

Beginning with the Bracero program in the 1940's in which the U.S. government imported Mexican workers to specifically work as farmhands, there has been a nearly-century-long trend in which Hispanic laborers have relocated to the United States in order to work in the agricultural sector. While the Hispanic migrant population has recently diversified in terms of the occupations they hold, there is still a very strong presence in the agricultural sector.

According to the U.S. Department of Labor, approximately four out of five hired farmworkers are Hispanic, and nearly three quarters of all farmhands were born in Latin America. Thus, there has been a very long-standing relationship between Hispanic migrant farmworkers and farm employers, such that there is certainly a strong feedback loop in that labor market. Therefore, I define a worker as belonging to an endogenous-wage market if they are of Hispanic ethnicity and are also an agricultural worker. Once these restrictions are enforced, the subsample of the labor force has a total of 6,274 observations.

Method 2

Since the subsample being used in Method 1 is relatively small, I will expand the analysis so as to include all races/ethnicities, as well as several occupations outside of (and including) agricultural work. Using public-use American Community Survey data from 2009-2011, researchers with The Center for Immigration Studies identified the economic occupations, as defined by the U.S. Census Bureau[29], that hire the highest shares of migrant workers. Table 5.12 on the next page displays the eight occupations in which immigrants comprise the largest percentage of workers. While many these occupations tend to pay a relatively low wage, none of them are characteristically minimum wage markets.

[29] These categories are congruent across the American Community Survey and the March Current Population Survey

And while these positions often require particular skills, they typically do not require advanced formal education. The occupational category with the most foreign-born workers was 'Maids and Housekeeping Cleaners:' with more than 800,000 migrant laborers (49% of the total workers in the occupation).[30] All eight of the occupations fall within four broad categories: personal services, agricultural work, textile work, and skill-specific construction.

As mentioned before, in 2003 there was a distinct change in how the U.S. Census Bureau categorized the hundreds of occupations that workers could hold. Some of the categories were expanded into multiple types, sometimes several

Table 5.12 Immigrant Laborers, by Occupation (2009-2011)

Graders/Sorters, Agricultural Products 50,723 (63%)	Miscellaneous Personal Appearance Workers 161,224 (59%)
Plasterers and Stucco Masons 23,991 (56%)	Sewing Machine Operators 120,346 (52%)
Miscellaneous Agricultural Workers 478,956 (52%)	Tailors, Dressmakers, and Sewers 46,479 (52%)
Maids and Housekeeping Cleaners 815,024 (49%)	Drywall and Ceiling Tile Installers and Tapers 83,694 (47%)

Source: Center for Immigration Studies, using American Community Survey Data from 2009-2011
Note: The figure in parenthesis displays the percentage of workers in the occupation that are foreign-born.

[30] While tempted to set the cutoff at 50%, removing maids and housekeeping cleaners would remove nearly half of the migrant observations in the subsample.

occupations were collapsed into a single category, and many of the occupations were simply relabeled. Table 5.13 below displays the occupations that I am including in the Method 2 analysis, according to the year of observation. As we can see, only a single occupation (agricultural sorters/graders) out of the eight was not relabeled or collapsed. The categories of 'Tailors' and 'Dressmakers and Seamstresses' were pooled into the occupation 'Tailors, Dressmakers, and Sewers,' and 'Maids and Housemen' was combined with 'Private Household Cleaners and Servants' to form the category 'Maids and Housekeeping

Table 5.13 Occupations Included in Endogenous-Wage Analysis

1998-2002	2003-2015
Sorters/Graders, Agricultural	Sorters/Graders, Agricultural
Hairdressers and Cosmetologists	Misc. Personal Appearance Workers
Plasterers	Plasterers and Stucco Masons
Textile Sewing Machine Operators	Sewing Machine Operators
Farm Workers	Miscellaneous Agricultural Workers[1]
Tailors Dressmakers and Seamstresses	Tailors, Dressmakers, and Sewers
Maids and Housemen Private Household Cleaners/Servants	Maids and Housekeeping Cleaners
Drywall Installers	Drywall/Ceiling Tile Installers and Tapers

[1] Category includes animal breeders.

Cleaners.'[31] I identify laborers working in those all of these occupations (according to the year of observation) as belonging to a minimum wage labor market. This subsample of workers has 36,851 observations, representing 2.7% of the entire U.S. labor market.

5.6.2 Results

<u>Method 1</u>

The regression results for endogenous-wage-market workers, as defined by Hispanic individuals who work in agriculture, are displayed in Table 5.14 on the next page. In addition to estimating the post-2002 screening effect on hours worked per week, I also present coefficient estimates for regressions where workers' log hourly wage is the dependent variable. For the restricted sample estimations, I find that there is a consistently positive screening impact on Hispanic agricultural migrants' wage rate (6.1 – 14.9%) and hours worked per week (1.5 - 1.9). While these coefficient estimates are much higher than the entire U.S. market estimations presented earlier in this chapter, several of them have a p-value exceeding 0.10. It is worth noting that this may be a result of the

[31] The terms 'seamstress,' 'housemen,' and 'servant' have all fallen out of use in the modern lexicon.

Table 5.14 Impact of Post-2002 Entry by Hispanic Migrants Working in Agriculture

		(1)	(2)	(3)	(4)	(5)	(6)
Log Real Hourly Wage	*Coefficient estimate*	0.005	0.012	0.061	0.104	0.149	0.129
(restricted sample)	*P-value*	*0.923*	*0.803*	*0.241*	*0.214*	*0.077*	*0.079*
Log Real Hourly Wage	*Coefficient estimate*	0.245	0.020	0.018	-0.013	0.020	0.003
(full sample)	*P-value*	*0.000*	*0.006*	*0.018*	*0.056*	*0.012*	*0.703*
Hispanic Agri. Migrant	*Coefficient estimate*	*-0.239*	*-0.070*	*-0.107*	*-0.032*	*-0.099*	*-0.094*
(full sample)	*P-value*	*0.000*	*0.118*	*0.030*	*0.491*	*0.036*	*0.045*
Hours Worked	*Coefficient estimate*	3.136	1.712	1.868	1.586	1.507	1.543
(restricted sample)	*P-value*	*0.001*	*0.021*	*0.003*	*0.081*	*0.058*	*0.065*
Hours Worked	*Coefficient estimate*	3.970	0.765	0.753	0.976	0.943	0.636
(full sample)	*P-value*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Hispanic Agri. Migrant	*Coefficient estimate*	*-0.834*	*0.374*	*0.203*	*0.809*	*0.543*	*0.640*
(full sample)	*P-value*	*0.384*	*0.584*	*0.777*	*0.281*	*0.466*	*0.399*
Demographic characteristics		No	Yes	Yes	Yes	Yes	Yes
Years of education - linear		No	Yes	No	Yes	No	No
Diploma attainment		No	No	Yes	No	Yes	Yes
Year of observation - linear and squared		No	Yes	No	No	No	No
Year of observation - fixed effects		No	No	Yes	Yes	Yes	Yes
Migrant interaction effects		No	No	No	Yes	Yes	Yes
Year of arrival - linear and squared		No	No	No	No	Yes	No
"Young migrants" excluded		No	No	No	No	No	Yes

Source: Center for Economic and Policy Research. 2016. March CPS Uniform Extracts, Version 1.0. Washington, DC
Note: Any individuals below the age of 18 or above the age of 65, belonging to the armed services, self-employed, or with an hourly real wage exceeding $10,000 were removed from the sample. All parameters estimated using CEPR Uniform Extract March CPS sampling weights, and errors are clustered by current state of residence. Demographic characteristics include experience, experience squared, and years since arrival, with dummy indicators for race/ethnicity, gender, and urban/rural status. For migrant interaction effects, new explanatory variables are introduced in which each independent variable is multiplied by a dummy indicator for whether the individual is a migrant. "Young migrants" are defined as individuals who relocated to the United States before having the chance to enter the labor force.

sample size reduction for this particular method of estimation, which removed 99.5% of the total observations.

For the full sample DIDID estimations, I obtain results that are congruent with the implications of the model. Overall, they indicate that there is a positive screening effect on the entire migrant labor in terms of both wages and hours worked. However, the wage effect is estimated to be significantly smaller ($\omega<0$) for Hispanic migrants working in the agricultural sector, which has been defined as an endogenous-wage market. Interestingly, it appears that the implementation of the HSA of 2002 had no remarkable differential impact ($\omega\approx0$) on the hours that Hispanic farm laborers worked per week.

<u>Method 2</u>

The regression results for endogenous-wage-market workers, as defined by migrants who work in occupations that are largely worked by migrants (>45%), are displayed in Table 5.15 on the next page. For the restricted sample estimations, I find that – for all six specifications – migrants who entered the United States after 2002 experienced a wage premium (4.9 – 9.3%) and worked more hours per week (1.0 – 1.2) relative to migrants who arrived before 2002. Although the measured screening effect is large, it is worth noting that the

Table 5.15 Impact of Post-2002 Entry by Migrants in Migrant-Intensive Occupations

		(1)	(2)	(3)	(4)	(5)	(6)
Log Real Hourly Wage	*Coefficient estimate*	0.113	0.094	0.093	0.066	0.060	0.049
(restricted sample)	*P-value*	*0.000*	*0.005*	*0.007*	*0.049*	*0.087*	*0.147*
Log Real Hourly Wage	*Coefficient estimate*	0.250	0.021	0.019	-0.011	0.020	0.020
(full sample)	*P-value*	*0.000*	*0.005*	*0.011*	*0.120*	*0.012*	*0.012*
High-Migrant Occupation	*Coefficient estimate*	*-0.137*	*-0.074*	*-0.076*	*-0.057*	*-0.074*	*-0.066*
(full sample)	*P-value*	*0.000*	*0.003*	*0.001*	*0.011*	*0.001*	*0.004*
Hours Worked	*Coefficient estimate*	2.074	1.204	1.192	0.977	1.023	0.996
(restricted sample)	*P-value*	*0.001*	*0.033*	*0.028*	*0.167*	*0.141*	*0.151*
Hours Worked	*Coefficient estimate*	4.025	0.793	0.778	0.997	0.958	0.653
(full sample)	*P-value*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
High-Migrant Occupation	*Coefficient estimate*	*-1.951*	*-0.927*	*-0.930*	*-0.616*	*-0.667*	*-0.542*
(full sample)	*P-value*	*0.001*	*0.098*	*0.089*	*0.251*	*0.203*	*0.301*
Demographic characteristics		No	Yes	Yes	Yes	Yes	Yes
Years of education - linear		No	Yes	No	Yes	No	No
Diploma attainment		No	No	Yes	No	Yes	Yes
Year of observation - linear and squared		No	Yes	No	No	No	No
Year of observation - fixed effects		No	No	Yes	Yes	Yes	Yes
Migrant interaction effects		No	No	No	Yes	Yes	Yes
Year of arrival - linear and squared		No	No	No	No	Yes	No
"Young migrants" excluded		No	No	No	No	No	Yes

Source: Center for Economic and Policy Research. 2016. March CPS Uniform Extracts, Version 1.0. Washington, DC
Note: Any individuals below the age of 18 or above the age of 65, belonging to the armed services, self-employed, or with an hourly real wage exceeding $10,000 were removed from the sample. All parameters estimated using CEPR Uniform Extract March CPS sampling weights, and errors are clustered by current state of residence. Demographic characteristics include experience, experience squared, and years since arrival, with dummy indicators for race/ethnicity, gender, and urban/rural status. For migrant interaction effects, new explanatory variables are introduced in which each independent variable is multiplied by a dummy indicator for whether the individual is a migrant. "Young migrants" are defined as individuals who relocated to the United States before having the chance to enter the labor force.

introduction of migrant interaction variables caused several of these estimations to be statistically insignificant at a 10% level of confidence.

The results of the full sample, difference-in-difference-in-difference regression estimations are also presented in the table above, and they look rather similar to the DIDID coefficient estimates obtained in the Hispanic agricultural demographic analysis. There was a general labor screening effect on all post-2002 migrants, particularly on hours worked per week with a p-value that is approximately zero for all six specifications. A statistically significant positive wage premium was estimated for most of the specifications, although the fourth generated an insignificantly negative coefficient. The differential screening effect on migrants in migrant-intensive occupations was congruent with the Hispanic agricultural analysis and the theoretical model presented in this paper: migrants working in these types of jobs experienced a relatively lower wage premium than other migrants arriving after 2002 ($\omega < 0$). Just as observed in the Method 1 endogenous-wage analysis, it appears that there was no differential impact on weekly hours worked, as all six specifications produced statistically insignificant ω coefficient estimates.

5.7 Interpreting the Results

In this subsection, I summarize the regression results presented in the three previous subsections, beginning with the difference-in-difference estimations before moving onto the difference-in-difference-in-difference specifications. Then, I draw three broad conclusions that can be inferred from the totality of these analyses.

For the first difference-in-difference analysis in which I examine the United States labor market as a whole, I find that migrants who entered the United States after 2002 earn a higher wage rate and work more hours per week relative to those who entered beforehand. The coefficient estimates in this analysis were extremely significant, with consistent p-values of approximately zero. When I restrict the sample to subsamples of particular labor markets or types of workers, most of the regressions also generated results that imply a positive post-2002 screening effect on migrants. The DID estimations in the endogenous-wage labor markets (i.e. Hispanic farmworkers and individuals in migrant-intensive occupations) determined that there was a significant wage premium and hike in weekly hours worked, although the level of significance of these estimates was worse than for the entire U.S. labor market.

For the exogenous-wage market, the DID regression results were mixed. I find that migrants working in the leisure industry and/or minimum-wage occupations that entered after the implementation of the HSA of 2002 worked roughly one additional hour per week, with statistical significance in eleven out of the twelve specifications. However, for migrants that are earning at or close to minimum wage, I obtain positive and negative β coefficient estimates, none of which are significant at α=0.10. The same type of results are observed when the sample is restricted to young, uneducated, part-time employees: only one coefficient estimate is positive and significant, while a couple other regressions produced negative estimates. These results are not what one would expect to see based on the inferences of the model. However, there may be an empirical explanation. In both instances (Method 1 and 2), a "successful" or relatively productive worker may take themselves out of the subsample. If a worker earning approximately minimum wage shows aptitude in their job, management may respond by giving them a raise instead of only increasing their hours. Or instead, they may decide to give the individual a full-time position with the company. In either case, laborers that are relatively more productive have a higher likelihood of being removed from the subsample, causing a downward bias in in the estimations.

The difference-in-difference-in-difference regression results for the exogenous-wage and endogenous-wage markets produced results that are in line with the models presented in this paper. The β coefficient estimates implied that, on the whole, migrants arriving after 2002 experienced a wage premium and worked longer hours. For workers in an exogenous-wage market, specifically those earning approximately minimum wage or working in a minimum wage-intensive sector or occupation, this screening effect is even more strongly pronounced: $\omega>0$. Hispanic farmworkers and migrants in migrant-intensive occupations, representing the endogenous-wage market, had a different experience. For them, the screening effect was significantly reduced in terms of their wage premium, and there was no discernable differential impact on hours worked per week. These results are congruent with interpretation of the exo-wage and endo-wage models: when there is a feedback information loop (i.e. endogenous wages), the initial rise in productivity brought about by additional border security causes wages to rise, enticing less productive migrants to enter the nation. Thus, we expect endogenous-wage markets to have a smaller screening response to a change in immigration control policy.

By comparing the results obtained in the six endogenous/exogenous labor market analyses to those obtained when looking at the U.S. labor market as a whole, one can infer that there may have been sectoral shifts that helped to drive the extremely significant results obtained in the latter. After restricting the subsample to a particular group of individuals or labor market, the β coefficients representing the screening effect are often smaller and always less significant, with p-values commonly between 0.01 and 0.1 (as opposed to p-value≈0 for the entire U.S. analysis). This could indicate that the powerful results for the total U.S. analysis were in part driven by sectoral changes in the migrant labor market: relatively strong growth of migrant employment in high-wage occupations/industries would drive the estimate for β for the entire U.S. labor market upward.

The H1-B visa program, which allows migrants working in specialized occupations requiring advanced education, underwent serious changes starting in 1999 that allowed many more (tens of thousands annually) of these high-earning migrants to enter the United States. While the education control variable in the entire U.S. analysis would pick up some of this variation, the H1-B policy change could cause an upward bias in the estimation of β. However, the fact that statistically significant results were obtained in the occupation-specific regressions imply that the passage of the Homeland Security Act of 2002 did cause a positive within-class screening effect on the unobservable abilities of migrants entering the United States, as these analyses are unaffected by cross-sectoral shifts in the migrant labor economy.

The comparative results of the sixth specification, in which 'young migrants' are removed from the sample, can also provide insight for the current political situation regarding DACA (Deferred Action for Childhood Arrivals) and the DREAMers. Recall that DACA was an executive order signed by President Obama in 2012 and rescinded by President Trump in 2018 that allowed migrants meeting certain circumstances to lawfully remain in the United States. Among other requirements, these migrants must have entered the country while under 16 years of age and could not be older than 30 on June 15, 2012. In other words, DREAMers were individuals who were relocated to the U.S. before having a chance to enter the labor force, and entered the nation between 1982 and 2017.

In my empirical analyses, the ‘young migrants’ that are excluded in the sixth specification were individuals who arrived in the U.S. before entering the labor force, including arrivals from 1942 until 2017.

I find that, when ‘young migrants’ are removed from the sample, the coefficient estimate measuring the post-2002 screening effect tends to decrease. For the regressions in which significant results were obtained, the estimated β coefficient for the sixth specification was lower than the estimates obtained through other three fixed effect models by approximately 16%, on average. In other words, the existence of ‘young migrants’ in the sample causes the measured labor screening effect of immigration control policy to increase. This implies that individuals entering the nation as children or young adults, such as DREAMers, are relatively more strongly ‘screened’ than their parents, even though they probably did not make the decision to migrate themselves. This finding is in congruence with the intergenerational mobility theory discussed in the literature review: individuals who witness their parents facing hardship in exchange for economic opportunity tend to embody those values themselves and earn a relatively higher wage rate.

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Appendix A: Proof of Positive Denominator in Labor Screening Effect

In order to find the inverse correlation that we would expect, the parenthesed term in the numerator must be positive: $0.5\delta + 0.5\delta M_H + K_j - U_{ALT} > 0$

Or: $0.5\delta + 0.5\delta M_H + K_j > U_{ALT}$

I show this to be true by starting with the fact that, in order for *any* migrants to enter nation j ($M_{min} < M_H$), the following must be true:

$W_{ij} - (\alpha P_j + \beta D_{jh} + \gamma E_{ji})(1 - M_H) > U_{ALT}$

We know that firms offer $W_{ij} = 0.5\delta\ (M_{min} + M_H) + K_j$:

$0.5\delta(M_{min} + M_H) - (\alpha P_j + \beta D_{jh} + \gamma E_{ji})(1 - M_H) > U_{ALT}$

I substitute for U_{ALT} in the original inequality under investigation (we can do this since the formula substituted in is larger than U_{ALT}, so the conclusion is valid if the inequality holds):

$0.5\delta + 0.5\delta M_H + K_j > U_{ALT}$

$0.5\delta + 0.5\delta M_H + K_j > 0.5\delta\ (M_{min} + M_H) + K_j - (\alpha P_j + \beta D_{jh} + \gamma E_{ji})(1 - M_H)$

$0.5\delta - 0.5\delta M_{min} + K_j > -(\alpha P_j + \beta D_{jh} + \gamma E_{ji})(1 - M_H)$

The inequality holds, since M_{min} and M_H both have an upper bound of 1, and the rest of the parameters and variables have a positive value. Therefore, the conclusion that there is an inverse correlation between immigration control policy and the number of migrants is valid.

Appendix B: Proof of Government Welfare Maximum

In order to ensure that this is a maximum, the government welfare function should be concave down. I take the second derivative and find:

$\partial^2 G_j/\partial P_j^2 = 2\psi\alpha^2 (W_{ji} - U_{ALT}) (\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-3} - \phi\delta\alpha^2 (W_{ji} - U_{ALT}) (\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-3}$

$\partial^2 G_j/\partial P_j^2 = \alpha^2 (2\psi - \phi\delta) (W_{ji} - U_{ALT}) (\alpha P_j + \beta D_{jh} + \gamma E_{ji})^{-3}$

We know that α, the wage premium, and the costs of migration are all positive. Therefore, in order for the second derivative to be negative, the term (2ψ – ϕδ) needs to be negative. This is extremely likely, since ϕ and δ both have positive values and, historically speaking, it is very rare for ψ to be positive.

For the rest of this paper, I make the assumption that nation j has a neutral or mixed attitude toward migrants: ψ = 0.

Therefore, ϕδ > 2ψ.

In the exceptional case where $2\psi > \phi\delta$ (nation j very strongly desires more immigrants), the government welfare function is concave up and the government will choose a corner solution of zero immigration policy: $P_j = 0$.

Appendix C: Ordering of Nations

Let's start with nation 1. I begin by proving that the costs of migration in nation 1 are lower than that of nation 0. I start with the fact that migrants with M_i = $M_{max,1}$ have the same utility in either nation:

$$W_0 - C_0\left(1 - M_{max,1}\right) = W_1 - C_1\left(1 - M_{max,1}\right)$$

I substitute W_1 for (W_0 + α) where α > 0, since $W_0 > W_1$:

$$W_0 - C_0\left(1 - M_{max,1}\right) = W_0 + \alpha - C_1\left(1 - M_{max,1}\right)$$

Solving for C_1:

$$C_1 = C_0 - \frac{\alpha}{1 - M_{max}}$$

Therefore: $C_1 < C_0$, and we know that:

$$\frac{W_0 - W_1}{C_0 - C_1} > 0$$

____

I now introduce nation 2 by comparing M_{max} to M_{min} for nation 1. We know that:

$M_{max,1} > M_{min,1}$

Substituting and simplifying, I find that:

$$0 < \frac{W_0 - W_1}{C_0 - C_1} < \frac{W_1 - W_2}{C_1 - C_2}$$

Since we know that the first fraction is positive, the second fraction must be positive too.

When we repeat the process for nation 2, comparing $M_{max,2} > M_{min,2}$, we get:

$$0 < \frac{W_0 - W_1}{C_0 - C_1} < \frac{W_1 - W_2}{C_1 - C_2} < \frac{W_2 - W_3}{C_2 - C_3}$$

And the process reiterates until there are no more viable nations. Recalling that $M_{min,J}=0$, we are left with:

$$0 < \frac{W_1 - W_0}{C_1 - C_0} < \frac{W_1 - W_2}{C_1 - C_2} < \cdots < \frac{W_{j-1} - W_j}{C_{j-1} - C_j} < \frac{W_j - W_{j+1}}{C_j - C_{j+1}} < \cdots \frac{W_{J-1} - W_J}{C_{J-1} - C_J} < 1$$

Appendix D: Proof that $W_{j-1} – W_j > 0$

There are two instances in which a particular nation is excluded from position j:

(1) $M_{min,j-2/j} > M_{min,j-2/j-1}$

When calculating the M_{min} for nation j-2, the M_{min} calculation is higher for nation j then j-1. In this case, the particular nation would take the position of j-1 rather than j, since it is the “next best alternative” for nation j-2.

(2) $M_{min,j-1/j} > M_{min,j-2/j}$

The M_{min} calculation between j and j-1 is larger than that between j and j-2. In this case, migrants’ derived utility is higher in nation j-2 when $M_i>M_{min,j-2/j-1}$, and higher in nation j-1 when $M_i<M_{min,j-1/j}$, and we know by definition that $M_{min,j-2/j-1}> M_{min,j-1/j}$. Thus, zero migrants would prefer nation j over j-1 or j-2. Therefore, nation j either needs to be moved to position j+1 or higher, or is not a “viable nation” at all.

I begin by defining:

$$W_j = W_{j-1} + x$$

$C_j = C_{j-1} + y$

Recalling the inequality found at the end of Appendix A.3, we know that:

$$1 > \frac{x}{y} > 0$$

Therefore, we know that x and y have the same sign. Also, we know that $|y| > |x|$.

Suppose that $x > 0$:

(1) $M_{min,j-2/j} > M_{min,j-2/j-1}$

$$\frac{W_{j-2} - W_j}{C_j - C_{j-2}} + 1 > \frac{W_{j-2} - W_{j-1}}{C_{j-1} - C_{j-2}} + 1$$

$$\frac{W_{j-2} - W_{j-1}\ -\ x}{C_{j-1} - C_{j-2} + y} > \frac{W_{j-2} - W_{j-1}}{C_{j-1} - C_{j-2}}$$

$$\frac{W_{j-2} - W_{j-1}\ -\ x}{C_{j-1} - C_{j-2} + y} > \frac{W_{j-2} - W_{j-1}}{C_{j-1} - C_{j-2}}$$

$$W_{j-2} - W_{j-1}\ -\ x > \frac{(W_{j-2} - W_{j-1})(C_{j-1} - C_{j-2} + y)}{C_{j-1} - C_{j-2}}$$

$$x > \frac{y(W_{j-2} - W_{j-1})}{C_{j-2} - C_{j-1}}$$

(2) $M_{min,j-1/j} > M_{min,j-2/j}$

$$\frac{W_{j-1} - W_j}{C_j - C_{j-1}} + 1 > \frac{W_{j-2} - W_j}{C_j - C_{j-2}} + 1$$

$$\frac{-x}{y} > \frac{W_{j-2} - W_j}{C_j - C_{j-2}}$$

$$x < \frac{y(W_{j-2} - W_{j-1})}{C_{j-2} - C_{j-1}}$$

Therefore, if x > 0 the nation in question either (1) needs to be moved “down” to position j-1 (or higher), or (2) needs to be moved “up” to position j+1 or higher, or is simply not a “viable nation.”

In the case that x < 0, the exclusion condition for (2) becomes:

$$x > \frac{y(W_{j-2} - W_{j-1})}{C_{j-2} - C_{j-1}}$$

Therefore, iff x < 0 and the condition $\frac{W_{j-1}-W_j}{C_{j-1}-C_j} < \frac{W_j-W_{j+1}}{C_j-C_{j+1}}$ holds true, is nation j is properly positioned.

Thus, the wage gap in question must be positive: $W_{j-1} - W_j > 0 \ \ and\ W_j - W_{j+1} > 0$

Appendix E: 26 Destination-nation Simulation

In order show that the wage gap is positive, I randomly generated wage rate [W_{ji}~N(100,20)] and migration cost data [C_{ji}~N(70,20)] for 26 destination nations. For the lowest-wage nation (A), I reduced the costs of migration to zero so that it may represent the origin-nation. I picked the highest-wage nation (I) as nation 0, then found the country (Z) with the highest M_{min} between 0 and 1 for nation 1. I then calculated $M_{min,1}$ for every country except I, and picked one the highest one between 0 and $M_{min,1}$ (Y) as nation 2. Repeating the same process, I determined that nation A is nation 3. This is also the last "viable" nation, as there are no more $M_{min,3}$ calculations that are between zero and $M_{min,2}$.

			Nation 0: I	**Nation 1: Z**	**Nation 2: Y**	**Nation 3: A**
Nation	Wage	Costs	Mmin,0	Mmin,1	Mmin,2	Mmin,3
A	68.32	0.00	0.34	0.19	0.16	
B	77.17	109.31	6.42	2.44	1.45	0.92
C	125.00	81.74	0.49	1.41	0.48	0.31
D	129.81	100.99	2.83	0.94	0.58	0.39
E	76.61	43.48	-0.03	-0.70	-21.54	0.81
F	78.45	66.48	-0.70	-5.70	2.27	0.85
G	106.93	104.97	5.39	1.68	0.98	0.63
H	122.32	95.73	-2.61	1.27	0.68	0.44
I	133.68	98.88				
J	102.72	65.40	0.08	-1.99	1.16	0.47
K	84.22	95.08	-12.03	3.08	1.43	0.83
L	117.92	74.72	0.35	13.66	0.60	0.34
M	95.31	57.56	0.07	-1.01	1.83	0.53
N	93.69	87.23	-2.43	3.59	1.29	0.71
O	137.63	55.84	1.09	1.52	-1.87	-0.24
P	89.25	64.59	-0.30	-3.18	1.84	0.68
Q	69.16	105.24	11.13	2.88	1.61	0.99
R	112.58	91.90	-2.02	1.87	0.86	0.52
S	88.25	102.64	13.06	2.39	1.31	0.81
T	86.76	83.63	-2.08	5.26	1.49	0.78
U	112.35	78.94	-0.07	4.15	0.81	0.44
V	86.71	58.48	-0.16	-1.69	2.40	0.69
W	123.55	70.75	0.64	-0.47	0.32	0.22
X	104.04	49.70	0.40	0.00	1.38	0.28
Y	105.93	44.78	0.49	0.24		
Z	128.19	73.91	0.78			

Thus, the four viable nations are:

Rank	Nation	Wage	Costs	I	E(Θ)
0	I	133.68	98.88	0.22	1.89
1	Z	128.19	73.91	0.54	1.51
2	Y	105.93	44.78	0.08	1.20
3	A	68.32	0.00	0.16	1.08

As we can see, the wage rates of the viable nations are ranked in descending order. In other words, the wage gap discussed in 1.D is positive: $W_{j-1} – W_j > 0$.

Appendix F: Temporary Worker Visa Preference Categories

Table A.1 Temporary Worker Visa Preference Categories

Category	*Description*
H-1B	To work in a specialty occupation. Requires a higher education degree or its equivalent. Includes fashion models of distinguished merit and ability and government-to-government research and development, or co-production projects administered by the Department of Defense.
H-1B1	To work in a specialty occupation. Requires a post-secondary degree involving at least four years of study in the field of specialization. (Note: This is not a petition-based visa. For application procedures, please refer to the website for the U.S. Embassy in Chile or the U.S. Embassy in Singapore.)
H-2A	For temporary or seasonal agricultural work. Limited to citizens or nationals of designated countries, with limited exceptions, if determined to be in the United States interest.
H-2B	For temporary or seasonal non- agricultural work. Limited to citizens or nationals of designated countries, with limited exceptions, if determined to be in the United States interest.
H-3	To receive training, other than graduate medical or academic, that is not available in the trainee's home country or practical training programs in the education of children with mental, physical, or emotional disabilities.
L	To work at a branch, parent, affiliate, or subsidiary of the current employer in a managerial or executive capacity, or in a position requiring specialized knowledge. Individual must have been employed by the same employer abroad continuously for 1 year within the three preceding years.

O	For persons with extraordinary ability or achievement in the sciences, arts, education, business, athletics, or extraordinary recognized achievements in the motion picture and television fields, demonstrated by sustained national or international acclaim, to work in their field of expertise. Includes persons providing essential services in support of the above individual.
P-1	To perform at a specific athletic competition as an athlete or as a member of an entertainment group. Requires an internationally recognized level of sustained performance. Includes persons providing essential services in support of the above individual.
P-2	For performance under a reciprocal exchange program between an organization in the United States and an organization in another country. Includes persons providing essential services in support of the above individual.
P-3	To perform, teach or coach under a program that is culturally unique or a traditional ethnic, folk, cultural, musical, theatrical, or artistic performance or presentation. Includes persons providing essential services in support of the above individual.
Q-1	For practical training and employment and for sharing of the history, culture, and traditions of your home country through participation in an international cultural exchange program.

Source: United States Department of State - Bureau of Consular Affairs

Appendix G: Regression Output

Specification (1), Entire U.S. Labor Market

```
Linear regression                               Number of obs     =  1,375,615
                                                F(3, 50)          =     468.84
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0378
                                                Root MSE          =     .71539

                                (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |  -.1789108   .0208638    -8.58   0.000    -.2208171   -.1370046
post911entry |  -.4058013   .0109555   -37.04   0.000    -.4278061   -.3837966
post911ent~t |   .2443614   .0132829    18.40   0.000     .2176818     .271041
       _cons |   2.982956   .0189798   157.17   0.000     2.944834    3.021078
------------------------------------------------------------------------------


Linear regression                               Number of obs     =  1,376,334
                                                F(3, 50)          =     533.45
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0236
                                                Root MSE          =     10.397

                                (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |  -.6275083   .1560116    -4.02   0.000    -.9408669   -.3141498
post911entry |  -5.018331   .1406891   -35.67   0.000    -5.300913   -4.735748
post911ent~t |   4.023865   .1745813    23.05   0.000     3.673208    4.374522
       _cons |   40.47215   .1182521   342.25   0.000     40.23464    40.70967
------------------------------------------------------------------------------
```

Specification (2), Entire U.S. Labor Market

```
Linear regression                               Number of obs     =  1,375,615
                                                F(14, 50)         =          .
                                                Prob > F          =          .
```

R-squared = 0.2738
Root MSE = .6215

(Std. Err. adjusted for 51 clusters in state)

lnwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	.0719664	.0051407	14.00	0.000	.0616411	.0822918
post911entry	-.0723596	.0038536	-18.78	0.000	-.0800997	-.0646196
post911ent~t	.0181346	.0069283	2.62	0.012	.0042187	.0320505
yearseduc	.1010469	.0024886	40.60	0.000	.0960484	.1060455
exp	.0360258	.0007624	47.25	0.000	.0344945	.0375571
exp_sq	-.0006276	.0000132	-47.39	0.000	-.0006542	-.000601
female	-.2464368	.0050028	-49.26	0.000	-.2564852	-.2363885
white	.1064268	.0121011	8.79	0.000	.082121	.1307326
black	-.0507494	.0162781	-3.12	0.003	-.0834449	-.0180538
asian	.1168612	.0217318	5.38	0.000	.0732115	.1605108
hispanic	.0232692	.0198782	1.17	0.247	-.0166574	.0631958
years_sinc~l	.0047219	.0004774	9.89	0.000	.0037631	.0056807
rural	-.1705233	.0142321	-11.98	0.000	-.1991092	-.1419373
year	2.588423	.3269113	7.92	0.000	1.931802	3.245044
year_sq	-.0006453	.0000815	-7.92	0.000	-.0008089	-.0004816
_cons	-2594.774	328.001	-7.91	0.000	-3253.583	-1935.965

Linear regression

Number of obs = 1,376,334
F(13, 50) = .
Prob > F = .
R-squared = 0.1148
Root MSE = 9.8993

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	.0365837	.0904761	0.40	0.688	-.1451429	.2183103
post911entry	-1.257838	.073261	-17.17	0.000	-1.404987	-1.110689
post911ent~t	.7130374	.1340383	5.32	0.000	.4438136	.9822613
yearseduc	.5140983	.0270987	18.97	0.000	.459669	.5685277
exp	.564869	.0113541	49.75	0.000	.5420637	.5876742
exp_sq	-.0105649	.0001905	-55.46	0.000	-.0109475	-.0101822
female	-4.777614	.1194686	-39.99	0.000	-5.017574	-4.537654
white	-.0336716	.1657066	-0.20	0.840	-.3665031	.2991599
black	-.2309035	.1635369	-1.41	0.164	-.5593771	.0975701
asian	-.7110509	.1862928	-3.82	0.000	-1.085231	-.3368708
hispanic	.1075727	.2103316	0.51	0.611	-.3148908	.5300362
years_sinc~l	-.0024886	.0018932	-1.31	0.195	-.0062912	.0013139
rural	.1793664	.0762342	2.35	0.023	.0262454	.3324873
year	-7.936851	3.856644	-2.06	0.045	-15.68315	-.1905537
year_sq	.0019693	.0009615	2.05	0.046	.0000381	.0039005
_cons	8026.429	3866.437	2.08	0.043	260.4628	15792.4

Specification (3), Entire U.S. Labor Market

Linear regression

Number of obs	=	1,375,615
F(34, 50)	=	4083.63
Prob > F	=	0.0000
R-squared	=	0.2885
Root MSE	=	.61519

(Std. Err. adjusted for 51 clusters in state)

lnwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	.0700353	.0067952	10.31	0.000	.0563867	.0836838
post911entry	-.0689519	.0041862	-16.47	0.000	-.0773601	-.0605437
post911ent~t	.0299543	.0055831	5.37	0.000	.0187404	.0411682
hsgrad	.2634568	.005257	50.12	0.000	.2528977	.2740158
assocgrad	.4456565	.0067982	65.56	0.000	.432002	.459311
bachgrad	.7063531	.0096429	73.25	0.000	.6869848	.7257215
mastgrad	.8837125	.0145473	60.75	0.000	.8544934	.9129316
doctorgrad	1.115152	.0127299	87.60	0.000	1.089583	1.14072
exp	.0307746	.0004892	62.91	0.000	.0297921	.0317571
exp_sq	-.0006131	.0000119	-51.67	0.000	-.000637	-.0005893
female	-.2424658	.0050457	-48.05	0.000	-.2526004	-.2323313
white	.0862186	.011587	7.44	0.000	.0629455	.1094917
black	-.0482985	.0165958	-2.91	0.005	-.0816321	-.0149649
asian	.1176587	.0217156	5.42	0.000	.0740417	.1612757
hispanic	-.0147903	.0182527	-0.81	0.422	-.051452	.0218714
years_sinc~l	.0081892	.0004012	20.41	0.000	.0073834	.0089949
rural	-.1670353	.0126502	-13.20	0.000	-.192444	-.1416266
year						
1999	.0296578	.0044939	6.60	0.000	.0206315	.0386842
2000	.0437704	.0040796	10.73	0.000	.0355762	.0519646
2001	.0615078	.0050118	12.27	0.000	.0514412	.0715743
2002	.068626	.0042439	16.17	0.000	.0601019	.07715
2003	.0737965	.0049711	14.85	0.000	.0638118	.0837812
2004	.0662444	.0050265	13.18	0.000	.0561484	.0763404
2005	.0550193	.0047325	11.63	0.000	.0455139	.0645247
2006	.0485835	.0057264	8.48	0.000	.0370818	.0600853
2007	.0506171	.0083452	6.07	0.000	.0338553	.0673788
2008	.0573816	.0071191	8.06	0.000	.0430825	.0716808
2009	.0396988	.0068346	5.81	0.000	.025971	.0534266
2010	.0565063	.0062916	8.98	0.000	.0438694	.0691433
2011	.0409959	.0068218	6.01	0.000	.027294	.0546978
2012	.0273835	.0077952	3.51	0.001	.0117263	.0430407
2013	.0137867	.0076215	1.81	0.076	-.0015215	.0290949
2014	.0150748	.0096917	1.56	0.126	-.0043915	.0345412
2015	.0149366	.0091727	1.63	0.110	-.0034873	.0333606
_cons	1.951551	.0153564	127.08	0.000	1.920707	1.982395

Linear regression

Number of obs	=	1,376,334
F(34, 50)	=	3597.66
Prob > F	=	0.0000
R-squared	=	0.1227
Root MSE	=	9.8548

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	-.3705058	.088469	-4.19	0.000	-.548201	-.1928106
post911entry	-1.286775	.0755081	-17.04	0.000	-1.438438	-1.135113
post911ent~t	.6500583	.1432788	4.54	0.000	.3622744	.9378422
hsgrad	1.783939	.1975991	9.03	0.000	1.38705	2.180829
assocgrad	2.41986	.1983657	12.20	0.000	2.021431	2.818289
bachgrad	4.112304	.1668535	24.65	0.000	3.777169	4.447439
mastgrad	5.027321	.1962847	25.61	0.000	4.633072	5.42157
doctorgrad	8.395625	.3097027	27.11	0.000	7.773569	9.017682
exp	.5517253	.0110331	50.01	0.000	.5295646	.5738861
exp_sq	-.0103638	.0001731	-59.88	0.000	-.0107115	-.0100162
female	-4.740076	.1187892	-39.90	0.000	-4.978671	-4.501481
white	-.1883389	.1572104	-1.20	0.237	-.5041053	.1274275
black	-.2250908	.158266	-1.42	0.161	-.5429773	.0927958
asian	-.8790014	.179202	-4.91	0.000	-1.238939	-.5190635
hispanic	-.024014	.2150514	-0.11	0.912	-.4559574	.4079294
years_sinc~l	-.0050767	.0025102	-2.02	0.049	-.0101186	-.0000347
rural	.2552281	.0832413	3.07	0.003	.0880331	.4224232
year						
1999	.1132456	.059296	1.91	0.062	-.005854	.2323451
2000	.1435715	.0882951	1.63	0.110	-.0337744	.3209174
2001	.1009955	.092171	1.10	0.278	-.0841353	.2861264
2002	-.1286008	.0686954	-1.87	0.067	-.2665795	.0093779
2003	-.3041418	.0830273	-3.66	0.001	-.4709069	-.1373766
2004	-.3348535	.1024144	-3.27	0.002	-.5405589	-.1291481
2005	-.2175847	.0847405	-2.57	0.013	-.387791	-.0473784
2006	-.0439383	.0937625	-0.47	0.641	-.2322658	.1443893
2007	.0118135	.082689	0.14	0.887	-.1542723	.1778993
2008	-.0211793	.0826461	-0.26	0.799	-.1871788	.1448202
2009	-.3725973	.0789702	-4.72	0.000	-.5312135	-.2139811
2010	-.7538585	.0826513	-9.12	0.000	-.9198685	-.5878486
2011	-.7330479	.079988	-9.16	0.000	-.8937085	-.5723872
2012	-.5760617	.0847063	-6.80	0.000	-.7461994	-.4059241
2013	-.450973	.0993293	-4.54	0.000	-.6504819	-.2514642
2014	-.4033786	.099816	-4.04	0.000	-.6038649	-.2028924
2015	-.1967885	.0923805	-2.13	0.038	-.3823403	-.0112368
_cons	34.84489	.2120274	164.34	0.000	34.41902	35.27076

Specification (4), Entire U.S. Labor Market

Linear regression

Number of obs	=	1,375,615
F(49, 50)	=	.
Prob > F	=	.
R-squared	=	0.2803
Root MSE	=	.61873

(Std. Err. adjusted for 51 clusters in state)

lnwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	.7712442	.0494547	15.59	0.000	.6719115	.8705769
post911entry	-.0707972	.0039406	-17.97	0.000	-.0787121	-.0628823
post911ent~t	.033843	.0081144	4.17	0.000	.0175447	.0501412
yearseduc	.112753	.0013176	85.58	0.000	.1101066	.1153995
migrantyea~c	-.0420036	.0026633	-15.77	0.000	-.0473531	-.0366541
exp	.0367186	.0006661	55.13	0.000	.0353808	.0380565
migrantexp	-.0127246	.0009193	-13.84	0.000	-.0145711	-.0108781
exp_sq	-.0006868	.000019	-36.17	0.000	-.000725	-.0006487
migrantexp~q	.0003163	.0000208	15.20	0.000	.0002745	.0003581
female	-.2501089	.004809	-52.01	0.000	-.259768	-.2404498
migrantfem~e	.016607	.0074099	2.24	0.029	.0017239	.0314901
1.migrant	0	(omitted)				
wbhao						
Black	-.15193	.0089992	-16.88	0.000	-.1700054	-.1338546
Hispanic	-.0624254	.0216678	-2.88	0.006	-.1059464	-.0189043
Asian	.0327421	.016077	2.04	0.047	.0004504	.0650338
Other	-.0983478	.0118949	-8.27	0.000	-.1222394	-.0744561
migrant# wbhao						
1#Black	-.0061478	.0198614	-0.31	0.758	-.0460406	.033745
1#Hispanic	-.1578541	.0228033	-6.92	0.000	-.2036558	-.1120523
1#Asian	-.0327837	.0188859	-1.74	0.089	-.0707173	.0051498
1#Other	.0103428	.0509891	0.20	0.840	-.0920719	.1127574
years_sinc~l	.0062695	.0007423	8.45	0.000	.0047785	.0077605
rural	-.1649927	.0123455	-13.36	0.000	-.1897893	-.1401961
migrantrural	.0822124	.019896	4.13	0.000	.0422502	.1221747
year						
1999	.0302908	.0049548	6.11	0.000	.0203388	.0402427
2000	.0409151	.0044386	9.22	0.000	.0319998	.0498303
2001	.0562655	.0054058	10.41	0.000	.0454076	.0671234
2002	.0625805	.0043537	14.37	0.000	.0538358	.0713251
2003	.0696354	.0047499	14.66	0.000	.0600949	.0791758
2004	.0640272	.0046321	13.82	0.000	.0547233	.0733311
2005	.0509271	.0039005	13.06	0.000	.0430928	.0587615
2006	.0418678	.0052176	8.02	0.000	.0313879	.0523476
2007	.0457825	.0080408	5.69	0.000	.0296321	.0619329
2008	.0522617	.0066146	7.90	0.000	.0389759	.0655475
2009	.0364528	.0067872	5.37	0.000	.0228204	.0500852
2010	.0525574	.0061876	8.49	0.000	.0401291	.0649856
2011	.0360523	.0060371	5.97	0.000	.0239264	.0481783
2012	.0227458	.0074747	3.04	0.004	.0077324	.0377593
2013	.0070817	.007144	0.99	0.326	-.0072674	.0214309
2014	.0110225	.0095385	1.16	0.253	-.008136	.0301811
2015	.0140424	.0084675	1.66	0.104	-.0029651	.03105
migrant#year						
1 1999	-.0171708	.0089023	-1.93	0.059	-.0350516	.00071
1 2000	.0104625	.0111014	0.94	0.350	-.0118352	.0327603
1 2001	.027369	.0124349	2.20	0.032	.0023927	.0523454
1 2002	.0323948	.0071133	4.55	0.000	.0181073	.0466824
1 2003	.0130047	.0126274	1.03	0.308	-.0123581	.0383675
1 2004	.0075911	.0124869	0.61	0.546	-.0174896	.0326718
1 2005	.0243837	.0113734	2.14	0.037	.0015395	.0472278

```
     1 2006  |   .0379078   .0100102     3.79   0.000     .0178018    .0580139
     1 2007  |   .0306461   .0088088     3.48   0.001     .0129531    .0483391
     1 2008  |    .024431   .0099897     2.45   0.018      .004366     .044496
     1 2009  |   .0181487   .0136869     1.33   0.191    -.0093421    .0456396
     1 2010  |   .0229796   .0103091     2.23   0.030     .0022731    .0436861
     1 2011  |   .0207727   .0116852     1.78   0.082    -.0026977    .0442432
     1 2012  |   .0232386   .0112244     2.07   0.044     .0006937    .0457836
     1 2013  |   .0346999   .0122826     2.83   0.007     .0100297    .0593702
     1 2014  |   .0285496   .0123927     2.30   0.025     .0036582    .0534411
     1 2015  |   .0119718    .016379     0.73   0.468    -.0209264    .0448699
             |
       _cons |   .8874796   .0255574    34.73   0.000     .8361462    .9388131
------------------------------------------------------------------------------



Linear regression                               Number of obs     =  1,376,334
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1184
                                                Root MSE          =     9.8791

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   6.738927   .6305383    10.69   0.000     5.472454    8.005401
post911entry |  -1.203721   .0713174   -16.88   0.000    -1.346966   -1.060476
post911ent~t |   1.042666   .1500274     6.95   0.000     .7413271    1.344005
   yearseduc |   .6230173   .0192582    32.35   0.000     .5843361    .6616985
migrantyea~c |  -.3512176   .0301366   -11.65   0.000    -.4117488   -.2906864
         exp |    .593179   .0108261    54.79   0.000     .5714341    .6149239
  migrantexp |  -.2324491   .0137321   -16.93   0.000    -.2600307   -.2048674
      exp_sq |  -.0115314   .0002059   -55.99   0.000    -.0119451   -.0111178
migrantexp~q |   .0053535   .0002776    19.29   0.000     .0047959     .005911
      female |   -4.89083   .1130984   -43.24   0.000    -5.117995   -4.663665
migrantfem~e |   .7686449   .1105749     6.95   0.000     .5465486    .9907411
   1.migrant |          0  (omitted)
             |
       wbhao |
      Black  |  -.0785456   .0776211    -1.01   0.316    -.2344521     .077361
   Hispanic  |   .0591471   .2332626     0.25   0.801    -.4093746    .5276688
      Asian  |  -.2873001   .2815503    -1.02   0.312    -.8528104    .2782102
      Other  |   .1194335   .1585059     0.75   0.455     -.198935    .4378019
             |
     migrant#|
       wbhao |
    1#Black  |  -.5597478   .1433701    -3.90   0.000    -.8477151   -.2717805
 1#Hispanic  |   -.540765   .1569938    -3.44   0.001    -.8560963   -.2254337
    1#Asian  |  -.3743392   .2670391    -1.40   0.167    -.9107031    .1620248
    1#Other  |  -.7355336   .4358223    -1.69   0.098    -1.610908    .1398413
             |
years_sinc~l |   .0088269   .0037515     2.35   0.023     .0012918     .016362
       rural |   .2273314   .0877453     2.59   0.013     .0510897    .4035731
migrantrural |   .8303317   .2765222     3.00   0.004     .2749205    1.385743
             |
        year |
```

```
        1999  |   .0990913   .0656096     1.51   0.137    -.0326895    .2308721
        2000  |   .1116998   .0908265     1.23   0.225    -.0707306    .2941301
        2001  |   .0531104    .098185     0.54   0.591       -.1441    .2503208
        2002  |  -.1476019   .0780837    -1.89   0.065    -.3044377     .009234
        2003  |  -.3388732   .0864319    -3.92   0.000    -.5124767   -.1652697
        2004  |  -.3498298   .1061803    -3.29   0.002    -.5630993   -.1365603
        2005  |  -.2250891   .0925326    -2.43   0.019    -.4109462    -.039232
        2006  |  -.1111937   .1069071    -1.04   0.303     -.325923    .1035355
        2007  |  -.0102472    .089434    -0.11   0.909    -.1898806    .1693862
        2008  |  -.0434478    .095344    -0.46   0.651    -.2349518    .1480561
        2009  |  -.3411045   .0919847    -3.71   0.001    -.5258611   -.1563479
        2010  |  -.6700069   .0975662    -6.87   0.000    -.8659744   -.4740395
        2011  |  -.6713802   .0901842    -7.44   0.000    -.8525206   -.4902399
        2012  |  -.5030165   .0963522    -5.22   0.000    -.6965456   -.3094873
        2013  |  -.3793571   .1146606    -3.31   0.002    -.6096598   -.1490545
        2014  |  -.3426775   .1095818    -3.13   0.003     -.562779   -.1225761
        2015  |   -.132977   .1003743    -1.32   0.191    -.3345848    .0686307
              |
 migrant#year |
      1 1999  |   .0654131   .1597571     0.41   0.684    -.2554684    .3862946
      1 2000  |   .2052425   .2098845     0.98   0.333    -.2163229    .6268078
      1 2001  |   .3144794   .1620985     1.94   0.058     -.011105    .6400638
      1 2002  |   .0636964   .1678702     0.38   0.706    -.2734809    .4008737
      1 2003  |   .1448027   .1695165     0.85   0.397    -.1956811    .4852866
      1 2004  |   .0273746   .2014288     0.14   0.892     -.377207    .4319563
      1 2005  |  -.0398953   .1235498    -0.32   0.748    -.2880523    .2082617
      1 2006  |   .3194029   .1750113     1.83   0.074    -.0321176    .6709234
      1 2007  |   .0324967   .1164815     0.28   0.781    -.2014632    .2664567
      1 2008  |  -.0193173   .1719346    -0.11   0.911    -.3646581    .3260235
      1 2009  |  -.3349765   .1604913    -2.09   0.042    -.6573328   -.0126203
      1 2010  |  -.6711416   .1511802    -4.44   0.000     -.974796   -.3674873
      1 2011  |  -.6189805   .1318664    -4.69   0.000     -.883842    -.354119
      1 2012  |  -.6540796   .1551614    -4.22   0.000    -.9657303   -.3424288
      1 2013  |  -.6531197   .1516072    -4.31   0.000    -.9576318   -.3486077
      1 2014  |  -.5312053   .1616927    -3.29   0.002    -.8559747    -.206436
      1 2015  |  -.5730828   .1309879    -4.38   0.000    -.8361798   -.3099858
              |
        _cons |   27.89892   .3991018    69.90   0.000      27.0973    28.70054
------------------------------------------------------------------------------
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Specification (5), Entire U.S. Labor Market

```
Linear regression                               Number of obs     =  1,375,615
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.2909
                                                Root MSE          =     .61416

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   .0317949   .0206432     1.54   0.130    -.0096682     .073258
post911entry |  -.0635805   .0037507   -16.95   0.000    -.0711139    -.056047
```

post911ent~t	.0446021	.0060608	7.36	0.000	.0324286	.0567757
hsgrad	.2520617	.0060711	41.52	0.000	.2398675	.2642559
assocgrad	.4176748	.007278	57.39	0.000	.4030565	.4322932
bachgrad	.6587619	.0123818	53.20	0.000	.6338924	.6836314
mastgrad	.7958327	.0183266	43.43	0.000	.7590227	.8326426
doctorgrad	1.026432	.0190285	53.94	0.000	.9882118	1.064652
migranthsg~d	-.0623704	.0061664	-10.11	0.000	-.0747559	-.0499848
migrantass~d	-.0262546	.0137894	-1.90	0.063	-.0539514	.0014422
migrantbac~d	.0030273	.012282	0.25	0.806	-.0216418	.0276964
migrantmas~d	.1582786	.021529	7.35	0.000	.1150362	.2015209
migrantdoc~d	.0457642	.0199053	2.30	0.026	.0057832	.0857453
exp	.0234073	.0012054	19.42	0.000	.0209863	.0258284
migrantexp	-.0015799	.0016707	-0.95	0.349	-.0049357	.0017759
exp_sq	-.000667	.000018	-36.97	0.000	-.0007033	-.0006308
migrantexp~q	.0002537	.000018	14.10	0.000	.0002175	.0002898
female	-.2466366	.0048353	-51.01	0.000	-.2563486	-.2369247
migrantfem~e	.0249048	.0067433	3.69	0.001	.0113606	.0384491
1.migrant	0	(omitted)				
wbhao						
Black	-.1423923	.0091559	-15.55	0.000	-.1607824	-.1240021
Hispanic	-.0627801	.0244876	-2.56	0.013	-.1119649	-.0135954
Asian	.0192981	.0163604	1.18	0.244	-.0135629	.052159
Other	-.0869131	.0118465	-7.34	0.000	-.1107074	-.0631188
migrant# wbhao						
1#Black	.0398333	.0177406	2.25	0.029	.0042002	.0754664
1#Hispanic	-.125705	.0220395	-5.70	0.000	-.1699726	-.0814374
1#Asian	-.0389857	.0141635	-2.75	0.008	-.0674338	-.0105376
1#Other	.0199001	.0536457	0.37	0.712	-.0878505	.1276507
years_sinc~l	.0180005	.0014277	12.61	0.000	.0151328	.0208681
rural	-.1684479	.0127779	-13.18	0.000	-.1941131	-.1427827
migrantrural	.0793794	.0155672	5.10	0.000	.0481117	.1106471
year						
1999	.0310711	.0049593	6.27	0.000	.02111	.0410322
2000	.0422085	.0043465	9.71	0.000	.0334783	.0509386
2001	.0576285	.0052063	11.07	0.000	.0471713	.0680856
2002	.0642462	.0043286	14.84	0.000	.0555519	.0729405
2003	.0720533	.0051077	14.11	0.000	.0617943	.0823124
2004	.0651062	.0049725	13.09	0.000	.0551186	.0750938
2005	.0512073	.004038	12.68	0.000	.0430967	.0593178
2006	.0428693	.0052622	8.15	0.000	.0323	.0534387
2007	.0451272	.007738	5.83	0.000	.029585	.0606694
2008	.0528503	.0066758	7.92	0.000	.0394416	.066259
2009	.0360287	.006751	5.34	0.000	.022469	.0495884
2010	.0515803	.0057921	8.91	0.000	.0399466	.063214
2011	.035426	.0060074	5.90	0.000	.0233598	.0474922
2012	.0215003	.0077546	2.77	0.008	.0059247	.0370759
2013	.0058407	.0071471	0.82	0.418	-.0085147	.0201961
2014	.007936	.0099534	0.80	0.429	-.0120561	.027928
2015	.0105375	.0089429	1.18	0.244	-.0074249	.0284999
migrant#year						
1 1999	-.0226939	.0089798	-2.53	0.015	-.0407303	-.0046575
1 2000	-.001599	.0090666	-0.18	0.861	-.0198099	.0166118
1 2001	.0066344	.0098726	0.67	0.505	-.0131952	.0264641
1 2002	.0008123	.0076765	0.11	0.916	-.0146065	.0162311

```
     1 2003  |   -.027862   .0126843    -2.20   0.033    -.0533391    -.002385
     1 2004  |  -.0409208   .0116134    -3.52   0.001    -.0642469   -.0175946
     1 2005  |  -.0303601   .0091853    -3.31   0.002    -.0488094   -.0119108
     1 2006  |  -.0294437   .0088796    -3.32   0.002     -.047279   -.0116084
     1 2007  |  -.0404232   .0116227    -3.48   0.001     -.063768   -.0170784
     1 2008  |  -.0592615   .0111646    -5.31   0.000    -.0816862   -.0368368
     1 2009  |   -.074429   .0149802    -4.97   0.000    -.1045176   -.0443403
     1 2010  |  -.0739388   .0132058    -5.60   0.000    -.1004633   -.0474142
     1 2011  |  -.0821064    .015999    -5.13   0.000    -.1142414   -.0499714
     1 2012  |  -.0912688   .0172223    -5.30   0.000    -.1258608   -.0566768
     1 2013  |  -.0910649   .0158096    -5.76   0.000    -.1228193   -.0593105
     1 2014  |  -.1022784   .0163212    -6.27   0.000    -.1350604   -.0694964
     1 2015  |   -.124487   .0195555    -6.37   0.000    -.1637653   -.0852087
             |
  entry_year |  -.0076068   .0011226    -6.78   0.000    -.0098616    -.005352
entry_year~q |   3.88e-06   5.69e-07     6.83   0.000     2.74e-06    5.03e-06
       _cons |   1.862676   .0259041    71.91   0.000     1.810646    1.914705
------------------------------------------------------------------------------


Linear regression                               Number of obs     =  1,376,334
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1246
                                                Root MSE          =     9.8444

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   3.410245   .4293464     7.94   0.000     2.547877    4.272612
post911entry |  -1.175312    .069429   -16.93   0.000    -1.314764   -1.035859
post911ent~t |   .9661468   .1497851     6.45   0.000     .6652945    1.266999
      hsgrad |   2.444585   .1289077    18.96   0.000     2.185666    2.703504
   assocgrad |   3.088487    .144307    21.40   0.000     2.798638    3.378336
    bachgrad |   4.862807   .1565985    31.05   0.000      4.54827    5.177345
    mastgrad |    5.82899   .2073469    28.11   0.000     5.412521    6.245459
  doctorgrad |   9.141177    .309406    29.54   0.000     8.519717    9.762638
migranthsg~d |  -1.850905   .1476028   -12.54   0.000    -2.147374   -1.554436
migrantass~d |  -2.050897   .2210795    -9.28   0.000    -2.494948   -1.606846
migrantbac~d |  -2.468691   .2332755   -10.58   0.000    -2.937239   -2.000144
migrantmas~d |  -2.525614   .3050123    -8.28   0.000    -3.138249   -1.912978
migrantdoc~d |  -1.988359    .262414    -7.58   0.000    -2.515433   -1.461285
         exp |   .6086812   .0143608    42.38   0.000     .5798366    .6375257
  migrantexp |  -.2515456   .0147647   -17.04   0.000    -.2812013   -.2218899
      exp_sq |  -.0112932   .0001956   -57.73   0.000    -.0116862   -.0109003
migrantexp~q |   .0049672   .0002657    18.69   0.000     .0044335    .0055009
      female |  -4.856355   .1126793   -43.10   0.000    -5.082678   -4.630032
migrantfem~e |    .847779   .1134545     7.47   0.000      .619899    1.075659
   1.migrant |          0  (omitted)
             |
       wbhao |
      Black  |   .0187584   .0784011     0.24   0.812    -.1387149    .1762316
   Hispanic  |   .0962406     .22774     0.42   0.674    -.3611886    .5536698
      Asian  |  -.3965989   .2700043    -1.47   0.148    -.9389185    .1457207
      Other  |   .2352278   .1554482     1.51   0.137    -.0769991    .5474548
             |
     migrant#|
       wbhao |
```

1#Black	-.3436106	.1485832	-2.31	0.025	-.6420488	-.0451724
1#Hispanic	-.3706864	.177653	-2.09	0.042	-.7275129	-.0138599
1#Asian	-.3594682	.2854267	-1.26	0.214	-.9327646	.2138281
1#Other	-.6956212	.4239599	-1.64	0.107	-1.54717	.1559273
years_sinc~l	-.0228817	.0095323	-2.40	0.020	-.0420279	-.0037356
rural	.243675	.0891576	2.73	0.009	.0645966	.4227534
migrantrural	.7601806	.2728118	2.79	0.008	.212222	1.308139
year						
1999	.1019392	.0659316	1.55	0.128	-.0304883	.2343667
2000	.1158942	.0902986	1.28	0.205	-.0654759	.2972642
2001	.060652	.0962583	0.63	0.532	-.1326886	.2539925
2002	-.138028	.0760662	-1.81	0.076	-.2908115	.0147555
2003	-.3267613	.0834279	-3.92	0.000	-.4943312	-.1591913
2004	-.3475385	.1040035	-3.34	0.002	-.5564357	-.1386413
2005	-.2251713	.0904945	-2.49	0.016	-.4069348	-.0434078
2006	-.1047124	.1040507	-1.01	0.319	-.3137043	.1042796
2007	-.0129821	.085986	-0.15	0.881	-.18569	.1597259
2008	-.0391747	.0942904	-0.42	0.680	-.2285625	.1502131
2009	-.3468873	.0914808	-3.79	0.000	-.530632	-.1631426
2010	-.6799749	.0950447	-7.15	0.000	-.8708778	-.4890719
2011	-.6773046	.0892932	-7.59	0.000	-.8566552	-.497954
2012	-.5110583	.0946246	-5.40	0.000	-.7011174	-.3209992
2013	-.3867372	.114978	-3.36	0.001	-.6176772	-.1557972
2014	-.3648671	.1099323	-3.32	0.002	-.5856725	-.1440616
2015	-.1545791	.1012569	-1.53	0.133	-.3579596	.0488013
migrant#year						
1 1999	.1143458	.1577696	0.72	0.472	-.2025437	.4312353
1 2000	.3012859	.2223148	1.36	0.181	-.1452465	.7478183
1 2001	.4291162	.1655033	2.59	0.012	.0966929	.7615394
1 2002	.2122354	.1608561	1.32	0.193	-.1108537	.5353245
1 2003	.3218186	.1645073	1.96	0.056	-.0086041	.6522413
1 2004	.2469469	.1960153	1.26	0.214	-.1467615	.6406553
1 2005	.2307228	.1444099	1.60	0.116	-.0593331	.5207786
1 2006	.5992478	.1723916	3.48	0.001	.252989	.9455066
1 2007	.3841247	.1416476	2.71	0.009	.099617	.6686323
1 2008	.3547861	.1941577	1.83	0.074	-.0351911	.7447634
1 2009	.0748032	.1660556	0.45	0.654	-.2587292	.4083356
1 2010	-.1961084	.141232	-1.39	0.171	-.4797813	.0875645
1 2011	-.0894417	.1467659	-0.61	0.545	-.3842297	.2053462
1 2012	-.1041532	.18381	-0.57	0.573	-.4733464	.2650399
1 2013	-.086105	.1736818	-0.50	0.622	-.4349551	.2627452
1 2014	.0706891	.1507414	0.47	0.641	-.2320839	.373462
1 2015	.056328	.1683877	0.33	0.739	-.2818886	.3945446
entry_year	.0357594	.0081103	4.41	0.000	.0194694	.0520494
entry_year~q	-.0000181	4.12e-06	-4.39	0.000	-.0000264	-9.82e-06
_cons	34.10328	.2316578	147.21	0.000	33.63798	34.56857

Specification (6), Entire U.S. Labor Market

Linear regression   Number of obs   = 1,364,949

```
                                                  F(49, 50)       =          .
                                                  Prob > F        =          .
                                                  R-squared       =     0.2902
                                                  Root MSE        =     .61398

                                    (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   .2709537   .0143077    18.94   0.000     .2422159    .2996915
post911entry |  -.0636863   .0037393   -17.03   0.000    -.0711969   -.0561757
post911ent~t |   .0307495   .0061767     4.98   0.000     .0183431    .0431559
      hsgrad |   .2723052   .0050024    54.44   0.000     .2622576    .2823527
   assocgrad |   .4468584   .0056578    78.98   0.000     .4354944    .4582224
    bachgrad |   .7028645   .0091553    76.77   0.000     .6844756    .7212534
    mastgrad |   .8553081   .0131981    64.81   0.000     .8287989    .8818173
  doctorgrad |   1.100986   .0128025    86.00   0.000     1.075271      1.1267
migranthsg~d |  -.0821192   .0050676   -16.20   0.000    -.0922977   -.0719407
migrantass~d |  -.0525136   .0140364    -3.74   0.000    -.0807065   -.0243207
migrantbac~d |  -.0444391   .0085175    -5.22   0.000    -.0615469   -.0273313
migrantmas~d |   .0945479   .0163354     5.79   0.000     .0617372    .1273585
migrantdoc~d |  -.0390245   .0146917    -2.66   0.011    -.0685336   -.0095153
         exp |   .0309869   .0006141    50.46   0.000     .0297534    .0322204
  migrantexp |  -.0131249   .0009938   -13.21   0.000     -.015121   -.0111288
      exp_sq |  -.0006689   .0000182   -36.81   0.000    -.0007054   -.0006324
migrantexp~q |   .0003206    .000019    16.84   0.000     .0002823    .0003588
      female |  -.2461992   .0048451   -50.81   0.000     -.255931   -.2364674
migrantfem~e |   .0187361   .0067935     2.76   0.008     .0050909    .0323813
   1.migrant |          0  (omitted)
             |
       wbhao |
      Black  |  -.1424841   .0091962   -15.49   0.000    -.1609553   -.1240129
   Hispanic  |  -.0594589   .0246295    -2.41   0.019    -.1089287   -.0099891
      Asian  |   .0301781   .0159053     1.90   0.064    -.0017686    .0621249
      Other  |  -.0868148   .0119203    -7.28   0.000    -.1107573   -.0628722
             |
     migrant#|
       wbhao |
    1#Black  |   .0408895   .0193404     2.11   0.040     .0020432    .0797359
 1#Hispanic  |  -.1355058   .0223382    -6.07   0.000    -.1803733   -.0906382
    1#Asian  |  -.0523794   .0148187    -3.53   0.001    -.0821436   -.0226153
    1#Other  |   .0178112   .0586863     0.30   0.763    -.1000637    .1356861
             |
years_sinc~l |   .0103154   .0006304    16.36   0.000     .0090492    .0115816
       rural |  -.1695731   .0127777   -13.27   0.000    -.1952379   -.1439083
migrantrural |   .0796229    .015451     5.15   0.000     .0485886    .1106572
             |
        year |
       1999  |   .0312188   .0049555     6.30   0.000     .0212653    .0411722
       2000  |   .0424483   .0043456     9.77   0.000     .0337198    .0511767
       2001  |    .058125   .0051866    11.21   0.000     .0477073    .0685426
       2002  |   .0649391   .0043506    14.93   0.000     .0562006    .0736777
       2003  |   .0728573   .0051577    14.13   0.000     .0624978    .0832169
       2004  |   .0661011    .004996    13.23   0.000     .0560662    .0761359
       2005  |   .0521734    .004032    12.94   0.000     .0440749    .0602719
       2006  |   .0441206   .0053072     8.31   0.000     .0334608    .0547805
       2007  |   .0464264   .0078015     5.95   0.000     .0307566    .0620963
       2008  |   .0544349   .0067102     8.11   0.000     .0409571    .0679128
       2009  |   .0375575   .0067529     5.56   0.000     .0239939     .051121
```

2010	.0531663	.0057773	9.20	0.000	.0415622	.0647703
2011	.0372247	.0060421	6.16	0.000	.0250888	.0493607
2012	.023446	.0077519	3.02	0.004	.0078759	.0390162
2013	.0080335	.0071631	1.12	0.267	-.006354	.022421
2014	.0100215	.0099125	1.01	0.317	-.0098884	.0299313
2015	.0128294	.0089489	1.43	0.158	-.0051449	.0308037
migrant#year						
1 1999	-.0152019	.0089399	-1.70	0.095	-.0331583	.0027545
1 2000	.0142262	.0089981	1.58	0.120	-.0038471	.0322994
1 2001	.0298874	.0111196	2.69	0.010	.007553	.0522219
1 2002	.0325524	.0079467	4.10	0.000	.016591	.0485137
1 2003	.0126341	.0129841	0.97	0.335	-.0134453	.0387136
1 2004	.009557	.0135066	0.71	0.482	-.0175718	.0366858
1 2005	.031584	.0116648	2.71	0.009	.0081546	.0550133
1 2006	.0416229	.0093799	4.44	0.000	.0227828	.060463
1 2007	.0418299	.0077618	5.39	0.000	.0262398	.05742
1 2008	.0281122	.0095238	2.95	0.005	.0089831	.0472412
1 2009	.0241682	.0122453	1.97	0.054	-.0004272	.0487636
1 2010	.0305352	.009571	3.19	0.002	.0113113	.0497591
1 2011	.0315952	.0108376	2.92	0.005	.0098272	.0533632
1 2012	.0297382	.0115152	2.58	0.013	.0066093	.0528671
1 2013	.0397721	.0126591	3.14	0.003	.0143456	.0651986
1 2014	.0312683	.011132	2.81	0.007	.0089091	.0536276
1 2015	.0165515	.0152735	1.08	0.284	-.0141262	.0472291
_cons	1.982314	.0152496	129.99	0.000	1.951684	2.012943

Linear regression

Number of obs	=	1,365,655
F(49, 50)	=	.
Prob > F	=	.
R-squared	=	0.1242
Root MSE	=	9.8386

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	4.090267	.3844497	10.64	0.000	3.318077	4.862457
post911entry	-1.177593	.0694628	-16.95	0.000	-1.317113	-1.038072
post911ent~t	.6636862	.146316	4.54	0.000	.3698018	.9575707
hsgrad	2.355946	.1262272	18.66	0.000	2.102411	2.609481
assocgrad	2.96433	.1395391	21.24	0.000	2.684058	3.244603
bachgrad	4.679648	.1424485	32.85	0.000	4.393532	4.965764
mastgrad	5.583974	.1845689	30.25	0.000	5.213257	5.954692
doctorgrad	8.835242	.2792238	31.64	0.000	8.274404	9.396079
migranthsg~d	-1.721266	.1376117	-12.51	0.000	-1.997667	-1.444865
migrantass~d	-2.04858	.2116912	-9.68	0.000	-2.473774	-1.623385
migrantbac~d	-2.515595	.2363063	-10.65	0.000	-2.99023	-2.04096
migrantmas~d	-2.597157	.2870189	-9.05	0.000	-3.173651	-2.020662
migrantdoc~d	-2.205001	.2606781	-8.46	0.000	-2.728588	-1.681413
exp	.5783957	.0103288	56.00	0.000	.5576497	.5991416
migrantexp	-.2841581	.0166433	-17.07	0.000	-.317587	-.2507291
exp_sq	-.0112906	.0001967	-57.39	0.000	-.0116858	-.0108955
migrantexp~q	.0060309	.0003074	19.62	0.000	.0054133	.0066484
female	-4.858505	.1127962	-43.07	0.000	-5.085063	-4.631947
migrantfem~e	.792158	.1186869	6.67	0.000	.5537684	1.030548

1.migrant	0	(omitted)				
wbhao						
Black	.0183765	.0784291	0.23	0.816	-.139153	.1759061
Hispanic	.1305497	.2227486	0.59	0.560	-.3168541	.5779535
Asian	-.3679261	.2662548	-1.38	0.173	-.9027147	.1668624
Other	.235802	.1554513	1.52	0.136	-.0764312	.5480353
migrant# wbhao						
1#Black	-.4513547	.1346905	-3.35	0.002	-.7218885	-.180821
1#Hispanic	-.6120421	.161362	-3.79	0.000	-.9361471	-.287937
1#Asian	-.4064781	.2531028	-1.61	0.115	-.9148501	.1018939
1#Other	-.7174614	.4551586	-1.58	0.121	-1.631674	.1967515
years_sinc~l	.0082077	.0043762	1.88	0.067	-.0005821	.0169975
rural	.2450466	.0892694	2.75	0.008	.0657437	.4243495
migrantrural	.7575299	.2831705	2.68	0.010	.1887651	1.326295
year						
1999	.1013855	.065978	1.54	0.131	-.0311353	.2339063
2000	.1143508	.0904862	1.26	0.212	-.067396	.2960977
2001	.0578155	.0963115	0.60	0.551	-.1356317	.2512628
2002	-.1416964	.0761034	-1.86	0.069	-.2945546	.0111618
2003	-.3302091	.0835568	-3.95	0.000	-.4980379	-.1623804
2004	-.3509079	.1041134	-3.37	0.001	-.5600257	-.14179
2005	-.2297593	.090414	-2.54	0.014	-.4113612	-.0481575
2006	-.1109018	.1039695	-1.07	0.291	-.3197306	.097927
2007	-.019603	.0859914	-0.23	0.821	-.1923218	.1531158
2008	-.046742	.0939428	-0.50	0.621	-.2354317	.1419477
2009	-.3546581	.0911338	-3.89	0.000	-.5377058	-.1716105
2010	-.6880813	.0946179	-7.27	0.000	-.8781269	-.4980358
2011	-.6865211	.0887609	-7.73	0.000	-.8648026	-.5082397
2012	-.5211022	.0942116	-5.53	0.000	-.7103317	-.3318727
2013	-.3980674	.1144389	-3.48	0.001	-.6279248	-.16821
2014	-.3764111	.1091179	-3.45	0.001	-.5955808	-.1572414
2015	-.166508	.1000635	-1.66	0.102	-.3674914	.0344754
migrant#year						
1 1999	.0793819	.158321	0.50	0.618	-.2386152	.397379
1 2000	.2388551	.2158183	1.11	0.274	-.1946287	.6723389
1 2001	.3317188	.164199	2.02	0.049	.0019155	.6615222
1 2002	.1195513	.1625831	0.74	0.466	-.2070064	.4461089
1 2003	.2591135	.1538532	1.68	0.098	-.0499098	.5681368
1 2004	.2096381	.1969353	1.06	0.292	-.185918	.6051942
1 2005	.2109304	.1320063	1.60	0.116	-.054212	.4760729
1 2006	.5633421	.1741541	3.23	0.002	.2135433	.9131409
1 2007	.2812249	.1189124	2.36	0.022	.0423823	.5200676
1 2008	.1623454	.1606859	1.01	0.317	-.1604018	.4850926
1 2009	-.0687908	.1544073	-0.45	0.658	-.3789269	.2413453
1 2010	-.446294	.1457079	-3.06	0.004	-.738957	-.153631
1 2011	-.348625	.1248861	-2.79	0.007	-.5994661	-.0977838
1 2012	-.4330985	.1475723	-2.93	0.005	-.7295061	-.1366909
1 2013	-.4508415	.1629966	-2.77	0.008	-.7782299	-.1234531
1 2014	-.2569489	.1619285	-1.59	0.119	-.5821919	.0682941
1 2015	-.2568827	.1384589	-1.86	0.069	-.5349857	.0212203
_cons	33.62722	.2309611	145.60	0.000	33.16332	34.09112

Specification (1), Exogenous-wage, Method 1, Restricted sample

```
Linear regression                               Number of obs     =     31,180
                                                F(3, 50)          =     200.42
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0386
                                                Root MSE          =     12.252

                                   (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   2.009349   .3178898     6.32   0.000     1.370849     2.64785
post911entry |  -4.730649   .2205009   -21.45   0.000    -5.173538    -4.28776
post911ent~t |    3.82615   .3702531    10.33   0.000     3.082475    4.569825
       _cons |   36.24275   .3116833   116.28   0.000     35.61672    36.86879
------------------------------------------------------------------------------
```

Specification (1), Exogenous-wage, Method 1, Full sample

```
Linear regression                               Number of obs     =  1,376,334
                                                F(6, 50)          =     464.77
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0263
                                                Root MSE          =     10.382

                                   (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |  -.5676735   .1496651    -3.79   0.000    -.8682847   -.2670622
post911entry |  -4.863412   .1418005   -34.30   0.000    -5.148227   -4.578598
post911ent~t |   3.847511   .1724498    22.31   0.000     3.501135    4.193886
     minwage |  -3.611898   .2266482   -15.94   0.000    -4.067134   -3.156662
post911min~e |  -.5416633   .3092232    -1.75   0.086    -1.162756    .0794298
post911min~t |   2.555662   .3452742     7.40   0.000     1.862159    3.249166
       _cons |   40.52908   .1173507   345.37   0.000     40.29337    40.76479
------------------------------------------------------------------------------
```

Specification (2), Exogenous-wage, Method 1, Restricted sample

```
Linear regression                               Number of obs     =     31,180
                                                F(14, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.0990
                                                Root MSE          =     11.863
```

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	.9875871	.3104675	3.18	0.003	.3639947	1.61118
post911entry	.033465	.3869689	0.09	0.931	-.743785	.810715
post911ent~t	-.3652609	.4644463	-0.79	0.435	-1.298129	.5676071
yearseduc	.0711293	.057329	1.24	0.220	-.0440194	.186278
exp	.7177603	.0353278	20.32	0.000	.6468024	.7887182
exp_sq	-.0131534	.0007012	-18.76	0.000	-.0145619	-.011745
female	-4.054896	.2566341	-15.80	0.000	-4.57036	-3.539431
white	-1.02647	.6627877	-1.55	0.128	-2.357718	.3047788
black	-.3647987	.5915354	-0.62	0.540	-1.552932	.823335
asian	-1.079178	.7679574	-1.41	0.166	-2.621666	.4633097
hispanic	.4512355	.7610869	0.59	0.556	-1.077453	1.979923
years_sinc~l	-.0035523	.0109158	-0.33	0.746	-.0254772	.0183727
rural	1.11408	.2803244	3.97	0.000	.5510315	1.677128
year	-13.71911	14.38783	-0.95	0.345	-42.61792	15.1797
year_sq	.0033891	.0035821	0.95	0.349	-.0038058	.010584
_cons	13913.81	14447.48	0.96	0.340	-15104.8	42932.42

<u>Specification (2), Exogenous-wage, Method 1, Full sample</u>

Linear regression

Number of obs	=	1,376,334
F(17, 50)	=	.
Prob > F	=	.
R-squared	=	0.1157
Root MSE	=	9.8945

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	.016717	.0975701	0.17	0.865	-.1792582	.2126923
post911entry	-1.173373	.0711243	-16.50	0.000	-1.31623	-1.030516
post911ent~t	.6700655	.1300768	5.15	0.000	.4087986	.9313324
minwage	-1.683488	.1866515	-9.02	0.000	-2.058388	-1.308587
post911min~e	-1.293057	.3035645	-4.26	0.000	-1.902785	-.68333
post911min~t	2.463315	.401161	6.14	0.000	1.657559	3.269071
yearseduc	.5026965	.026301	19.11	0.000	.4498693	.5555236
exp	.5580119	.0102531	54.42	0.000	.537418	.5786059
exp_sq	-.0104936	.0001876	-55.93	0.000	-.0108705	-.0101168
female	-4.760072	.1185834	-40.14	0.000	-4.998253	-4.52189
white	-.0436029	.1639119	-0.27	0.791	-.3728298	.2856239
black	-.2290147	.1609387	-1.42	0.161	-.5522696	.0942402
asian	-.7228424	.1862437	-3.88	0.000	-1.096924	-.3487609
hispanic	.1034334	.2083862	0.50	0.622	-.3151226	.5219894
years_sinc~l	.0043891	.0026883	1.63	0.109	-.0010106	.0097888
rural	.1879079	.0758092	2.48	0.017	.0356407	.3401751
year	-8.365126	3.898173	-2.15	0.037	-16.19484	-.5354144
year_sq	.0020764	.0009716	2.14	0.037	.000125	.0040279
_cons	8454.647	3908.174	2.16	0.035	604.8488	16304.44

Specification (3), Exogenous-wage, Method 1, Restricted sample

```
Linear regression                               Number of obs     =     31,180
                                                F(30, 50)         =     512.76
                                                Prob > F          =     0.0000
                                                R-squared         =     0.1005
                                                Root MSE          =     11.856

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   .9801381   .3091547     3.17   0.003     .3591826    1.601094
post911entry |   .0605854   .3818379     0.16   0.875    -.7063586    .8275293
post911ent~t |  -.3420245   .4668573    -0.73   0.467    -1.279735     .595686
  yearseduc |   .0725588   .0570853     1.27   0.210    -.0421004    .1872181
         exp |    .720541   .0354349    20.33   0.000      .649368    .7917141
      exp_sq |  -.0132014   .0007034   -18.77   0.000    -.0146141   -.0117887
      female |  -4.063416    .255732   -15.89   0.000    -4.577069   -3.549764
       white |   -1.01053   .6566277    -1.54   0.130    -2.329406    .3083453
       black |  -.3554661   .5852904    -0.61   0.546    -1.531056    .8201242
       asian |  -1.085566   .7618566    -1.42   0.160      -2.6158    .4446683
    hispanic |   .4700903   .7498187     0.63   0.534    -1.035965    1.976145
years_sinc~l |  -.0032287   .0109274    -0.30   0.769     -.025177    .0187196
       rural |   1.111733   .2803237     3.97   0.000      .548686    1.674779
             |
        year |
       1999  |   .4507361   .7268908     0.62   0.538    -1.009267    1.910739
       2000  |   .6791371   .6432969     1.06   0.296    -.6129627    1.971237
       2001  |   .2192515   .7304159     0.30   0.765    -1.247832    1.686335
       2002  |  -.0132112    .605141    -0.02   0.983    -1.228673     1.20225
       2003  |  -.0541528   .4683769    -0.12   0.908    -.9949155    .8866099
       2004  |  -.2217241   .5976332    -0.37   0.712    -1.422106    .9786575
       2005  |  -.1017459   .7099981    -0.14   0.887    -1.527819    1.324327
       2006  |  -.2499165   .6719668    -0.37   0.712    -1.599602    1.099769
       2007  |  -.2520854   .5994542    -0.42   0.676    -1.456125    .9519538
       2008  |  -.6794085   .6175538    -1.10   0.277    -1.919802    .5609848
       2009  |  -.6080213   .6374165    -0.95   0.345     -1.88831    .6722675
       2010  |  -1.841969   .7101446    -2.59   0.012    -3.268337   -.4156021
       2011  |  -2.232223   .6475213    -3.45   0.001    -3.532808   -.9316382
       2012  |  -.7450222   .4697947    -1.59   0.119    -1.688633    .1985882
       2013  |  -.8937863   .5648044    -1.58   0.120    -2.028229    .2406567
       2014  |   -1.64489   .6201611    -2.65   0.011     -2.89052   -.3992593
       2015  |  -1.015416   .5799268    -1.75   0.086    -2.180233    .1494014
             |
       _cons |   31.76816   .9098172    34.92   0.000     29.94073    33.59558
------------------------------------------------------------------------------
```

Specification (3), Exogenous-wage, Method 1, Full sample

```
Linear regression                               Number of obs     =  1,376,334
                                                F(37, 50)         =    5186.97
```

Prob > F	=	0.0000
R-squared	=	0.1235
Root MSE	=	9.8506

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	-.3880092	.0999886	-3.88	0.000	-.5888422	-.1871762
post911entry	-1.205613	.0745726	-16.17	0.000	-1.355396	-1.055829
post911ent~t	.671481	.1345902	4.99	0.000	.4011486	.9418134
minwage	-1.606227	.186768	-8.60	0.000	-1.981361	-1.231092
post911min~e	-1.123912	.2880176	-3.90	0.000	-1.702413	-.545412
post911min~t	2.307318	.3799103	6.07	0.000	1.544246	3.07039
hsgrad	1.719802	.1938768	8.87	0.000	1.330389	2.109215
assocgrad	2.327959	.1916661	12.15	0.000	1.942986	2.712932
bachgrad	3.995717	.1574067	25.38	0.000	3.679556	4.311877
mastgrad	4.89696	.1827507	26.80	0.000	4.529895	5.264026
doctorgrad	8.25476	.2940193	28.08	0.000	7.664205	8.845315
exp	.5430349	.009529	56.99	0.000	.5238952	.5621745
exp_sq	-.0103018	.0001704	-60.44	0.000	-.0106441	-.0099594
female	-4.72383	.1180099	-40.03	0.000	-4.960859	-4.4868
white	-.1961626	.1556477	-1.26	0.213	-.5087903	.116465
black	-.2226183	.1559217	-1.43	0.160	-.5357962	.0905596
asian	-.8897425	.179253	-4.96	0.000	-1.249783	-.5297023
hispanic	-.0278744	.213531	-0.13	0.897	-.4567641	.4010152
years_sinc~l	.0073008	.0024678	2.96	0.005	.0023441	.0122575
rural	.2639553	.0826268	3.19	0.002	.0979944	.4299162
year						
1999	.1179085	.0585414	2.01	0.049	.0003246	.2354925
2000	.144968	.0867221	1.67	0.101	-.0292184	.3191544
2001	.103346	.091481	1.13	0.264	-.0803991	.287091
2002	-.1266074	.0680158	-1.86	0.069	-.2632212	.0100063
2003	-.3020542	.0820852	-3.68	0.001	-.4669271	-.1371813
2004	-.3364741	.1008813	-3.34	0.002	-.5391002	-.1338481
2005	-.213573	.0842704	-2.53	0.014	-.382835	-.044311
2006	-.0504349	.0928155	-0.54	0.589	-.2368603	.1359905
2007	.0151382	.0824051	0.18	0.855	-.1503773	.1806537
2008	-.0136561	.0818738	-0.17	0.868	-.1781045	.1507924
2009	-.3608722	.0785988	-4.59	0.000	-.5187426	-.2030018
2010	-.7401064	.0806973	-9.17	0.000	-.9021918	-.578021
2011	-.7192314	.0793568	-9.06	0.000	-.8786243	-.5598385
2012	-.5549956	.0829871	-6.69	0.000	-.7216802	-.388311
2013	-.4367806	.0963932	-4.53	0.000	-.630392	-.2431692
2014	-.3896752	.0988481	-3.94	0.000	-.5882173	-.191133
2015	-.1799277	.0912439	-1.97	0.054	-.3631964	.0033411
_cons	34.88435	.216555	161.09	0.000	34.44939	35.31932

Specification (4), Exogenous-wage, Method 1, Restricted sample

Linear regression

Number of obs	=	31,180
F(49, 50)	=	.
Prob > F	=	.
R-squared	=	0.1053

Root MSE = 11.829

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	6.016505	1.157278	5.20	0.000	3.692044	8.340966
post911entry	.1201072	.3780116	0.32	0.752	-.6391515	.8793659
post911ent~t	.0264376	.4844789	0.05	0.957	-.9466669	.9995422
yearseduc	.283629	.047486	5.97	0.000	.1882506	.3790075
migrantyea~c	-.3444541	.0526588	-6.54	0.000	-.4502224	-.2386859
exp	.8183695	.031972	25.60	0.000	.7541518	.8825871
migrantexp	-.3206295	.0495881	-6.47	0.000	-.4202302	-.2210288
exp_sq	-.0157184	.0006272	-25.06	0.000	-.0169781	-.0144586
migrantexp~q	.0076055	.0009547	7.97	0.000	.005688	.009523
female	-4.040326	.2860205	-14.13	0.000	-4.614815	-3.465837
migrantfem~e	-.1468092	.4401751	-0.33	0.740	-1.030927	.7373084
1.migrant	0	(omitted)				
wbhao						
Black	.7484955	.2900001	2.58	0.013	.1660131	1.330978
Hispanic	1.415973	.5741045	2.47	0.017	.2628504	2.569096
Asian	-.1769841	.4087733	-0.43	0.667	-.9980295	.6440612
Other	1.089066	.6529736	1.67	0.102	-.2224704	2.400602
migrant# wbhao						
1#Black	-.9959165	.9718847	-1.02	0.310	-2.948004	.9561714
1#Hispanic	-.2004411	1.19327	-0.17	0.867	-2.597195	2.196313
1#Asian	-.0065455	.7416646	-0.01	0.993	-1.496223	1.483132
1#Other	-3.370447	5.443342	-0.62	0.539	-14.30372	7.562826
years_sinc~l	-.0050306	.0122132	-0.41	0.682	-.0295615	.0195003
rural	1.102545	.2958695	3.73	0.000	.508274	1.696817
migrantrural	.7514631	.8244101	0.91	0.366	-.9044134	2.407339
year						
1999	.2795173	.830974	0.34	0.738	-1.389543	1.948578
2000	.3772774	.6752851	0.56	0.579	-.9790728	1.733627
2001	-.0103707	.7739623	-0.01	0.989	-1.56492	1.544178
2002	-.6365125	.5991587	-1.06	0.293	-1.839958	.5669331
2003	-.5704385	.5615994	-1.02	0.315	-1.698444	.557567
2004	-.6181988	.6074012	-1.02	0.314	-1.8382	.6018024
2005	-.2725039	.695984	-0.39	0.697	-1.670429	1.125421
2006	-1.027041	.7604582	-1.35	0.183	-2.554466	.5003842
2007	-.8125097	.6599973	-1.23	0.224	-2.138153	.5131338
2008	-1.113024	.7115679	-1.56	0.124	-2.542251	.3162017
2009	-.6993609	.7637236	-0.92	0.364	-2.233345	.8346231
2010	-1.929901	.6914494	-2.79	0.007	-3.318718	-.5410843
2011	-2.537293	.6057584	-4.19	0.000	-3.753995	-1.320592
2012	-.7135812	.55328	-1.29	0.203	-1.824877	.3977144
2013	-.9071527	.6423167	-1.41	0.164	-2.197284	.3829783
2014	-1.974711	.6544383	-3.02	0.004	-3.289189	-.660233
2015	-1.372061	.5952624	-2.30	0.025	-2.56768	-.176441
migrant#year						
1 1999	1.267525	1.122155	1.13	0.264	-.986389	3.521438
1 2000	1.928049	.749418	2.57	0.013	.4227985	3.433299
1 2001	1.378982	1.458498	0.95	0.349	-1.550497	4.308461

1 2002	3.033837	1.410645	2.15	0.036	.2004727	5.867201
1 2003	2.531244	1.160159	2.18	0.034	.2009972	4.861492
1 2004	2.135241	1.241084	1.72	0.092	-.3575495	4.628031
1 2005	1.046723	.8410077	1.24	0.219	-.6424909	2.735937
1 2006	3.468526	1.320385	2.63	0.011	.8164556	6.120597
1 2007	2.782131	1.033943	2.69	0.010	.7053949	4.858867
1 2008	2.073074	1.181979	1.75	0.086	-.3010002	4.447147
1 2009	.6570249	1.293327	0.51	0.614	-1.940699	3.254748
1 2010	.7313393	.9169613	0.80	0.429	-1.110432	2.57311
1 2011	1.333324	1.017346	1.31	0.196	-.7100757	3.376724
1 2012	.2058602	1.05763	0.19	0.846	-1.918453	2.330174
1 2013	.2111736	1.171836	0.18	0.858	-2.142528	2.564875
1 2014	1.304496	1.06963	1.22	0.228	-.8439189	3.452912
1 2015	1.449093	1.007928	1.44	0.157	-.5753904	3.473577
_cons	27.83319	.8948006	31.11	0.000	26.03593	29.63045

Specification (4), Exogenous-wage, Method 1, Full sample

Linear regression

Number of obs	=	1,376,334
F(49, 50)	=	.
Prob > F	=	.
R-squared	=	0.1192
Root MSE	=	9.8746

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	6.656373	.6355005	10.47	0.000	5.379932	7.932813
post911entry	-1.130187	.0731439	-15.45	0.000	-1.2771	-.9832726
post911ent~t	.9275158	.1442015	6.43	0.000	.6378784	1.217153
minwage	-1.670902	.1880975	-8.88	0.000	-2.048707	-1.293097
post911min~e	-1.136205	.2892902	-3.93	0.000	-1.717261	-.5551483
post911min~t	1.969704	.3751114	5.25	0.000	1.216271	2.723138
yearseduc	.6229143	.0170326	36.57	0.000	.5887034	.6571253
migrantyea~c	-.3576172	.0300884	-11.89	0.000	-.4180515	-.2971828
exp	.5968964	.0109624	54.45	0.000	.5748779	.618915
migrantexp	-.2384527	.0144003	-16.56	0.000	-.2673766	-.2095289
exp_sq	-.0114465	.0002047	-55.93	0.000	-.0118575	-.0110354
migrantexp~q	.0053039	.0002807	18.89	0.000	.00474	.0058677
female	-4.873679	.1121953	-43.44	0.000	-5.099029	-4.648328
migrantfem~e	.7757597	.1086319	7.14	0.000	.5575662	.9939532
1.migrant	0	(omitted)				
wbhao						
Black	-.066236	.0777094	-0.85	0.398	-.2223199	.089848
Hispanic	.0398931	.2349123	0.17	0.866	-.4319421	.5117283
Asian	-.3343823	.2826183	-1.18	0.242	-.9020378	.2332732
Other	.1289105	.1568234	0.82	0.415	-.1860785	.4438994
migrant# wbhao						
1#Black	-.5751638	.1439296	-4.00	0.000	-.864255	-.2860727

```
 1#Hispanic  |  -.5057795   .1601613    -3.16   0.003    -.8274729   -.1840861
    1#Asian  |  -.3296121   .2637871    -1.25   0.217    -.8594441    .2002198
    1#Other  |  -.7573843   .4373294    -1.73   0.089    -1.635786    .1210178
             |
years_sinc~l |   .0078529   .0023773     3.30   0.002     .0030779    .0126279
       rural |   .2373513   .0872556     2.72   0.009     .0620933    .4126094
migrantrural |   .8163501   .2745017     2.97   0.005     .2649971    1.367703
             |
        year |
       1999  |   .1039002   .0653638     1.59   0.118    -.0273868    .2351872
       2000  |   .1145098   .0902256     1.27   0.210    -.0667136    .2957332
       2001  |   .0546822   .0978443     0.56   0.579    -.1418439    .2512082
       2002  |  -.1456787   .0779224    -1.87   0.067    -.3021905     .010833
       2003  |   -.336166   .0862505    -3.90   0.000    -.5094052   -.1629268
       2004  |  -.3485913      .1059    -3.29   0.002    -.5612978   -.1358849
       2005  |  -.2185724   .0920409    -2.37   0.021    -.4034419   -.0337028
       2006  |  -.1135561   .1066533    -1.06   0.292    -.3277754    .1006633
       2007  |   -.001465   .0894645    -0.02   0.987    -.1811597    .1782296
       2008  |  -.0310023   .0952235    -0.33   0.746    -.2222644    .1602598
       2009  |  -.3219956   .0915563    -3.52   0.001    -.5058918   -.1380993
       2010  |  -.6482386   .0967784    -6.70   0.000    -.8426237   -.4538536
       2011  |  -.6488047   .0890983    -7.28   0.000    -.8277638   -.4698455
       2012  |  -.4722136   .0947342    -4.98   0.000    -.6624929   -.2819344
       2013  |  -.3537606   .1116333    -3.17   0.003    -.5779827   -.1295385
       2014  |  -.3151662    .108712    -2.90   0.006    -.5335206   -.0968117
       2015  |   -.100453   .0998597    -1.01   0.319    -.3010272    .1001211
             |
migrant#year |
     1 1999  |   .0721229   .1563913     0.46   0.647    -.2419983    .3862441
     1 2000  |   .1958183   .2067819     0.95   0.348    -.2195153    .6111519
     1 2001  |   .3166873   .1617536     1.96   0.056    -.0082044     .641579
     1 2002  |   .0594961   .1671225     0.36   0.723    -.2761793    .3951715
     1 2003  |   .1391534   .1687575     0.82   0.414     -.199806    .4781128
     1 2004  |   .0191691   .2005061     0.10   0.924    -.3835593    .4218976
     1 2005  |  -.0356609   .1241538    -0.29   0.775    -.2850311    .2137094
     1 2006  |   .3207805   .1783659     1.80   0.078     -.037478    .6790389
     1 2007  |   .0366378    .118137     0.31   0.758    -.2006474    .2739231
     1 2008  |  -.0003561   .1739939    -0.00   0.998    -.3498332    .3491209
     1 2009  |  -.3217153   .1654109    -1.94   0.057    -.6539528    .0105222
     1 2010  |  -.6547564   .1574865    -4.16   0.000    -.9710772   -.3384355
     1 2011  |  -.5985728   .1355032    -4.42   0.000     -.870739   -.3264065
     1 2012  |  -.6284982   .1568311    -4.01   0.000    -.9435027   -.3134937
     1 2013  |  -.6325266   .1566577    -4.04   0.000    -.9471829   -.3178703
     1 2014  |  -.5057732   .1722361    -2.94   0.005    -.8517195   -.1598269
     1 2015  |  -.5414523   .1357831    -3.99   0.000    -.8141806    -.268724
             |
       _cons |    28.1293   .4009894    70.15   0.000     27.32389    28.93471
------------------------------------------------------------------------------
```

Specification (5), Exogenous-wage, Method 1, Restricted sample

```
Linear regression                               Number of obs     =     31,180
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1056
                                                Root MSE          =     11.827

                                 (Std. Err. adjusted for 51 clusters in state)
```

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	2.266835	1.575119	1.44	0.156	-.8968837	5.430554
post911entry	.10629	.3813234	0.28	0.782	-.6596205	.8722005
post911ent~t	-.0476034	.5375425	-0.09	0.930	-1.127289	1.032082
yearseduc	.2860373	.0471757	6.06	0.000	.1912822	.3807925
migrantyea~c	-.3418105	.0530523	-6.44	0.000	-.4483691	-.2352519
exp	.8163046	.0321351	25.40	0.000	.7517594	.8808499
migrantexp	-.3160702	.049986	-6.32	0.000	-.4164701	-.2156703
exp_sq	-.0156792	.0006296	-24.91	0.000	-.0169437	-.0144147
migrantexp~q	.0076075	.0009439	8.06	0.000	.0057117	.0095033
female	-4.039862	.2856508	-14.14	0.000	-4.613608	-3.466115
migrantfem~e	-.1382482	.435698	-0.32	0.752	-1.013373	.736877
1.migrant	0	(omitted)				
wbhao						
Black	.7473659	.2895464	2.58	0.013	.1657947	1.328937
Hispanic	1.355517	.5602333	2.42	0.019	.2302559	2.480779
Asian	-.2083593	.4142019	-0.50	0.617	-1.040308	.6235897
Other	1.093972	.653701	1.67	0.100	-.2190253	2.406969
migrant# wbhao						
1#Black	-1.005604	.9744042	-1.03	0.307	-2.962753	.9515439
1#Hispanic	-.125022	1.183617	-0.11	0.916	-2.502386	2.252342
1#Asian	.0172861	.7060834	0.02	0.981	-1.400924	1.435496
1#Other	-3.346677	5.420106	-0.62	0.540	-14.23328	7.539927
years_sinc~l	-.2970799	.070999	-4.18	0.000	-.4396856	-.1544743
rural	1.108604	.2949195	3.76	0.000	.5162406	1.700967
migrantrural	.7617861	.8251271	0.92	0.360	-.8955305	2.419103
year						
1999	.3049494	.8435588	0.36	0.719	-1.389388	1.999287
2000	.3954453	.6743599	0.59	0.560	-.9590465	1.749937
2001	.0321365	.7779299	0.04	0.967	-1.530382	1.594655
2002	-.6073521	.6070709	-1.00	0.322	-1.82669	.6119856
2003	-.5201734	.5657145	-0.92	0.362	-1.656444	.6160977
2004	-.568295	.6115008	-0.93	0.357	-1.796531	.6599406
2005	-.2198127	.7063087	-0.31	0.757	-1.638476	1.19885
2006	-.9708027	.7662344	-1.27	0.211	-2.50983	.5682244
2007	-.7522127	.6669144	-1.13	0.265	-2.09175	.5873243
2008	-1.037436	.7192021	-1.44	0.155	-2.481995	.4071243
2009	-.6221416	.7681438	-0.81	0.422	-2.165004	.9207207
2010	-1.84317	.697912	-2.64	0.011	-3.244968	-.4413726
2011	-2.445591	.6096675	-4.01	0.000	-3.670144	-1.221038
2012	-.6167949	.5521254	-1.12	0.269	-1.725771	.4921816
2013	-.8004893	.6479182	-1.24	0.222	-2.101871	.5008927
2014	-1.868662	.6623422	-2.82	0.007	-3.199015	-.5383086
2015	-1.257066	.6015352	-2.09	0.042	-2.465285	-.0488468
migrant#year						
1 1999	1.540037	1.148408	1.34	0.186	-.7666088	3.846683
1 2000	2.486856	.7957241	3.13	0.003	.8885968	4.085114
1 2001	2.202834	1.503105	1.47	0.149	-.8162411	5.221909
1 2002	4.15903	1.500592	2.77	0.008	1.145002	7.173059
1 2003	3.908131	1.325797	2.95	0.005	1.245189	6.571074
1 2004	3.791569	1.457356	2.60	0.012	.8643842	6.718754

1 2005	2.994226	1.048943	2.85	0.006	.8873621	5.101089
1 2006	5.690018	1.550298	3.67	0.001	2.576153	8.803883
1 2007	5.294133	1.281876	4.13	0.000	2.71941	7.868856
1 2008	4.870052	1.473939	3.30	0.002	1.909559	7.830546
1 2009	3.731711	1.774675	2.10	0.041	.1671716	7.29625
1 2010	4.082487	1.420032	2.87	0.006	1.230269	6.934704
1 2011	4.961925	1.55516	3.19	0.002	1.838295	8.085556
1 2012	4.110299	1.725382	2.38	0.021	.6447685	7.57583
1 2013	4.396308	1.817655	2.42	0.019	.7454418	8.047175
1 2014	5.751254	1.70956	3.36	0.001	2.317502	9.185005
1 2015	6.095481	1.690855	3.60	0.001	2.699299	9.491664
entry_year	.2865525	.0701284	4.09	0.000	.1456956	.4274095
entry_year~q	-.0001425	.0000349	-4.08	0.000	-.0002126	-.0000723
_cons	27.74075	.8991925	30.85	0.000	25.93467	29.54683

Specification (5), Exogenous-wage, Method 1, Full sample

```
Linear regression                               Number of obs     =  1,376,334
                                                F(50, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1253
                                                Root MSE          =     9.8405

                                  (Std. Err. adjusted for 51 clusters in state)
```

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	2.969325	.3891351	7.63	0.000	2.187725	3.750926
post911entry	-1.109929	.071418	-15.54	0.000	-1.253376	-.9664819
post911ent~t	.8904002	.1464179	6.08	0.000	.5963112	1.184489
minwage	-1.609656	.1885065	-8.54	0.000	-1.988282	-1.231029
post911min~e	-1.038393	.2832297	-3.67	0.001	-1.607277	-.4695098
post911min~t	1.990782	.3580393	5.56	0.000	1.271639	2.709925
hsgrad	2.342034	.1206836	19.41	0.000	2.099634	2.584435
assocgrad	2.939451	.1301495	22.59	0.000	2.678038	3.200864
bachgrad	4.652141	.1292593	35.99	0.000	4.392517	4.911766
mastgrad	5.569329	.1700119	32.76	0.000	5.227851	5.910808
doctorgrad	8.835426	.2521501	35.04	0.000	8.328967	9.341884
migranthsg~d	-1.794562	.1388773	-12.92	0.000	-2.073505	-1.515618
migrantass~d	-1.97605	.2048222	-9.65	0.000	-2.387448	-1.564653
migrantbac~d	-2.334598	.2096894	-11.13	0.000	-2.755771	-1.913424
migrantmas~d	-2.351891	.272432	-8.63	0.000	-2.899087	-1.804695
migrantdoc~d	-1.77189	.2552037	-6.94	0.000	-2.284482	-1.259299
exp	.5818562	.0104856	55.49	0.000	.5607952	.6029171
migrantexp	-.2279968	.014135	-16.13	0.000	-.2563878	-.1996058
exp_sq	-.0112147	.0001957	-57.31	0.000	-.0116077	-.0108217
migrantexp~q	.0049254	.0002667	18.47	0.000	.0043897	.0054612
female	-4.841137	.112035	-43.21	0.000	-5.066166	-4.616108
migrantfem~e	.8547993	.1129373	7.57	0.000	.6279581	1.08164
1.migrant	0	(omitted)				
wbhao						
Black	.0289486	.0784941	0.37	0.714	-.1287114	.1866087
Hispanic	.1135084	.2270898	0.50	0.619	-.3426148	.5696316
Asian	-.4044038	.2663938	-1.52	0.135	-.9394715	.1306639

```
       Other  |   .2429068    .153912     1.58   0.121    -.0662347    .5520482
              |
     migrant#|
        wbhao |
     1#Black  |  -.3519416   .1485689    -2.37   0.022     -.650351   -.0535321
  1#Hispanic  |  -.3725396   .1784404    -2.09   0.042    -.7309478   -.0141315
     1#Asian  |  -.3479873   .2797811    -1.24   0.219    -.9099441    .2139695
     1#Other  |  -.7125909   .4263648    -1.67   0.101     -1.56897     .143788
              |
years_sinc~l  |   -.013268   .0127629    -1.04   0.304     -.038903     .012367
        rural |    .253603   .0887052     2.86   0.006     .0754334    .4317727
migrantrural  |   .7464159   .2707804     2.76   0.008     .2025375    1.290294
              |
         year |
        1999  |   .1064879   .0657805     1.62   0.112    -.0256361     .238612
        2000  |   .1181542   .0899175     1.31   0.195    -.0624505     .298759
        2001  |   .0610474   .0962833     0.63   0.529    -.1323433     .254438
        2002  |  -.1377368   .0760541    -1.81   0.076    -.2904961    .0150224
        2003  |  -.3252784   .0834928    -3.90   0.000    -.4929787   -.1575781
        2004  |  -.3469362   .1040017    -3.34   0.002    -.5558298   -.1380426
        2005  |  -.2200625   .0901811    -2.44   0.018    -.4011966   -.0389285
        2006  |  -.1090384   .1039076    -1.05   0.299    -.3177429    .0996661
        2007  |  -.0065667   .0862989    -0.08   0.940    -.1799032    .1667699
        2008  |  -.0294816   .0941158    -0.31   0.755    -.2185187    .1595555
        2009  |  -.3305625   .0912457    -3.62   0.001    -.5138349     -.14729
        2010  |  -.6609353   .0937238    -7.05   0.000     -.849185   -.4726856
        2011  |  -.6579744   .0881162    -7.47   0.000    -.8349611   -.4809877
        2012  |  -.4842887   .0933832    -5.19   0.000    -.6718544   -.2967231
        2013  |  -.3653187   .1118697    -3.27   0.002    -.5900156   -.1406219
        2014  |  -.3415443   .1084262    -3.15   0.003    -.5593247    -.123764
        2015  |  -.1263415   .1003098    -1.26   0.214    -.3278196    .0751367
              |
migrant#year  |
      1 1999  |   .1111813   .1518117     0.73   0.467    -.1937415    .4161041
      1 2000  |   .2761763   .2197205     1.26   0.215    -.1651453    .7174979
      1 2001  |   .4093614   .1593223     2.57   0.013     .0893531    .7293697
      1 2002  |    .179055    .163468     1.10   0.279    -.1492801      .50739
      1 2003  |   .2783775   .1690002     1.65   0.106    -.0610694    .6178243
      1 2004  |   .1898786   .2056367     0.92   0.360    -.2231549     .602912
      1 2005  |    .176873   .1533229     1.15   0.254    -.1310851    .4848311
      1 2006  |   .5342604    .198834     2.69   0.010     .1348906    .9336301
      1 2007  |    .311896   .1646644     1.89   0.064    -.0188422    .6426343
      1 2008  |   .2874458   .2110372     1.36   0.179    -.1364348    .7113265
      1 2009  |  -.0080328   .2109769    -0.04   0.970    -.4317925    .4157268
      1 2010  |  -.2850014    .211578    -1.35   0.184    -.7099683    .1399654
      1 2011  |  -.1833519   .1987758    -0.92   0.361    -.5826049     .215901
      1 2012  |  -.2016224    .230203    -0.88   0.385    -.6639988    .2607539
      1 2013  |  -.1973212   .2455937    -0.80   0.426    -.6906106    .2959682
      1 2014  |  -.0504575   .2676334    -0.19   0.851     -.588015    .4871001
      1 2015  |  -.0718976   .2296167    -0.31   0.755    -.5330964    .3893011
              |
  entry_year  |   .0286379   .0135914     2.11   0.040     .0013389     .055937
entry_year~q  |  -.0000143   6.78e-06    -2.11   0.040     -.000028   -7.10e-07
        _cons |   33.85436   .2420943   139.84   0.000      33.3681    34.34062
------------------------------------------------------------------------------
```

Specification (6), Exogenous-wage, Method 1, Restricted sample

```
Linear regression                               Number of obs     =     30,636
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1052
                                                Root MSE          =     11.846

                                  (Std. Err. adjusted for 51 clusters in state)
```

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	7.905769	1.30381	6.06	0.000	5.286989	10.52455
post911entry	.1200174	.3780803	0.32	0.752	-.6393793	.8794141
post911ent~t	-.4355519	.4864501	-0.90	0.375	-1.412616	.5415118
yearseduc	.2836491	.0474732	5.97	0.000	.1882963	.3790019
migrantyea~c	-.3607019	.0562815	-6.41	0.000	-.4737467	-.2476572
exp	.8183339	.0319745	25.59	0.000	.7541112	.8825565
migrantexp	-.4334894	.0482299	-8.99	0.000	-.530362	-.3366168
exp_sq	-.0157182	.0006271	-25.07	0.000	-.0169778	-.0144587
migrantexp~q	.0094106	.00088	10.69	0.000	.0076431	.011178
female	-4.040423	.2860017	-14.13	0.000	-4.614874	-3.465972
migrantfem~e	-.267715	.4334493	-0.62	0.540	-1.138324	.6028936
1.migrant	0	(omitted)				
wbhao						
Black	.7485518	.2899931	2.58	0.013	.1660836	1.33102
Hispanic	1.413986	.5739604	2.46	0.017	.2611528	2.566819
Asian	-.1804799	.4080328	-0.44	0.660	-1.000038	.6390781
Other	1.089236	.65299	1.67	0.102	-.2223329	2.400805
migrant#wbhao						
1#Black	-1.040946	.8954723	-1.16	0.251	-2.839555	.7576629
1#Hispanic	-.8154238	1.113773	-0.73	0.468	-3.052503	1.421655
1#Asian	-.1544528	.6634817	-0.23	0.817	-1.487095	1.178189
1#Other	-3.777703	5.379541	-0.70	0.486	-14.58283	7.027422
years_sinc~l	-.0037509	.0124582	-0.30	0.765	-.0287739	.0212721
rural	1.102696	.2958736	3.73	0.000	.5084168	1.696976
migrantrural	.6105212	.8641468	0.71	0.483	-1.125169	2.346211
year						
1999	.2798005	.8309334	0.34	0.738	-1.389178	1.948779
2000	.3772144	.675202	0.56	0.579	-.9789687	1.733397
2001	-.0101494	.773883	-0.01	0.990	-1.564539	1.54424
2002	-.6363993	.5992803	-1.06	0.293	-1.840089	.5672907
2003	-.5701946	.561601	-1.02	0.315	-1.698203	.5578141
2004	-.6179857	.6074671	-1.02	0.314	-1.838119	.6021478
2005	-.2724047	.6960788	-0.39	0.697	-1.67052	1.125711
2006	-1.026952	.7605453	-1.35	0.183	-2.554553	.5006478
2007	-.8124815	.6600599	-1.23	0.224	-2.138251	.5132878
2008	-1.112794	.7116542	-1.56	0.124	-2.542193	.3166058
2009	-.6993005	.7637788	-0.92	0.364	-2.233395	.8347944
2010	-1.92969	.6915784	-2.79	0.007	-3.318766	-.5406138
2011	-2.53675	.6058317	-4.19	0.000	-3.753598	-1.319901
2012	-.7130704	.5534833	-1.29	0.204	-1.824774	.3986335
2013	-.9069094	.6424728	-1.41	0.164	-2.197354	.3835352
2014	-1.974195	.6545945	-3.02	0.004	-3.288986	-.6594031
2015	-1.371693	.5952855	-2.30	0.025	-2.567359	-.1760264

```
migrant#year |
     1 1999  |   1.215766   1.150819     1.06   0.296    -1.095722    3.527254
     1 2000  |   1.998541   .7457138     2.68   0.010     .5007307    3.496351
     1 2001  |   1.448698   1.479561     0.98   0.332    -1.523088    4.420484
     1 2002  |   3.008652   1.418934     2.12   0.039     .1586392    5.858665
     1 2003  |   2.679136   1.140168     2.35   0.023     .3890405    4.969231
     1 2004  |   2.585756    1.32265     1.95   0.056    -.0708653    5.242377
     1 2005  |   1.864337   .8845265     2.11   0.040     .0877137    3.640961
     1 2006  |   4.049353   1.415241     2.86   0.006     1.206757    6.891948
     1 2007  |   3.145509   .9727225     3.23   0.002     1.191739     5.09928
     1 2008  |   2.461729   1.219496     2.02   0.049     .0122994    4.911158
     1 2009  |   1.495757   1.227366     1.22   0.229    -.9694798    3.960994
     1 2010  |   1.252431    .939366     1.33   0.188    -.6343415    3.139203
     1 2011  |   1.861934   .9687056     1.92   0.060    -.0837689    3.807636
     1 2012  |   .4555787   1.066287     0.43   0.671    -1.686122    2.597279
     1 2013  |    .385854   1.213339     0.32   0.752    -2.051208    2.822916
     1 2014  |   1.625145   1.130736     1.44   0.157    -.6460045    3.896295
     1 2015  |   1.879473   .9809125     1.92   0.061    -.0907483    3.849693
             |
       _cons |   27.83292   .8947799    31.11   0.000      26.0357    29.63014
------------------------------------------------------------------------------
```

Specification (6), Exogenous-wage, Method 1, Full sample

```
Linear regression                               Number of obs     =  1,365,655
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1249
                                                Root MSE          =     9.8345

                                   (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |    3.92594   .3983204     9.86   0.000      3.12589     4.72599
post911entry |  -1.107748   .0713553   -15.52   0.000    -1.251069   -.9644267
post911ent~t |   .6015125   .1287621     4.67   0.000     .3428862    .8601388
     minwage |  -1.577819   .1880387    -8.39   0.000    -1.955506   -1.200132
post911min~e |  -1.070038   .2845364    -3.76   0.000    -1.641546   -.4985301
post911min~t |   1.961707   .3563113     5.51   0.000     1.246035     2.67738
      hsgrad |   2.343504   .1205233    19.44   0.000     2.101426    2.585582
   assocgrad |   2.941155   .1299241    22.64   0.000     2.680195    3.202115
    bachgrad |    4.65375    .129252    36.01   0.000     4.394139     4.91336
    mastgrad |   5.571019   .1699609    32.78   0.000     5.229642    5.912395
  doctorgrad |   8.836971   .2518852    35.08   0.000     8.331045    9.342897
migranthsg~d |  -1.757202   .1391404   -12.63   0.000    -2.036673    -1.47773
migrantass~d |  -2.102367   .2164705    -9.71   0.000    -2.537161   -1.667573
migrantbac~d |   -2.56638   .2316417   -11.08   0.000    -3.031647   -2.101114
migrantmas~d |  -2.669308   .2700511    -9.88   0.000    -3.211721   -2.126894
migrantdoc~d |  -2.294328   .2584009    -8.88   0.000    -2.813342   -1.775315
         exp |   .5818744   .0104849    55.50   0.000     .5608148     .602934
  migrantexp |  -.2902577   .0173094   -16.77   0.000    -.3250246   -.2554908
      exp_sq |  -.0112146   .0001957   -57.31   0.000    -.0116076   -.0108215
migrantexp~q |   .0059773   .0003097    19.30   0.000     .0053552    .0065994
      female |  -4.841351   .1120193   -43.22   0.000    -5.066348   -4.616353
migrantfem~e |   .7973156   .1167893     6.83   0.000     .5627375    1.031894
```

1.migrant	0	(omitted)				
wbhao						
Black	.0286195	.0784722	0.36	0.717	-.1289966	.1862355
Hispanic	.1021902	.2238576	0.46	0.650	-.347441	.5518214
Asian	-.4249046	.2669199	-1.59	0.118	-.9610289	.1112198
Other	.243033	.1538724	1.58	0.121	-.0660288	.5520949
migrant# wbhao						
1#Black	-.4589567	.1350949	-3.40	0.001	-.7303027	-.1876106
1#Hispanic	-.5675025	.162595	-3.49	0.001	-.8940841	-.2409208
1#Asian	-.3440512	.2480062	-1.39	0.172	-.8421863	.154084
1#Other	-.7327593	.4559897	-1.61	0.114	-1.648642	.1831229
years_sinc~l	.0109069	.0023777	4.59	0.000	.006131	.0156827
rural	.2539471	.0886882	2.86	0.006	.0758116	.4320825
migrantrural	.7434832	.2813798	2.64	0.011	.1783152	1.308651
year						
1999	.1059925	.0657723	1.61	0.113	-.0261149	.2381
2000	.1172114	.0898281	1.30	0.198	-.0632137	.2976365
2001	.0596771	.0960076	0.62	0.537	-.1331599	.252514
2002	-.1394455	.075914	-1.84	0.072	-.2919233	.0130322
2003	-.3273033	.08331	-3.93	0.000	-.4946364	-.1599701
2004	-.3494912	.1038029	-3.37	0.001	-.5579854	-.1409969
2005	-.2230865	.0898959	-2.48	0.016	-.4036479	-.0425252
2006	-.1124516	.1036895	-1.08	0.283	-.320718	.0958148
2007	-.0105149	.0859976	-0.12	0.903	-.1832461	.1622163
2008	-.0340811	.0937188	-0.36	0.718	-.2223208	.1541587
2009	-.3356259	.0906593	-3.70	0.001	-.5177204	-.1535314
2010	-.6664397	.0937623	-7.11	0.000	-.8547668	-.4781127
2011	-.66391	.0876327	-7.58	0.000	-.8399254	-.4878946
2012	-.4907057	.0926573	-5.30	0.000	-.6768134	-.3045979
2013	-.3723637	.1114948	-3.34	0.002	-.5963076	-.1484198
2014	-.348812	.1080156	-3.23	0.002	-.5657678	-.1318562
2015	-.1343567	.0994467	-1.35	0.183	-.3341013	.065388
migrant#year						
1 1999	.0833423	.1542633	0.54	0.591	-.2265046	.3931892
1 2000	.2285872	.212111	1.08	0.286	-.1974503	.6546247
1 2001	.3338429	.163682	2.04	0.047	.005078	.6626079
1 2002	.1155923	.1616502	0.72	0.478	-.2090916	.4402762
1 2003	.253002	.1526948	1.66	0.104	-.0536944	.5596985
1 2004	.197458	.1959139	1.01	0.318	-.1960466	.5909625
1 2005	.2055744	.1320462	1.56	0.126	-.0596483	.4707971
1 2006	.5540359	.1767034	3.14	0.003	.1991166	.9089552
1 2007	.2733305	.1183844	2.31	0.025	.0355483	.5111126
1 2008	.1660395	.1601614	1.04	0.305	-.1556541	.4877331
1 2009	-.0748233	.1588099	-0.47	0.640	-.3938023	.2441558
1 2010	-.449564	.1527093	-2.94	0.005	-.7562896	-.1428384
1 2011	-.3516432	.1256408	-2.80	0.007	-.6040001	-.0992863
1 2012	-.4328384	.1487034	-2.91	0.005	-.731518	-.1341588
1 2013	-.4581659	.166835	-2.75	0.008	-.793264	-.1230679
1 2014	-.260534	.1757392	-1.48	0.144	-.6135166	.0924486
1 2015	-.261824	.14111	-1.86	0.069	-.5452518	.0216037
_cons	33.85483	.2421628	139.80	0.000	33.36843	34.34123

Specification (1), Exogenous-wage, Method 2, Restricted sample

```
Linear regression                               Number of obs     =     18,961
                                                F(3, 50)          =     374.51
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0691
                                                Root MSE          =     8.4621

                                 (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   3.399085   .2039193    16.67   0.000     2.989501    3.808669
post911entry |  -3.043817   .1963339   -15.50   0.000    -3.438165   -2.649469
post911ent~t |   3.445092   .4370817     7.88   0.000     2.567188    4.322997
       _cons |   22.72649   .2745094    82.79   0.000     22.17512    23.27785
------------------------------------------------------------------------------
```

Specification (1), Exogenous-wage, Method 2, Full sample

```
Linear regression                               Number of obs     =  1,376,334
                                                F(7, 50)          =    5536.51
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0543
                                                Root MSE          =     10.232

                                 (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |  -.6373058   .1569584    -4.06   0.000    -.9525661   -.3220456
post911entry |  -4.439733   .1586767   -27.98   0.000    -4.758444   -4.121021
post911ent~t |   3.564527   .2013972    17.70   0.000     3.160009    3.969045
 minwagedemo |  -20.54823   .1673399  -122.79   0.000    -20.88435   -20.21212
mi~o_migrant |   2.390976   .3071897     7.78   0.000     1.773968    3.007985
minwaged~911 |    2.52152   .2577039     9.78   0.000     2.003906    3.039133
mi~1_migrant |  -1.952781   .5731618    -3.41   0.001    -3.104011   -.8015519
       _cons |   40.58296   .1174857   345.43   0.000     40.34699    40.81894
------------------------------------------------------------------------------
```

Specification (2), Exogenous-wage, Method 2, Restricted sample

```
Linear regression                               Number of obs     =     18,961
                                                F(14, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.2048
                                                Root MSE          =     7.8232

                                 (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
```

migrant	.7167347	.4494572	1.59	0.117	-.1860266	1.619496
post911entry	-.3803468	.2088023	-1.82	0.075	-.7997385	.0390449
post911ent~t	.4220927	.4898326	0.86	0.393	-.561765	1.40595
yearseduc	.4629159	.065472	7.07	0.000	.3314114	.5944204
exp	1.826511	.0990891	18.43	0.000	1.627484	2.025537
exp_sq	-.0606875	.0055312	-10.97	0.000	-.0717972	-.0495777
female	-.7825739	.1762122	-4.44	0.000	-1.136506	-.4286413
white	-.4704269	.6613828	-0.71	0.480	-1.798853	.8579996
black	.7509087	.6192378	1.21	0.231	-.4928671	1.994684
asian	-1.938767	.7554907	-2.57	0.013	-3.456215	-.4213194
hispanic	1.363842	.6574631	2.07	0.043	.043289	2.684396
years_sinc~l	-.022391	.0316808	-0.71	0.483	-.0860239	.0412418
rural	.3266408	.2312109	1.41	0.164	-.1377601	.7910416
year	11.76676	13.271	0.89	0.380	-14.88882	38.42234
year_sq	-.0029587	.0033067	-0.89	0.375	-.0096004	.0036829
_cons	-11687.21	13314.99	-0.88	0.384	-38431.16	15056.75

Specification (2), Exogenous-wage, Method 2, Full sample

Linear regression

Number of obs	=	1,376,334
F(17, 50)	=	.
Prob > F	=	.
R-squared	=	0.1345
Root MSE	=	9.7882

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	-.1104543	.0977958	-1.13	0.264	-.3068829	.0859744
post911entry	-1.221956	.0817897	-14.94	0.000	-1.386236	-1.057677
post911ent~t	.7833885	.1442754	5.43	0.000	.4936028	1.073174
minwagedemo	-15.66849	.1632538	-95.98	0.000	-15.9964	-15.34059
mi~o_migrant	1.283739	.3064663	4.19	0.000	.6681835	1.899295
minwaged~911	-.1861945	.2159833	-0.86	0.393	-.6200098	.2476207
mi~1_migrant	.2601262	.5980285	0.43	0.665	-.9410494	1.461302
yearseduc	.4377373	.0218295	20.05	0.000	.3938916	.4815831
exp	.4985852	.0090909	54.84	0.000	.4803256	.5168448
exp_sq	-.0095439	.0001591	-60.00	0.000	-.0098634	-.0092245
female	-4.760956	.1187524	-40.09	0.000	-4.999478	-4.522435
white	-.004669	.1655553	-0.03	0.978	-.3371966	.3278585
black	-.2366979	.1602133	-1.48	0.146	-.5584958	.0851
asian	-.6853726	.1811435	-3.78	0.000	-1.04921	-.3215351
hispanic	.0145764	.2073986	0.07	0.944	-.4019959	.4311487
years_sinc~l	.0062211	.0026726	2.33	0.024	.0008531	.0115891
rural	.1773003	.0770166	2.30	0.026	.0226079	.3319927
year	-7.441315	3.716156	-2.00	0.051	-14.90543	.0228035
year_sq	.0018451	.0009261	1.99	0.052	-.000015	.0037052
_cons	7533.993	3724.773	2.02	0.048	52.56625	15015.42

Specification (3), Exogenous-wage, Method 2, Restricted sample

```
Linear regression                               Number of obs     =     18,961
                                                F(30, 50)         =     267.36
                                                Prob > F          =     0.0000
                                                R-squared         =     0.2057
                                                Root MSE          =     7.8218

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   .7003378   .4353917     1.61   0.114    -.1741722    1.574848
post911entry |  -.4195212   .2380387    -1.76   0.084     -.897636    .0585937
post911ent~t |   .4570722   .4899649     0.93   0.355    -.5270512    1.441196
   yearseduc |   .4615503   .0653427     7.06   0.000     .3303058    .5927949
         exp |   1.822735   .1006361    18.11   0.000     1.620601    2.024868
      exp_sq |  -.0605506   .0055779   -10.86   0.000    -.0717541   -.0493471
      female |  -.7811445   .1770215    -4.41   0.000    -1.136703   -.4255863
       white |  -.4596369   .6657308    -0.69   0.493    -1.796797    .8775228
       black |   .7550998    .621096     1.22   0.230    -.4924083    2.002608
       asian |   -1.94303   .7514928    -2.59   0.013    -3.452448   -.4336123
    hispanic |   1.380776   .6600932     2.09   0.042     .0549392    2.706612
years_sinc~l |  -.0226264   .0315964    -0.72   0.477    -.0860896    .0408369
       rural |   .3283321   .2288642     1.43   0.158    -.1313552    .7880194
             |
        year |
       1999  |  -.7448814   .4365456    -1.71   0.094    -1.621709    .1319463
       2000  |   .2354792   .4074698     0.58   0.566     -.582948    1.053906
       2001  |  -.4327926   .4739346    -0.91   0.366    -1.384718     .519133
       2002  |  -.4217095   .3833614    -1.10   0.277    -1.191713    .3482945
       2003  |  -.6491215   .3922297    -1.65   0.104    -1.436938    .1386951
       2004  |   -.909954   .4447281    -2.05   0.046    -1.803217   -.0166914
       2005  |  -.4246642   .4618421    -0.92   0.362    -1.352301     .502973
       2006  |  -.4138701    .290829    -1.42   0.161    -.9980173     .170277
       2007  |  -.9134553   .3950312    -2.31   0.025    -1.706899   -.1200117
       2008  |  -.7996767   .5327002    -1.50   0.140    -1.869637    .2702831
       2009  |   -1.28723   .4299992    -2.99   0.004    -2.150909   -.4235515
       2010  |  -1.550404   .3544629    -4.37   0.000    -2.262364   -.8384444
       2011  |  -1.374015   .4404425    -3.12   0.003     -2.25867   -.4893605
       2012  |  -1.509183   .5670536    -2.66   0.010    -2.648144   -.3702229
       2013  |  -1.417994   .4286029    -3.31   0.002    -2.278869   -.5571199
       2014  |  -1.587909   .3962197    -4.01   0.000     -2.38374   -.7920784
       2015  |  -2.086402   .4321751    -4.83   0.000    -2.954451   -1.218352
             |
       _cons |   11.78712   1.042879    11.30   0.000     9.692434     13.8818
------------------------------------------------------------------------------
```

Specification (3), Exogenous-wage, Method 2, Full sample

```
Linear regression                               Number of obs     =  1,376,334
                                                F(38, 50)         =   13059.52
                                                Prob > F          =     0.0000
                                                R-squared         =     0.1422
                                                Root MSE          =     9.7451

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
```

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	-.7499548	.1187117	-6.32	0.000	-.9883942	-.5115154
post911entry	-1.264555	.089392	-14.15	0.000	-1.444104	-1.085006
post911ent~t	.7837397	.1578738	4.96	0.000	.4666409	1.100838
minwagedemo	-16.36229	.1847873	-88.55	0.000	-16.73345	-15.99114
mi~o_migrant	1.512248	.3116018	4.85	0.000	.8863774	2.138119
minwaged~911	-.021872	.2202225	-0.10	0.921	-.464202	.420458
mi~1_migrant	-.2346927	.6109803	-0.38	0.703	-1.461883	.9924974
hsgrad	-.0184474	.1067411	-0.17	0.863	-.2328431	.1959484
assocgrad	.6351623	.1021743	6.22	0.000	.4299391	.8403855
bachgrad	2.256735	.0809383	27.88	0.000	2.094165	2.419304
mastgrad	3.217967	.1092447	29.46	0.000	2.998543	3.437392
doctorgrad	6.567646	.1806291	36.36	0.000	6.204842	6.930451
exp	.4859654	.0084011	57.85	0.000	.4690913	.5028394
exp_sq	-.0094545	.0001474	-64.13	0.000	-.0097506	-.0091583
female	-4.689602	.1171732	-40.02	0.000	-4.924951	-4.454253
white	-.1088718	.1557913	-0.70	0.488	-.4217879	.2040442
black	-.2020571	.1578504	-1.28	0.206	-.519109	.1149948
asian	-.7539063	.1716262	-4.39	0.000	-1.098628	-.409185
hispanic	-.2676336	.214615	-1.25	0.218	-.6987005	.1634334
years_sinc~l	.0110062	.0025331	4.35	0.000	.0059185	.016094
rural	.2390895	.0847327	2.82	0.007	.0688989	.4092801
year						
1999	.1201024	.0587373	2.04	0.046	.0021251	.2380797
2000	.1654855	.0870953	1.90	0.063	-.0094504	.3404215
2001	.1108663	.0901201	1.23	0.224	-.0701453	.2918778
2002	-.1116823	.0650034	-1.72	0.092	-.2422456	.0188809
2003	-.2825787	.0755223	-3.74	0.000	-.4342698	-.1308877
2004	-.3122651	.0977952	-3.19	0.002	-.5086926	-.1158376
2005	-.2037599	.0834406	-2.44	0.018	-.3713554	-.0361645
2006	-.0347611	.0892125	-0.39	0.698	-.2139496	.1444275
2007	.0170499	.079726	0.21	0.832	-.1430844	.1771842
2008	-.0160247	.07963	-0.20	0.841	-.1759663	.1439168
2009	-.3572007	.0764307	-4.67	0.000	-.5107163	-.2036851
2010	-.7311347	.0826021	-8.85	0.000	-.8970459	-.5652235
2011	-.711943	.0810848	-8.78	0.000	-.8748066	-.5490794
2012	-.552917	.0840934	-6.58	0.000	-.7218236	-.3840103
2013	-.441923	.0939333	-4.70	0.000	-.6305936	-.2532524
2014	-.4010441	.1010425	-3.97	0.000	-.6039938	-.1980943
2015	-.1894813	.0919683	-2.06	0.045	-.3742052	-.0047575
_cons	37.23887	.222865	167.09	0.000	36.79123	37.68651

Specification (4), Exogenous-wage, Method 2, Restricted sample

Linear regression

Number of obs	=	18,961
F(49, 50)	=	.
Prob > F	=	.
R-squared	=	0.2118
Root MSE	=	7.7973

(Std. Err. adjusted for 51 clusters in state)

	Robust

hoursworked	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	4.178698	1.492726	2.80	0.007	1.180469	7.176927
post911entry	-.2534664	.2989811	-0.85	0.401	-.8539875	.3470548
post911ent~t	.0444389	.456773	0.10	0.923	-.8730166	.9618944
yearseduc	.5168508	.0885184	5.84	0.000	.3390564	.6946452
migrantyea~c	-.0883551	.1132075	-0.78	0.439	-.315739	.1390289
exp	2.219178	.1310605	16.93	0.000	1.955935	2.48242
migrantexp	-1.04966	.2051858	-5.12	0.000	-1.461788	-.6375325
exp_sq	-.0890008	.0074511	-11.94	0.000	-.1039668	-.0740348
migrantexp~q	.0613165	.0116925	5.24	0.000	.0378315	.0848015
female	-.5425867	.1668358	-3.25	0.002	-.8776863	-.2074871
migrantfem~e	-1.4829	.2976343	-4.98	0.000	-2.080716	-.8850839
1.migrant	0	(omitted)				
wbhao						
Black	1.098787	.2498918	4.40	0.000	.596865	1.60071
Hispanic	1.701197	.3195253	5.32	0.000	1.059411	2.342982
Asian	-1.04257	.6178778	-1.69	0.098	-2.283614	.1984745
Other	.4406113	.6569571	0.67	0.506	-.8789258	1.760148
migrant#						
wbhao						
1#Black	.4766015	1.017558	0.47	0.642	-1.567223	2.520426
1#Hispanic	1.124414	.9683347	1.16	0.251	-.8205434	3.069372
1#Asian	-.5598626	1.227416	-0.46	0.650	-3.0252	1.905475
1#Other	-2.162777	1.840444	-1.18	0.246	-5.859417	1.533864
years_sinc~l	-.0243338	.0354982	-0.69	0.496	-.0956341	.0469666
rural	.3624564	.2323351	1.56	0.125	-.1042023	.8291151
migrantrural	-.5899919	.6201741	-0.95	0.346	-1.835648	.6556645
year						
1999	-.7270419	.4511789	-1.61	0.113	-1.633261	.1791776
2000	.0553646	.4534317	0.12	0.903	-.8553797	.9661089
2001	-.5092863	.4800865	-1.06	0.294	-1.473568	.4549958
2002	-.3794829	.4022	-0.94	0.350	-1.187325	.4283595
2003	-.749685	.3879778	-1.93	0.059	-1.528961	.0295913
2004	-1.030847	.5541221	-1.86	0.069	-2.143834	.0821396
2005	-.4258916	.5111713	-0.83	0.409	-1.452609	.6008262
2006	-.6606352	.3721237	-1.78	0.082	-1.408068	.0867972
2007	-1.403108	.4905667	-2.86	0.006	-2.38844	-.4177759
2008	-1.020285	.6036487	-1.69	0.097	-2.232749	.1921792
2009	-1.508972	.5261781	-2.87	0.006	-2.565832	-.4521118
2010	-1.933364	.4480939	-4.31	0.000	-2.833387	-1.033341
2011	-1.815408	.5754985	-3.15	0.003	-2.97133	-.6594848
2012	-1.877443	.6153312	-3.05	0.004	-3.113372	-.6415135
2013	-1.655127	.608028	-2.72	0.009	-2.876387	-.433867
2014	-1.475066	.5201077	-2.84	0.007	-2.519733	-.4303987
2015	-2.30666	.5126652	-4.50	0.000	-3.336379	-1.276942
migrant#year						
1 1999	-.5828877	.7898444	-0.74	0.464	-2.169337	1.003561
1 2000	1.266806	.9260909	1.37	0.177	-.5933019	3.126915
1 2001	.3676085	.7123432	0.52	0.608	-1.063175	1.798392
1 2002	-.5862739	.7862851	-0.75	0.459	-2.165574	.9930262
1 2003	.5009853	.9280121	0.54	0.592	-1.362982	2.364952
1 2004	.4566983	.8500654	0.54	0.593	-1.250708	2.164105
1 2005	-.4546227	.7535281	-0.60	0.549	-1.968128	1.058883
1 2006	.7263613	1.020175	0.71	0.480	-1.32272	2.775442

```
       1 2007  |   2.226671   .8970986     2.48   0.016     .4247953    4.028546
       1 2008  |   .8304585   .7957883     1.04   0.302    -.7679293    2.428846
       1 2009  |   .4618456   .8354526     0.55   0.583     -1.21621    2.139901
       1 2010  |    1.33122    .742111     1.79   0.079    -.1593535    2.821794
       1 2011  |   1.575738   .9005689     1.75   0.086    -.2331076    3.384584
       1 2012  |    1.29669    1.29742     1.00   0.322    -1.309255    3.902636
       1 2013  |   .7808569   .9911432     0.79   0.435    -1.209913    2.771627
       1 2014  |  -.8271853   1.043006    -0.79   0.431    -2.922124    1.267753
       1 2015  |   .7107802   .9469529     0.75   0.456    -1.191231    2.612791
               |
         _cons |   9.883509   1.148658     8.60   0.000     7.576363    12.19066
------------------------------------------------------------------------------
```

Specification (4), Exogenous-wage, Method 2, Full sample

```
Linear regression                               Number of obs     =  1,376,334
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1374
                                                Root MSE          =     9.7723

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   5.645127   .6345277     8.90   0.000     4.370641    6.919614
post911entry |  -1.175211   .0799375   -14.70   0.000     -1.33577   -1.014652
post911ent~t |    1.02048    .153152     6.66   0.000     .7128652    1.328095
 minwagedemo |  -15.14772   .2028684   -74.67   0.000     -15.5552   -14.74025
mi~o_migrant |   -.438851   .3213981    -1.37   0.178    -1.084398     .206696
minwaged~911 |  -.2954896   .2088758    -1.41   0.163    -.7150289    .1240497
mi~1_migrant |   .4768193   .5864003     0.81   0.420    -.7010004    1.654639
   yearseduc |    .539902   .0172497    31.30   0.000     .5052551     .574549
migrantyea~c |  -.2993099   .0304162    -9.84   0.000    -.3604025   -.2382172
         exp |    .535999   .0116779    45.90   0.000     .5125433    .5594546
  migrantexp |  -.2191925   .0151085   -14.51   0.000    -.2495388   -.1888462
      exp_sq |  -.0104456   .0002179   -47.94   0.000    -.0108832    -.010008
migrantexp~q |   .0048806    .000288    16.94   0.000     .0043021    .0054591
      female |  -4.874951   .1118806   -43.57   0.000    -5.099669   -4.650232
migrantfem~e |   .7833414   .1048985     7.47   0.000     .5726466    .9940363
   1.migrant |          0  (omitted)
             |
       wbhao |
      Black  |  -.1296225   .0741855    -1.75   0.087    -.2786285    .0193835
   Hispanic  |  -.0559648   .2328739    -0.24   0.811    -.5237058    .4117763
      Asian  |  -.4122498   .2885105    -1.43   0.159    -.9917403    .1672407
      Other  |   .0761098   .1582752     0.48   0.633    -.2417952    .3940148
             |
    migrant#|
       wbhao |
    1#Black  |  -.5114527   .1327488    -3.85   0.000    -.7780865   -.2448189
 1#Hispanic  |  -.4513473   .1568765    -2.88   0.006    -.7664431   -.1362516
    1#Asian  |  -.2699623   .2656645    -1.02   0.314    -.8035651    .2636405
    1#Other  |  -.6217977    .418246    -1.49   0.143    -1.461869    .2182741
             |
years_sinc~l |   .0088343   .0024753     3.57   0.001     .0038626    .0138061
       rural |   .2135583   .0884261     2.42   0.019     .0359492    .3911674
```

```
migrantrural |   .8284397   .2628599     3.15   0.003     .3004701    1.356409
             |
        year |
       1999  |   .1128209   .0672271     1.68   0.100    -.0222088    .2478506
       2000  |   .1376039   .0928869     1.48   0.145     -.048965    .3241728
       2001  |    .058859   .0946759     0.62   0.537    -.1313032    .2490211
       2002  |  -.1279485   .0735372    -1.74   0.088    -.2756523    .0197553
       2003  |  -.3197224   .0826575    -3.87   0.000    -.4857448   -.1536999
       2004  |  -.3345607   .1047419    -3.19   0.002    -.5449409   -.1241804
       2005  |  -.2187707   .0917024    -2.39   0.021    -.4029604    -.034581
       2006  |  -.1076388    .105147    -1.02   0.311    -.3188326    .1035551
       2007  |  -.0083407   .0879647    -0.09   0.925     -.185023    .1683415
       2008  |  -.0501885   .0955514    -0.53   0.602    -.2421092    .1417322
       2009  |  -.3429247   .0905334    -3.79   0.000    -.5247663    -.161083
       2010  |  -.6713351   .0978455    -6.86   0.000    -.8678635   -.4748066
       2011  |  -.6762919    .090219    -7.50   0.000    -.8575021   -.4950817
       2012  |  -.5047067   .0956226    -5.28   0.000    -.6967704    -.312643
       2013  |  -.3965072   .1096045    -3.62   0.001    -.6166544     -.17636
       2014  |  -.3685289   .1119743    -3.29   0.002    -.5934359   -.1436218
       2015  |   -.150668   .1017139    -1.48   0.145    -.3549663    .0536303
             |
migrant#year |
     1 1999  |   .0123529   .1555472     0.08   0.937    -.3000727    .3247786
     1 2000  |   .1299131   .2072025     0.63   0.534    -.2862655    .5460916
     1 2001  |   .2708066   .1546694     1.75   0.086    -.0398561    .5814692
     1 2002  |  -.0163238   .1603163    -0.10   0.919    -.3383286     .305681
     1 2003  |   .0837763   .1635471     0.51   0.611    -.2447177    .4122704
     1 2004  |  -.0079608   .1891683    -0.04   0.967    -.3879165    .3719948
     1 2005  |  -.0800377   .1229917    -0.65   0.518    -.3270738    .1669983
     1 2006  |   .2544998   .1787638     1.42   0.161    -.1045579    .6135575
     1 2007  |  -.0372762   .1180324    -0.32   0.753    -.2743512    .1997988
     1 2008  |  -.0893781   .1698676    -0.53   0.601    -.4305673    .2518111
     1 2009  |  -.3770793   .1592743    -2.37   0.022    -.6969912   -.0571674
     1 2010  |  -.7013859   .1539404    -4.56   0.000    -1.010584   -.3921875
     1 2011  |  -.6462928   .1380126    -4.68   0.000    -.9234993   -.3690862
     1 2012  |  -.6913321   .1559551    -4.43   0.000    -1.004577   -.3780871
     1 2013  |  -.6938069    .149711    -4.63   0.000    -.9945102   -.3931035
     1 2014  |  -.5414492   .1696481    -3.19   0.002    -.8821974   -.2007009
     1 2015  |  -.5776247   .1320315    -4.37   0.000    -.8428177   -.3124317
             |
       _cons |     30.116   .4247502    70.90   0.000     29.26286    30.96914
------------------------------------------------------------------------------
```

<u>Specification (5), Exogenous-wage, Method 2, Restricted sample</u>

```
Linear regression                               Number of obs     =     18,961
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.2119
                                                Root MSE          =     7.7974

                                   (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   3.041743   1.576429     1.93   0.059    -.1246082    6.208094
post911entry |  -.2564114   .2992781    -0.86   0.396    -.8575291    .3447064
```

post911ent~t	-.1300773	.6006687	-0.22	0.829	-1.336556	1.076401
yearseduc	.5185563	.0888767	5.83	0.000	.3400422	.6970704
migrantyea~c	-.0764471	.1119085	-0.68	0.498	-.3012219	.1483277
exp	2.220364	.1314113	16.90	0.000	1.956416	2.484311
migrantexp	-1.054483	.2045239	-5.16	0.000	-1.465281	-.6436846
exp_sq	-.0890896	.0074858	-11.90	0.000	-.1041252	-.074054
migrantexp~q	.0618259	.0117105	5.28	0.000	.0383047	.0853472
female	-.5409787	.1674782	-3.23	0.002	-.8773685	-.2045889
migrantfem~e	-1.478802	.2980022	-4.96	0.000	-2.077357	-.8802471
1.migrant	0	(omitted)				
wbhao						
Black	1.100114	.2497561	4.40	0.000	.5984636	1.601764
Hispanic	1.673169	.3248483	5.15	0.000	1.020692	2.325646
Asian	-1.055379	.6297814	-1.68	0.100	-2.320332	.2095744
Other	.4389732	.6556556	0.67	0.506	-.8779498	1.755896
migrant# wbhao						
1#Black	.4701161	1.002438	0.47	0.641	-1.543339	2.483571
1#Hispanic	1.163798	.9603031	1.21	0.231	-.7650273	3.092624
1#Asian	-.5204034	1.228737	-0.42	0.674	-2.988394	1.947587
1#Other	-2.20306	1.855289	-1.19	0.241	-5.929517	1.523398
years_sinc~l	-.1053606	.1004247	-1.05	0.299	-.3070696	.0963484
rural	.3636956	.2321166	1.57	0.123	-.1025243	.8299154
migrantrural	-.5894528	.6179492	-0.95	0.345	-1.83064	.6517348
year						
1999	-.7314551	.4488005	-1.63	0.109	-1.632897	.1699872
2000	.0562489	.45298	0.12	0.902	-.8535882	.966086
2001	-.5100897	.4783453	-1.07	0.291	-1.470875	.4506951
2002	-.3827008	.4034288	-0.95	0.347	-1.193011	.4276098
2003	-.7489033	.3852159	-1.94	0.058	-1.522632	.0248257
2004	-1.024305	.5556136	-1.84	0.071	-2.140288	.0916777
2005	-.4176451	.511321	-0.82	0.418	-1.444664	.6093733
2006	-.6502413	.3748354	-1.73	0.089	-1.40312	.1026377
2007	-1.392816	.4887247	-2.85	0.006	-2.374448	-.4111831
2008	-1.008667	.6036718	-1.67	0.101	-2.221177	.2038439
2009	-1.496078	.5257861	-2.85	0.006	-2.552151	-.440006
2010	-1.919474	.4515289	-4.25	0.000	-2.826397	-1.012552
2011	-1.799686	.5772541	-3.12	0.003	-2.959135	-.6402374
2012	-1.860599	.6185835	-3.01	0.004	-3.103061	-.6181376
2013	-1.636319	.6152252	-2.66	0.010	-2.872035	-.4006024
2014	-1.457113	.5182951	-2.81	0.007	-2.498139	-.4160865
2015	-2.286047	.5192787	-4.40	0.000	-3.329049	-1.243045
migrant#year						
1 1999	-.49104	.8119709	-0.60	0.548	-2.121932	1.139852
1 2000	1.388138	.9290187	1.49	0.141	-.4778513	3.254127
1 2001	.5260663	.7937237	0.66	0.511	-1.068175	2.120307
1 2002	-.3471692	.9532122	-0.36	0.717	-2.261752	1.567414
1 2003	.7815198	.9306082	0.84	0.405	-1.087662	2.650701
1 2004	.8232966	.9505568	0.87	0.391	-1.085953	2.732546
1 2005	-.0129526	.95903	-0.01	0.989	-1.939221	1.913316
1 2006	1.230948	1.400125	0.88	0.384	-1.581286	4.043182
1 2007	2.816003	1.327071	2.12	0.039	.1505025	5.481503
1 2008	1.500082	1.344456	1.12	0.270	-1.200338	4.200502
1 2009	1.196893	1.486161	0.81	0.424	-1.788149	4.181934
1 2010	2.128945	1.241295	1.72	0.093	-.3642705	4.62216

```
     1 2011  |    2.45402   1.410253     1.74   0.088    -.3785573    5.286598
     1 2012  |   2.241502     1.4767     1.52   0.135    -.7245368    5.207541
     1 2013  |   1.802214   1.766798     1.02   0.313    -1.746504    5.350932
     1 2014  |    .274227   2.145685     0.13   0.899    -4.035509    4.583963
     1 2015  |    1.87029   1.816042     1.03   0.308    -1.777338    5.517919
             |
  entry_year |   .0598052    .108495     0.55   0.584    -.1581133    .2777238
entry_year~q |  -.0000296   .0000542    -0.55   0.587    -.0001384    .0000792
       _cons |    9.85247   1.152891     8.55   0.000     7.536821    12.16812
------------------------------------------------------------------------------
```

Specification (5), Exogenous-wage, Method 2, Full sample

```
Linear regression                               Number of obs     =  1,376,334
                                                F(50, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1432
                                                Root MSE          =     9.7391

                                   (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   1.335053   .3835308     3.48   0.001     .5647085    2.105397
post911entry |  -1.123339   .0772032   -14.55   0.000    -1.278407    -.968272
post911ent~t |   .9833671   .1527234     6.44   0.000      .676613    1.290121
 minwagedemo |  -16.11475   .1989155   -81.01   0.000    -16.51428   -15.71521
mi~o_migrant |   .4720268   .3282785     1.44   0.157    -.1873399    1.131394
minwaged~911 |  -.1820798   .2048511    -0.89   0.378    -.5935354    .2293758
mi~1_migrant |   .1955743   .5792188     0.34   0.737     -.967821     1.35897
      hsgrad |  -.0242747   .1060705    -0.23   0.820    -.2373236    .1887743
   assocgrad |   .6326326   .0981874     6.44   0.000     .4354173    .8298478
    bachgrad |   2.294879   .0921752    24.90   0.000      2.10974    2.480018
    mastgrad |   3.277641   .1163617    28.17   0.000     3.043922    3.511361
  doctorgrad |   6.520038   .1895662    34.39   0.000     6.139283    6.900793
migranthsg~d |   .1112138   .0876786     1.27   0.211    -.0648939    .2873214
migrantass~d |  -.1051454   .1480477    -0.71   0.481     -.402508    .1922173
migrantbac~d |  -.4448068   .1672853    -2.66   0.011    -.7808093   -.1088043
migrantmas~d |  -.5471752   .2602195    -2.10   0.041    -1.069841   -.0245089
migrantdoc~d |   .0584111    .235131     0.25   0.805    -.4138634    .5306855
         exp |   .5274777   .0108468    48.63   0.000     .5056913    .5492641
  migrantexp |   -.217521   .0146609   -14.84   0.000    -.2469683   -.1880738
      exp_sq |  -.0103769   .0001995   -52.03   0.000    -.0107775   -.0099763
migrantexp~q |   .0046612   .0002725    17.11   0.000     .0041139    .0052085
      female |  -4.809149   .1108434   -43.39   0.000    -5.031784   -4.586513
migrantfem~e |   .8470589   .1073548     7.89   0.000     .6314305    1.062687
   1.migrant |          0  (omitted)
             |
       wbhao |
      Black  |  -.0751821   .0719595    -1.04   0.301    -.2197171    .0693529
   Hispanic  |  -.0993107   .2063647    -0.48   0.632    -.5138065    .3151851
      Asian  |  -.5013507   .2669899    -1.88   0.066    -1.037616    .0349143
      Other  |   .1261133   .1553708     0.81   0.421    -.1859581    .4381848
             |
     migrant#|
       wbhao |
```

```
     1#Black  |  -.2456829   .1349377    -1.82   0.075    -.5167133    .0253475
  1#Hispanic  |  -.2754085   .1616608    -1.70   0.095    -.6001138    .0492968
     1#Asian  |  -.2749753   .2784873    -0.99   0.328    -.8343335    .2843829
     1#Other  |  -.5312569   .4050653    -1.31   0.196    -1.344854    .2823407
              |
years_sinc~l  |  -.0001511   .0135633    -0.01   0.991    -.0273938    .0270915
       rural  |   .2147137   .0880547     2.44   0.018     .0378506    .3915769
migrantrural  |   .7567106   .2599793     2.91   0.005     .2345267    1.278894
              |
        year  |
        1999  |   .1169633   .0654996     1.79   0.080    -.0145966    .2485232
        2000  |   .1484999   .0903769     1.64   0.107    -.0330275    .3300273
        2001  |   .0749596   .0932985     0.80   0.426    -.1124358    .2623551
        2002  |   -.111679   .0724317    -1.54   0.129    -.2571623    .0338042
        2003  |  -.2950188   .0782148    -3.77   0.000    -.4521179   -.1379197
        2004  |  -.3146215    .101385    -3.10   0.003    -.5182593   -.1109837
        2005  |  -.2012075   .0886088    -2.27   0.028    -.3791835   -.0232315
        2006  |  -.0826093   .1001687    -0.82   0.413     -.283804    .1185854
        2007  |   .0049301    .083297     0.06   0.953    -.1623768    .1722371
        2008  |   -.019088   .0918468    -0.21   0.836    -.2035677    .1653918
        2009  |  -.3198673   .0883854    -3.62   0.001    -.4973946     -.14234
        2010  |  -.6483437   .0939528    -6.90   0.000    -.8370535   -.4596338
        2011  |   -.646415   .0880285    -7.34   0.000    -.8232254   -.4696047
        2012  |  -.4794386   .0931259    -5.15   0.000    -.6664874   -.2923897
        2013  |  -.3662402   .1065496    -3.44   0.001    -.5802514   -.1522291
        2014  |  -.3516009   .1093739    -3.21   0.002    -.5712848   -.1319171
        2015  |   -.139505   .0989667    -1.41   0.165    -.3382855    .0592755
              |
migrant#year  |
      1 1999  |   .0362296   .1489917     0.24   0.809    -.2630289    .3354882
      1 2000  |   .1838944   .2226329     0.83   0.413     -.263277    .6310659
      1 2001  |   .3298946    .155127     2.13   0.038     .0183128    .6414765
      1 2002  |   .0601955     .16149     0.37   0.711    -.2641667    .3845577
      1 2003  |    .163245   .1711252     0.95   0.345      -.18047      .50696
      1 2004  |    .088537   .2060213     0.43   0.669    -.3252689    .5023429
      1 2005  |   .0498589   .1570582     0.32   0.752    -.2656018    .3653195
      1 2006  |   .3729957   .2046326     1.82   0.074    -.0380209    .7840123
      1 2007  |   .1349994   .1774448     0.76   0.450     -.221409    .4914079
      1 2008  |    .077798   .2219488     0.35   0.727    -.3679993    .5235952
      1 2009  |  -.1951372   .2239767    -0.87   0.388    -.6450076    .2547333
      1 2010  |  -.4741095   .2232506    -2.12   0.039    -.9225215   -.0256974
      1 2011  |  -.3846507   .2210229    -1.74   0.088    -.8285883    .0592869
      1 2012  |  -.4238375   .2408245    -1.76   0.085    -.9075478    .0598729
      1 2013  |  -.4358341    .264366    -1.65   0.105    -.9668289    .0951607
      1 2014  |  -.2822292   .2890957    -0.98   0.334     -.862895    .2984367
      1 2015  |  -.3084083    .258115    -1.19   0.238    -.8268475    .2100309
              |
  entry_year  |   .0189786   .0149713     1.27   0.211    -.0110921    .0490494
entry_year~q  |  -9.57e-06   7.47e-06    -1.28   0.206    -.0000246    5.44e-06
       _cons  |   36.81889   .1891412   194.66   0.000     36.43898    37.19879
------------------------------------------------------------------------------
```

Specification (6), Exogenous-wage, Method 2, Restricted sample

```
Linear regression                               Number of obs     =     18,495
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.2126
```

```
                                                Root MSE          =     7.7855

                                (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   5.781343   1.481332     3.90   0.000        2.806    8.756685
post911entry |  -.2533597   .2990782    -0.85   0.401     -.854076    .3473566
post911ent~t |  -.0064392   .5543613    -0.01   0.991    -1.119907    1.107028
  yearseduc |   .5171008   .0886916     5.83   0.000     .3389584    .6952431
migrantyea~c |  -.1670645    .111602    -1.50   0.141    -.3912236    .0570947
         exp |   2.219643   .1311885    16.92   0.000     1.956143    2.483143
  migrantexp |  -1.238386   .1785427    -6.94   0.000       -1.597   -.8797726
      exp_sq |  -.0890553   .0074622   -11.93   0.000    -.1040435    -.074067
migrantexp~q |     .06736   .0105179     6.40   0.000     .0462342    .0884858
      female |  -.5425375   .1669634    -3.25   0.002    -.8778935   -.2071816
migrantfem~e |  -1.358082   .2947601    -4.61   0.000    -1.950125   -.7660385
   1.migrant |          0  (omitted)
             |
       wbhao |
      Black  |   1.100211   .2499881     4.40   0.000     .5980952    1.602327
   Hispanic  |   1.690097   .3153929     5.36   0.000     1.056612    2.323582
      Asian  |  -1.062533    .616416    -1.72   0.091    -2.300641    .1755752
      Other  |   .4405953   .6565986     0.67   0.505    -.8782218    1.759412
             |
    migrant#|
       wbhao |
    1#Black  |   .5020807   1.159775     0.43   0.667    -1.827396    2.831557
 1#Hispanic  |   1.158842    1.16134     1.00   0.323    -1.173779    3.491462
    1#Asian  |  -1.034775   1.525324    -0.68   0.501    -4.098479     2.02893
    1#Other  |  -2.953618   2.702299    -1.09   0.280    -8.381345    2.474108
             |
years_sinc~l |  -.0084113   .0415845    -0.20   0.841    -.0919362    .0751136
       rural |   .3631708   .2323687     1.56   0.124    -.1035555     .829897
migrantrural |  -.8920474   .7148762    -1.25   0.218    -2.327918    .5438237
             |
        year |
       1999  |  -.7289111   .4503122    -1.62   0.112     -1.63339    .1755677
       2000  |   .0539248   .4534274     0.12   0.906     -.856811    .9646606
       2001  |   -.510767   .4795328    -1.07   0.292    -1.473937    .4524029
       2002  |  -.3806705   .4019412    -0.95   0.348    -1.187993    .4266521
       2003  |   -.751506    .387316    -1.94   0.058    -1.529453    .0264411
       2004  |  -1.031921   .5532882    -1.87   0.068    -2.143233    .0793916
       2005  |  -.4262889   .5104816    -0.84   0.408    -1.451621    .5990435
       2006  |  -.6601616   .3720687    -1.77   0.082    -1.407484    .0871602
       2007  |  -1.402706   .4903423    -2.86   0.006    -2.387587   -.4178244
       2008  |  -1.020648   .6027524    -1.69   0.097    -2.231312    .1900162
       2009  |  -1.508731   .5255951    -2.87   0.006     -2.56442   -.4530425
       2010  |  -1.932289   .4473853    -4.32   0.000    -2.830889   -1.033689
       2011  |   -1.81426   .5756163    -3.15   0.003    -2.970419   -.6581006
       2012  |  -1.875601   .6149697    -3.05   0.004    -3.110804   -.6403976
       2013  |  -1.655878   .6070458    -2.73   0.009    -2.875166   -.4365907
       2014  |  -1.473041   .5198905    -2.83   0.007    -2.517272   -.4288105
       2015  |  -2.304413   .5128251    -4.49   0.000    -3.334453   -1.274374
             |
migrant#year |
     1 1999  |  -.7077363   .7706707    -0.92   0.363    -2.255674    .8402013
     1 2000  |   1.222484   .9414137     1.30   0.200    -.6684016    3.113369
     1 2001  |   .2635291   .6938882     0.38   0.706    -1.130186    1.657244
```

1 2002	-.6494053	.7912471	-0.82	0.416	-2.238672	.9398613
1 2003	.7539418	.8666568	0.87	0.388	-.9867897	2.494673
1 2004	.5712626	.8886783	0.64	0.523	-1.2137	2.356225
1 2005	-.0725934	.831922	-0.09	0.931	-1.743558	1.598371
1 2006	1.317836	1.055109	1.25	0.217	-.8014127	3.437085
1 2007	1.820473	.9170236	1.99	0.053	-.0214235	3.662369
1 2008	.9957658	.9374065	1.06	0.293	-.8870706	2.878602
1 2009	.7987407	.863975	0.92	0.360	-.9366041	2.534085
1 2010	1.243908	.8226109	1.51	0.137	-.4083547	2.896171
1 2011	1.672596	1.151153	1.45	0.152	-.6395619	3.984755
1 2012	1.237847	1.663418	0.74	0.460	-2.103225	4.57892
1 2013	.4870908	1.173602	0.42	0.680	-1.870158	2.844339
1 2014	-.3695801	1.30822	-0.28	0.779	-2.997217	2.258057
1 2015	1.430074	1.169582	1.22	0.227	-.9191003	3.779249
_cons	9.87847	1.150977	8.58	0.000	7.566665	12.19027

Specification (6), Exogenous-wage, Method 2, Full sample

Linear regression

Number of obs	=	1,365,655
F(49, 50)	=	.
Prob > F	=	.
R-squared	=	0.1426
Root MSE	=	9.7346

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	1.905923	.3552869	5.36	0.000	1.192308	2.619537
post911entry	-1.121849	.0772155	-14.53	0.000	-1.276941	-.9667573
post911ent~t	.6532614	.1350088	4.84	0.000	.3820883	.9244345
minwagedemo	-16.11246	.1990906	-80.93	0.000	-16.51234	-15.71257
mi~o_migrant	.5146584	.2881494	1.79	0.080	-.0641067	1.093423
minwaged~911	-.1804748	.2046811	-0.88	0.382	-.5915887	.2306392
mi~1_migrant	-.0211461	.6112603	-0.03	0.973	-1.248898	1.206606
hsgrad	-.0211282	.1058806	-0.20	0.843	-.2337956	.1915392
assocgrad	.6356958	.0978832	6.49	0.000	.4390917	.8322999
bachgrad	2.297555	.0922847	24.90	0.000	2.112196	2.482914
mastgrad	3.280359	.1163154	28.20	0.000	3.046733	3.513986
doctorgrad	6.522775	.1893994	34.44	0.000	6.142356	6.903195
migranthsg~d	.2682695	.087255	3.07	0.003	.0930127	.4435264
migrantass~d	-.1057175	.1534146	-0.69	0.494	-.4138597	.2024247
migrantbac~d	-.5503258	.1816342	-3.03	0.004	-.9151488	-.1855027
migrantmas~d	-.7408814	.2338454	-3.17	0.003	-1.210574	-.2711891
migrantdoc~d	-.3350606	.2372541	-1.41	0.164	-.8115995	.1414783
exp	.5274339	.0108267	48.72	0.000	.5056878	.54918
migrantexp	-.2766518	.0176177	-15.70	0.000	-.312038	-.2412657
exp_sq	-.0103752	.0001991	-52.10	0.000	-.0107752	-.0099752
migrantexp~q	.005701	.0003127	18.23	0.000	.0050729	.0063292
female	-4.80907	.1108461	-43.39	0.000	-5.03171	-4.586429
migrantfem~e	.7843071	.1112996	7.05	0.000	.5607552	1.007859
1.migrant	0	(omitted)				
wbhao						
Black	-.0753163	.0719488	-1.05	0.300	-.2198296	.0691971

```
   Hispanic  |   -.121033   .2031214    -0.60   0.554    -.5290142    .2869483
      Asian  |  -.5346662   .2662863    -2.01   0.050    -1.069518    .0001857
      Other  |   .1261206   .1553094     0.81   0.421    -.1858275    .4380687
             |
    migrant#|
       wbhao |
    1#Black  |  -.3578962   .1229625    -2.91   0.005    -.6048736   -.1109188
 1#Hispanic  |  -.4357598   .1451862    -3.00   0.004    -.7273749   -.1441448
    1#Asian  |  -.2625687   .2465667    -1.06   0.292    -.7578125    .2326751
    1#Other  |   -.573518   .4378217    -1.31   0.196    -1.452909    .3058726
             |
years_sinc~l |   .0110202    .002621     4.20   0.000     .0057557    .0162846
       rural |   .2158281   .0880743     2.45   0.018     .0389255    .3927306
migrantrural |   .7511839   .2694995     2.79   0.007     .2098782     1.29249
             |
        year |
       1999  |   .1165821   .0655198     1.78   0.081    -.0150183    .2481826
       2000  |   .1480029   .0903122     1.64   0.108    -.0333945    .3294002
       2001  |   .0741887   .0931126     0.80   0.429    -.1128334    .2612107
       2002  |  -.1126854   .0724417    -1.56   0.126    -.2581889    .0328181
       2003  |  -.2962769   .0781987    -3.79   0.000    -.4533436   -.1392103
       2004  |  -.3163853   .1013195    -3.12   0.003    -.5198915   -.1128791
       2005  |  -.2029729   .0884759    -2.29   0.026     -.380682   -.0252637
       2006  |  -.0846642   .1000706    -0.85   0.402    -.2856618    .1163335
       2007  |   .0027046   .0832472     0.03   0.974    -.1645023    .1699114
       2008  |  -.0217453   .0918136    -0.24   0.814    -.2061584    .1626677
       2009  |  -.3226457   .0880003    -3.67   0.001    -.4993996   -.1458918
       2010  |  -.6513226   .0943497    -6.90   0.000    -.8408295   -.4618157
       2011  |   -.649652   .0881649    -7.37   0.000    -.8267365   -.4725676
       2012  |  -.4827647   .0926866    -5.21   0.000    -.6689312   -.2965981
       2013  |  -.3700399   .1063385    -3.48   0.001     -.583627   -.1564528
       2014  |  -.3553203   .1095441    -3.24   0.002    -.5753462   -.1352944
       2015  |  -.1437415   .0985163    -1.46   0.151    -.3416173    .0541342
             |
migrant#year |
     1 1999  |   .0198309   .1509099     0.13   0.896    -.2832804    .3229423
     1 2000  |   .1541723    .212192     0.73   0.471    -.2720278    .5803724
     1 2001  |   .2789089   .1554341     1.79   0.079    -.0332897    .5911076
     1 2002  |   .0337413   .1545494     0.22   0.828    -.2766804    .3441629
     1 2003  |   .1808924    .146899     1.23   0.224     -.114163    .4759478
     1 2004  |   .1305312   .1832277     0.71   0.480    -.2374925    .4985548
     1 2005  |   .1203759    .126947     0.95   0.348    -.1346047    .3753565
     1 2006  |   .4583274   .1667835     2.75   0.008     .1233329    .7933218
     1 2007  |   .1846403   .1164779     1.59   0.119    -.0493123     .418593
     1 2008  |   .0522399    .156101     0.33   0.739    -.2612982    .3657779
     1 2009  |  -.1542408   .1521857    -1.01   0.316    -.4599148    .1514333
     1 2010  |    -.52197   .1476975    -3.53   0.001    -.8186292   -.2253107
     1 2011  |   -.431673   .1224558    -3.53   0.001    -.6776327   -.1857132
     1 2012  |  -.5154124   .1487557    -3.46   0.001    -.8141969   -.2166278
     1 2013  |  -.5386463   .1544925    -3.49   0.001    -.8489535    -.228339
     1 2014  |  -.3235785   .1689806    -1.91   0.061     -.662986    .0158289
     1 2015  |  -.3138137   .1338562    -2.34   0.023    -.5826719   -.0449555
             |
       _cons |   36.81608   .1891009   194.69   0.000     36.43626     37.1959
------------------------------------------------------------------------------
```

Specification (1), Exogenous-wage, Method 3, Restricted sample

```
Linear regression                               Number of obs     =     63,913
                                                F(3, 50)          =     464.28
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0816
                                                Root MSE          =     11.755

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   1.503457   .3821296     3.93   0.000     .7359273    2.270987
post911entry |  -7.024003   .2090462   -33.60   0.000    -7.443884   -6.604121
post911ent~t |   6.033192   .2854321    21.14   0.000     5.459885    6.606499
       _cons |   36.89085   .1902058   193.95   0.000     36.50881    37.27289
------------------------------------------------------------------------------
```

Specification (1), Exogenous-wage, Method 3, Full sample

```
Linear regression                               Number of obs     =  1,376,334
                                                F(7, 50)          =     550.22
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0311
                                                Root MSE          =     10.357

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |  -.6430164   .1478991    -4.35   0.000    -.9400805   -.3459522
post911entry |  -4.335104   .1369148   -31.66   0.000    -4.610106   -4.060103
post911ent~t |   3.444302   .1990042    17.31   0.000      3.04459    3.844013
     leisure |   -3.68887   .1452387   -25.40   0.000     -3.98059   -3.397149
leisure_mi~t |   2.146473    .272374     7.88   0.000     1.599394    2.693553
leisure_~911 |  -2.688898   .1812962   -14.83   0.000    -3.053043   -2.324754
leisure_po~t |    2.58889   .3082612     8.40   0.000     1.969729    3.208051
       _cons |   40.57972    .118588   342.19   0.000     40.34153    40.81791
------------------------------------------------------------------------------
```

Specification (2), Exogenous-wage, Method 3, Restricted sample

```
Linear regression                               Number of obs     =     63,913
                                                F(14, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1640
                                                Root MSE          =     11.217

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   1.006525   .2924301     3.44   0.001     .4191621    1.593889
post911entry |  -.9055406    .177681    -5.10   0.000    -1.262423   -.5486577
```

```
post911ent~t |   1.144534   .2568407     4.46   0.000     .6286546    1.660414
  yearseduc |   .4698338   .0578056     8.13   0.000     .3537278    .5859397
        exp |    .882775   .0197792    44.63   0.000     .8430474    .9225027
     exp_sq |   -.016277   .0004082   -39.87   0.000    -.0170969   -.015457
     female |  -4.102795   .1455133   -28.20   0.000    -4.395067   -3.810523
      white |  -.6014496   .4810982    -1.25   0.217    -1.567764    .3648646
      black |  -.5410794   .5117593    -1.06   0.295    -1.568978    .4868195
      asian |  -.1429137   .5659952    -0.25   0.802    -1.279749    .9939212
   hispanic |   .4881586   .4804518     1.02   0.315    -.4768572    1.453174
years_sinc~l |   .0025797   .0124812     0.21   0.837    -.0224896     .027649
      rural |  -.2697939   .2242645    -1.20   0.235    -.7202423    .1806545
       year |   7.289121   16.21504     0.45   0.655    -25.27974    39.85798
    year_sq |   -.001838   .0040352    -0.46   0.651    -.0099429    .0062668
      _cons |  -7200.782   16289.13    -0.44   0.660    -39918.47    25516.91
------------------------------------------------------------------------------
```

Specification (2), Exogenous-wage, Method 3, Full sample

```
Linear regression                               Number of obs     =  1,376,334
                                                F(17, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1188
                                                Root MSE          =     9.8769

                                 (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |  -.0793621   .0999222    -0.79   0.431    -.2800617    .1213375
post911entry |  -.8321537   .0726021   -11.46   0.000    -.9779792   -.6863281
post911ent~t |   .3637528   .1501702     2.42   0.019      .062127    .6653786
     leisure |  -2.412394   .1019721   -23.66   0.000    -2.617211   -2.207577
leisure_mi~t |   1.805136   .2229848     8.10   0.000     1.357258    2.253015
leisure_~911 |   -2.57045   .1706097   -15.07   0.000    -2.913129    -2.22777
leisure_po~t |   2.663535   .3179876     8.38   0.000     2.024838    3.302232
   yearseduc |   .4884359   .0255886    19.09   0.000     .4370396    .5398322
         exp |   .5503785    .010183    54.05   0.000     .5299254    .5708316
      exp_sq |  -.0103919   .0001884   -55.16   0.000    -.0107703   -.0100135
      female |  -4.749385   .1178076   -40.31   0.000    -4.986009   -4.512762
       white |  -.0583898   .1634603    -0.36   0.722    -.3867094    .2699299
       black |  -.2561863   .1608568    -1.59   0.118    -.5792767    .0669042
       asian |   -.713241   .1876917    -3.80   0.000    -1.090231   -.3362512
    hispanic |   .0466149   .2120669     0.22   0.827    -.3793339    .4725637
years_sinc~l |   .0053133   .0026615     2.00   0.051    -.0000326    .0106592
       rural |   .1596978   .0762686     2.09   0.041     .0065079    .3128877
        year |  -5.033984   3.614647    -1.39   0.170    -12.29422    2.226248
     year_sq |   .0012469   .0009012     1.38   0.173    -.0005631     .003057
       _cons |   5110.668   3623.954     1.41   0.165    -2168.257    12389.59
------------------------------------------------------------------------------
```

Specification (3), Exogenous-wage, Method 3, Restricted sample

```
Linear regression                               Number of obs     =     63,913
                                                F(30, 50)         =    1120.63
                                                Prob > F          =     0.0000
```

R-squared	=	0.1653
Root MSE	=	11.209

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	.985683	.2959889	3.33	0.002	.3911717	1.580194
post911entry	-.8728149	.1890912	-4.62	0.000	-1.252616	-.4930141
post911ent~t	1.196799	.2547601	4.70	0.000	.6850985	1.7085
yearseduc	.4715723	.0588957	8.01	0.000	.3532769	.5898677
exp	.8866522	.0201635	43.97	0.000	.8461526	.9271517
exp_sq	-.016353	.00041	-39.89	0.000	-.0171764	-.0155295
female	-4.10049	.1457787	-28.13	0.000	-4.393295	-3.807685
white	-.6048879	.4874844	-1.24	0.220	-1.584029	.3742533
black	-.5462562	.5187048	-1.05	0.297	-1.588105	.4955931
asian	-.1607236	.562804	-0.29	0.776	-1.291149	.9697014
hispanic	.4806027	.4796024	1.00	0.321	-.4827071	1.443912
years_sinc~l	.0041304	.0126043	0.33	0.745	-.0211862	.0294469
rural	-.2605537	.2252935	-1.16	0.253	-.713069	.1919616
year						
1999	1.132592	.763053	1.48	0.144	-.4000446	2.66523
2000	.8638841	.5573903	1.55	0.127	-.2556672	1.983435
2001	1.101253	.6892716	1.60	0.116	-.2831902	2.485695
2002	.5488782	.6271599	0.88	0.386	-.7108095	1.808566
2003	.7977446	.729237	1.09	0.279	-.6669711	2.26246
2004	.1514277	.6987634	0.22	0.829	-1.25208	1.554935
2005	.3312853	.6577859	0.50	0.617	-.9899165	1.652487
2006	.3789133	.6709506	0.56	0.575	-.9687307	1.726557
2007	1.101566	.7726748	1.43	0.160	-.4503974	2.653529
2008	.834719	.7542205	1.11	0.274	-.6801774	2.349615
2009	.0497448	.7290504	0.07	0.946	-1.414596	1.514086
2010	-.8440978	.8446007	-1.00	0.322	-2.540528	.8523327
2011	-.7107203	.6598007	-1.08	0.287	-2.035969	.6145284
2012	-.5156964	.6846963	-0.75	0.455	-1.890949	.8595566
2013	-.5795299	.7013231	-0.83	0.413	-1.988179	.8291191
2014	-.223101	.7237863	-0.31	0.759	-1.676869	1.230667
2015	-.1553318	.8640411	-0.18	0.858	-1.890809	1.580146
_cons	24.45764	1.201718	20.35	0.000	22.04392	26.87137

Specification (3), Exogenous-wage, Method 3, Full sample

Linear regression

Number of obs	=	1,376,334
F(38, 50)	=	6392.98
Prob > F	=	0.0000
R-squared	=	0.1262
Root MSE	=	9.8351

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]

```
     migrant |  -.4728804    .100083    -4.72   0.000     -.673903   -.2718578
post911entry |   -.880974     .07665   -11.49   0.000     -1.03493   -.7270179
post911ent~t |   .3763438   .1553625     2.42   0.019     .0642891    .6883986
     leisure |  -2.267527   .1015215   -22.34   0.000    -2.471439   -2.063615
leisure_mi~t |   1.720577   .2108814     8.16   0.000     1.297009    2.144144
leisure_~911 |  -2.411572   .1649325   -14.62   0.000    -2.742849   -2.080295
leisure_po~t |   2.567037   .3101088     8.28   0.000     1.944165    3.189908
      hsgrad |   1.669548   .1859173     8.98   0.000     1.296122    2.042973
   assocgrad |   2.229856   .1825131    12.22   0.000     1.863267    2.596444
    bachgrad |   3.863733   .1485208    26.01   0.000      3.56542    4.162045
    mastgrad |   4.749806   .1745909    27.21   0.000      4.39913    5.100482
  doctorgrad |   8.097747   .2882359    28.09   0.000     7.518808    8.676686
         exp |   .5365383   .0094988    56.48   0.000     .5174593    .5556173
      exp_sq |  -.0102183   .0001718   -59.46   0.000    -.0105635   -.0098732
      female |  -4.712695   .1170404   -40.27   0.000    -4.947778   -4.477613
       white |  -.2036539   .1559778    -1.31   0.198    -.5169445    .1096366
       black |  -.2477887   .1559721    -1.59   0.118     -.561068    .0654905
       asian |  -.8738372   .1813095    -4.82   0.000    -1.238008   -.5096663
    hispanic |  -.0799354    .217195    -0.37   0.714    -.5161843    .3563136
years_sinc~l |   .0081557   .0024556     3.32   0.002     .0032235    .0130878
       rural |   .2342394   .0834879     2.81   0.007      .066549    .4019299
             |
        year |
       1999  |    .113663   .0588559     1.93   0.059    -.0045526    .2318786
       2000  |   .1463487   .0875046     1.67   0.101    -.0294094    .3221068
       2001  |    .104846   .0917273     1.14   0.258    -.0793938    .2890858
       2002  |  -.1227001    .068108    -1.80   0.078    -.2594991    .0140989
       2003  |   -.229582   .0787291    -2.92   0.005     -.387714     -.07145
       2004  |  -.2615393   .0966797    -2.71   0.009    -.4557263   -.0673524
       2005  |  -.1458031   .0807942    -1.80   0.077     -.308083    .0164767
       2006  |   .0211647   .0898984     0.24   0.815    -.1594016     .201731
       2007  |   .0729892   .0783816     0.93   0.356    -.0844449    .2304233
       2008  |   .0465008   .0783618     0.59   0.556    -.1108936    .2038951
       2009  |  -.3041771   .0769979    -3.95   0.000     -.458832   -.1495222
       2010  |  -.6912897    .078938    -8.76   0.000    -.8498414   -.5327379
       2011  |  -.6689199   .0779942    -8.58   0.000     -.825576   -.5122638
       2012  |    -.51775   .0819914    -6.31   0.000    -.6824347   -.3530654
       2013  |  -.3912254   .0968522    -4.04   0.000    -.5857589    -.196692
       2014  |  -.3512457   .0981356    -3.58   0.001    -.5483569   -.1541344
       2015  |  -.1448177   .0891673    -1.62   0.111    -.3239154    .0342801
             |
       _cons |   35.07202   .2145561   163.46   0.000     34.64107    35.50297
------------------------------------------------------------------------------
```

Specification (4), Exogenous-wage, Method 3, Restricted sample

```
Linear regression                               Number of obs     =     63,913
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1727
                                                Root MSE          =     11.162

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   9.534752   1.697939     5.62   0.000      6.12434    12.94516
```

```
post911entry |  -.7725973   .2015548    -3.83   0.000    -1.177432   -.3677626
post911ent~t |   1.246652   .2994861     4.16   0.000     .6451168    1.848188
  yearseduc |   .8210674   .0520409    15.78   0.000     .7165402    .9255946
migrantyea~c |  -.6431216   .0617414   -10.42   0.000    -.7671329   -.5191104
        exp |   .9777878   .0235659    41.49   0.000     .9304542    1.025121
 migrantexp |  -.3125741    .031544    -9.91   0.000     -.375932   -.2492161
     exp_sq |  -.0188477   .0005359   -35.17   0.000    -.0199242   -.0177713
migrantexp~q |   .0074713   .0005875    12.72   0.000     .0062913    .0086513
     female |  -3.683069    .181249   -20.32   0.000    -4.047118    -3.31902
migrantfem~e |  -1.556881   .2740261    -5.68   0.000    -2.107279   -1.006484
  1.migrant |          0  (omitted)
             |
       wbhao |
       Black  |   .3257508    .253818     1.28   0.205    -.1840576    .8355592
   Hispanic  |   1.013369   .4368997     2.32   0.024     .1358305    1.890908
      Asian  |   .6460422   .5616801     1.15   0.256    -.4821255     1.77421
      Other  |    .805196    .474944     1.70   0.096    -.1487571    1.759149
             |
    migrant#|
       wbhao |
    1#Black  |  -1.110221   .7467066    -1.49   0.143    -2.610025    .3895834
 1#Hispanic  |  -.3102402   .4943677    -0.63   0.533    -1.303207    .6827266
    1#Asian  |  -.2867574   .7186925    -0.40   0.692    -1.730294    1.156779
    1#Other  |  -6.194784   2.171956    -2.85   0.006    -10.55728   -1.832282
             |
years_sinc~l |   .0101948   .0123376     0.83   0.413    -.0145861    .0349757
      rural |  -.1944163    .211022    -0.92   0.361    -.6182665    .2294339
migrantrural |   1.111819   .7792705     1.43   0.160    -.4533917     2.67703
             |
        year |
       1999  |   1.079705   .7005828     1.54   0.130    -.3274565    2.486867
       2000  |   .4590759   .6007181     0.76   0.448    -.7475019    1.665654
       2001  |   .7713026   .7346728     1.05   0.299    -.7043312    2.246936
       2002  |   .4031438   .5417548     0.74   0.460    -.6850028     1.49129
       2003  |   .6440046   .7026097     0.92   0.364    -.7672285    2.055238
       2004  |  -.0991273   .6777485    -0.15   0.884    -1.460425    1.262171
       2005  |   -.008939   .6804632    -0.01   0.990     -1.37569    1.357812
       2006  |  -.0934664   .6502878    -0.14   0.886    -1.399608    1.212675
       2007  |   .9466814   .7307903     1.30   0.201    -.5211541    2.414517
       2008  |   .6512445   .7055895     0.92   0.360    -.7659738    2.068463
       2009  |    -.00048   .7012984    -0.00   0.999    -1.409079    1.408119
       2010  |  -.7606949   .7785448    -0.98   0.333    -2.324448    .8030583
       2011  |  -.6046439   .6060039    -1.00   0.323    -1.821839    .6125507
       2012  |  -.6240583    .614511    -1.02   0.315     -1.85834    .6102234
       2013  |  -.6819657   .6954856    -0.98   0.332     -2.07889    .7149583
       2014  |  -.3829526   .6840807    -0.56   0.578    -1.756969    .9910639
       2015  |  -.3059235   .8262495    -0.37   0.713    -1.965494    1.353647
             |
migrant#year |
     1 1999  |  -.0239421   2.723572    -0.01   0.993    -5.494397    5.446513
     1 2000  |   3.812966   2.311221     1.65   0.105    -.8292578    8.455189
     1 2001  |   2.984595   1.778884     1.68   0.100    -.5883979    6.557588
     1 2002  |   1.259559   1.399712     0.90   0.373    -1.551845    4.070963
     1 2003  |   2.457585    1.24064     1.98   0.053    -.0343146    4.949484
     1 2004  |   2.937019   1.196679     2.45   0.018      .533418     5.34062
     1 2005  |   3.267873   1.349255     2.42   0.019     .5578155    5.977931
     1 2006  |   3.570936   1.487794     2.40   0.020     .5826148    6.559258
     1 2007  |   2.403381   1.478498     1.63   0.110    -.5662702    5.373033
     1 2008  |   2.505547    1.43146     1.75   0.086    -.3696257     5.38072
     1 2009  |   1.748661   1.222036     1.43   0.159    -.7058699    4.203193
```

```
     1 2010  |   1.238486   1.365761     0.91   0.369    -1.504727    3.981698
     1 2011  |   1.060768   1.429777     0.74   0.462    -1.811025     3.93256
     1 2012  |   2.094395    1.44969     1.44   0.155    -.8173936    5.006183
     1 2013  |   1.947431   1.215875     1.60   0.116    -.4947246    4.389587
     1 2014  |   1.979685   1.403727     1.41   0.165    -.8397839    4.799154
     1 2015  |   2.043151   1.493744     1.37   0.177    -.9571223    5.043424
             |
       _cons |   18.72482   1.165651    16.06   0.000     16.38354     21.0661
------------------------------------------------------------------------------
```

Specification (4), Exogenous-wage, Method 3, Full sample

```
Linear regression                               Number of obs     =  1,376,334
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1221
                                                Root MSE          =     9.8583

                                   (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   6.244962   .6325593     9.87   0.000     4.974429    7.515494
post911entry |  -.8070706   .0739836   -10.91   0.000    -.9556711   -.6584702
post911ent~t |   .6610025   .1655794     3.99   0.000     .3284264    .9935786
     leisure |  -2.291348   .1065412   -21.51   0.000    -2.505342   -2.077353
leisure_mi~t |   1.444341   .2104305     6.86   0.000     1.021679    1.867003
leisure_~911 |  -2.507622   .1674847   -14.97   0.000    -2.844025   -2.171219
leisure_po~t |   2.454106   .3185263     7.70   0.000     1.814327    3.093885
   yearseduc |   .6030121   .0171496    35.16   0.000     .5685661     .637458
migrantyea~c |  -.3375509   .0302789   -11.15   0.000     -.398368   -.2767339
         exp |   .5882736   .0106739    55.11   0.000     .5668344    .6097128
  migrantexp |  -.2299817   .0143931   -15.98   0.000     -.258891   -.2010724
      exp_sq |  -.0113253    .000198   -57.19   0.000    -.0117231   -.0109276
migrantexp~q |   .0051697   .0002785    18.56   0.000     .0046103    .0057292
      female |  -4.858279   .1118399   -43.44   0.000    -5.082916   -4.633642
migrantfem~e |   .7374671   .1065943     6.92   0.000     .5233662     .951568
   1.migrant |          0  (omitted)
             |
       wbhao |
      Black  |  -.0837093   .0775228    -1.08   0.285    -.2394185    .0719998
   Hispanic  |   .0047044   .2402586     0.02   0.984    -.4778692    .4872781
      Asian  |  -.3177019   .2903464    -1.09   0.279    -.9008798    .2654759
      Other  |   .1380448   .1568884     0.88   0.383    -.1770749    .4531645
             |
     migrant#|
       wbhao |
    1#Black  |  -.5695715   .1425247    -4.00   0.000    -.8558409   -.2833021
 1#Hispanic  |  -.4762275   .1620491    -2.94   0.005    -.8017127   -.1507422
    1#Asian  |  -.3342233   .2688212    -1.24   0.220    -.8741664    .2057199
    1#Other  |  -.7640198   .4376947    -1.75   0.087    -1.643155    .1151159
             |
years_sinc~l |   .0080838   .0024129     3.35   0.002     .0032373    .0129304
       rural |   .2051611   .0878968     2.33   0.024     .0286152     .381707
migrantrural |   .8361301   .2725357     3.07   0.003     .2887261    1.383534
             |
        year |
```

```
        1999  |   .1007571   .0652907     1.54   0.129    -.0303831    .2318974
        2000  |   .1151824   .0902624     1.28   0.208     -.066115    .2964798
        2001  |   .0566243   .0978736     0.58   0.565    -.1399605    .2532092
        2002  |  -.1420752   .0779408    -1.82   0.074    -.2986238    .0144734
        2003  |  -.2578662   .0824776    -3.13   0.003    -.4235274   -.0922051
        2004  |  -.2677582   .1002305    -2.67   0.010    -.4690771   -.0664392
        2005  |  -.1435008   .0885257    -1.62   0.111    -.3213098    .0343082
        2006  |  -.0357511   .1033841    -0.35   0.731    -.2434042    .1719019
        2007  |   .0623806   .0845572     0.74   0.464    -.1074576    .2322188
        2008  |   .0386587   .0913792     0.42   0.674    -.1448818    .2221992
        2009  |  -.2578995   .0885659    -2.91   0.005    -.4357893   -.0800097
        2010  |  -.5924912   .0935024    -6.34   0.000    -.7802962   -.4046862
        2011  |  -.5905328   .0876477    -6.74   0.000    -.7665785   -.4144871
        2012  |  -.4289301   .0931985    -4.60   0.000    -.6161247   -.2417354
        2013  |  -.3018682   .1115113    -2.71   0.009    -.5258453   -.0778911
        2014  |  -.2715571   .1080893    -2.51   0.015    -.4886609   -.0544533
        2015  |  -.0607119   .0980668    -0.62   0.539    -.2576849    .1362611
              |
migrant#year |
      1 1999  |   .0638795   .1592362     0.40   0.690    -.2559557    .3837148
      1 2000  |   .2018387   .2097404     0.96   0.341    -.2194374    .6231148
      1 2001  |   .3102264   .1614495     1.92   0.060    -.0140544    .6345072
      1 2002  |   .0600464   .1675494     0.36   0.722    -.2764864    .3965792
      1 2003  |   .1240416   .1749593     0.71   0.482    -.2273744    .4754576
      1 2004  |   .0044993   .2074302     0.02   0.983    -.4121367    .4211352
      1 2005  |  -.0606913   .1185924    -0.51   0.611    -.2988912    .1775085
      1 2006  |   .3072278   .1705769     1.80   0.078     -.035386    .6498416
      1 2007  |   .0174397   .1170975     0.15   0.882    -.2177576     .252637
      1 2008  |  -.0442193   .1755394    -0.25   0.802    -.3968006    .3083621
      1 2009  |   -.351403     .16081    -2.19   0.034    -.6743994   -.0284066
      1 2010  |  -.6833252   .1528076    -4.47   0.000    -.9902484   -.3764021
      1 2011  |  -.6318092    .135434    -4.67   0.000    -.9038363    -.359782
      1 2012  |  -.6501605   .1502625    -4.33   0.000    -.9519716   -.3483494
      1 2013  |  -.6568336   .1563451    -4.20   0.000    -.9708619   -.3428053
      1 2014  |  -.5304952   .1672494    -3.17   0.003    -.8664254    -.194565
      1 2015  |  -.5603436   .1384196    -4.05   0.000    -.8383675   -.2823198
              |
       _cons |   28.52581    .403817    70.64   0.000     27.71472     29.3369
------------------------------------------------------------------------------
```

Specification (5), Exogenous-wage, Method 3, Restricted sample

```
Linear regression                               Number of obs     =     63,913
                                                F(50, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1727
                                                Root MSE          =     11.162

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   9.684102   1.924581     5.03   0.000     5.818467    13.54974
post911entry |  -.7703546    .201702    -3.82   0.000    -1.175485   -.3652242
post911ent~t |   1.137122   .3223241     3.53   0.001      .489715    1.784529
  yearseduc |   .8213925   .0517985    15.86   0.000     .7173521    .9254328
migrantyea~c |  -.6413103   .0615098   -10.43   0.000    -.7648565   -.5177642
```

exp	.9779103	.0235374	41.55	0.000	.9306341	1.025187
migrantexp	-.3124138	.0313258	-9.97	0.000	-.3753336	-.249494
exp_sq	-.0188505	.0005346	-35.26	0.000	-.0199243	-.0177767
migrantexp~q	.007503	.000586	12.80	0.000	.006326	.00868
female	-3.683635	.1813689	-20.31	0.000	-4.047925	-3.319345
migrantfem~e	-1.557675	.2742568	-5.68	0.000	-2.108536	-1.006813
1.migrant	0	(omitted)				
wbhao						
Black	.3260873	.2539253	1.28	0.205	-.1839368	.8361114
Hispanic	1.000058	.4400079	2.27	0.027	.1162757	1.883839
Asian	.6112767	.5653684	1.08	0.285	-.5242992	1.746853
Other	.8053548	.4741173	1.70	0.096	-.1469378	1.757647
migrant#						
wbhao						
1#Black	-1.121983	.7495449	-1.50	0.141	-2.627489	.3835219
1#Hispanic	-.3116862	.4956049	-0.63	0.532	-1.307138	.6837655
1#Asian	-.2608057	.7219173	-0.36	0.719	-1.710819	1.189208
1#Other	-6.217456	2.17869	-2.85	0.006	-10.59348	-1.841428
years_sinc~l	.0499755	.0720438	0.69	0.491	-.0947287	.1946796
rural	-.1936902	.2105376	-0.92	0.362	-.6165674	.2291869
migrantrural	1.122696	.7806607	1.44	0.157	-.4453067	2.6907
year						
1999	1.080491	.7000442	1.54	0.129	-.3255893	2.486571
2000	.4571369	.5997326	0.76	0.450	-.7474614	1.661735
2001	.7690419	.7346632	1.05	0.300	-.7065726	2.244656
2002	.4003495	.5419633	0.74	0.464	-.6882157	1.488915
2003	.6406599	.702885	0.91	0.366	-.7711263	2.052446
2004	-.1039126	.6796136	-0.15	0.879	-1.468957	1.261131
2005	-.0141321	.6815169	-0.02	0.984	-1.382999	1.354735
2006	-.1000511	.6519964	-0.15	0.879	-1.409624	1.209522
2007	.9390637	.7336584	1.28	0.206	-.5345325	2.41266
2008	.6433244	.707493	0.91	0.368	-.7777171	2.064366
2009	-.0113362	.7067847	-0.02	0.987	-1.430955	1.408283
2010	-.7704131	.7831157	-0.98	0.330	-2.343347	.802521
2011	-.6141378	.607694	-1.01	0.317	-1.834727	.6064515
2012	-.633986	.6141496	-1.03	0.307	-1.867542	.5995698
2013	-.6938696	.6972406	-1.00	0.324	-2.094318	.7065793
2014	-.3946972	.6865439	-0.57	0.568	-1.773661	.9842668
2015	-.3170611	.8286514	-0.38	0.704	-1.981456	1.347334
migrant#year						
1 1999	-.0787509	2.753489	-0.03	0.977	-5.609296	5.451794
1 2000	3.724856	2.34263	1.59	0.118	-.9804544	8.430167
1 2001	2.864508	1.811077	1.58	0.120	-.7731474	6.502164
1 2002	1.073556	1.515867	0.71	0.482	-1.971152	4.118264
1 2003	2.197834	1.36736	1.61	0.114	-.5485903	4.944258
1 2004	2.645605	1.356586	1.95	0.057	-.0791777	5.370389
1 2005	2.939933	1.522929	1.93	0.059	-.1189599	5.998826
1 2006	3.207826	1.705492	1.88	0.066	-.2177564	6.633408
1 2007	1.997883	1.707881	1.17	0.248	-1.432497	5.428264
1 2008	2.05558	1.720606	1.19	0.238	-1.400359	5.511519
1 2009	1.262037	1.522063	0.83	0.411	-1.795118	4.319191
1 2010	.7088702	1.726185	0.41	0.683	-2.758274	4.176014
1 2011	.485564	1.863922	0.26	0.796	-3.258233	4.229361
1 2012	1.477119	1.894595	0.78	0.439	-2.328286	5.282524
1 2013	1.293486	1.733857	0.75	0.459	-2.189069	4.77604

1 2014	1.307713	1.938295	0.67	0.503	-2.585467	5.200894
1 2015	1.343878	2.100918	0.64	0.525	-2.87594	5.563696
entry_year	-.0480668	.0746747	-0.64	0.523	-.1980554	.1019217
entry_year~q	.000024	.0000372	0.65	0.521	-.0000508	.0000988
_cons	18.7254	1.160836	16.13	0.000	16.39379	21.057

Specification (5), Exogenous-wage, Method 3, Full sample

Linear regression

Number of obs	=	1,376,334
F(50, 50)	=	.
Prob > F	=	.
R-squared	=	0.1279
Root MSE	=	9.8257

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	2.717485	.3885777	6.99	0.000	1.937003	3.497966
post911entry	-.8033343	.0720134	-11.16	0.000	-.9479775	-.6586911
post911ent~t	.6380808	.1660892	3.84	0.000	.3044809	.9716808
leisure	-2.213565	.1036025	-21.37	0.000	-2.421656	-2.005473
leisure_mi~t	1.566156	.2001137	7.83	0.000	1.164215	1.968096
leisure_~911	-2.356038	.1611857	-14.62	0.000	-2.679789	-2.032287
leisure_po~t	2.35942	.3077576	7.67	0.000	1.74127	2.977569
hsgrad	2.255552	.1169816	19.28	0.000	2.020587	2.490516
assocgrad	2.801968	.1255785	22.31	0.000	2.549736	3.0542
bachgrad	4.476934	.1270857	35.23	0.000	4.221675	4.732193
mastgrad	5.377219	.1662491	32.34	0.000	5.043298	5.711141
doctorgrad	8.625798	.2493134	34.60	0.000	8.125037	9.126559
migranthsg~d	-1.683389	.1357914	-12.40	0.000	-1.956134	-1.410644
migrantass~d	-1.815692	.1996589	-9.09	0.000	-2.216719	-1.414665
migrantbac~d	-2.144504	.2054073	-10.44	0.000	-2.557077	-1.731932
migrantmas~d	-2.152667	.2584135	-8.33	0.000	-2.671706	-1.633629
migrantdoc~d	-1.553607	.2499525	-6.22	0.000	-2.055652	-1.051563
exp	.5743636	.0102086	56.26	0.000	.553859	.5948681
migrantexp	-.2200707	.0140629	-15.65	0.000	-.2483169	-.1918244
exp_sq	-.0111138	.0001891	-58.76	0.000	-.0114937	-.0107339
migrantexp~q	.0048053	.0002636	18.23	0.000	.004276	.0053347
female	-4.825184	.111583	-43.24	0.000	-5.049305	-4.601063
migrantfem~e	.8156561	.1111344	7.34	0.000	.5924362	1.038876
1.migrant	0	(omitted)				
wbhao						
Black	.0074528	.0781004	0.10	0.924	-.1494164	.164322
Hispanic	.0749193	.2321022	0.32	0.748	-.3912716	.5411102
Asian	-.3867086	.2741276	-1.41	0.165	-.93731	.1638928
Other	.2465946	.1543645	1.60	0.116	-.0634557	.5566449
migrant# wbhao						
1#Black	-.3411902	.1459707	-2.34	0.023	-.6343809	-.0479995
1#Hispanic	-.3423502	.1804912	-1.90	0.064	-.7048775	.0201771
1#Asian	-.3547877	.2857867	-1.24	0.220	-.9288072	.2192318

```
    1#Other  |  -.7116983   .4261219    -1.67   0.101    -1.567589    .1441928
             |
years_sinc~l |  -.0127628   .0128388    -0.99   0.325    -.0385503    .0130248
       rural |   .2213677   .0893384     2.48   0.017     .0419263    .4008091
migrantrural |   .7700176   .2694797     2.86   0.006     .2287517    1.311284
             |
        year |
       1999  |   .1033997   .0656495     1.58   0.122    -.0284611    .2352605
       2000  |   .1188732   .0899507     1.32   0.192    -.0617981    .2995444
       2001  |   .0631772   .0963259     0.66   0.515    -.1302992    .2566535
       2002  |   -.133922   .0760851    -1.76   0.084    -.2867435    .0188995
       2003  |  -.2493424   .0800702    -3.11   0.003    -.4101681   -.0885168
       2004  |  -.2682928    .098696    -2.72   0.009    -.4665295   -.0700561
       2005  |  -.1467568   .0869293    -1.69   0.098    -.3213595    .0278459
       2006  |  -.0331936   .1008143    -0.33   0.743     -.235685    .1692978
       2007  |   .0563617   .0819396     0.69   0.495    -.1082188    .2209423
       2008  |   .0391538   .0906761     0.43   0.668    -.1429745     .221282
       2009  |  -.2669298   .0887278    -3.01   0.004    -.4451449   -.0887146
       2010  |  -.6050261   .0907777    -6.66   0.000    -.7873584   -.4226938
       2011  |  -.5993157   .0869501    -6.89   0.000    -.7739601   -.4246713
       2012  |  -.4397406   .0921637    -4.77   0.000    -.6248569   -.2546243
       2013  |  -.3123697   .1119394    -2.79   0.007    -.5372065   -.0875329
       2014  |  -.2961312   .1081341    -2.74   0.009    -.5133248   -.0789375
       2015  |  -.0846125   .0986914    -0.86   0.395      -.28284     .113615
             |
migrant#year |
     1 1999  |   .1033922   .1553162     0.67   0.509    -.2085695    .4153539
     1 2000  |   .2816118   .2231653     1.26   0.213    -.1666289    .7298526
     1 2001  |   .4024856   .1589131     2.53   0.015     .0832993    .7216718
     1 2002  |   .1783276   .1643772     1.08   0.283    -.1518337    .5084888
     1 2003  |   .2508858    .176852     1.42   0.162    -.1043319    .6061036
     1 2004  |   .1624622   .2140191     0.76   0.451    -.2674079    .5923322
     1 2005  |   .1386578    .149218     0.93   0.357    -.1610553    .4383709
     1 2006  |   .5061625   .1951001     2.59   0.012     .1142925    .8980325
     1 2007  |   .2793324   .1653711     1.69   0.097    -.0528252      .61149
     1 2008  |   .2311996   .2124166     1.09   0.282    -.1954517    .6578509
     1 2009  |  -.0527904   .2085181    -0.25   0.801    -.4716112    .3660305
     1 2010  |  -.3292205   .2089518    -1.58   0.121    -.7489126    .0904716
     1 2011  |  -.2329865   .1996126    -1.17   0.249    -.6339202    .1679473
     1 2012  |  -.2424253   .2246617    -1.08   0.286    -.6936717    .2088211
     1 2013  |  -.2398749   .2497031    -0.96   0.341    -.7414183    .2616685
     1 2014  |  -.0907368   .2695089    -0.34   0.738    -.6320613    .4505877
     1 2015  |  -.1081611   .2355249    -0.46   0.648    -.5812268    .3649046
             |
  entry_year |   .0284646   .0137773     2.07   0.044      .000792    .0561372
entry_year~q |  -.0000142   6.88e-06    -2.07   0.043    -.0000281   -4.37e-07
       _cons |   34.07537   .2422885   140.64   0.000     33.58872    34.56202
------------------------------------------------------------------------------
```

Specification (6), Exogenous-wage, Method 3, Full sample

```
Linear regression                               Number of obs     =     62,653
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1737
                                                Root MSE          =     11.172

                                  (Std. Err. adjusted for 51 clusters in state)
```

```
------------------------------------------------------------------------------
             |               Robust
hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   11.44745   1.816711     6.30   0.000      7.79848    15.09642
post911entry |   -.772629   .2015567    -3.83   0.000    -1.177468   -.3677904
post911ent~t |     .70457   .3455153     2.04   0.047     .0105821    1.398558
  yearseduc |   .8210823   .0520276    15.78   0.000     .7165817    .9255829
migrantyea~c |  -.6656548   .0644663   -10.33   0.000    -.7951392   -.5361704
         exp |    .977756   .0235646    41.49   0.000     .9304251    1.025087
  migrantexp |  -.4415277   .0418581   -10.55   0.000    -.5256022   -.3574532
      exp_sq |  -.0188474   .0005359   -35.17   0.000    -.0199237   -.0177711
migrantexp~q |   .0095794   .0006482    14.78   0.000     .0082774    .0108814
      female |  -3.683038   .1812464   -20.32   0.000    -4.047082   -3.318994
migrantfem~e |  -1.758078   .2585425    -6.80   0.000    -2.277376    -1.23878
   1.migrant |          0  (omitted)
             |
       wbhao |
      Black  |   .3258059   .2538036     1.28   0.205    -.1839737    .8355855
   Hispanic  |   1.012348   .4375822     2.31   0.025     .1334382    1.891258
      Asian  |   .6421799   .5642101     1.14   0.260    -.4910694    1.775429
      Other  |   .8051529    .474898     1.70   0.096    -.1487078    1.759014
             |
    migrant#|
       wbhao |
    1#Black  |  -1.537053   .7903366    -1.94   0.057    -3.124491    .0503849
 1#Hispanic  |  -.7253389   .5274838    -1.38   0.175    -1.784821    .3341436
    1#Asian  |  -.3014937   .7767223    -0.39   0.700    -1.861586    1.258599
    1#Other  |  -5.614544   2.230075    -2.52   0.015    -10.09378   -1.135307
             |
years_sinc~l |   .0110558   .0128382     0.86   0.393    -.0147305     .036842
       rural |  -.1943691   .2110191    -0.92   0.361    -.6182133    .2294752
migrantrural |   1.222902   .7919052     1.54   0.129     -.367687     2.81349
             |
        year |
       1999  |   1.079567   .7006768     1.54   0.130    -.3277839    2.486918
       2000  |   .4590154   .6007548     0.76   0.448    -.7476361    1.665667
       2001  |   .7712025    .734735     1.05   0.299    -.7045561    2.246961
       2002  |   .4030595   .5418928     0.74   0.460    -.6853642    1.491483
       2003  |    .643945   .7026643     0.92   0.364    -.7673977    2.055288
       2004  |  -.0992545   .6778686    -0.15   0.884    -1.460794    1.262285
       2005  |  -.0089368   .6804896    -0.01   0.990     -1.37574    1.357867
       2006  |  -.0935896   .6503746    -0.14   0.886    -1.399905    1.212726
       2007  |   .9467491   .7308296     1.30   0.201    -.5211655    2.414664
       2008  |   .6513122   .7056179     0.92   0.360     -.765963    2.068588
       2009  |  -.0005704   .7014078    -0.00   0.999     -1.40939    1.408249
       2010  |  -.7607858   .7786718    -0.98   0.333    -2.324794    .8032225
       2011  |  -.6045848   .6060467    -1.00   0.323    -1.821865    .6126957
       2012  |  -.6240079     .61451    -1.02   0.315    -1.858288    .6102716
       2013  |  -.6818907   .6955127    -0.98   0.332    -2.078869    .7150876
       2014  |  -.3828819    .684087    -0.56   0.578    -1.756911    .9911472
       2015  |  -.3057907   .8262577    -0.37   0.713    -1.965378    1.353797
             |
migrant#year |
     1 1999  |  -.0549493   2.798675    -0.02   0.984    -5.676253    5.566355
     1 2000  |    3.78668   2.247947     1.68   0.098    -.7284549    8.301816
     1 2001  |   2.978788   1.792025     1.66   0.103    -.6206003    6.578176
     1 2002  |   1.631625   1.406508     1.16   0.252     -1.19343     4.45668
     1 2003  |    2.59848   1.186039     2.19   0.033     .2162498     4.98071
     1 2004  |   3.184975   1.186584     2.68   0.010     .8016518    5.568298
```

1 2005	3.705322	1.346064	2.75	0.008	1.001674	6.408971
1 2006	4.231666	1.433148	2.95	0.005	1.353104	7.110229
1 2007	2.77255	1.415799	1.96	0.056	-.0711655	5.616266
1 2008	2.995892	1.412905	2.12	0.039	.1579892	5.833795
1 2009	2.098755	1.181316	1.78	0.082	-.273987	4.471497
1 2010	1.736791	1.385706	1.25	0.216	-1.046482	4.520064
1 2011	1.544497	1.415737	1.09	0.281	-1.299096	4.388089
1 2012	2.68862	1.349285	1.99	0.052	-.0214989	5.398738
1 2013	2.425552	1.195436	2.03	0.048	.0244491	4.826655
1 2014	2.475456	1.351518	1.83	0.073	-.2391479	5.19006
1 2015	2.611473	1.488576	1.75	0.085	-.3784206	5.601366
_cons	18.72474	1.165606	16.06	0.000	16.38355	21.06593

Specification (6), Exogenous-wage, Method 3, Full sample

Linear regression

Number of obs	=	1,365,655
F(49, 50)	=	.
Prob > F	=	.
R-squared	=	0.1276
Root MSE	=	9.8196

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	3.652408	.3936158	9.28	0.000	2.861807	4.443009
post911entry	-.8022525	.0720005	-11.14	0.000	-.9468698	-.6576352
post911ent~t	.3839084	.148437	2.59	0.013	.0857639	.6820529
leisure	-2.213906	.1036496	-21.36	0.000	-2.422092	-2.005719
leisure_mi~t	1.887405	.2037027	9.27	0.000	1.478256	2.296554
leisure_~911	-2.355563	.1612213	-14.61	0.000	-2.679385	-2.031741
leisure_po~t	1.952085	.3096737	6.30	0.000	1.330087	2.574083
hsgrad	2.256479	.1169144	19.30	0.000	2.02165	2.491309
assocgrad	2.80289	.1254224	22.35	0.000	2.550972	3.054809
bachgrad	4.477621	.1270304	35.25	0.000	4.222473	4.732769
mastgrad	5.3779	.1662744	32.34	0.000	5.043928	5.711872
doctorgrad	8.626345	.2490952	34.63	0.000	8.126023	9.126667
migranthsg~d	-1.640485	.135638	-12.09	0.000	-1.912922	-1.368048
migrantass~d	-1.927097	.2096096	-9.19	0.000	-2.34811	-1.506084
migrantbac~d	-2.360185	.2268371	-10.40	0.000	-2.815801	-1.90457
migrantmas~d	-2.451137	.2549878	-9.61	0.000	-2.963295	-1.938979
migrantdoc~d	-2.055328	.2559937	-8.03	0.000	-2.569506	-1.541149
exp	.5743196	.010202	56.29	0.000	.5538283	.5948109
migrantexp	-.2821918	.0171568	-16.45	0.000	-.3166522	-.2477314
exp_sq	-.0111126	.000189	-58.79	0.000	-.0114923	-.0107329
migrantexp~q	.0058593	.000305	19.21	0.000	.0052467	.0064719
female	-4.825135	.1115858	-43.24	0.000	-5.049262	-4.601008
migrantfem~e	.7569895	.1155444	6.55	0.000	.5249117	.9890674
1.migrant	0	(omitted)				
wbhao						
Black	.0073008	.078099	0.09	0.926	-.1495657	.1641672
Hispanic	.063083	.2287846	0.28	0.784	-.3964444	.5226104
Asian	-.4080816	.2743441	-1.49	0.143	-.9591178	.1429547

```
       Other  |   .2468666   .1543166     1.60   0.116    -.0630875    .5568206
              |
     migrant#|
       wbhao |
    1#Black  |  -.4446222   .1333774    -3.33   0.002    -.7125187   -.1767257
 1#Hispanic  |  -.5380641   .1642244    -3.28   0.002    -.8679185   -.2082098
    1#Asian  |  -.3539239   .2537835    -1.39   0.169     -.863663    .1558152
    1#Other  |  -.7325783   .4558199    -1.61   0.114    -1.648119    .1829629
              |
years_sinc~l |   .0113414   .0024228     4.68   0.000      .006475    .0162078
       rural |   .2218942   .0893401     2.48   0.016     .0424494     .401339
migrantrural |   .7701934     .28033     2.75   0.008     .2071341    1.333253
              |
        year |
       1999  |   .1029946    .065638     1.57   0.123    -.0288433    .2348325
       2000  |   .1179856   .0898538     1.31   0.195    -.0624911    .2984622
       2001  |   .0618385   .0960403     0.64   0.523    -.1310641     .254741
       2002  |  -.1356018   .0759489    -1.79   0.080    -.2881497    .0169461
       2003  |  -.2513388   .0798949    -3.15   0.003    -.4118124   -.0908651
       2004  |  -.2708419   .0984899    -2.75   0.008    -.4686647   -.0730191
       2005  |  -.1497014   .0866165    -1.73   0.090    -.3236757    .0242729
       2006  |  -.0366093    .100571    -0.36   0.717    -.2386122    .1653936
       2007  |   .0525472   .0816325     0.64   0.523    -.1114165    .2165109
       2008  |     .03478   .0902798     0.39   0.702    -.1465522    .2161122
       2009  |  -.2716584   .0881129    -3.08   0.003    -.4486384   -.0946784
       2010  |  -.6101625   .0908401    -6.72   0.000    -.7926202   -.4277049
       2011  |  -.6048787    .086531    -6.99   0.000    -.7786814   -.4310761
       2012  |  -.4457069   .0914424    -4.87   0.000    -.6293743   -.2620395
       2013  |  -.3189152   .1116134    -2.86   0.006    -.5430974    -.094733
       2014  |  -.3028724   .1078069    -2.81   0.007     -.519409   -.0863358
       2015  |  -.0920972   .0978896    -0.94   0.351    -.2887142    .1045199
              |
migrant#year |
     1 1999  |   .0760412   .1577078     0.48   0.632    -.2407243    .3928067
     1 2000  |   .2344288   .2154625     1.09   0.282    -.1983404    .6671981
     1 2001  |    .328038   .1638325     2.00   0.051    -.0010292    .6571052
     1 2002  |   .1150379   .1628773     0.71   0.483    -.2121108    .4421866
     1 2003  |   .2039101   .1597954     1.28   0.208    -.1170483    .5248686
     1 2004  |   .1497601    .204525     0.73   0.467    -.2610405    .5605607
     1 2005  |   .1489663   .1246851     1.19   0.238     -.101471    .3994037
     1 2006  |   .5069214   .1731513     2.93   0.005     .1591367     .854706
     1 2007  |   .2217597   .1175078     1.89   0.065    -.0142617    .4577811
     1 2008  |   .0915544   .1605649     0.57   0.571    -.2309497    .4140586
     1 2009  |  -.1375192   .1617076    -0.85   0.399    -.4623185    .1872802
     1 2010  |  -.5121142   .1504683    -3.40   0.001    -.8143386   -.2098898
     1 2011  |  -.4197107   .1297995    -3.23   0.002    -.6804207   -.1590007
     1 2012  |  -.4928751   .1452122    -3.39   0.001    -.7845424   -.2012077
     1 2013  |  -.5193974   .1721873    -3.02   0.004    -.8652458   -.1735489
     1 2014  |  -.3206247   .1738797    -1.84   0.071    -.6698723    .0286229
     1 2015  |  -.3142494   .1464425    -2.15   0.037    -.6083877    -.020111
              |
       _cons |   34.07732   .2419996   140.82   0.000     33.59125    34.56339
------------------------------------------------------------------------------
```

Specification (1), Exogenous-wage, Method 4, Restricted sample

```
Linear regression                               Number of obs     =     64,196
```

```
                                                F(3, 50)          =     404.51
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0807
                                                Root MSE          =     10.894

                                   (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   4.247376   .3540353    12.00   0.000     3.536275    4.958477
post911entry |  -4.914008   .1416533   -34.69   0.000    -5.198527   -4.629489
post911ent~t |   4.122721   .2959227    13.93   0.000     3.528342    4.717099
       _cons |   33.38632   .2662895   125.38   0.000     32.85146    33.92118
------------------------------------------------------------------------------
```

Specification (1), Exogenous-wage, Method 4, Full sample

```
Linear regression                               Number of obs     =  1,376,334
                                                F(7, 50)          =     547.41
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0404
                                                Root MSE          =     10.307

                                   (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |  -.6797175   .1454907    -4.67   0.000    -.9719441    -.387491
post911entry |  -4.472576   .1411621   -31.68   0.000    -4.756109   -4.189044
post911ent~t |   3.548343   .1842652    19.26   0.000     3.178235     3.91845
  minwageocc |  -7.310098    .194428   -37.60   0.000    -7.700618   -6.919578
mi~c_migrant |   4.927093   .2736965    18.00   0.000     4.377358    5.476829
minwageo~911 |  -.4414321   .1926983    -2.29   0.026    -.8284781   -.0543862
mi~1_migrant |   .5743778   .2861779     2.01   0.050    -.0004275    1.149183
       _cons |   40.69642   .1159498   350.98   0.000     40.46352    40.92931
------------------------------------------------------------------------------
```

Specification (2), Exogenous-wage, Method 3, Restricted sample

```
Linear regression                               Number of obs     =     64,196
                                                F(13, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1496
                                                Root MSE          =     10.478

                                   (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   2.399453   .2561524     9.37   0.000     1.884956     2.91395
post911entry |  -.4086644   .2056494    -1.99   0.052    -.8217234    .0043946
post911ent~t |   .5553151   .2977153     1.87   0.068    -.0426638    1.153294
   yearseduc |   .1451696   .0403334     3.60   0.001     .0641575    .2261816
```

exp	.6825121	.0198991	34.30	0.000	.6425436	.7224807
exp_sq	-.0121309	.0004364	-27.80	0.000	-.0130074	-.0112544
female	-3.805144	.1811025	-21.01	0.000	-4.168899	-3.441389
white	-1.953474	.4959647	-3.94	0.000	-2.949648	-.9572994
black	-.4365744	.5203348	-0.84	0.405	-1.481698	.6085487
asian	-1.300202	.5179911	-2.51	0.015	-2.340618	-.2597861
hispanic	-.1331107	.5150717	-0.26	0.797	-1.167663	.9014414
years_sinc~l	-.016872	.0119273	-1.41	0.163	-.0408287	.0070847
rural	.2143976	.2434419	0.88	0.383	-.2745699	.7033652
year	8.635006	11.01258	0.78	0.437	-13.48441	30.75443
year_sq	-.0021754	.0027436	-0.79	0.432	-.0076861	.0033352
_cons	-8538.869	11050.24	-0.77	0.443	-30733.93	13656.2

Specification (2), Exogenous-wage, Method 4, Full sample

Linear regression

Number of obs	=	1,376,334
F(18, 50)	=	.
Prob > F	=	.
R-squared	=	0.1235
Root MSE	=	9.8508

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	-.1406812	.0958312	-1.47	0.148	-.3331639	.0518014
post911entry	-.984194	.0740622	-13.29	0.000	-1.132952	-.8354357
post911ent~t	.5233431	.1355848	3.86	0.000	.2510131	.795673
minwageocc	-4.972071	.1602544	-31.03	0.000	-5.293951	-4.65019
mi~c_migrant	3.758157	.212333	17.70	0.000	3.331674	4.184641
minwageo~911	-1.339231	.1910179	-7.01	0.000	-1.722902	-.9555604
mi~1_migrant	1.460918	.3035267	4.81	0.000	.8512671	2.07057
yearseduc	.4674446	.0245671	19.03	0.000	.4181002	.5167891
exp	.5368948	.0096452	55.66	0.000	.5175219	.5562677
exp_sq	-.0101569	.000176	-57.72	0.000	-.0105103	-.0098035
female	-4.6834	.1137363	-41.18	0.000	-4.911846	-4.454954
white	-.0731224	.1650991	-0.44	0.660	-.4047337	.258489
black	-.2436008	.1637905	-1.49	0.143	-.5725837	.085382
asian	-.7063945	.1916075	-3.69	0.001	-1.09125	-.3215395
hispanic	.0186205	.2177291	0.09	0.932	-.4187012	.4559422
years_sinc~l	.0057231	.0024883	2.30	0.026	.0007252	.010721
rural	.184591	.0768167	2.40	0.020	.0303001	.3388818
year	-6.511943	3.644089	-1.79	0.080	-13.83131	.8074246
year_sq	.0016145	.0009084	1.78	0.082	-.0002102	.0034391
_cons	6597.034	3654.198	1.81	0.077	-742.6378	13936.71

Specification (3), Exogenous-wage, Method 4, Restricted sample

Linear regression

Number of obs	=	64,196
F(30, 50)	=	419.73
Prob > F	=	0.0000
R-squared	=	0.1508

Root MSE	=	10.472

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	2.391685	.2551513	9.37	0.000	1.879198	2.904171
post911entry	-.3692561	.2041001	-1.81	0.076	-.7792032	.0406909
post911ent~t	.5966726	.3003226	1.99	0.052	-.0065431	1.199888
yearseduc	.1455787	.0407859	3.57	0.001	.0636578	.2274995
exp	.6851069	.0197695	34.65	0.000	.6453987	.7248151
exp_sq	-.0121783	.0004311	-28.25	0.000	-.0130442	-.0113125
female	-3.812825	.1801241	-21.17	0.000	-4.174615	-3.451035
white	-1.948617	.4981963	-3.91	0.000	-2.949274	-.9479608
black	-.4362525	.5205042	-0.84	0.406	-1.481716	.609211
asian	-1.312366	.5207968	-2.52	0.015	-2.358417	-.2663146
hispanic	-.1349842	.5170442	-0.26	0.795	-1.173498	.9035297
years_sinc~l	-.0160844	.0119442	-1.35	0.184	-.040075	.0079061
rural	.2204281	.2412763	0.91	0.365	-.2641897	.7050458
year						
1999	1.24333	.3735076	3.33	0.002	.4931177	1.993542
2000	.6606377	.3468727	1.90	0.063	-.0360766	1.357352
2001	.3503258	.4100452	0.85	0.397	-.4732742	1.173926
2002	.562699	.2784338	2.02	0.049	.0034482	1.12195
2003	.6725327	.3809548	1.77	0.084	-.0926375	1.437703
2004	-.1055515	.5037213	-0.21	0.835	-1.117305	.9062024
2005	.0006126	.411401	0.00	0.999	-.8257106	.8269359
2006	.2656704	.4052497	0.66	0.515	-.5482975	1.079638
2007	.5278605	.5004226	1.05	0.297	-.4772678	1.532989
2008	.4221285	.3098757	1.36	0.179	-.2002751	1.044532
2009	-.3526382	.3495172	-1.01	0.318	-1.054664	.3493878
2010	-1.085239	.3109932	-3.49	0.001	-1.709887	-.4605904
2011	-.7032756	.4561117	-1.54	0.129	-1.619403	.2128518
2012	-.7142751	.4502896	-1.59	0.119	-1.618708	.1901582
2013	-.9565792	.4759946	-2.01	0.050	-1.912642	-.000516
2014	-.5464082	.508199	-1.08	0.287	-1.567156	.4743396
2015	-.5704444	.367927	-1.55	0.127	-1.309447	.1685587
_cons	28.74449	.6045443	47.55	0.000	27.53022	29.95875

Specification (3), Exogenous-wage, Method 4, Full sample

Linear regression

Number of obs	=	1,376,334
F(38, 50)	=	6416.71
Prob > F	=	0.0000
R-squared	=	0.1307
Root MSE	=	9.8101

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]

```
     migrant |  -.5259224   .0944406    -5.57   0.000    -.7156119   -.3362328
post911entry |  -1.025535   .0776392   -13.21   0.000    -1.181478   -.8695922
post911ent~t |   .5284214   .1376924     3.84   0.000      .251858    .8049848
  minwageocc |  -4.812726   .1469743   -32.75   0.000    -5.107933    -4.51752
mi~c_migrant |   3.580441   .2030951    17.63   0.000     3.172513     3.98837
minwageo~911 |  -1.184114   .1840962    -6.43   0.000    -1.553882   -.8143459
mi~1_migrant |   1.387538   .3034295     4.57   0.000     .7780815    1.996994
      hsgrad |   1.542772   .1793213     8.60   0.000     1.182595    1.902949
   assocgrad |   2.032124   .1742783    11.66   0.000     1.682075    2.382172
    bachgrad |   3.635801   .1401397    25.94   0.000     3.354322     3.91728
    mastgrad |   4.527215   .1667131    27.16   0.000     4.192361    4.862068
  doctorgrad |   7.886511   .2805776    28.11   0.000     7.322954    8.450067
         exp |   .5240654   .0090362    58.00   0.000     .5059156    .5422152
      exp_sq |  -.0100012   .0001613   -62.02   0.000    -.0103251   -.0096773
      female |  -4.645691   .1127891   -41.19   0.000    -4.872234   -4.419147
       white |  -.2129486   .1572273    -1.35   0.182    -.5287488    .1028517
       black |  -.2358927    .159019    -1.48   0.144    -.5552918    .0835065
       asian |  -.8624845   .1846292    -4.67   0.000    -1.233323   -.4916459
    hispanic |  -.1068836   .2219096    -0.48   0.632    -.5526021    .3388349
years_sinc~l |   .0084539   .0023094     3.66   0.001     .0038154    .0130925
       rural |    .256346   .0841935     3.04   0.004     .0872384    .4254535
             |
        year |
       1999  |   .1146544   .0588889     1.95   0.057    -.0036275    .2329362
       2000  |   .1502555   .0860128     1.75   0.087    -.0225064    .3230173
       2001  |    .104639   .0917238     1.14   0.259    -.0795937    .2888717
       2002  |  -.1123466   .0659297    -1.70   0.095    -.2447704    .0200771
       2003  |  -.2654961   .0788268    -3.37   0.001    -.4238244   -.1071679
       2004  |  -.3085705   .0977119    -3.16   0.003    -.5048306   -.1123104
       2005  |  -.1889507   .0817351    -2.31   0.025    -.3531204    -.024781
       2006  |  -.0218241   .0911478    -0.24   0.812    -.2048998    .1612516
       2007  |   .0292001   .0797345     0.37   0.716    -.1309513    .1893516
       2008  |   .0038023   .0807593     0.05   0.963    -.1584077    .1660122
       2009  |  -.3443027   .0779088    -4.42   0.000    -.5007872   -.1878182
       2010  |  -.7251514   .0808009    -8.97   0.000    -.8874449    -.562858
       2011  |  -.7005324   .0812499    -8.62   0.000    -.8637276   -.5373371
       2012  |  -.5470797   .0832638    -6.57   0.000      -.71432   -.3798395
       2013  |  -.4240628   .0971474    -4.37   0.000    -.6191892   -.2289365
       2014  |  -.3922484     .09828    -3.99   0.000    -.5896495   -.1948473
       2015  |  -.1916721     .09083    -2.11   0.040    -.3741095   -.0092347
             |
       _cons |   35.45082   .2094797   169.23   0.000     35.03007    35.87158
------------------------------------------------------------------------------
```

<u>Specification (4), Exogenous-wage, Method 4, Restricted sample</u>

```
Linear regression                               Number of obs     =     64,196
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1553
                                                Root MSE          =     10.447

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

migrant	8.841862	1.224917	7.22	0.000	6.381543	11.30218
post911entry	-.4750767	.1990152	-2.39	0.021	-.8748105	-.0753429
post911ent~t	1.106343	.2545832	4.35	0.000	.5949979	1.617689
yearseduc	.332296	.0479016	6.94	0.000	.2360829	.4285092
migrantyea~c	-.2842578	.0505598	-5.62	0.000	-.3858101	-.1827054
exp	.7312294	.0242015	30.21	0.000	.6826193	.7798395
migrantexp	-.1873292	.0333192	-5.62	0.000	-.2542528	-.1204057
exp_sq	-.0134495	.0005197	-25.88	0.000	-.0144933	-.0124056
migrantexp~q	.004448	.0006227	7.14	0.000	.0031974	.0056987
female	-3.250832	.1747126	-18.61	0.000	-3.601752	-2.899911
migrantfem~e	-2.022256	.3165321	-6.39	0.000	-2.658029	-1.386482
1.migrant	0	(omitted)				
wbhao						
Black	1.832073	.2076253	8.82	0.000	1.415045	2.249101
Hispanic	1.628019	.419551	3.88	0.000	.7853259	2.470712
Asian	1.453484	.4350376	3.34	0.002	.5796848	2.327282
Other	2.041989	.502291	4.07	0.000	1.033107	3.05087
migrant# wbhao						
1#Black	-2.488926	.5425977	-4.59	0.000	-3.578765	-1.399086
1#Hispanic	-.3043046	.5399011	-0.56	0.576	-1.388728	.7801186
1#Asian	-1.53975	.4763227	-3.23	0.002	-2.496472	-.5830276
1#Other	-1.874119	3.558208	-0.53	0.601	-9.020991	5.272752
years_sinc~l	-.0076099	.0116604	-0.65	0.517	-.0310304	.0158107
rural	.2535537	.2251917	1.13	0.266	-.1987572	.7058646
migrantrural	.1160609	.7235855	0.16	0.873	-1.337303	1.569425
year						
1999	1.208424	.3466747	3.49	0.001	.5121068	1.90474
2000	.6532505	.4244486	1.54	0.130	-.1992797	1.505781
2001	.2659428	.3978863	0.67	0.507	-.5332355	1.065121
2002	.368233	.3278674	1.12	0.267	-.290308	1.026774
2003	.7878705	.3993319	1.97	0.054	-.0142112	1.589952
2004	-.0530737	.4638484	-0.11	0.909	-.9847406	.8785932
2005	.0692497	.3617447	0.19	0.849	-.6573359	.7958353
2006	.1073638	.3716194	0.29	0.774	-.6390558	.8537834
2007	.7853851	.47646	1.65	0.106	-.171613	1.742383
2008	.4470695	.3600047	1.24	0.220	-.2760211	1.17016
2009	-.0584565	.394305	-0.15	0.883	-.8504414	.7335284
2010	-.8120548	.331514	-2.45	0.018	-1.47792	-.1461894
2011	-.2562105	.4502002	-0.57	0.572	-1.160464	.6480433
2012	-.5339362	.4177642	-1.28	0.207	-1.37304	.3051679
2013	-.6756466	.4951483	-1.36	0.179	-1.670181	.318888
2014	-.3134357	.5337002	-0.59	0.560	-1.385404	.7585327
2015	-.4373678	.39886	-1.10	0.278	-1.238502	.363766
migrant#year						
1 1999	.0865629	1.019349	0.08	0.933	-1.96086	2.133986
1 2000	.1633295	1.023288	0.16	0.874	-1.892004	2.218663
1 2001	.2961221	.8608088	0.34	0.732	-1.432863	2.025107
1 2002	.6273215	.6742987	0.93	0.357	-.7270473	1.98169
1 2003	-.538441	.7369068	-0.73	0.468	-2.018562	.9416799
1 2004	-.2278788	.9003803	-0.25	0.801	-2.036346	1.580588
1 2005	-.2179954	.8498917	-0.26	0.799	-1.925053	1.489062
1 2006	.484028	.8930286	0.54	0.590	-1.309673	2.277729
1 2007	-.9620025	.8822958	-1.09	0.281	-2.734146	.8101407
1 2008	.007869	.891591	0.01	0.993	-1.782944	1.798682

1 2009	-1.254497	.9231001	-1.36	0.180	-3.108598	.5996039
1 2010	-1.100169	.7738855	-1.42	0.161	-2.654564	.4542255
1 2011	-1.879795	.7725753	-2.43	0.019	-3.431558	-.328032
1 2012	-.7717194	.7999044	-0.96	0.339	-2.378375	.8349357
1 2013	-1.179286	1.10029	-1.07	0.289	-3.389284	1.030711
1 2014	-1.05681	.973485	-1.09	0.283	-3.012112	.8984919
1 2015	-.5204231	.9459401	-0.55	0.585	-2.4204	1.379554
_cons	23.77837	.710656	33.46	0.000	22.35097	25.20576

Specification (4), Exogenous-wage, Method 4, Full sample

Linear regression

Number of obs	=	1,376,334
F(49, 50)	=	.
Prob > F	=	.
R-squared	=	0.1265
Root MSE	=	9.8336

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	5.881667	.6247363	9.41	0.000	4.626848	7.136487
post911entry	-.9621964	.0749324	-12.84	0.000	-1.112702	-.8116904
post911ent~t	.8090078	.1511854	5.35	0.000	.5053429	1.112673
minwageocc	-4.748234	.1420416	-33.43	0.000	-5.033533	-4.462935
mi~c_migrant	3.085006	.1980449	15.58	0.000	2.687221	3.482791
minwageo~911	-1.367317	.1878435	-7.28	0.000	-1.744612	-.9900225
mi~1_migrant	1.54267	.2977726	5.18	0.000	.9445761	2.140764
yearseduc	.5771716	.0167089	34.54	0.000	.5436109	.6107324
migrantyea~c	-.3204715	.0298948	-10.72	0.000	-.380517	-.260426
exp	.5729366	.0103967	55.11	0.000	.5520543	.5938189
migrantexp	-.215799	.0140719	-15.34	0.000	-.2440633	-.1875347
exp_sq	-.0110508	.0001933	-57.16	0.000	-.0114391	-.0106625
migrantexp~q	.0049062	.0002745	17.87	0.000	.0043548	.0054576
female	-4.786227	.1081558	-44.25	0.000	-5.003464	-4.56899
migrantfem~e	.6800004	.0990066	6.87	0.000	.4811398	.8788609
1.migrant	0	(omitted)				
wbhao						
Black	-.0589069	.0764763	-0.77	0.445	-.2125142	.0947003
Hispanic	-.0082041	.2450629	-0.03	0.973	-.5004274	.4840192
Asian	-.3063369	.2925082	-1.05	0.300	-.8938569	.2811831
Other	.1501478	.158485	0.95	0.348	-.1681788	.4684744
migrant# wbhao						
1#Black	-.5898383	.1451295	-4.06	0.000	-.8813395	-.298337
1#Hispanic	-.4367235	.164167	-2.66	0.010	-.7664626	-.1069845
1#Asian	-.3310817	.2730824	-1.21	0.231	-.8795837	.2174204
1#Other	-.798765	.4315591	-1.85	0.070	-1.665577	.068047
years_sinc~l	.0078308	.0022982	3.41	0.001	.0032147	.0124469
rural	.2265363	.0882389	2.57	0.013	.0493032	.4037694

```
migrantrural |   .8035325   .2689117     2.99   0.004     .2634075    1.343658
             |
        year |
       1999  |   .1031002   .0658538     1.57   0.124     -.029171    .2353713
       2000  |   .1213639   .0890862     1.36   0.179     -.057571    .3002987
       2001  |   .0569618   .0983424     0.58   0.565    -.1405647    .2544883
       2002  |   -.128975   .0767672    -1.68   0.099    -.2831665    .0252166
       2003  |  -.2934139   .0837031    -3.51   0.001    -.4615366   -.1252912
       2004  |  -.3144579   .1040231    -3.02   0.004    -.5233945   -.1055213
       2005  |  -.1862745   .0902827    -2.06   0.044    -.3676127   -.0049363
       2006  |  -.0783741   .1062855    -0.74   0.464    -.2918548    .1351066
       2007  |    .019505   .0875034     0.22   0.825    -.1562507    .1952607
       2008  |  -.0038448   .0952499    -0.04   0.968    -.1951598    .1874703
       2009  |  -.2975625   .0906025    -3.28   0.002     -.479543    -.115582
       2010  |  -.6262274   .0962829    -6.50   0.000    -.8196173   -.4328376
       2011  |   -.620595   .0917396    -6.76   0.000    -.8048594   -.4363307
       2012  |  -.4580801   .0943114    -4.86   0.000    -.6475102     -.26865
       2013  |  -.3334004   .1123036    -2.97   0.005    -.5589689    -.107832
       2014  |  -.3123809   .1080275    -2.89   0.006    -.5293606   -.0954012
       2015  |  -.1079854   .1000702    -1.08   0.286    -.3089823    .0930115
             |
migrant#year |
     1 1999  |   .0547118   .1638977     0.33   0.740    -.2744864    .3839101
     1 2000  |   .1803144   .2093944     0.86   0.393    -.2402666    .6008955
     1 2001  |   .3028908   .1634299     1.85   0.070    -.0253678    .6311494
     1 2002  |   .0409915   .1745163     0.23   0.815    -.3095348    .3915179
     1 2003  |   .0967179   .1751743     0.55   0.583      -.25513    .4485657
     1 2004  |  -.0252569    .206866    -0.12   0.903    -.4407594    .3902456
     1 2005  |  -.0905316   .1230036    -0.74   0.465    -.3375916    .1565284
     1 2006  |   .2791184   .1819807     1.53   0.131    -.0864007    .6446374
     1 2007  |  -.0139707   .1212507    -0.12   0.909    -.2575099    .2295685
     1 2008  |   -.072598   .1794016    -0.40   0.687    -.4329368    .2877408
     1 2009  |  -.3837045   .1688196    -2.27   0.027    -.7227887   -.0446203
     1 2010  |  -.7112766   .1574279    -4.52   0.000     -1.02748   -.3950733
     1 2011  |  -.6682303   .1415264    -4.72   0.000    -.9524945   -.3839662
     1 2012  |  -.6789879   .1583288    -4.29   0.000    -.9970007   -.3609751
     1 2013  |  -.6952195   .1585548    -4.38   0.000    -1.013686   -.3767529
     1 2014  |   -.558577   .1767366    -3.16   0.003     -.913563    -.203591
     1 2015  |  -.5857108   .1401723    -4.18   0.000    -.8672551   -.3041666
             |
       _cons |   29.12193   .3913043    74.42   0.000     28.33597    29.90789
------------------------------------------------------------------------------
```

Specification (5), Exogenous-wage, Method 4, Restricted sample

```
Linear regression                               Number of obs     =     64,196
                                                F(50, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1559
                                                Root MSE          =     10.443

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
```

migrant	4.862485	1.559428	3.12	0.003	1.730282	7.994687
post911entry	-.4744543	.2005402	-2.37	0.022	-.8772511	-.0716575
post911ent~t	.7058834	.3064498	2.30	0.025	.0903609	1.321406
yearseduc	.3369072	.0471066	7.15	0.000	.2422907	.4315236
migrantyea~c	-.2741854	.0500017	-5.48	0.000	-.3746168	-.173754
exp	.7299332	.0239431	30.49	0.000	.681842	.7780244
migrantexp	-.1800334	.0327354	-5.50	0.000	-.2457844	-.1142824
exp_sq	-.0134231	.000517	-25.96	0.000	-.0144615	-.0123846
migrantexp~q	.0045431	.0006266	7.25	0.000	.0032845	.0058018
female	-3.24429	.1737794	-18.67	0.000	-3.593336	-2.895244
migrantfem~e	-2.01355	.3164998	-6.36	0.000	-2.649258	-1.377841
1.migrant	0	(omitted)				
wbhao						
Black	1.844561	.2073559	8.90	0.000	1.428075	2.261048
Hispanic	1.476984	.4229279	3.49	0.001	.6275079	2.326459
Asian	1.183747	.4640591	2.55	0.014	.2516569	2.115837
Other	2.050734	.5008465	4.09	0.000	1.044754	3.056714
migrant# wbhao						
1#Black	-2.611444	.5447466	-4.79	0.000	-3.7056	-1.517289
1#Hispanic	-.233866	.5213936	-0.45	0.656	-1.281116	.813384
1#Asian	-1.373423	.4800335	-2.86	0.006	-2.337598	-.4092469
1#Other	-1.916329	3.556494	-0.54	0.592	-9.059757	5.227099
years_sinc~l	-.2400588	.0638536	-3.76	0.000	-.3683125	-.1118051
rural	.265205	.2243661	1.18	0.243	-.1854476	.7158576
migrantrural	.131895	.7165647	0.18	0.855	-1.307368	1.571158
year						
1999	1.219461	.3456489	3.53	0.001	.5252043	1.913717
2000	.6636043	.4265697	1.56	0.126	-.1931861	1.520395
2001	.2620931	.3986166	0.66	0.514	-.5385519	1.062738
2002	.3877759	.3283617	1.18	0.243	-.271758	1.04731
2003	.8196097	.4006928	2.05	0.046	.0147946	1.624425
2004	-.023011	.4673798	-0.05	0.961	-.9617711	.915749
2005	.1064226	.3605945	0.30	0.769	-.6178527	.8306978
2006	.1425196	.3714747	0.38	0.703	-.6036094	.8886485
2007	.8349755	.4765047	1.75	0.086	-.1221124	1.792063
2008	.5052864	.3609594	1.40	0.168	-.219722	1.230295
2009	-.0094584	.3997338	-0.02	0.981	-.8123475	.7934306
2010	-.7509128	.328823	-2.28	0.027	-1.411373	-.0904525
2011	-.1903871	.4463836	-0.43	0.672	-1.086975	.7062007
2012	-.4587554	.4190898	-1.09	0.279	-1.300522	.3830112
2013	-.5941699	.493381	-1.20	0.234	-1.585155	.396815
2014	-.2283631	.5353873	-0.43	0.672	-1.30372	.8469939
2015	-.3468096	.3923835	-0.88	0.381	-1.134935	.4413159
migrant#year						
1 1999	.2986504	1.027536	0.29	0.773	-1.765217	2.362518
1 2000	.5524168	1.019351	0.54	0.590	-1.49501	2.599843
1 2001	.8724095	.9015698	0.97	0.338	-.9384467	2.683266
1 2002	1.366114	.7839287	1.74	0.088	-.2084535	2.940681
1 2003	.3629974	.8153792	0.45	0.658	-1.27474	2.000735
1 2004	.9244086	1.039899	0.89	0.378	-1.164291	3.013108
1 2005	1.144443	1.063278	1.08	0.287	-.9912129	3.280099
1 2006	2.107812	1.073745	1.96	0.055	-.0488687	4.264493
1 2007	.8720363	1.018633	0.86	0.396	-1.173949	2.918021
1 2008	2.023594	1.110669	1.82	0.074	-.2072509	4.254439

1 2009	1.006003	1.141452	0.88	0.382	-1.286672	3.298677
1 2010	1.358222	1.14623	1.18	0.242	-.9440497	3.660493
1 2011	.7970806	1.204689	0.66	0.511	-1.622608	3.21677
1 2012	2.106687	1.183911	1.78	0.081	-.2712673	4.484642
1 2013	1.928979	1.388375	1.39	0.171	-.8596535	4.717612
1 2014	2.298888	1.338393	1.72	0.092	-.3893536	4.987129
1 2015	3.015695	1.436925	2.10	0.041	.1295466	5.901843
entry_year	.2023859	.0696911	2.90	0.005	.0624072	.3423646
entry_year~q	-.0001002	.0000348	-2.88	0.006	-.0001701	-.0000304
_cons	23.65937	.7066628	33.48	0.000	22.24	25.07875

Specification (5), Exogenous-wage, Method 4, Full sample

Linear regression

Number of obs	=	1,376,334
F(50, 50)	=	.
Prob > F	=	.
R-squared	=	0.1322
Root MSE	=	9.8017

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	2.391434	.3867005	6.18	0.000	1.614723	3.168144
post911entry	-.9539205	.0727689	-13.11	0.000	-1.100081	-.8077599
post911ent~t	.7674041	.1510726	5.08	0.000	.4639659	1.070842
minwageocc	-4.675803	.1385845	-33.74	0.000	-4.954158	-4.397448
mi~c_migrant	3.168528	.1899415	16.68	0.000	2.787019	3.550037
minwageo~911	-1.206426	.1822216	-6.62	0.000	-1.572429	-.8404229
mi~1_migrant	1.439535	.2965005	4.86	0.000	.8439966	2.035074
hsgrad	2.090316	.1151399	18.15	0.000	1.859051	2.321582
assocgrad	2.566192	.1221366	21.01	0.000	2.320873	2.81151
bachgrad	4.208134	.1225875	34.33	0.000	3.96191	4.454358
mastgrad	5.115665	.161594	31.66	0.000	4.791094	5.440236
doctorgrad	8.376244	.2437437	34.36	0.000	7.88667	8.865818
migranthsg~d	-1.550453	.1383832	-11.20	0.000	-1.828403	-1.272502
migrantass~d	-1.658515	.1994963	-8.31	0.000	-2.059215	-1.257815
migrantbac~d	-1.967229	.203149	-9.68	0.000	-2.375266	-1.559192
migrantmas~d	-1.992388	.2608107	-7.64	0.000	-2.516241	-1.468534
migrantdoc~d	-1.406372	.2512323	-5.60	0.000	-1.910987	-.9017576
exp	.5600377	.0100016	55.99	0.000	.5399489	.5801264
migrantexp	-.2066917	.0138307	-14.94	0.000	-.2344714	-.178912
exp_sq	-.0108581	.0001855	-58.54	0.000	-.0112307	-.0104856
migrantexp~q	.0045693	.0002607	17.53	0.000	.0040457	.0050929
female	-4.751456	.1078956	-44.04	0.000	-4.968171	-4.534741
migrantfem~e	.756341	.1038912	7.28	0.000	.5476693	.9650126
1.migrant	0	(omitted)				
wbhao						
Black	.0280889	.0766076	0.37	0.715	-.1257821	.1819598
Hispanic	.0529324	.2365728	0.22	0.824	-.4222379	.5281028
Asian	-.3805477	.2758284	-1.38	0.174	-.9345654	.1734699
Other	.2537584	.1555787	1.63	0.109	-.0587307	.5662475

```
     migrant#|
        wbhao |
     1#Black  |  -.3656561   .1492027    -2.45   0.018    -.6653385   -.0659738
  1#Hispanic  |   -.300016   .1845401    -1.63   0.110    -.6706756    .0706436
     1#Asian  |  -.3466199   .2891075    -1.20   0.236    -.9273093    .2340696
     1#Other  |  -.7439118   .4213459    -1.77   0.084     -1.59021    .1023864
              |
years_sinc~l |  -.0155294    .012921    -1.20   0.235     -.041482    .0104233
        rural |   .2429947   .0895305     2.71   0.009     .0631674    .4228219
migrantrural |   .7360682    .266616     2.76   0.008     .2005543    1.271582
              |
         year |
         1999  |   .1054759   .0661234     1.60   0.117    -.0273368    .2382886
         2000  |   .1249585   .0887666     1.41   0.165    -.0533345    .3032514
         2001  |    .063909   .0968243     0.66   0.512    -.1305684    .2583865
         2002  |  -.1209357   .0749309    -1.61   0.113    -.2714388    .0295675
         2003  |  -.2827658    .080981    -3.49   0.001    -.4454209   -.1201108
         2004  |  -.3122477   .1020414    -3.06   0.004     -.517204   -.1072914
         2005  |  -.1864735   .0883908    -2.11   0.040    -.3640116   -.0089353
         2006  |  -.0728634   .1033891    -0.70   0.484    -.2805265    .1347998
         2007  |    .016719    .084525     0.20   0.844    -.1530543    .1864924
         2008  |   .0005398   .0940167     0.01   0.995    -.1882982    .1893778
         2009  |  -.3024404   .0902761    -3.35   0.002    -.4837654   -.1211155
         2010  |  -.6344415    .093391    -6.79   0.000    -.8220229   -.4468602
         2011  |  -.6247954    .090729    -6.89   0.000    -.8070299   -.4425609
         2012  |  -.4641344   .0931643    -4.98   0.000    -.6512605   -.2770083
         2013  |  -.3386081   .1122681    -3.02   0.004    -.5641053    -.113111
         2014  |  -.3311137   .1076842    -3.07   0.003    -.5474038   -.1148236
         2015  |  -.1260102   .1002593    -1.26   0.215     -.327387    .0753667
              |
migrant#year |
      1 1999  |   .0960171   .1586051     0.61   0.548    -.2225506    .4145847
      1 2000  |   .2635096   .2222047     1.19   0.241    -.1828016    .7098208
      1 2001  |   .3983773   .1606558     2.48   0.017     .0756907    .7210639
      1 2002  |   .1646397   .1699157     0.97   0.337     -.176646    .5059254
      1 2003  |   .2415181   .1753642     1.38   0.175    -.1107113    .5937474
      1 2004  |   .1534792   .2117436     0.72   0.472    -.2718204    .5787787
      1 2005  |   .1306408   .1539514     0.85   0.400    -.1785798    .4398613
      1 2006  |   .5024871   .2056022     2.44   0.018      .089523    .9154512
      1 2007  |   .2730179   .1667896     1.64   0.108    -.0619889    .6080247
      1 2008  |   .2290154   .2163218     1.06   0.295    -.2054798    .6635107
      1 2009  |  -.0557309   .2139386    -0.26   0.796    -.4854392    .3739774
      1 2010  |  -.3278151   .2103866    -1.56   0.126    -.7503891    .0947589
      1 2011  |  -.2379888   .1998705    -1.19   0.239    -.6394404    .1634629
      1 2012  |  -.2374414   .2329033    -1.02   0.313    -.7052415    .2303586
      1 2013  |  -.2425213   .2497181    -0.97   0.336    -.7440949    .2590523
      1 2014  |  -.0820623   .2708009    -0.30   0.763    -.6259819    .4618573
      1 2015  |  -.0926454   .2341776    -0.40   0.694    -.5630051    .3777142
              |
  entry_year |   .0297507   .0138171     2.15   0.036     .0019983    .0575031
entry_year~q |  -.0000149   6.89e-06    -2.16   0.036    -.0000287   -1.02e-06
        _cons |   34.48952   .2334487   147.74   0.000     34.02062    34.95841
------------------------------------------------------------------------------
```

Specification (6), Exogenous-wage, Method 4, Restricted sample

```
Linear regression                               Number of obs     =     63,218
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1561
                                                Root MSE          =     10.449

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |    10.3929   1.219001     8.53   0.000     7.944464    12.84133
post911entry |   -.475024   .1990206    -2.39   0.021    -.8747685   -.0752794
post911ent~t |   .6504929   .2970118     2.19   0.033     .0539272    1.247059
   yearseduc |   .3323184   .0478771     6.94   0.000     .2361544    .4284824
migrantyea~c |  -.3005651   .0511616    -5.87   0.000    -.4033262   -.1978041
         exp |   .7312064   .0241857    30.23   0.000     .6826279    .7797849
  migrantexp |  -.2769418   .0440568    -6.29   0.000    -.3654325    -.188451
      exp_sq |  -.0134494   .0005196   -25.88   0.000    -.0144931   -.0124057
migrantexp~q |   .0058554   .0007625     7.68   0.000     .0043239    .0073869
      female |  -3.250798   .1746993   -18.61   0.000    -3.601692   -2.899904
migrantfem~e |  -2.123101    .339127    -6.26   0.000    -2.804258   -1.441944
   1.migrant |          0  (omitted)
             |
       wbhao |
      Black  |   1.832245   .2074883     8.83   0.000     1.415492    2.248997
   Hispanic  |   1.626344   .4220657     3.85   0.000     .7786001    2.474088
      Asian  |   1.449144   .4388503     3.30   0.002     .5676867      2.3306
      Other  |   2.042065   .5022411     4.07   0.000     1.033284    3.050845
             |
     migrant#|
       wbhao |
    1#Black  |  -2.895791   .5563926    -5.20   0.000    -4.013339   -1.778244
 1#Hispanic  |  -.7572395   .5214268    -1.45   0.153    -1.804556     .290077
    1#Asian  |  -1.653075    .500179    -3.30   0.002    -2.657714   -.6484363
    1#Other  |  -2.043674   3.483547    -0.59   0.560    -9.040584    4.953236
             |
years_sinc~l |  -.0067025   .0107817    -0.62   0.537    -.0283582    .0149532
       rural |   .2536931   .2252585     1.13   0.265     -.198752    .7061382
migrantrural |   .1444765   .7188363     0.20   0.842    -1.299349    1.588302
             |
        year |
       1999  |   1.208476   .3466755     3.49   0.001     .5121578    1.904794
       2000  |   .6532331   .4244529     1.54   0.130    -.1993056    1.505772
       2001  |   .2659075   .3978577     0.67   0.507    -.5332133    1.065028
       2002  |   .3683082   .3279336     1.12   0.267    -.2903659    1.026982
       2003  |   .7879229   .3993761     1.97   0.054    -.0142475    1.590093
       2004  |   -.053123   .4638542    -0.11   0.909    -.9848015    .8785555
       2005  |   .0691943     .36172     0.19   0.849    -.6573417    .7957303
       2006  |   .1072631   .3715482     0.29   0.774    -.6390133    .8535396
       2007  |   .7855215   .4765764     1.65   0.106    -.1717104    1.742753
       2008  |   .4472349   .3599711     1.24   0.220    -.2757884    1.170258
       2009  |  -.0584773   .3943176    -0.15   0.883    -.8504875    .7335328
       2010  |  -.8120425   .3315097    -2.45   0.018    -1.477899   -.1461858
       2011  |  -.2560796   .4503744    -0.57   0.572    -1.160683     .648524
       2012  |  -.5338219   .4179299    -1.28   0.207    -1.373259    .3056151
       2013  |  -.6755335   .4952364    -1.36   0.179    -1.670245    .3191781
       2014  |  -.3132841   .5338253    -0.59   0.560    -1.385504    .7589357
       2015  |  -.4372335   .3988798    -1.10   0.278    -1.238407    .3639401
             |
```

	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant#year						
1 1999	.0972596	1.006906	0.10	0.923	-1.92517	2.119689
1 2000	.1433203	1.002306	0.14	0.887	-1.869871	2.156512
1 2001	.3307253	.8494988	0.39	0.699	-1.375543	2.036994
1 2002	.6848782	.6689405	1.02	0.311	-.6587283	2.028485
1 2003	-.5106533	.7348915	-0.69	0.490	-1.986726	.9654197
1 2004	-.0318106	.9054982	-0.04	0.972	-1.850557	1.786936
1 2005	.0880075	.8453995	0.10	0.918	-1.610027	1.786042
1 2006	.8924254	.8543099	1.04	0.301	-.8235066	2.608357
1 2007	-.6787933	.8776766	-0.77	0.443	-2.441659	1.084072
1 2008	.424374	.9017202	0.47	0.640	-1.386784	2.235532
1 2009	-1.027557	.9723386	-1.06	0.296	-2.980557	.9254426
1 2010	-.8755281	.7836399	-1.12	0.269	-2.449515	.6984589
1 2011	-1.4418	.7633206	-1.89	0.065	-2.974974	.091375
1 2012	-.2711369	.8395574	-0.32	0.748	-1.957438	1.415164
1 2013	-.7336392	1.122637	-0.65	0.516	-2.988522	1.521243
1 2014	-.5686171	.9619132	-0.59	0.557	-2.500677	1.363442
1 2015	-.2013664	.8891241	-0.23	0.822	-1.987225	1.584492
_cons	23.77806	.7105358	33.46	0.000	22.35091	25.20521

Specification (6), Exogenous-wage, Method 4, Full sample

Linear regression

Number of obs	=	1,365,655
F(49, 50)	=	.
Prob > F	=	.
R-squared	=	0.1319
Root MSE	=	9.7955

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	3.396626	.3906225	8.70	0.000	2.612038	4.181215
post911entry	-.9529985	.072756	-13.10	0.000	-1.099133	-.8068638
post911ent~t	.5137671	.1336313	3.84	0.000	.2453608	.7821734
minwageocc	-4.676143	.1384434	-33.78	0.000	-4.954214	-4.398071
mi~c_migrant	3.344539	.1941446	17.23	0.000	2.954588	3.73449
minwageo~911	-1.206421	.1821417	-6.62	0.000	-1.572264	-.8405786
mi~1_migrant	1.193919	.3028389	3.94	0.000	.5856491	1.802189
hsgrad	2.090629	.11513	18.16	0.000	1.859384	2.321875
assocgrad	2.566522	.1220465	21.03	0.000	2.321384	2.811659
bachgrad	4.208296	.1225286	34.35	0.000	3.962191	4.454402
mastgrad	5.115812	.161655	31.65	0.000	4.791118	5.440505
doctorgrad	8.376224	.2435375	34.39	0.000	7.887065	8.865383
migranthsg~d	-1.510642	.1381149	-10.94	0.000	-1.788054	-1.23323
migrantass~d	-1.776893	.2088904	-8.51	0.000	-2.196462	-1.357324
migrantbac~d	-2.190373	.2242415	-9.77	0.000	-2.640775	-1.73997
migrantmas~d	-2.301867	.2566383	-8.97	0.000	-2.81734	-1.786394
migrantdoc~d	-1.91929	.2566593	-7.48	0.000	-2.434806	-1.403775
exp	.5600015	.0099985	56.01	0.000	.539919	.580084
migrantexp	-.2692812	.0168371	-15.99	0.000	-.3030995	-.235463
exp_sq	-.0108573	.0001854	-58.56	0.000	-.0112297	-.0104848
migrantexp~q	.0056199	.0003008	18.68	0.000	.0050157	.0062241
female	-4.75142	.1078962	-44.04	0.000	-4.968136	-4.534704

```
migrantfem~e |   .6962482   .1081525     6.44   0.000     .4790174    .9134789
   1.migrant |          0  (omitted)
             |
       wbhao |
      Black  |   .0279365   .0766086     0.36   0.717    -.1259365    .1818095
   Hispanic  |   .0449415   .2330198     0.19   0.848    -.4230926    .5129756
      Asian  |  -.3967671   .2763026    -1.44   0.157    -.9517371     .158203
      Other  |   .2541076   .1555386     1.63   0.109    -.0583009    .5665162
             |
     migrant#|
       wbhao |
    1#Black  |    -.46977   .1351036    -3.48   0.001    -.7411335   -.1984065
 1#Hispanic  |  -.4979505   .1664774    -2.99   0.004    -.8323302   -.1635707
    1#Asian  |  -.3464843   .2557109    -1.35   0.182    -.8600947    .1671262
    1#Other  |  -.7573739    .451862    -1.68   0.100    -1.664965    .1502177
             |
years_sinc~l |   .0109523   .0022984     4.77   0.000     .0063359    .0155688
       rural |   .2433007   .0895336     2.72   0.009     .0634672    .4231342
migrantrural |   .7329204   .2768724     2.65   0.011     .1768058    1.289035
             |
        year |
       1999  |   .1050837   .0661075     1.59   0.118     -.027697    .2378645
       2000  |   .1239989   .0886867     1.40   0.168    -.0541336    .3021314
       2001  |   .0624687   .0965481     0.65   0.521    -.1314539    .2563912
       2002  |    -.12273   .0747976    -1.64   0.107    -.2729653    .0275054
       2003  |  -.2848814   .0808327    -3.52   0.001    -.4472387   -.1225241
       2004  |  -.3148931   .1018908    -3.09   0.003    -.5195467   -.1102395
       2005  |  -.1896175   .0881451    -2.15   0.036    -.3666622   -.0125728
       2006  |   -.076511   .1032215    -0.74   0.462    -.2838374    .1308155
       2007  |    .012627   .0842476     0.15   0.881    -.1565894    .1818433
       2008  |  -.0041168   .0936296    -0.04   0.965    -.1921775    .1839439
       2009  |  -.3075048   .0897402    -3.43   0.001    -.4877534   -.1272563
       2010  |  -.6399513   .0934758    -6.85   0.000     -.827703   -.4521996
       2011  |  -.6307601   .0903526    -6.98   0.000    -.8122386   -.4492816
       2012  |   -.470572   .0925116    -5.09   0.000     -.656387   -.2847571
       2013  |  -.3456288   .1119758    -3.09   0.003    -.5705388   -.1207188
       2014  |  -.3384039   .1073492    -3.15   0.003     -.554021   -.1227867
       2015  |  -.1340647   .0994389    -1.35   0.184    -.3337936    .0656641
             |
migrant#year |
     1 1999  |   .0675603   .1606491     0.42   0.676     -.255113    .3902335
     1 2000  |     .21531   .2144026     1.00   0.320    -.2153304    .6459503
     1 2001  |   .3210954   .1646185     1.95   0.057    -.0095507    .6517415
     1 2002  |   .0980751   .1684551     0.58   0.563     -.240277    .4364272
     1 2003  |   .2120643   .1580228     1.34   0.186     -.105334    .5294625
     1 2004  |   .1562427   .2018178     0.77   0.442    -.2491203    .5616056
     1 2005  |   .1544744   .1293694     1.19   0.238    -.1053718    .4143206
     1 2006  |   .5143401   .1803792     2.85   0.006     .1520378    .8766423
     1 2007  |   .2236009   .1207658     1.85   0.070    -.0189644    .4661662
     1 2008  |   .0952587   .1643087     0.58   0.565     -.234765    .4252824
     1 2009  |  -.1342338   .1626493    -0.83   0.413    -.4609245    .1924569
     1 2010  |  -.5079693   .1531942    -3.32   0.002    -.8156688   -.2002697
     1 2011  |  -.4235063   .1303281    -3.25   0.002    -.6852781   -.1617346
     1 2012  |  -.4861706   .1517726    -3.20   0.002    -.7910148   -.1813263
     1 2013  |  -.5217638   .1697644    -3.07   0.003    -.8627457   -.1807819
     1 2014  |  -.3170741   .1814989    -1.75   0.087    -.6816253     .047477
     1 2015  |   -.306252   .1467518    -2.09   0.042    -.6010116   -.0114924
             |
       _cons |   34.49263   .2331845   147.92   0.000     34.02427      34.961
------------------------------------------------------------------------------
```

Specification (1), Endogenous-wage, Method 1, Restricted sample

```
Linear regression                               Number of obs     =      6,268
                                                F(3, 50)          =      25.57
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0089
                                                Root MSE          =     .59926

                                 (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |  -.0865057   .0228228    -3.79   0.000    -.1323467   -.0406647
post911entry |  -.1372859   .0431919    -3.18   0.003    -.2240394   -.0505323
post911ent~t |   .0053483    .054699     0.10   0.923    -.1045179    .1152146
       _cons |   2.401514   .0296205    81.08   0.000     2.342019    2.461008
------------------------------------------------------------------------------

Linear regression                               Number of obs     =      6,274
                                                F(3, 50)          =      13.14
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0034
                                                Root MSE          =     9.7295

                                 (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   .3588713   .4039665     0.89   0.379    -.4525192    1.170262
post911entry |  -2.127318   .5938886    -3.58   0.001    -3.320179   -.9344579
post911ent~t |   3.135594   .8826356     3.55   0.001     1.362768     4.90842
       _cons |   42.13951    .446953    94.28   0.000     41.24178    43.03724
------------------------------------------------------------------------------
```

Specification (1), Endogenous-wage, Method 1, Full sample

```
Linear regression                               Number of obs     =  1,375,615
                                                F(7, 50)          =     551.63
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0398
                                                Root MSE          =     .71466

                                  (Std. Err. adjusted for 51 clusters in state)
-------------------------------------------------------------------------------
              |               Robust
       lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
      migrant |  -.1673845   .0196783    -8.51   0.000    -.2069096   -.1278595
 post911entry |  -.4059013   .0109461   -37.08   0.000    -.4278872   -.3839155
post911entr~t |   .2445723   .0136701    17.89   0.000     .2171151    .2720295
     hispagri |  -.5818399   .0272055   -21.39   0.000    -.6364838    -.527196
```

	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
hispagri_mi~t	.0808789	.0377403	2.14	0.037	.0050753	.1566824
hispagri_~911	.2686155	.0479796	5.60	0.000	.1722456	.3649853
hispagri_po~t	-.239224	.0619658	-3.86	0.000	-.363686	-.1147619
_cons	2.983354	.0190407	156.68	0.000	2.945109	3.021598

Linear regression

Number of obs	=	1,376,334
F(7, 50)	=	353.94
Prob > F	=	0.0000
R-squared	=	0.0239
Root MSE	=	10.395

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf. Interval]	
migrant	-.6910483	.1741035	-3.97	0.000	-1.040745	-.3413511
post911entry	-5.021516	.142101	-35.34	0.000	-5.306934	-4.736098
post911entr~t	3.969871	.1673273	23.73	0.000	3.633784	4.305958
hispagri	1.668503	.3794808	4.40	0.000	.9062937	2.430713
hispagri_mi~t	1.04992	.4535037	2.32	0.025	.1390306	1.960809
hispagri_~911	2.894198	.643165	4.50	0.000	1.602363	4.186033
hispagri_po~t	-.8342767	.9494047	-0.88	0.384	-2.741212	1.072659
_cons	40.47101	.1179903	343.00	0.000	40.23402	40.708

Specification (2), Endogenous-wage, Method 1, Restricted sample

Linear regression

Number of obs	=	6,268
F(9, 50)	=	.
Prob > F	=	.
R-squared	=	0.0520
Root MSE	=	.58645

(Std. Err. adjusted for 51 clusters in state)

lnwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf. Interval]	
migrant	-.1278133	.028011	-4.56	0.000	-.184075	-.0715515
post911entry	-.0804071	.0386863	-2.08	0.043	-.1581109	-.0027033
post911ent~t	.0120201	.0479159	0.25	0.803	-.0842218	.108262
yearseduc	.0222341	.0017738	12.53	0.000	.0186713	.025797
exp	.0128848	.0017488	7.37	0.000	.0093721	.0163974
exp_sq	-.0001587	.0000283	-5.60	0.000	-.0002156	-.0001018
female	-.1402748	.0259022	-5.42	0.000	-.1923009	-.0882487
white	0	(omitted)				
black	0	(omitted)				
asian	0	(omitted)				
hispanic	0	(omitted)				
years_sinc~l	.0058398	.0008929	6.54	0.000	.0040463	.0076332
rural	-.0740167	.0216028	-3.43	0.001	-.1174073	-.0306261
year	2.159553	1.735121	1.24	0.219	-1.325539	5.644646
year_sq	-.0005372	.0004323	-1.24	0.220	-.0014055	.0003312
_cons	-2168.381	1740.935	-1.25	0.219	-5665.151	1328.389

```
Linear regression                               Number of obs     =      6,274
                                                F(10, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.0494
                                                Root MSE          =      9.508

                                 (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   .1858705   .4415168     0.42   0.676    -.7009421    1.072683
post911entry |   -.067948   .6763794    -0.10   0.920    -1.426496      1.2906
post911ent~t |   1.711941   .7182737     2.38   0.021     .2692455    3.154636
   yearseduc |   .0997337   .0353827     2.82   0.007     .0286654    .1708019
         exp |   .2464904   .0504315     4.89   0.000     .1451958     .347785
      exp_sq |  -.0037432   .0007716    -4.85   0.000     -.005293   -.0021934
      female |   -4.05011    .647831    -6.25   0.000    -5.351317   -2.748903
       white |          0  (omitted)
       black |          0  (omitted)
       asian |          0  (omitted)
    hispanic |          0  (omitted)
years_sinc~l |   .0307068    .021867     1.40   0.166    -.0132143     .074628
       rural |   2.420164   .6350826     3.81   0.000     1.144563    3.695765
        year |   4.415661    30.6258     0.14   0.886    -57.09807    65.92939
     year_sq |  -.0011091   .0076319    -0.15   0.885    -.0164382    .0142201
       _cons |  -4356.745   30724.51    -0.14   0.888    -66068.74    57355.25
------------------------------------------------------------------------------
```

Specification (2), Endogenous-wage, Method 1, Full sample

```
Linear regression                               Number of obs     =  1,375,615
                                                F(18, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.2734
                                                Root MSE          =      .6217

                                  (Std. Err. adjusted for 51 clusters in state)
-------------------------------------------------------------------------------
              |               Robust
       lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
      migrant |  -.0644349   .0153822    -4.19   0.000    -.0953309   -.0335389
 post911entry |  -.0851638   .0053978   -15.78   0.000    -.0960056   -.0743219
post911entr~t |   .0200178   .0070417     2.84   0.006     .0058742    .0341615
     hispagri |  -.1701266   .0392392    -4.34   0.000    -.2489409   -.0913122
hispagri_mi~t |   .2399328   .0446595     5.37   0.000     .1502315     .329634
hispagri_~911 |   .0386245   .0523769     0.74   0.464    -.0665775    .1438266
hispagri_po~t |  -.0697456   .0438198    -1.59   0.118    -.1577604    .0182691
    yearseduc |   .1055384   .0023019    45.85   0.000      .100915    .1101618
          exp |   .0400437   .0006907    57.97   0.000     .0386563     .041431
       exp_sq |  -.0006273   .0000129   -48.75   0.000    -.0006531   -.0006014
       female |  -.2465545   .0050045   -49.27   0.000    -.2566063   -.2365026
        white |   .1071785   .0121437     8.83   0.000     .0827871    .1315699
        black |  -.0513105   .0161096    -3.19   0.002    -.0836677   -.0189534
        asian |   .1046886   .0208531     5.02   0.000      .062804    .1465732
     hispanic |   .0178247   .0197154     0.90   0.370    -.0217748    .0574242
years_since~l |   .0022937   .0002577     8.90   0.000     .0017762    .0028112
```

```
       rural |  -.1692006    .014101   -12.00   0.000    -.1975233   -.1408779
        year |   2.541797   .3218947     7.90   0.000     1.895252    3.188341
     year_sq |  -.0006336   .0000801    -7.91   0.000    -.0007945   -.0004726
       _cons |  -2548.321   322.8372    -7.89   0.000    -3196.758   -1899.883
------------------------------------------------------------------------------

Linear regression                               Number of obs     =  1,376,334
                                                F(18, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1155
                                                Root MSE          =     9.8955

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |  -.0845211   .0955863    -0.88   0.381    -.2765119    .1074696
post911entry |  -1.264126   .0747278   -16.92   0.000    -1.414221   -1.114031
post911entr~t |   .7651821   .1280843     5.97   0.000     .5079172    1.022447
    hispagri |   2.451654    .252499     9.71   0.000     1.944495    2.958813
hispagri_mi~t |   1.755041   .4061155     4.32   0.000     .9393342    2.570748
hispagri_~911 |   1.282383   .5749291     2.23   0.030     .1276039    2.437162
hispagri_po~t |    .374068   .6783217     0.55   0.584    -.9883812    1.736517
   yearseduc |   .5207196   .0233414    22.31   0.000     .4738371    .5676022
         exp |   .5616085   .0103858    54.07   0.000      .540748     .582469
      exp_sq |  -.0105526   .0001916   -55.08   0.000    -.0109374   -.0101679
      female |  -4.766973    .121777   -39.15   0.000    -5.011569   -4.522377
       white |  -.0415873   .1644103    -0.25   0.801    -.3718152    .2886406
       black |  -.2286006   .1643345    -1.39   0.170    -.5586761    .1014749
       asian |  -.6818325   .1845998    -3.69   0.001    -1.052612   -.3110528
    hispanic |   .0243176    .221177     0.11   0.913    -.4199295    .4685646
years_since~l |   .0057698   .0027775     2.08   0.043     .0001911    .0113485
       rural |   .1676555   .0770163     2.18   0.034     .0129637    .3223473
        year |  -7.393409   3.979415    -1.86   0.069     -15.3863    .5994801
     year_sq |   .0018339   .0009921     1.85   0.070    -.0001589    .0038267
       _cons |   7481.052    3991.17     1.87   0.067    -535.4497    15497.55
------------------------------------------------------------------------------
```

<u>Specification (3), Endogenous-wage, Method 1, Restricted sample</u>

```
Linear regression                               Number of obs     =      6,268
                                                F(30, 50)         =     347.69
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0609
                                                Root MSE          =     .58458

                                 (Std. Err. adjusted for 51 clusters in state)
-----------------------------------------------------------------------------
            |               Robust
     lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
------------+----------------------------------------------------------------
    migrant |  -.1591126   .0277121    -5.74   0.000    -.2147741   -.1034512
post911entry |  -.1223909   .0384813    -3.18   0.003    -.1996829   -.0450989
post911ent~t |   .0605401     .05099     1.19   0.241    -.0418763    .1629565
     hsgrad |   .1477631   .0238255     6.20   0.000     .0999082    .1956179
```

assocgrad	.2358755	.0782341	3.01	0.004	.0787377	.3930133
bachgrad	.4764619	.0796638	5.98	0.000	.3164523	.6364714
mastgrad	.3616794	.0800404	4.52	0.000	.2009135	.5224453
doctorgrad	.2610433	.148448	1.76	0.085	-.0371233	.5592099
exp	.011739	.0019177	6.12	0.000	.0078871	.0155909
exp_sq	-.0001743	.0000309	-5.65	0.000	-.0002363	-.0001123
female	-.1484482	.0243209	-6.10	0.000	-.1972983	-.0995982
white	0	(omitted)				
black	0	(omitted)				
asian	0	(omitted)				
hispanic	0	(omitted)				
years_sinc~l	.006675	.000844	7.91	0.000	.0049798	.0083703
rural	-.0706976	.0227989	-3.10	0.003	-.1164906	-.0249046
year						
1999	.0999727	.0376433	2.66	0.011	.024364	.1755815
2000	.106121	.0343474	3.09	0.003	.0371321	.1751098
2001	.12492	.0586995	2.13	0.038	.0070186	.2428215
2002	.1139487	.0482394	2.36	0.022	.0170569	.2108404
2003	.2086046	.0461521	4.52	0.000	.1159053	.3013039
2004	.1275148	.0654746	1.95	0.057	-.0039949	.2590244
2005	.1978094	.0524502	3.77	0.000	.0924601	.3031587
2006	.1128132	.0514951	2.19	0.033	.0093822	.2162441
2007	.0641671	.0524194	1.22	0.227	-.0411205	.1694546
2008	.0844612	.0610493	1.38	0.173	-.0381599	.2070823
2009	.06327	.0408769	1.55	0.128	-.0188335	.1453736
2010	.1819673	.0426817	4.26	0.000	.0962386	.2676961
2011	.116373	.0604344	1.93	0.060	-.0050131	.2377591
2012	.1931685	.0585685	3.30	0.002	.0755302	.3108067
2013	.1850745	.0531514	3.48	0.001	.0783168	.2918323
2014	.1751484	.0568192	3.08	0.003	.0610237	.289273
2015	.1320795	.0555327	2.38	0.021	.0205388	.2436202
_cons	2.088235	.0776293	26.90	0.000	1.932312	2.244158

Linear regression

Number of obs	=	6,274
F(30, 50)	=	161.09
Prob > F	=	0.0000
R-squared	=	0.0561
Root MSE	=	9.489

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	-.184846	.4451692	-0.42	0.680	-1.078995	.7093027
post911entry	-.3451802	.6569186	-0.53	0.602	-1.66464	.9742795
post911ent~t	1.868354	.6016685	3.11	0.003	.659867	3.07684
hsgrad	.0290503	.3884741	0.07	0.941	-.751223	.8093235
assocgrad	2.666593	1.142288	2.33	0.024	.3722405	4.960946
bachgrad	.0632162	1.042568	0.06	0.952	-2.030843	2.157275
mastgrad	-.0313941	1.114024	-0.03	0.978	-2.268977	2.206189
doctorgrad	-5.542317	3.138158	-1.77	0.083	-11.84549	.7608591
exp	.2186775	.0519902	4.21	0.000	.1142521	.323103
exp_sq	-.003612	.0007921	-4.56	0.000	-.0052029	-.0020211
female	-4.087822	.6314769	-6.47	0.000	-5.356181	-2.819463
white	0	(omitted)				
black	0	(omitted)				

asian	0	(omitted)				
hispanic	0	(omitted)				
years_sinc~l	.0390418	.0222432	1.76	0.085	-.0056349	.0837185
rural	2.414182	.6515831	3.71	0.001	1.105438	3.722925
year						
1999	.8100464	.7379912	1.10	0.278	-.6722526	2.292345
2000	1.160502	.5909196	1.96	0.055	-.026395	2.347399
2001	.8293243	.4207549	1.97	0.054	-.0157868	1.674435
2002	-.4575031	.6676943	-0.69	0.496	-1.798606	.8836003
2003	.6942152	.8533246	0.81	0.420	-1.019738	2.408168
2004	.9715905	1.323766	0.73	0.466	-1.687272	3.630453
2005	2.37915	.8248384	2.88	0.006	.7224136	4.035887
2006	.712139	1.043838	0.68	0.498	-1.384472	2.80875
2007	.9446295	.9568693	0.99	0.328	-.977299	2.866558
2008	-.0812366	.6270895	-0.13	0.897	-1.340783	1.17831
2009	.4555419	.7743036	0.59	0.559	-1.099693	2.010776
2010	-.877156	.7496429	-1.17	0.248	-2.382858	.628546
2011	-.6667562	.5965863	-1.12	0.269	-1.865035	.5315226
2012	.1022123	.9345766	0.11	0.913	-1.77494	1.979365
2013	1.245782	.4797095	2.60	0.012	.2822569	2.209307
2014	-.368638	.5349684	-0.69	0.494	-1.443154	.7058777
2015	.9573508	.7097032	1.35	0.183	-.46813	2.382832
_cons	39.20853	.8501775	46.12	0.000	37.5009	40.91616

Specification (3), Endogenous-wage, Method 1, Full sample

Linear regression

Number of obs	=	1,375,615
F(38, 50)	=	5642.17
Prob > F	=	0.0000
R-squared	=	0.2867
Root MSE	=	.61599

(Std. Err. adjusted for 51 clusters in state)

lnwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	-.1486573	.0156275	-9.51	0.000	-.1800461	-.1172686
post911entry	-.0909	.0070764	-12.85	0.000	-.1051134	-.0766866
post911entr~t	.0184565	.0075521	2.44	0.018	.0032876	.0336253
hispagri	-.2265389	.0280537	-8.08	0.000	-.2828864	-.1701914
hispagri_mi~t	.0618565	.0237085	2.61	0.012	.0142366	.1094765
hispagri_~911	.1254768	.0458898	2.73	0.009	.0333045	.2176491
hispagri_po~t	-.1069514	.0478684	-2.23	0.030	-.203098	-.0108049
hsgrad	.2899978	.0061949	46.81	0.000	.2775549	.3024407
assocgrad	.4805943	.007434	64.65	0.000	.4656627	.4955259
bachgrad	.7541151	.0104779	71.97	0.000	.7330697	.7751606
mastgrad	.9479411	.0154992	61.16	0.000	.91681	.9790722
doctorgrad	1.190902	.0132575	89.83	0.000	1.164274	1.217531
exp	.0377616	.0005992	63.02	0.000	.036558	.0389651
exp_sq	-.0006146	.0000121	-50.77	0.000	-.0006389	-.0005903
female	-.2426443	.0049097	-49.42	0.000	-.2525058	-.2327828
white	.0876652	.0116479	7.53	0.000	.0642697	.1110608
black	-.0496243	.0164021	-3.03	0.004	-.0825689	-.0166798
asian	.0968508	.0206545	4.69	0.000	.0553651	.1383365

```
     hispanic |   -.023119   .0189533    -1.22   0.228    -.0611877    .0149498
years_since~l |   .0030835    .000282    10.94   0.000     .0025172    .0036498
        rural |  -.1652797   .0126437   -13.07   0.000    -.1906753   -.1398841
              |
         year |
        1999  |   .0299934   .0044123     6.80   0.000     .0211311    .0388557
        2000  |   .0441921   .0040406    10.94   0.000     .0360762    .0523079
        2001  |   .0619232   .0049718    12.45   0.000     .0519371    .0719094
        2002  |   .0696848   .0042778    16.29   0.000     .0610925     .078277
        2003  |    .074736   .0049366    15.14   0.000     .0648205    .0846515
        2004  |   .0682783   .0050269    13.58   0.000     .0581815     .078375
        2005  |   .0579559   .0047858    12.11   0.000     .0483433    .0675685
        2006  |    .052455    .005906     8.88   0.000     .0405925    .0643175
        2007  |   .0554085   .0088758     6.24   0.000      .037581     .073236
        2008  |   .0627884   .0074669     8.41   0.000     .0477907     .077786
        2009  |   .0456505   .0070742     6.45   0.000     .0314415    .0598595
        2010  |   .0633403   .0069087     9.17   0.000     .0494638    .0772168
        2011  |   .0483587   .0071914     6.72   0.000     .0339143     .062803
        2012  |   .0353867   .0080773     4.38   0.000      .019163    .0516105
        2013  |   .0225052   .0079911     2.82   0.007     .0064547    .0385557
        2014  |    .025793   .0095629     2.70   0.010     .0065853    .0450006
        2015  |   .0275905    .008885     3.11   0.003     .0097444    .0454366
              |
        _cons |   2.094187   .0136031   153.95   0.000     2.066864    2.121509
------------------------------------------------------------------------------

Linear regression                               Number of obs     =  1,376,334
                                                F(38, 50)         =    3748.38
                                                Prob > F          =     0.0000
                                                R-squared         =     0.1232
                                                Root MSE          =     9.8523

                             (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
              |               Robust
  hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
      migrant |  -.4681034   .1053169    -4.44   0.000    -.6796386   -.2565681
 post911entry |  -1.286775   .0782062   -16.45   0.000    -1.443856   -1.129693
post911entr~t |   .7530427   .1330946     5.66   0.000     .4857142    1.020371
     hispagri |    2.24152   .2584999     8.67   0.000     1.722308    2.760733
hispagri_mi~t |   .9882731   .3667494     2.69   0.010     .2516353    1.724911
hispagri_~911 |   1.677939   .5495219     3.05   0.004     .5741921    2.781687
hispagri_po~t |   .2026241   .7106687     0.29   0.777    -1.224796    1.630044
       hsgrad |    1.82349   .1748488    10.43   0.000     1.472296    2.174684
    assocgrad |    2.45226   .1750916    14.01   0.000     2.100578    2.803941
     bachgrad |   4.135329   .1431606    28.89   0.000     3.847783    4.422876
     mastgrad |   5.040937   .1749722    28.81   0.000     4.689495    5.392379
   doctorgrad |   8.402136   .2807667    29.93   0.000       7.8382    8.966073
          exp |   .5464449   .0096458    56.65   0.000     .5270708     .565819
       exp_sq |  -.0103629   .0001728   -59.99   0.000    -.0107099   -.0100159
       female |  -4.732185   .1206969   -39.21   0.000    -4.974612   -4.489758
        white |  -.1928541   .1569388    -1.23   0.225     -.508075    .1223668
        black |  -.2236598   .1586773    -1.41   0.165    -.5423725    .0950529
        asian |  -.8531545   .1780773    -4.79   0.000    -1.210833   -.4954757
     hispanic |  -.0962503   .2242079    -0.43   0.670    -.5465851    .3540845
years_since~l |   .0085056    .002578     3.30   0.002     .0033276    .0136836
        rural |   .2431342    .083611     2.91   0.005     .0751965    .4110718
              |
         year |
```

	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
1999	.1128834	.0596206	1.89	0.064	-.006868	.2326348
2000	.1424332	.0877254	1.62	0.111	-.0337683	.3186348
2001	.102042	.0920742	1.11	0.273	-.0828944	.2869784
2002	-.1261192	.0691097	-1.82	0.074	-.2649301	.0126917
2003	-.2940161	.0861843	-3.41	0.001	-.4671225	-.1209098
2004	-.3280337	.1053055	-3.12	0.003	-.539546	-.1165214
2005	-.2119063	.085456	-2.48	0.017	-.3835498	-.0402628
2006	-.0370427	.0965395	-0.38	0.703	-.230948	.1568626
2007	.0189301	.0846945	0.22	0.824	-.1511838	.1890441
2008	-.0189976	.0831076	-0.23	0.820	-.1859241	.147929
2009	-.3719849	.0799235	-4.65	0.000	-.532516	-.2114539
2010	-.7557826	.0819631	-9.22	0.000	-.9204102	-.5911549
2011	-.7340569	.0808743	-9.08	0.000	-.8964977	-.5716161
2012	-.5780272	.0864422	-6.69	0.000	-.7516515	-.404403
2013	-.4546658	.1007112	-4.51	0.000	-.6569501	-.2523815
2014	-.4057354	.0994888	-4.08	0.000	-.6055646	-.2059062
2015	-.2042134	.0919146	-2.22	0.031	-.3888293	-.0195975
_cons	34.72221	.2297557	151.13	0.000	34.26073	35.18369

<u>Specification (4), Endogenous-wage, Method 1, Restricted sample</u>

Linear regression

Number of obs	=	6,268
F(48, 50)	>	99999.00
Prob > F	=	0.0000
R-squared	=	0.0638
Root MSE	=	.58454

(Std. Err. adjusted for 51 clusters in state)

lnwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	.1653001	.2599976	0.64	0.528	-.3569204	.6875207
post911entry	-.1546109	.07113	-2.17	0.034	-.2974797	-.0117422
post911ent~t	.104482	.083062	1.26	0.214	-.0623529	.2713169
yearseduc	.0470701	.0067725	6.95	0.000	.0334671	.0606732
migrantyea~c	-.0267758	.0070207	-3.81	0.000	-.0408774	-.0126742
exp	.0133219	.007056	1.89	0.065	-.0008505	.0274943
migrantexp	-.0009691	.008291	-0.12	0.907	-.0176221	.0156838
exp_sq	-.0001815	.0001163	-1.56	0.125	-.0004151	.0000521
migrantexp~q	.0000388	.0001366	0.28	0.778	-.0002356	.0003132
female	-.1568977	.032892	-4.77	0.000	-.2229631	-.0908322
migrantfem~e	.011997	.0332947	0.36	0.720	-.0548775	.0788714
1.migrant	0	(omitted)				
wbhao						
Hispanic	0	(omitted)				
migrant# wbhao						
1#Hispanic	0	(omitted)				
years_sinc~l	.0058394	.0009134	6.39	0.000	.0040047	.007674
rural	-.0633563	.0458493	-1.38	0.173	-.1554474	.0287348

```
migrantrural |  -.0054723   .0511161    -0.11   0.915     -.108142    .0971974
             |
        year |
       1999  |   .1785315   .2312786     0.77   0.444    -.2860051    .6430682
       2000  |   .1037366   .1710556     0.61   0.547    -.2398387    .4473119
       2001  |   .0501627   .1796081     0.28   0.781    -.3105908    .4109161
       2002  |   .1960847   .2459122     0.80   0.429    -.2978445    .6900138
       2003  |   .1654187   .1610826     1.03   0.309    -.1581252    .4889625
       2004  |   .1737592   .1700897     1.02   0.312    -.1678761    .5153944
       2005  |   .2345199   .1537373     1.53   0.133    -.0742706    .5433103
       2006  |   .2499611   .2594441     0.96   0.340    -.2711478      .77107
       2007  |   .1516054   .2333507     0.65   0.519    -.3170933     .620304
       2008  |  -.0709908   .1374103    -0.52   0.608    -.3469875    .2050059
       2009  |   .1236063   .1877616     0.66   0.513    -.2535239    .5007364
       2010  |   .0786968   .2823518     0.28   0.782    -.4884234    .6458171
       2011  |    .034483    .162382     0.21   0.833    -.2916708    .3606368
       2012  |   .2532494   .1747137     1.45   0.153    -.0976734    .6041721
       2013  |   .3066465   .2799611     1.10   0.279    -.2556719    .8689648
       2014  |   .0877544   .1616845     0.54   0.590    -.2369985    .4125072
       2015  |   .2877758   .1631684     1.76   0.084    -.0399576    .6155092
             |
migrant#year |
     1 1999  |    -.09093   .2595546    -0.35   0.728    -.6122609    .4304008
     1 2000  |   .0016047   .2185848     0.01   0.994    -.4374358    .4406452
     1 2001  |   .0871757   .2689792     0.32   0.747    -.4530849    .6274363
     1 2002  |  -.0991855    .327711    -0.30   0.763    -.7574124    .5590414
     1 2003  |   .0451094   .1857334     0.24   0.809    -.3279471    .4181658
     1 2004  |  -.0632631   .2252201    -0.28   0.780     -.515631    .3891049
     1 2005  |  -.0418896   .1591442    -0.26   0.793    -.3615401    .2777609
     1 2006  |  -.1565111   .3109842    -0.50   0.617    -.7811413    .4681191
     1 2007  |  -.1161142   .2711163    -0.43   0.670    -.6606674    .4284391
     1 2008  |   .1468669    .129869     1.13   0.263    -.1139826    .4077163
     1 2009  |   -.076955   .2119902    -0.36   0.718    -.5027499    .3488398
     1 2010  |   .1045203   .3120327     0.33   0.739    -.5222158    .7312563
     1 2011  |   .0787242   .2216177     0.36   0.724    -.3664079    .5238564
     1 2012  |   -.088259   .1944221    -0.45   0.652    -.4787672    .3022493
     1 2013  |  -.1564372   .2930154    -0.53   0.596    -.7449761    .4321016
     1 2014  |   .0867046   .2130084     0.41   0.686    -.3411353    .5145445
     1 2015  |  -.2120743   .2062121    -1.03   0.309    -.6262636     .202115
             |
       _cons |   1.637074   .2029757     8.07   0.000     1.229385    2.044763
------------------------------------------------------------------------------

Linear regression                               Number of obs     =      6,274
                                                F(48, 50)         =   12520.52
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0607
                                                Root MSE          =     9.4796

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |    4.50035   1.316641     3.42   0.001     1.855798    7.144902
post911entry |   .1356062   .7510462     0.18   0.857    -1.372915    1.644127
post911ent~t |     1.5863   .8899697     1.78   0.081    -.2012564    3.373857
  yearseduc |   .2046974   .0710975     2.88   0.006     .0618939    .3475009
migrantyea~c |  -.1264833   .0846756    -1.49   0.142    -.2965592    .0435926
         exp |   .2318983   .0841519     2.76   0.008     .0628742    .4009225
```

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  migrantexp |  -.0127689   .0788333    -0.16   0.872    -.1711101    .1455724
      exp_sq |  -.0025817   .0015266    -1.69   0.097     -.005648    .0004846
migrantexp~q |  -.0009764   .0014292    -0.68   0.498     -.003847    .0018941
      female |   -4.83725   .8403448    -5.76   0.000    -6.525133   -3.149368
migrantfem~e |   .9232599   .5810184     1.59   0.118    -.2437499     2.09027
   1.migrant |          0  (omitted)
             |
       wbhao |
   Hispanic  |          0  (omitted)
             |
     migrant#|
       wbhao |
 1#Hispanic  |          0  (omitted)
             |
years_sinc~l |   .0432981   .0226176     1.91   0.061    -.0021307     .088727
       rural |   1.337217   .8809589     1.52   0.135    -.4322408    3.106675
migrantrural |   1.205066   .6112537     1.97   0.054    -.0226729    2.432805
             |
        year |
       1999  |   4.445067   1.634742     2.72   0.009      1.16159    7.728544
       2000  |   3.488065   1.564948     2.23   0.030     .3447737    6.631356
       2001  |   1.602332   1.567754     1.02   0.312    -1.546595    4.751258
       2002  |   2.113997   1.254858     1.68   0.098    -.4064596    4.634453
       2003  |   1.843328   2.092005     0.88   0.382    -2.358588    6.045243
       2004  |   6.086759   3.266554     1.86   0.068    -.4743087    12.64783
       2005  |   4.281941   1.292788     3.31   0.002       1.6853    6.878583
       2006  |   4.287328   2.033551     2.11   0.040     .2028212    8.371835
       2007  |   3.751086   1.642838     2.28   0.027     .4513496    7.050823
       2008  |    2.05646   2.279607     0.90   0.371    -2.522266    6.635186
       2009  |   4.516293   1.142806     3.95   0.000     2.220899    6.811687
       2010  |   3.113962   2.033897     1.53   0.132    -.9712414    7.199165
       2011  |   .5845951   1.345446     0.43   0.666    -2.117813    3.287003
       2012  |   2.285158   1.234648     1.85   0.070    -.1947047     4.76502
       2013  |   4.138476   1.512968     2.74   0.009     1.099589    7.177362
       2014  |   2.805485   1.552381     1.81   0.077    -.3125651    5.923534
       2015  |   .6341994   1.556605     0.41   0.685    -2.492335    3.760733
             |
migrant#year |
     1 1999  |    -4.5859   2.070951    -2.21   0.031    -8.745528   -.4262713
     1 2000  |    -2.8937   1.844696    -1.57   0.123    -6.598881    .8114811
     1 2001  |  -1.036152   1.626296    -0.64   0.527    -4.302664     2.23036
     1 2002  |  -3.223138   1.078353    -2.99   0.004    -5.389074   -1.057202
     1 2003  |   -1.43935   2.006226    -0.72   0.476    -5.468974    2.590274
     1 2004  |  -6.050619   2.564941    -2.36   0.022    -11.20245   -.8987831
     1 2005  |  -2.475288   1.476303    -1.68   0.100     -5.44053    .4899534
     1 2006  |  -4.362684   1.938425    -2.25   0.029    -8.256125   -.4692437
     1 2007  |  -3.567638    1.79654    -1.99   0.053    -7.176096    .0408189
     1 2008  |  -2.860959   1.764573    -1.62   0.111    -6.405208    .6832912
     1 2009  |   -4.94631   1.635982    -3.02   0.004    -8.232277   -1.660344
     1 2010  |  -4.944572   1.939936    -2.55   0.014    -8.841049   -1.048096
     1 2011  |  -1.841968   1.312818    -1.40   0.167     -4.47884    .7949042
     1 2012  |  -2.945248   1.509694    -1.95   0.057    -5.977557    .0870612
     1 2013  |  -3.820794   1.751336    -2.18   0.034    -7.338457   -.3031319
     1 2014  |  -4.187879   2.002744    -2.09   0.042    -8.210507   -.1652498
     1 2015  |  -.0002877   2.153264    -0.00   1.000    -4.325246     4.32467
             |
       _cons |   34.42889   1.456532    23.64   0.000     31.50336    37.35442
------------------------------------------------------------------------------
```

Specification (4), Endogenous-wage, Method 1, Full sample

Linear regression	Number of obs =	1,375,615
	F(49, 50) =	.
	Prob > F =	.
	R-squared =	0.2798
	Root MSE =	.61895

(Std. Err. adjusted for 51 clusters in state)

lnwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	.756274	.0466762	16.20	0.000	.662522	.8500259
post911entry	-.0700326	.0039032	-17.94	0.000	-.0778724	-.0621928
post911entr~t	-.012706	.0065029	-1.95	0.056	-.0257674	.0003554
hispagri	-.136432	.0415568	-3.28	0.002	-.2199012	-.0529628
hispagri_mi~t	.0868001	.0549868	1.58	0.121	-.023644	.1972442
hispagri_~911	.0170011	.0528963	0.32	0.749	-.0892443	.1232464
hispagri_po~t	-.0322015	.0464288	-0.69	0.491	-.1254566	.0610535
yearseduc	.1190368	.0016572	71.83	0.000	.1157082	.1223654
migrantyear~c	-.0468552	.0030038	-15.60	0.000	-.0528885	-.040822
exp	.0428686	.0009589	44.71	0.000	.0409426	.0447946
migrantexp	-.0180519	.0010445	-17.28	0.000	-.0201498	-.0159539
exp_sq	-.0006862	.0000188	-36.46	0.000	-.0007241	-.0006484
migrantexp_sq	.0003239	.0000209	15.50	0.000	.0002819	.0003658
female	-.2500924	.0047962	-52.14	0.000	-.2597257	-.240459
migrantfemale	.0174556	.0075175	2.32	0.024	.0023562	.0325549
1.migrant	0	(omitted)				
wbhao						
Black	-.1518499	.0089582	-16.95	0.000	-.169843	-.1338567
Hispanic	-.0764323	.0199271	-3.84	0.000	-.116457	-.0364077
Asian	.013459	.0145058	0.93	0.358	-.0156766	.0425947
Other	-.098624	.0118753	-8.30	0.000	-.1224762	-.0747718
migrant#wbhao						
1#Black	-.0121485	.02044	-0.59	0.555	-.0532034	.0289064
1#Hispanic	-.1444235	.0230849	-6.26	0.000	-.1907908	-.0980561
1#Asian	-.0196292	.0182197	-1.08	0.286	-.0562246	.0169662
1#Other	.0064684	.0493434	0.13	0.896	-.0926407	.1055775
years_since~l	.0030332	.0003451	8.79	0.000	.0023401	.0037263
rural	-.1639237	.0122867	-13.34	0.000	-.1886022	-.1392451
migrantrural	.0855772	.0213099	4.02	0.000	.0427751	.1283793
year						
1999	.030152	.0049145	6.14	0.000	.0202809	.0400232
2000	.0408534	.0044427	9.20	0.000	.03193	.0497768
2001	.0563617	.0054093	10.42	0.000	.0454968	.0672267
2002	.0626513	.0043404	14.43	0.000	.0539332	.0713693
2003	.0694801	.0047253	14.70	0.000	.059989	.0789713
2004	.0636754	.0046092	13.81	0.000	.0544175	.0729333
2005	.0508692	.0039039	13.03	0.000	.043028	.0587104
2006	.0419336	.0051909	8.08	0.000	.0315073	.0523599
2007	.0459058	.0080625	5.69	0.000	.0297118	.0620998
2008	.0522989	.0066232	7.90	0.000	.0389959	.065602
2009	.0365479	.0067845	5.39	0.000	.0229209	.0501749
2010	.0526705	.0062077	8.48	0.000	.040202	.065139

```
        2011  |   .0362103   .0060188     6.02   0.000     .0241212    .0482995
        2012  |   .0230206   .0074496     3.09   0.003     .0080577    .0379835
        2013  |   .0073823   .0071067     1.04   0.304    -.0068919    .0216564
        2014  |   .0115185   .0094525     1.22   0.229    -.0074674    .0305045
        2015  |   .0144357    .008281     1.74   0.087    -.0021971    .0310684
              |
 migrant#year |
      1 1999  |  -.0156731   .0088361    -1.77   0.082     -.033421    .0020747
      1 2000  |   .0112351   .0107333     1.05   0.300    -.0103233    .0327936
      1 2001  |   .0265847   .0123313     2.16   0.036     .0018165    .0513529
      1 2002  |   .0313543   .0069041     4.54   0.000      .017487    .0452217
      1 2003  |   .0117831   .0130666     0.90   0.371    -.0144619    .0380281
      1 2004  |   .0102436   .0130397     0.79   0.436    -.0159475    .0364347
      1 2005  |   .0287528   .0116169     2.48   0.017     .0054197     .052086
      1 2006  |   .0443172   .0102891     4.31   0.000     .0236509    .0649836
      1 2007  |   .0385201   .0081505     4.73   0.000     .0221492    .0548909
      1 2008  |   .0349016   .0092075     3.79   0.000     .0164079    .0533953
      1 2009  |   .0305504   .0122748     2.49   0.016     .0058958     .055205
      1 2010  |   .0370373   .0100027     3.70   0.001     .0169462    .0571283
      1 2011  |   .0362051   .0112237     3.23   0.002     .0136617    .0587485
      1 2012  |   .0398891   .0116278     3.43   0.001      .016534    .0632443
      1 2013  |   .0531355   .0121466     4.37   0.000     .0287384    .0775326
      1 2014  |   .0545694   .0122912     4.44   0.000     .0298818    .0792569
      1 2015  |   .0449979   .0155692     2.89   0.006     .0137262    .0762696
              |
        _cons |   .9192936   .0228431    40.24   0.000     .8734119    .9651753
------------------------------------------------------------------------------

Linear regression                               Number of obs     =  1,376,334
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1189
                                                Root MSE          =     9.8766

                                   (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
              |               Robust
  hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
      migrant |   6.375828   .5916084    10.78   0.000     5.187547    7.564108
 post911entry |  -1.203509    .071585   -16.81   0.000    -1.347292   -1.059726
post911entr~t |   .9761974   .1353219     7.21   0.000     .7043953    1.247999
     hispagri |   2.917467   .2579093    11.31   0.000     2.399441    3.435493
hispagri_mi~t |   .2668884   .4165515     0.64   0.525      -.56978    1.103557
hispagri_~911 |   1.068186   .5830904     1.83   0.073    -.1029855    2.239358
hispagri_po~t |   .8097867   .7425996     1.09   0.281    -.6817685    2.301342
    yearseduc |   .6327532   .0172479    36.69   0.000     .5981098    .6673967
migrantyear~c |   -.340793   .0258415   -13.19   0.000    -.3926972   -.2888888
          exp |   .6017142   .0109897    54.75   0.000     .5796407    .6237877
   migrantexp |   -.241604    .014649   -16.49   0.000    -.2710274   -.2121805
       exp_sq |  -.0115299    .000205   -56.25   0.000    -.0119416   -.0111181
migrantexp_sq |   .0053846   .0002869    18.77   0.000     .0048084    .0059608
       female |  -4.888233   .1136706   -43.00   0.000    -5.116547   -4.659919
migrantfemale |   .8155771   .1113924     7.32   0.000     .5918389    1.039315
    1.migrant |          0  (omitted)
              |
        wbhao |
       Black  |  -.0779227   .0775415    -1.00   0.320    -.2336694    .0778239
    Hispanic  |   .0000217    .239694     0.00   1.000    -.4814178    .4814611
       Asian  |  -.3307701   .2850268    -1.16   0.251    -.9032632    .2417231
```

```
       Other |   .1196934   .1584018     0.76   0.453    -.1984659    .4378527
             |
migrant#wbhao |
     1#Black |  -.5504659   .1464108    -3.76   0.000    -.8445406   -.2563911
  1#Hispanic |   -.560894   .1525043    -3.68   0.001    -.8672078   -.2545802
     1#Asian |  -.3393359   .2666218    -1.27   0.209    -.8748615    .1961896
     1#Other |  -.7015363   .4379806    -1.60   0.116    -1.581246    .1781736
             |
years_since~l |   .0083901   .0024682     3.40   0.001     .0034325    .0133476
       rural |   .2273902   .0879216     2.59   0.013     .0507943     .403986
migrantrural |   .5929472   .2472106     2.40   0.020     .0964101    1.089484
             |
        year |
        1999 |   .0992354   .0656679     1.51   0.137    -.0326624    .2311333
        2000 |   .1130177   .0909094     1.24   0.220    -.0695792    .2956147
        2001 |   .0535899   .0981726     0.55   0.588    -.1435955    .2507753
        2002 |  -.1465094   .0780245    -1.88   0.066    -.3032263    .0102075
        2003 |  -.3373451   .0866559    -3.89   0.000    -.5113986   -.1632915
        2004 |   -.347977   .1065992    -3.26   0.002    -.5620878   -.1338662
        2005 |  -.2225464   .0928318    -2.40   0.020    -.4090045   -.0360883
        2006 |  -.1081903    .107437    -1.01   0.319    -.3239838    .1076032
        2007 |  -.0072639   .0896887    -0.08   0.936    -.1874091    .1728812
        2008 |  -.0402737   .0956398    -0.42   0.675    -.2323719    .1518245
        2009 |   -.338008   .0924161    -3.66   0.001    -.5236312   -.1523848
        2010 |   -.667619   .0976494    -6.84   0.000    -.8637537   -.4714843
        2011 |   -.669042   .0904384    -7.40   0.000    -.8506928   -.4873912
        2012 |  -.4997896   .0969608    -5.15   0.000     -.694541   -.3050382
        2013 |  -.3764669   .1151891    -3.27   0.002     -.607831   -.1451027
        2014 |  -.3394843    .109567    -3.10   0.003    -.5595562   -.1194125
        2015 |  -.1306109   .1003426    -1.30   0.199    -.3321549     .070933
             |
migrant#year |
      1 1999 |   .0610954   .1633481     0.37   0.710    -.2669989    .3891897
      1 2000 |   .1885632   .2069423     0.91   0.367    -.2270927    .6042191
      1 2001 |    .315946   .1608596     1.96   0.055    -.0071501     .639042
      1 2002 |   .0742248    .166484     0.45   0.658    -.2601683    .4086178
      1 2003 |    .206426   .1806394     1.14   0.259    -.1563989    .5692509
      1 2004 |   .0805913   .2127928     0.38   0.706    -.3468157    .5079983
      1 2005 |   .0077916   .1189858     0.07   0.948    -.2311984    .2467817
      1 2006 |    .380071   .1668802     2.28   0.027     .0448824    .7152597
      1 2007 |   .0974774   .1200833     0.81   0.421     -.143717    .3386718
      1 2008 |   .0223412   .1789004     0.12   0.901    -.3369907    .3816731
      1 2009 |  -.2951791   .1632267    -1.81   0.077    -.6230295    .0326714
      1 2010 |  -.6362054   .1582747    -4.02   0.000    -.9541095   -.3183012
      1 2011 |   -.569727   .1391216    -4.10   0.000    -.8491608   -.2902931
      1 2012 |  -.6093103   .1507563    -4.04   0.000    -.9121133   -.3065073
      1 2013 |  -.6129688   .1588309    -3.86   0.000    -.9319901   -.2939476
      1 2014 |  -.4681855   .1712459    -2.73   0.009     -.812143    -.124228
      1 2015 |  -.5195497   .1407285    -3.69   0.001    -.8022111   -.2368883
             |
       _cons |   27.92925   .4072553    68.58   0.000     27.11125    28.74725
------------------------------------------------------------------------------
```

Specification (5), Endogenous-wage, Method 1, Restricted sample

```
Linear regression                               Number of obs     =      6,268
                                                F(50, 50)         =          .
                                                Prob > F          =          .
```

```
                                                R-squared         =     0.0693
                                                Root MSE          =     .58328

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |  -.1195849   .3848473    -0.31   0.757    -.8925735    .6534037
post911entry |  -.1951371   .0746035    -2.62   0.012    -.3449825   -.0452917
post911ent~t |   .1492923    .082786     1.80   0.077    -.0169883    .3155728
      hsgrad |   .2542653   .0376645     6.75   0.000     .1786139    .3299167
   assocgrad |    .460964   .0814237     5.66   0.000     .2974198    .6245082
    bachgrad |   .8897999   .0828866    10.74   0.000     .7233173    1.056283
    mastgrad |   .2323178   .1841192     1.26   0.213    -.1374966    .6021321
  doctorgrad |   1.119734   .1125626     9.95   0.000     .8936458    1.345823
migranthsg~d |  -.1334563   .0386438    -3.45   0.001    -.2110747    -.055838
migrantass~d |  -.3013068   .1217928    -2.47   0.017    -.5459347   -.0566788
migrantbac~d |  -.5222171   .0962589    -5.43   0.000    -.7155588   -.3288754
migrantmas~d |   .1730543   .2067982     0.84   0.407     -.242312    .5884206
migrantdoc~d |  -1.151796   .1875689    -6.14   0.000    -1.528539   -.7750523
         exp |   .0143138   .0080373     1.78   0.081    -.0018297    .0304572
  migrantexp |  -.0038154   .0092021    -0.41   0.680    -.0222984    .0146677
      exp_sq |  -.0002513   .0001316    -1.91   0.062    -.0005156    .0000131
migrantexp~q |   .0000975   .0001478     0.66   0.513    -.0001995    .0003944
      female |  -.1771355    .029525    -6.00   0.000    -.2364382   -.1178328
migrantfem~e |   .0275497   .0312266     0.88   0.382    -.0351707    .0902701
   1.migrant |          0  (omitted)
             |
      wbhao |
   Hispanic  |          0  (omitted)
             |
     migrant#|
       wbhao |
 1#Hispanic  |          0  (omitted)
             |
years_sinc~l |  -.0086244    .016696    -0.52   0.608    -.0421593    .0249105
       rural |  -.0666756   .0472378    -1.41   0.164    -.1615556    .0282043
migrantrural |   .0042548   .0516508     0.08   0.935    -.0994888    .1079985
             |
        year |
       1999  |   .1511135   .2226996     0.68   0.501    -.2961919    .5984188
       2000  |   .1192816   .1617852     0.74   0.464    -.2056736    .4442368
       2001  |   .0468087   .1512324     0.31   0.758    -.2569505    .3505679
       2002  |   .2304185   .2338122     0.99   0.329    -.2392072    .7000442
       2003  |   .2215887   .1492953     1.48   0.144    -.0782797    .5214571
       2004  |   .1749856   .1371567     1.28   0.208    -.1005017     .450473
       2005  |   .2332616   .1513607     1.54   0.130    -.0707553    .5372785
       2006  |   .2384578   .2239189     1.06   0.292    -.2112965    .6882121
       2007  |   .1626852   .2387097     0.68   0.499    -.3167773    .6421477
       2008  |  -.0436593   .1316848    -0.33   0.742     -.308156    .2208375
       2009  |   .1735945   .1808723     0.96   0.342    -.1896982    .5368872
       2010  |   .1509853   .2778718     0.54   0.589    -.4071366    .7091073
       2011  |    .095716   .1591737     0.60   0.550    -.2239939    .4154259
       2012  |   .2978095   .1857662     1.60   0.115     -.075313    .6709319
       2013  |   .3433124    .256175     1.34   0.186    -.1712302     .857855
       2014  |   .1218772   .1249977     0.98   0.334    -.1291881    .3729424
       2015  |     .33527   .1648281     2.03   0.047      .004203     .666337
             |
migrant#year |
```

```
     1 1999  |  -.0428289   .2499793    -0.17   0.865     -.544927    .4592693
     1 2000  |   .0159851   .2101782     0.08   0.940    -.4061703    .4381405
     1 2001  |   .1391982   .2454653     0.57   0.573    -.3538333    .6322297
     1 2002  |  -.0713359   .3283751    -0.22   0.829    -.7308967     .588225
     1 2003  |   .0640181    .184408     0.35   0.730    -.3063763    .4344125
     1 2004  |   .0317481   .2153576     0.15   0.883    -.4008103    .4643065
     1 2005  |   .0684092   .1924993     0.36   0.724     -.318237    .4550555
     1 2006  |  -.0206333   .3088196    -0.07   0.947    -.6409157    .5996491
     1 2007  |   .0238522   .3144402     0.08   0.940    -.6077195    .6554239
     1 2008  |   .2917934   .1218824     2.39   0.020     .0469854    .5366014
     1 2009  |   .0447628   .2516669     0.18   0.860     -.460725    .5502507
     1 2010  |   .2260111   .3077041     0.73   0.466    -.3920309     .844053
     1 2011  |   .2325111   .2798583     0.83   0.410    -.3296008     .794623
     1 2012  |   .0973421   .2724612     0.36   0.722    -.4499123    .6445965
     1 2013  |   .0474521   .3632268     0.13   0.897    -.6821104    .7770145
     1 2014  |   .3133576   .2761202     1.13   0.262    -.2412462    .8679613
     1 2015  |   .0104397   .3027855     0.03   0.973    -.5977228    .6186022
             |
  entry_year |   .0161438   .0170716     0.95   0.349    -.0181456    .0504332
entry_year~q |  -8.06e-06   8.49e-06    -0.95   0.347    -.0000251    8.99e-06
       _cons |   1.988063   .1604569    12.39   0.000     1.665776     2.31035
------------------------------------------------------------------------------

Linear regression                               Number of obs     =      6,274
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.0627
                                                Root MSE          =     9.4769

                                 (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   5.838792   1.861289     3.14   0.003     2.100284    9.577301
post911entry |   .2825537   .6327044     0.45   0.657    -.9882704    1.553378
post911ent~t |   1.507468   .7758433     1.94   0.058    -.0508588    3.065795
      hsgrad |   .4539778   .8840354     0.51   0.610     -1.32166    2.229615
   assocgrad |   4.950577    2.57928     1.92   0.061     -.23006     10.13121
    bachgrad |    .587085    2.42685     0.24   0.810    -4.287387    5.461557
    mastgrad |   6.410464   1.307227     4.90   0.000     3.784822    9.036106
  doctorgrad |   4.637393   4.159562     1.11   0.270    -3.717333    12.99212
migranthsg~d |  -.5685054   .8966166    -0.63   0.529    -2.369413    1.232402
migrantass~d |  -3.751512   2.830041    -1.33   0.191    -9.435817    1.932793
migrantbac~d |  -.6698874   2.300656    -0.29   0.772    -5.290892    3.951117
migrantmas~d |  -7.881222   1.204829    -6.54   0.000    -10.30119   -5.461251
migrantdoc~d |  -13.51316   5.240078    -2.58   0.013    -24.03817   -2.988158
         exp |    .262742    .081297     3.23   0.002     .0994521    .4260319
  migrantexp |  -.0694937   .0749896    -0.93   0.359    -.2201147    .0811273
      exp_sq |  -.0034477   .0016491    -2.09   0.042      -.00676   -.0001355
migrantexp~q |  -.0000179   .0014714    -0.01   0.990    -.0029732    .0029374
      female |   -4.90226   .7235762    -6.78   0.000    -6.355606   -3.448915
migrantfem~e |   .9604873   .5576357     1.72   0.091     -.159557    2.080532
   1.migrant |          0  (omitted)
             |
       wbhao |
   Hispanic  |          0  (omitted)
             |
     migrant#|
       wbhao |
```

```
 1#Hispanic  |          0  (omitted)
             |
years_sinc~l |   .1468663   .1598385     0.92   0.363    -.1741788    .4679115
       rural |   1.235003   .8685323     1.42   0.161    -.5094957    2.979501
migrantrural |   1.360247   .6173254     2.20   0.032     .1203126    2.600182
             |
        year |
       1999  |   4.450886   1.611807     2.76   0.008     1.213477    7.688296
       2000  |   3.604432   1.549387     2.33   0.024     .4923971    6.716466
       2001  |   1.560281   1.474437     1.06   0.295    -1.401213    4.521775
       2002  |   2.318018   1.161527     2.00   0.051     -.014978    4.651013
       2003  |   2.000292   2.033182     0.98   0.330    -2.083474    6.084057
       2004  |   5.550671   3.021338     1.84   0.072    -.5178653    11.61921
       2005  |   4.256545   1.344968     3.16   0.003     1.555097    6.957993
       2006  |   4.204825   1.871332     2.25   0.029     .4461439    7.963505
       2007  |   3.524419   1.632387     2.16   0.036     .2456723    6.803166
       2008  |   1.919578   2.027121     0.95   0.348    -2.152013     5.99117
       2009  |   4.271599   1.074453     3.98   0.000     2.113497      6.4297
       2010  |   3.117006   1.975622     1.58   0.121     -.851148     7.08516
       2011  |   .6508826   1.257764     0.52   0.607    -1.875411    3.177176
       2012  |   2.251395   1.175404     1.92   0.061    -.1094741    4.612264
       2013  |     3.9567   1.447679     2.73   0.009      1.04895     6.86445
       2014  |   2.606375   1.518063     1.72   0.092     -.442744    5.655494
       2015  |   .5264076    1.52806     0.34   0.732    -2.542791    3.595606
             |
migrant#year |
     1 1999  |  -4.575206   2.017413    -2.27   0.028      -8.6273   -.5231126
     1 2000  |  -3.229547   1.839907    -1.76   0.085    -6.925109    .4660144
     1 2001  |  -1.282503   1.636823    -0.78   0.437    -4.570158    2.005152
     1 2002  |  -3.789008   1.269596    -2.98   0.004    -6.339066    -1.23895
     1 2003  |  -2.125602   1.906557    -1.11   0.270    -5.955034     1.70383
     1 2004  |  -6.066576   2.387917    -2.54   0.014    -10.86285   -1.270303
     1 2005  |  -3.036706   2.087954    -1.45   0.152    -7.230484    1.157072
     1 2006  |  -5.026614   1.873704    -2.68   0.010    -8.790059   -1.263168
     1 2007  |  -4.150899   1.952659    -2.13   0.038     -8.07293   -.2288683
     1 2008  |  -3.531767   2.107203    -1.68   0.100     -7.76421    .7006753
     1 2009  |  -5.678731   2.166907    -2.62   0.012    -10.03109   -1.326371
     1 2010  |   -6.01655   2.653455    -2.27   0.028    -11.34617   -.6869283
     1 2011  |  -3.007175   2.205983    -1.36   0.179    -7.438022    1.423673
     1 2012  |  -4.141377    2.67883    -1.55   0.128    -9.521965     1.23921
     1 2013  |  -4.955986   2.926845    -1.69   0.097    -10.83473    .9227545
     1 2014  |  -5.434965   2.952279    -1.84   0.072    -11.36479    .4948613
     1 2015  |   -1.41757   3.288126    -0.43   0.668    -8.021967    5.186826
             |
  entry_year |  -.0894105   .1497307    -0.60   0.553    -.3901534    .2113324
entry_year~q |   .0000442   .0000745     0.59   0.556    -.0001054    .0001938
       _cons |   36.32322   1.325805    27.40   0.000     33.66026    38.98618
------------------------------------------------------------------------------
```

<u>Specification (5), Endogenous-wage, Method 1, Full sample</u>

```
Linear regression                               Number of obs     =  1,375,615
                                                F(50, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.2895
                                                Root MSE          =     .61476

                                  (Std. Err. adjusted for 51 clusters in state)
```

```
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   .3558109   .0319365    11.14   0.000      .2916646    .4199572
post911entry |  -.0628346   .0037511   -16.75   0.000     -.0703689   -.0553004
post911entr~t |   .0198273   .0075804     2.62   0.012      .0046017     .035053
    hispagri |  -.2456312   .0290849    -8.45   0.000     -.3040499   -.1872124
hispagri_mi~t |   .0887647   .0320102     2.77   0.008      .0244704    .1530591
hispagri_~911 |   .1082227   .0434167     2.49   0.016      .0210176    .1954277
hispagri_po~t |  -.0989858   .0459453    -2.15   0.036     -.1912696   -.0067019
      hsgrad |   .3005191   .0060088    50.01   0.000        .28845    .3125882
   assocgrad |   .4869109    .005925    82.18   0.000      .4750101    .4988117
    bachgrad |   .7626389   .0102068    74.72   0.000      .7421379    .7831399
    mastgrad |   .9357019   .0137747    67.93   0.000      .9080345    .9633692
  doctorgrad |   1.201576   .0130393    92.15   0.000      1.175386    1.227767
migranthsgrad |  -.1087156   .0055282   -19.67   0.000     -.1198194   -.0976118
migrantasso~d |  -.0893212   .0116341    -7.68   0.000     -.1126889   -.0659535
migrantbach~d |  -.0970236   .0109879    -8.83   0.000     -.1190934   -.0749537
migrantmast~d |   .0233328   .0155736     1.50   0.140     -.0079476    .0546132
migrantdoct~d |  -.1233904   .0141125    -8.74   0.000     -.1517361   -.0950447
         exp |   .0410852   .0009308    44.14   0.000      .0392156    .0429548
  migrantexp |  -.0182869   .0009967   -18.35   0.000     -.0202888    -.016285
      exp_sq |  -.0006699   .0000183   -36.67   0.000     -.0007066   -.0006332
migrantexp_sq |   .0002565   .0000185    13.88   0.000      .0002194    .0002936
      female |  -.2456887   .0048406   -50.76   0.000     -.2554114   -.2359661
migrantfemale |   .0232146    .006973     3.33   0.002      .0092089    .0372204
   1.migrant |          0  (omitted)
             |
       wbhao |
      Black  |  -.1425905   .0092206   -15.46   0.000     -.1611106   -.1240703
   Hispanic  |  -.0679097   .0244467    -2.78   0.008     -.1170124   -.0188071
      Asian  |   .0210588   .0162589     1.30   0.201     -.0115982    .0537157
      Other  |  -.0867905   .0119687    -7.25   0.000     -.1108305   -.0627506
             |
migrant#wbhao |
    1#Black  |   .0362921   .0181237     2.00   0.051     -.0001105    .0726947
 1#Hispanic  |    -.11648   .0211052    -5.52   0.000     -.1588709    -.074089
    1#Asian  |  -.0444337   .0142033    -3.13   0.003     -.0729619   -.0159054
    1#Other  |   .0162193   .0525022     0.31   0.759     -.0892345    .1216731
             |
years_since~l |   .0095459   .0012066     7.91   0.000      .0071225    .0119694
       rural |  -.1700708   .0128976   -13.19   0.000     -.1959763   -.1441652
migrantrural |   .0916447   .0162979     5.62   0.000      .0589095    .1243799
             |
        year |
       1999  |   .0311793   .0049301     6.32   0.000      .0212769    .0410816
       2000  |   .0423695   .0043612     9.72   0.000      .0336097    .0511292
       2001  |   .0583211   .0051889    11.24   0.000      .0478988    .0687433
       2002  |   .0651945   .0043638    14.94   0.000      .0564296    .0739595
       2003  |   .0729471   .0052143    13.99   0.000      .0624739    .0834203
       2004  |   .0659916    .005023    13.14   0.000      .0559027    .0760805
       2005  |    .052099   .0040617    12.83   0.000      .0439409     .060257
       2006  |   .0442711   .0053263     8.31   0.000      .0335728    .0549694
       2007  |   .0465224   .0077809     5.98   0.000       .030894    .0621509
       2008  |   .0546043   .0067511     8.09   0.000      .0410443    .0681642
       2009  |    .037598   .0068012     5.53   0.000      .0239373    .0512587
       2010  |   .0531627   .0057303     9.28   0.000       .041653    .0646724
       2011  |   .0373577   .0060953     6.13   0.000      .0251149    .0496005
       2012  |   .0236244   .0078044     3.03   0.004      .0079489    .0392999
```

```
        2013  |   .0083182    .007219     1.15   0.255    -.0061816    .0228181
        2014  |   .0102354   .0099966     1.02   0.311    -.0098435    .0303142
        2015  |   .0129371   .0089916     1.44   0.156    -.0051231    .0309973
              |
 migrant#year |
      1 1999  |  -.0153796   .0090266    -1.70   0.095    -.0335101    .0027509
      1 2000  |   .0119152   .0091531     1.30   0.199    -.0064694    .0302998
      1 2001  |   .0242805   .0110585     2.20   0.033     .0020688    .0464923
      1 2002  |   .0240472   .0072868     3.30   0.002     .0094114    .0386831
      1 2003  |  -.0006085   .0129361    -0.05   0.963    -.0265913    .0253744
      1 2004  |  -.0049105   .0130626    -0.38   0.709    -.0311476    .0213265
      1 2005  |   .0130735   .0129656     1.01   0.318    -.0129686    .0391156
      1 2006  |   .0205759   .0106282     1.94   0.059    -.0007715    .0419232
      1 2007  |   .0166566   .0111149     1.50   0.140    -.0056683    .0389816
      1 2008  |   .0058746   .0120331     0.49   0.628    -.0182946    .0300437
      1 2009  |  -.0017813   .0152108    -0.12   0.907     -.032333    .0287704
      1 2010  |   .0064252   .0148259     0.43   0.667    -.0233535    .0362038
      1 2011  |   .0046554   .0152994     0.30   0.762    -.0260743    .0353852
      1 2012  |   .0024167   .0165697     0.15   0.885    -.0308645    .0356979
      1 2013  |   .0096407   .0171226     0.56   0.576     -.024751    .0440324
      1 2014  |   .0015057   .0192281     0.08   0.938     -.037115    .0401264
      1 2015  |  -.0159559   .0228291    -0.70   0.488    -.0618094    .0298976
              |
   entry_year |  -.0017898   .0009402    -1.90   0.063    -.0036783    .0000986
entry_year_sq |   8.26e-07   4.67e-07     1.77   0.083    -1.11e-07    1.76e-06
        _cons |   2.142764   .0078967   271.35   0.000     2.126904    2.158625
------------------------------------------------------------------------------

Linear regression                               Number of obs     =  1,376,334
                                                F(51, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1249
                                                Root MSE          =     9.8426

                                 (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
              |               Robust
  hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
      migrant |   2.881023   .4027868     7.15   0.000     2.072002    3.690044
 post911entry |  -1.178139    .069698   -16.90   0.000    -1.318131   -1.038146
post911entr~t |   .9433112   .1388782     6.79   0.000     .6643661    1.222256
     hispagri |    2.52103   .2663468     9.47   0.000     1.986057    3.056004
hispagri_mi~t |   .1817646   .3945216     0.46   0.647    -.6106553    .9741845
hispagri_~911 |   1.483514     .55393     2.68   0.010     .3709124    2.596115
hispagri_po~t |   .5434315    .739279     0.74   0.466     -.941454    2.028317
       hsgrad |   2.390392   .1214004    19.69   0.000     2.146552    2.634231
    assocgrad |   3.008578    .131605    22.86   0.000     2.744242    3.272915
     bachgrad |    4.73848   .1316355    36.00   0.000     4.474082    5.002877
     mastgrad |   5.658689   .1723568    32.83   0.000       5.3125    6.004878
   doctorgrad |   8.926062   .2542774    35.10   0.000     8.415331    9.436793
migranthsgrad |  -1.677612   .1346605   -12.46   0.000    -1.948086   -1.407139
migrantasso~d |  -1.859134   .1923165    -9.67   0.000    -2.245413   -1.472855
migrantbach~d |  -2.231418   .2090386   -10.67   0.000    -2.651284   -1.811552
migrantmast~d |  -2.243932    .301026    -7.45   0.000    -2.848561   -1.639304
migrantdoct~d |  -1.660426   .2470645    -6.72   0.000     -2.15667   -1.164183
          exp |   .5861767   .0104914    55.87   0.000      .565104    .6072493
   migrantexp |  -.2304672   .0142285   -16.20   0.000    -.2590459   -.2018885
       exp_sq |  -.0112896   .0001958   -57.65   0.000    -.0116829   -.0108963
migrantexp_sq |   .0049639   .0002649    18.74   0.000     .0044319    .0054958
```

female	-4.855715	.1134377	-42.81	0.000	-5.083561	-4.627868
migrantfemale	.887013	.1142574	7.76	0.000	.6575203	1.116506
1.migrant	0	(omitted)				
wbhao						
Black	.0190582	.0784175	0.24	0.809	-.1384479	.1765644
Hispanic	.0799813	.2317898	0.35	0.731	-.3855822	.5455448
Asian	-.3993852	.2686218	-1.49	0.143	-.938928	.1401575
Other	.2357101	.1553665	1.52	0.136	-.0763528	.547773
migrant#wbhao						
1#Black	-.3388908	.1497248	-2.26	0.028	-.639622	-.0381597
1#Hispanic	-.4416303	.1637227	-2.70	0.010	-.7704771	-.1127835
1#Asian	-.3530615	.2823461	-1.25	0.217	-.9201704	.2140474
1#Other	-.6634575	.4266199	-1.56	0.126	-1.520349	.1934338
years_since~l	-.0104918	.0127564	-0.82	0.415	-.0361138	.0151303
rural	.2438772	.0894077	2.73	0.009	.0642966	.4234579
migrantrural	.5466263	.2472769	2.21	0.032	.0499561	1.043296
year						
1999	.1020387	.066037	1.55	0.129	-.0306006	.234678
2000	.1165956	.0905742	1.29	0.204	-.0653281	.2985193
2001	.0598718	.0965489	0.62	0.538	-.1340524	.2537961
2002	-.1386589	.0761087	-1.82	0.074	-.2915277	.0142099
2003	-.3266308	.0838557	-3.90	0.000	-.4950599	-.1582017
2004	-.3468174	.104646	-3.31	0.002	-.5570051	-.1366297
2005	-.2244675	.0909207	-2.47	0.017	-.4070871	-.0418479
2006	-.1045532	.1046686	-1.00	0.323	-.3147863	.1056799
2007	-.0128801	.0864754	-0.15	0.882	-.1865709	.1608108
2008	-.0392619	.0944609	-0.42	0.679	-.2289922	.1504685
2009	-.346911	.0920273	-3.77	0.000	-.5317533	-.1620686
2010	-.6806669	.0944915	-7.20	0.000	-.8704587	-.4908752
2011	-.6786023	.08934	-7.60	0.000	-.858047	-.4991576
2012	-.5119992	.0953202	-5.37	0.000	-.7034554	-.320543
2013	-.3885742	.1151461	-3.37	0.001	-.6198519	-.1572964
2014	-.3664795	.1093383	-3.35	0.002	-.5860919	-.1468671
2015	-.156778	.1007436	-1.56	0.126	-.3591274	.0455714
migrant#year						
1 1999	.1016444	.1591011	0.64	0.526	-.2179196	.4212084
1 2000	.2694234	.2204616	1.22	0.227	-.1733868	.7122336
1 2001	.4051342	.1592132	2.54	0.014	.085345	.7249233
1 2002	.1876138	.1646119	1.14	0.260	-.1430189	.5182466
1 2003	.3320096	.1807531	1.84	0.072	-.0310437	.6950629
1 2004	.2370537	.2167503	1.09	0.279	-.1983022	.6724095
1 2005	.2051131	.152478	1.35	0.185	-.101148	.5113742
1 2006	.5752544	.1933473	2.98	0.004	.1869049	.9636039
1 2007	.3544102	.1696939	2.09	0.042	.0135699	.6952505
1 2008	.2936128	.2154338	1.36	0.179	-.1390988	.7263243
1 2009	.000428	.2096543	0.00	0.998	-.420675	.421531
1 2010	-.2840803	.211613	-1.34	0.186	-.7091176	.140957
1 2011	-.1753837	.203259	-0.86	0.392	-.5836415	.2328741
1 2012	-.2035591	.2278588	-0.89	0.376	-.661227	.2541088
1 2013	-.1992905	.2477262	-0.80	0.425	-.6968633	.2982823
1 2014	-.036196	.2669219	-0.14	0.893	-.5723243	.4999324
1 2015	-.0735656	.2354512	-0.31	0.756	-.5464833	.399352
entry_year	.0270704	.0135249	2.00	0.051	-.0000953	.054236
entry_year_sq	-.0000136	6.75e-06	-2.01	0.050	-.0000271	-5.41e-09

_cons	33.73922	.2468831	136.66	0.000	33.24334	34.2351

Specification (6), Endogenous-wage, Method 1, Restricted sample

Linear regression

Number of obs	=	6,115
F(49, 50)	=	.
Prob > F	=	.
R-squared	=	0.0707
Root MSE	=	.58433

(Std. Err. adjusted for 51 clusters in state)

lnwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	-.0445019	.2214391	-0.20	0.842	-.4892753	.4002716
post911entry	-.1851448	.0604442	-3.06	0.004	-.3065504	-.0637391
post911ent~t	.1287598	.0717803	1.79	0.079	-.0154151	.2729347
hsgrad	.2495763	.0439269	5.68	0.000	.1613465	.3378061
assocgrad	.4454983	.0889972	5.01	0.000	.2667421	.6242545
bachgrad	.8806937	.079242	11.11	0.000	.7215315	1.039856
mastgrad	.2391151	.186151	1.28	0.205	-.1347803	.6130104
doctorgrad	1.111088	.1264139	8.79	0.000	.8571784	1.364998
migranthsg~d	-.1234688	.0434155	-2.84	0.006	-.2106714	-.0362662
migrantass~d	-.2565448	.1339567	-1.92	0.061	-.5256047	.0125151
migrantbac~d	-.454381	.081024	-5.61	0.000	-.6171226	-.2916395
migrantmas~d	.1688543	.2089605	0.81	0.423	-.2508553	.5885639
migrantdoc~d	-1.242569	.1985524	-6.26	0.000	-1.641373	-.843765
exp	.0149021	.006229	2.39	0.021	.0023908	.0274134
migrantexp	-.0044424	.0075786	-0.59	0.560	-.0196644	.0107796
exp_sq	-.0002647	.0000997	-2.65	0.011	-.000465	-.0000643
migrantexp~q	.0001129	.0001216	0.93	0.357	-.0001313	.0003572
female	-.1761387	.0322364	-5.46	0.000	-.2408875	-.11139
migrantfem~e	.0247718	.0319604	0.78	0.442	-.0394225	.0889661
1.migrant	0	(omitted)				
wbhao						
Hispanic	0	(omitted)				
migrant# wbhao						
1#Hispanic	0	(omitted)				
years_sinc~l	.0069981	.0009059	7.72	0.000	.0051785	.0088176
rural	-.0655394	.0484833	-1.35	0.183	-.162921	.0318421
migrantrural	.0046875	.050068	0.09	0.926	-.0958771	.1052521
year						
1999	.155137	.2194029	0.71	0.483	-.2855466	.5958207
2000	.1209296	.1605966	0.75	0.455	-.2016381	.4434973
2001	.045147	.1489121	0.30	0.763	-.2539517	.3442457
2002	.2255152	.2314298	0.97	0.335	-.2393252	.6903557
2003	.2131471	.1474805	1.45	0.155	-.0830762	.5093703
2004	.1676269	.1417185	1.18	0.242	-.1170232	.452277
2005	.2196136	.147687	1.49	0.143	-.0770243	.5162516
2006	.2298332	.2286623	1.01	0.320	-.2294485	.689115
2007	.1499485	.2410235	0.62	0.537	-.3341613	.6340584
2008	-.0574977	.119096	-0.48	0.631	-.2967091	.1817137
2009	.1615349	.1806056	0.89	0.375	-.201222	.5242919

```
        2010  |   .1300693   .2717732     0.48   0.634    -.4158033    .6759419
        2011  |   .0771434   .1553738     0.50   0.622    -.2349341    .3892208
        2012  |   .2845772   .1863926     1.53   0.133    -.0898034    .6589578
        2013  |   .3232034   .2588615     1.25   0.218    -.1967352    .8431421
        2014  |   .1031324   .1183049     0.87   0.388      -.13449    .3407548
        2015  |   .3058052   .1606399     1.90   0.063    -.0168495    .6284599
              |
migrant#year |
      1 1999  |  -.0621587   .2459298    -0.25   0.801    -.5561233     .431806
      1 2000  |  -.0180098   .2062363    -0.09   0.931    -.4322475     .396228
      1 2001  |   .0930637   .2335922     0.40   0.692      -.37612    .5622474
      1 2002  |  -.1310039   .3156653    -0.42   0.680    -.7650363    .5030285
      1 2003  |  -.0073878   .1756215    -0.04   0.967     -.360134    .3453583
      1 2004  |  -.0545688   .1948498    -0.28   0.781    -.4459362    .3367986
      1 2005  |  -.0294051   .1491622    -0.20   0.845    -.3290062    .2701961
      1 2006  |  -.1363821    .278061    -0.49   0.626     -.694884    .4221198
      1 2007  |  -.1020113   .2845749    -0.36   0.722    -.6735968    .4695742
      1 2008  |   .1455019   .1213507     1.20   0.236    -.0982381     .389242
      1 2009  |  -.0954118   .2129175    -0.45   0.656    -.5230691    .3322455
      1 2010  |   .0453976   .3015557     0.15   0.881    -.5602948      .65109
      1 2011  |    .047834   .2161915     0.22   0.826    -.3863994    .4820674
      1 2012  |  -.1043727    .210706    -0.50   0.623     -.527588    .3188427
      1 2013  |  -.1694221   .2742595    -0.62   0.540    -.7202884    .3814442
      1 2014  |   .0915744   .1621463     0.56   0.575     -.234106    .4172547
      1 2015  |  -.2189377   .2040265    -1.07   0.288    -.6287369    .1908615
              |
       _cons  |   1.994183   .1611891    12.37   0.000     1.670425    2.317941
------------------------------------------------------------------------------

Linear regression                               Number of obs     =      6,121
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.0616
                                                Root MSE          =     9.4865

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   3.613375   1.114494     3.24   0.002     1.374848    5.851902
post911entry |   .0661627   .6700931     0.10   0.922    -1.279759    1.412084
post911ent~t |   1.543264   .8194625     1.88   0.065    -.1026753    3.189202
      hsgrad |   .5711841   .8506805     0.67   0.505    -1.137458    2.279826
   assocgrad |   5.055342   2.622355     1.93   0.060    -.2118126     10.3225
    bachgrad |   .5183676   2.401719     0.22   0.830    -4.305628    5.342363
    mastgrad |     6.5331   1.299641     5.03   0.000     3.922695    9.143505
  doctorgrad |   4.812416   4.135257     1.16   0.250    -3.493492    13.11832
migranthsg~d |  -.5634257   .8214623    -0.69   0.496    -2.213381     1.08653
migrantass~d |  -3.610899   2.962988    -1.22   0.229    -9.562236    2.340439
migrantbac~d |  -1.660086   2.087407    -0.80   0.430    -5.852766    2.532594
migrantmas~d |  -7.976956   1.199843    -6.65   0.000    -10.38691      -5.567
migrantdoc~d |  -13.31076   5.751553    -2.31   0.025     -24.8631   -1.758431
         exp |   .2291798   .0851089     2.69   0.010     .0582335     .400126
  migrantexp |  -.0418443   .0863844    -0.48   0.630    -.2153526     .131664
      exp_sq |  -.0028493   .0016248    -1.75   0.086    -.0061128    .0004142
migrantexp~q |  -.0004401   .0015863    -0.28   0.783    -.0036264    .0027461
      female |  -4.848479   .7291054    -6.65   0.000     -6.31293   -3.384028
migrantfem~e |   .9523785   .5446248     1.75   0.086    -.1415326     2.04629
   1.migrant |          0  (omitted)
```

```
              |
        wbhao |
    Hispanic  |          0  (omitted)
              |
     migrant#|
        wbhao |
  1#Hispanic  |          0  (omitted)
              |
years_sinc~l |   .0486586   .0211826     2.30   0.026     .0061121     .091205
        rural |   1.290476   .9185436     1.40   0.166    -.5544735    3.135425
migrantrural |   1.293543   .6716631     1.93   0.060    -.0555322    2.642618
              |
         year |
        1999  |   4.290194   1.611758     2.66   0.010     1.052883    7.527506
        2000  |   3.494112   1.581565     2.21   0.032     .3174454    6.670778
        2001  |   1.461591   1.525816     0.96   0.343    -1.603101    4.526282
        2002  |   2.256934   1.227345     1.84   0.072    -.2082604    4.722128
        2003  |   2.008898   2.090572     0.96   0.341     -2.19014    6.207936
        2004  |    5.74413   2.990724     1.92   0.060    -.2629154    11.75118
        2005  |   4.171577   1.315533     3.17   0.003     1.529251    6.813902
        2006  |   4.440847   1.844029     2.41   0.020     .7370059    8.144689
        2007  |   3.709509   1.547884     2.40   0.020     .6004934    6.818525
        2008  |   2.083166   2.004489     1.04   0.304    -1.942968      6.1093
        2009  |   4.518915   1.057118     4.27   0.000     2.395632    6.642199
        2010  |   3.301183   1.996597     1.65   0.105    -.7091004    7.311466
        2011  |   .8598069   1.248696     0.69   0.494    -1.648272    3.367886
        2012  |   2.515293   1.228949     2.05   0.046     .0468751     4.98371
        2013  |   4.177739   1.508598     2.77   0.008     1.147631    7.207848
        2014  |   2.908779   1.510234     1.93   0.060    -.1246151    5.942172
        2015  |   .7694978   1.581028     0.49   0.629     -2.40609    3.945085
              |
migrant#year |
      1 1999  |    -4.3221   2.058658    -2.10   0.041    -8.457037   -.1871638
      1 2000  |  -2.930523   1.903423    -1.54   0.130    -6.753661    .8926145
      1 2001  |  -.9146636   1.650138    -0.55   0.582    -4.229063    2.399735
      1 2002  |  -3.370878   1.087806    -3.10   0.003      -5.5558   -1.185957
      1 2003  |  -1.653723   1.987937    -0.83   0.409    -5.646612    2.339165
      1 2004  |  -5.671739   2.149996    -2.64   0.011    -9.990133   -1.353345
      1 2005  |  -2.321646   1.558584    -1.49   0.143    -5.452155     .808862
      1 2006  |  -4.508543   1.826206    -2.47   0.017    -8.176587   -.8404999
      1 2007  |  -3.451945   1.713251    -2.01   0.049    -6.893111   -.0107787
      1 2008  |  -2.873261   1.472605    -1.95   0.057    -5.831075    .0845539
      1 2009  |   -4.71803   1.511506    -3.12   0.003    -7.753979   -1.682081
      1 2010  |  -5.287673   1.926176    -2.75   0.008    -9.156511   -1.418836
      1 2011  |  -2.095911   1.240528    -1.69   0.097    -4.587586    .3957637
      1 2012  |  -3.112464    1.50126    -2.07   0.043    -6.127834   -.0970934
      1 2013  |  -3.735407   1.801464    -2.07   0.043    -7.353753   -.1170608
      1 2014  |   -4.04703   2.008495    -2.01   0.049    -8.081212   -.0128485
      1 2015  |   .0966194   2.272326     0.04   0.966    -4.467482    4.660721
              |
        _cons |   36.34587   1.321499    27.50   0.000     33.69156    39.00018
------------------------------------------------------------------------------
```

Specification (6), Endogenous-wage, Method 1, Full sample

```
Linear regression                               Number of obs     =  1,364,949
                                                F(50, 50)         =          .
                                                Prob > F          =          .
```

R-squared = 0.2893
Root MSE = .61437

(Std. Err. adjusted for 51 clusters in state)

lnwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	.4058298	.0328477	12.35	0.000	.3398532	.4718063
post911entry	-.0629156	.0037462	-16.79	0.000	-.07044	-.0553912
post911entr~t	.0027438	.0071676	0.38	0.703	-.0116527	.0171404
hispagri	-.2461976	.028991	-8.49	0.000	-.3044278	-.1879673
hispagri_mi~t	.0876503	.0319919	2.74	0.009	.0233927	.151908
hispagri_~911	.1086289	.0431688	2.52	0.015	.0219217	.195336
hispagri_po~t	-.0939632	.0457243	-2.05	0.045	-.1858031	-.0021232
hsgrad	.3004801	.0059929	50.14	0.000	.288443	.3125172
assocgrad	.4868699	.00591	82.38	0.000	.4749993	.4987406
bachgrad	.7626128	.0101922	74.82	0.000	.7421411	.7830845
mastgrad	.935677	.0137618	67.99	0.000	.9080356	.9633183
doctorgrad	1.201565	.0130283	92.23	0.000	1.175397	1.227733
migranthsgrad	-.1098805	.005195	-21.15	0.000	-.120315	-.0994461
migrantasso~d	-.0888181	.0122146	-7.27	0.000	-.113352	-.0642843
migrantbach~d	-.1021365	.01046	-9.76	0.000	-.123146	-.081127
migrantmast~d	.0173237	.0158994	1.09	0.281	-.0146113	.0492587
migrantdoct~d	-.1363923	.0143673	-9.49	0.000	-.16525	-.1075347
exp	.0410882	.0009312	44.12	0.000	.0392179	.0429586
migrantexp	-.0226256	.0010842	-20.87	0.000	-.0248033	-.020448
exp_sq	-.00067	.0000183	-36.67	0.000	-.0007067	-.0006333
migrantexp_sq	.0003252	.0000191	17.01	0.000	.0002868	.0003636
female	-.2456918	.0048429	-50.73	0.000	-.255419	-.2359646
migrantfemale	.0170019	.0069622	2.44	0.018	.0030179	.0309859
1.migrant	0	(omitted)				
wbhao						
Black	-.1425775	.0092218	-15.46	0.000	-.1611	-.1240549
Hispanic	-.0671695	.024505	-2.74	0.008	-.1163894	-.0179497
Asian	.0225145	.0162852	1.38	0.173	-.0101953	.0552244
Other	-.0868192	.0119733	-7.25	0.000	-.1108683	-.0627701
migrant#wbhao						
1#Black	.0370696	.0196714	1.88	0.065	-.0024415	.0765808
1#Hispanic	-.124851	.0216632	-5.76	0.000	-.1683628	-.0813392
1#Asian	-.0485691	.0147042	-3.30	0.002	-.0781033	-.0190349
1#Other	.0137706	.0577155	0.24	0.812	-.1021543	.1296956
years_since~l	.0073274	.0011115	6.59	0.000	.0050949	.0095598
rural	-.1700996	.0128937	-13.19	0.000	-.1959973	-.1442018
migrantrural	.0908561	.0163893	5.54	0.000	.0579373	.1237748
year						
1999	.0312127	.0049241	6.34	0.000	.0213224	.0411031
2000	.0424498	.0043598	9.74	0.000	.0336928	.0512068
2001	.0584419	.0051888	11.26	0.000	.0480199	.068864
2002	.0653453	.0043585	14.99	0.000	.056591	.0740996
2003	.0731252	.0052064	14.05	0.000	.0626679	.0835825
2004	.0662151	.0050158	13.20	0.000	.0561405	.0762897
2005	.0523634	.0040439	12.95	0.000	.044241	.0604857
2006	.0445777	.0053187	8.38	0.000	.0338947	.0552606
2007	.0468664	.0077797	6.02	0.000	.0312404	.0624924
2008	.0549961	.0067375	8.16	0.000	.0414635	.0685287

2009	.0380239	.0067898	5.60	0.000	.0243861	.0516616
2010	.0536259	.005744	9.34	0.000	.0420888	.0651631
2011	.0378593	.0060758	6.23	0.000	.0256557	.0500629
2012	.0241652	.007793	3.10	0.003	.0085125	.0398178
2013	.0089088	.0072087	1.24	0.222	-.0055703	.023388
2014	.0108476	.0099816	1.09	0.282	-.0092011	.0308963
2015	.0136141	.0089759	1.52	0.136	-.0044145	.0316428
migrant#year						
1 1999	-.0131874	.0088875	-1.48	0.144	-.0310384	.0046637
1 2000	.0172559	.0092583	1.86	0.068	-.0013401	.0358518
1 2001	.0319855	.0108402	2.95	0.005	.0102124	.0537586
1 2002	.0350293	.0070942	4.94	0.000	.0207801	.0492785
1 2003	.0138842	.0131097	1.06	0.295	-.0124474	.0402158
1 2004	.0144629	.0131892	1.10	0.278	-.0120285	.0409543
1 2005	.0387368	.0123052	3.15	0.003	.0140212	.0634525
1 2006	.0502789	.0095896	5.24	0.000	.0310176	.0695403
1 2007	.0521933	.0098512	5.30	0.000	.0324066	.07198
1 2008	.0416253	.0100778	4.13	0.000	.0213834	.0618672
1 2009	.0397591	.0136992	2.90	0.005	.0122434	.0672748
1 2010	.0486218	.0134111	3.63	0.001	.0216848	.0755587
1 2011	.0508937	.0130039	3.91	0.000	.0247746	.0770127
1 2012	.0506065	.0150377	3.37	0.001	.0204024	.0808106
1 2013	.0626738	.0151431	4.14	0.000	.032258	.0930896
1 2014	.0584174	.0167123	3.50	0.001	.0248497	.0919851
1 2015	.0486811	.0198799	2.45	0.018	.0087512	.088611
entry_year	.0007229	.0009006	0.80	0.426	-.0010859	.0025318
entry_year_sq	-4.30e-07	4.48e-07	-0.96	0.342	-1.33e-06	4.70e-07
_cons	2.142523	.0079	271.21	0.000	2.126655	2.15839

Linear regression

Number of obs	=	1,365,655
F(49, 50)	=	.
Prob > F	=	.
R-squared	=	0.1246
Root MSE	=	9.8367

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	3.809941	.4016474	9.49	0.000	3.003209	4.616674
post911entry	-1.176975	.069705	-16.89	0.000	-1.316982	-1.036969
post911entr~t	.6363845	.1203474	5.29	0.000	.3946596	.8781094
hispagri	2.524794	.2658917	9.50	0.000	1.990735	3.058853
hispagri_mi~t	.1186315	.4018272	0.30	0.769	-.6884622	.9257253
hispagri_~911	1.484565	.5534925	2.68	0.010	.3728424	2.596287
hispagri_po~t	.6398562	.7515262	0.85	0.399	-.8696287	2.149341
hsgrad	2.391555	.1212812	19.72	0.000	2.147955	2.635156
assocgrad	3.009736	.1313996	22.91	0.000	2.745812	3.27366
bachgrad	4.739389	.1315648	36.02	0.000	4.475133	5.003644
mastgrad	5.659607	.1723466	32.84	0.000	5.313439	6.005775
doctorgrad	8.926872	.2540024	35.14	0.000	8.416693	9.437051
migranthsgrad	-1.639933	.1388156	-11.81	0.000	-1.918753	-1.361114
migrantasso~d	-1.985823	.2075043	-9.57	0.000	-2.402608	-1.569038
migrantbach~d	-2.464493	.2288624	-10.77	0.000	-2.924177	-2.00481
migrantmast~d	-2.5647	.2942192	-8.72	0.000	-3.155656	-1.973743
migrantdoct~d	-2.185114	.2437131	-8.97	0.000	-2.674626	-1.695602

exp	.5861356	.0104829	55.91	0.000	.5650801	.6071911
migrantexp	-.2935183	.0175308	-16.74	0.000	-.3287299	-.2583066
exp_sq	-.0112884	.0001956	-57.70	0.000	-.0116813	-.0108954
migrantexp_sq	.0060315	.0003097	19.48	0.000	.0054095	.0066536
female	-4.855662	.1134419	-42.80	0.000	-5.083517	-4.627807
migrantfemale	.8291426	.1182644	7.01	0.000	.5916015	1.066684
1.migrant	0	(omitted)				
wbhao						
Black	.0188974	.0784107	0.24	0.811	-.1385951	.1763898
Hispanic	.0669507	.2289236	0.29	0.771	-.3928559	.5267572
Asian	-.4220241	.2694824	-1.57	0.124	-.9632954	.1192472
Other	.2359467	.1553233	1.52	0.135	-.0760294	.5479228
migrant#wbhao						
1#Black	-.4461915	.1355169	-3.29	0.002	-.7183851	-.1739979
1#Hispanic	-.6357553	.1515781	-4.19	0.000	-.9402088	-.3313017
1#Asian	-.3486413	.2506265	-1.39	0.170	-.8520394	.1547568
1#Other	-.6862724	.4561279	-1.50	0.139	-1.602432	.2298875
years_since~l	.0115816	.0025375	4.56	0.000	.006485	.0166782
rural	.244465	.0894091	2.73	0.009	.0648816	.4240484
migrantrural	.5472726	.2561066	2.14	0.038	.0328674	1.061678
year						
1999	.1016372	.0660265	1.54	0.130	-.0309808	.2342553
2000	.115765	.09048	1.28	0.207	-.0659694	.2974993
2001	.058613	.096284	0.61	0.545	-.1347792	.2520051
2002	-.1402424	.0759826	-1.85	0.071	-.2928579	.0123732
2003	-.3285205	.0836799	-3.93	0.000	-.4965965	-.1604445
2004	-.3492414	.104449	-3.34	0.002	-.5590334	-.1394493
2005	-.2272379	.090646	-2.51	0.015	-.4093058	-.0451699
2006	-.1077711	.1044407	-1.03	0.307	-.3175465	.1020043
2007	-.0164638	.0862022	-0.19	0.849	-.1896061	.1566785
2008	-.0433839	.0941156	-0.46	0.647	-.2324206	.1456527
2009	-.3513564	.0914932	-3.84	0.000	-.5351259	-.1675869
2010	-.6854892	.0945486	-7.25	0.000	-.8753956	-.4955828
2011	-.6838288	.0889409	-7.69	0.000	-.8624718	-.5051857
2012	-.5175809	.0947163	-5.46	0.000	-.7078241	-.3273377
2013	-.3947248	.1148593	-3.44	0.001	-.6254265	-.1640231
2014	-.3727888	.1089752	-3.42	0.001	-.5916719	-.1539058
2015	-.1637923	.0999213	-1.64	0.107	-.3644901	.0369055
migrant#year						
1 1999	.0756971	.1612842	0.47	0.641	-.2482516	.3996459
1 2000	.2250827	.2132149	1.06	0.296	-.203172	.6533374
1 2001	.3339562	.1633416	2.04	0.046	.0058749	.6620374
1 2002	.1297622	.1630186	0.80	0.430	-.1976703	.4571947
1 2003	.3132598	.165318	1.89	0.064	-.0187913	.6453109
1 2004	.2539175	.2088187	1.22	0.230	-.1655071	.6733422
1 2005	.2472708	.1250531	1.98	0.054	-.0039058	.4984474
1 2006	.6102099	.1700843	3.59	0.001	.2685856	.9518342
1 2007	.3324825	.1218603	2.73	0.009	.0877189	.5772462
1 2008	.1902472	.1636357	1.16	0.251	-.1384248	.5189193
1 2009	-.0445093	.1626084	-0.27	0.785	-.3711179	.2820993
1 2010	-.4255475	.1535477	-2.77	0.008	-.7339571	-.117138
1 2011	-.3167405	.1326721	-2.39	0.021	-.5832202	-.0502608
1 2012	-.4048999	.1446801	-2.80	0.007	-.6954985	-.1143014
1 2013	-.4296333	.1714202	-2.51	0.015	-.7739409	-.0853257
1 2014	-.2148146	.1737922	-1.24	0.222	-.5638864	.1342573

1 2015	-.2274949	.1461957	-1.56	0.126	-.5211376	.0661479
_cons	33.74054	.2466233	136.81	0.000	33.24518	34.2359

Specification (1), Endogenous-wage, Method 2, Restricted sample

Linear regression

Number of obs	=	36,851
F(3, 50)	=	91.04
Prob > F	=	0.0000
R-squared	=	0.0087
Root MSE	=	.6358

(Std. Err. adjusted for 51 clusters in state)

lnwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	-.0692838	.0210257	-3.30	0.002	-.1115151	-.0270525
post911entry	-.2039532	.0179011	-11.39	0.000	-.2399087	-.1679977
post911ent~t	.1130039	.0222898	5.07	0.000	.0682335	.1577742
_cons	2.407137	.0145723	165.19	0.000	2.377868	2.436407

Linear regression

Number of obs	=	36,948
F(3, 50)	=	14.79
Prob > F	=	0.0000
R-squared	=	0.0060
Root MSE	=	11.47

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	1.310909	.3142527	4.17	0.000	.6797134	1.942104
post911entry	-2.225288	.430101	-5.17	0.000	-3.089171	-1.361405
post911ent~t	2.074008	.5705033	3.64	0.001	.9281181	3.219897
_cons	36.8746	.1692745	217.84	0.000	36.53461	37.2146

Specification (1), Endogenous-wage, Method 2, Full sample

Linear regression

Number of obs	=	1,375,615
F(7, 50)	=	548.52
Prob > F	=	0.0000
R-squared	=	0.0511
Root MSE	=	.71044

(Std. Err. adjusted for 51 clusters in state)

lnwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	-.1531493	.0190851	-8.02	0.000	-.1914828	-.1148159
post911entry	-.4119625	.0108569	-37.94	0.000	-.4337692	-.3901559
post911entr~t	.2500305	.0131519	19.01	0.000	.223614	.276447

```
highmigrant~c |  -.5863068   .0134106   -43.72   0.000    -.6132428   -.5593708
hig~c_migrant |   .0838655   .0194085     4.32   0.000     .0448825    .1228486
highmigra~911 |   .2080093   .0203935    10.20   0.000     .1670477    .2489709
hig~1_migrant |  -.1370266   .0246056    -5.57   0.000    -.1864485   -.0876048
        _cons |   2.993444    .018833   158.95   0.000     2.955617    3.031271
------------------------------------------------------------------------------
```

```
Linear regression                               Number of obs     =  1,376,334
                                                F(7, 50)          =     515.33
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0254
                                                Root MSE          =     10.387

                                   (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
  hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
      migrant |  -.5642804   .1678803    -3.36   0.001    -.9014779   -.2270828
 post911entry |  -5.074641    .140013   -36.24   0.000    -5.355865   -4.793416
post911entr~t |   4.024917     .17091    23.55   0.000     3.681635      4.3682
highmigrant~c |  -3.663275   .1435874   -25.51   0.000    -3.951679   -3.374871
hig~c_migrant |   1.875189   .4132958     4.54   0.000      1.04506    2.705318
highmigra~911 |   2.849353   .4194365     6.79   0.000      2.00689    3.691816
hig~1_migrant |   -1.95091   .5799203    -3.36   0.001    -3.115714   -.7861056
        _cons |   40.53788   .1193098   339.77   0.000     40.29824    40.77752
------------------------------------------------------------------------------
```

Specification (2), Endogenous-wage, Method 2, Restricted sample

```
Linear regression                               Number of obs     =     36,851
                                                F(14, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.0489
                                                Root MSE          =     .62291

                                 (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |  -.0608848    .028154    -2.16   0.035    -.1174337   -.0043359
post911entry |   -.114277   .0271791    -4.20   0.000    -.1688679   -.0596861
post911ent~t |   .0936968   .0320124     2.93   0.005      .029398    .1579956
  yearseduc |   .0283612   .0023302    12.17   0.000     .0236809    .0330416
         exp |   .0133462   .0015178     8.79   0.000     .0102977    .0163947
      exp_sq |  -.0001879   .0000255    -7.37   0.000     -.000239   -.0001367
      female |  -.1553111   .0102617   -15.14   0.000    -.1759223   -.1346998
       white |   .1057775   .0415129     2.55   0.014     .0223964    .1891587
       black |   .0360547   .0479959     0.75   0.456    -.0603479    .1324572
       asian |   .0527978   .0487793     1.08   0.284    -.0451783    .1507739
    hispanic |   .0010063   .0458675     0.02   0.983    -.0911213    .0931339
years_sinc~l |   .0045887   .0007562     6.07   0.000     .0030698    .0061076
       rural |   -.112393   .0141672    -7.93   0.000    -.1408486   -.0839373
        year |   .6347149   1.183456     0.54   0.594    -1.742327    3.011756
     year_sq |  -.0001586   .0002947    -0.54   0.593    -.0007505    .0004333
       _cons |  -633.0807   1188.252    -0.53   0.597    -3019.756    1753.595
------------------------------------------------------------------------------
```

Linear regression

Number of obs	=	36,948
F(14, 50)	=	.
Prob > F	=	.
R-squared	=	0.0903
Root MSE	=	10.975

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	.3162149	.1909488	1.66	0.104	-.0673171	.6997468
post911entry	-.9693009	.4481808	-2.16	0.035	-1.869499	-.0691033
post911ent~t	1.203864	.5492989	2.19	0.033	.1005646	2.307163
yearseduc	-.0483661	.0388007	-1.25	0.218	-.1262996	.0295674
exp	.2926203	.0278439	10.51	0.000	.2366943	.3485464
exp_sq	-.0055071	.0005728	-9.62	0.000	-.0066576	-.0043567
female	-6.640903	.3425822	-19.38	0.000	-7.329	-5.952807
white	-1.399454	.7262525	-1.93	0.060	-2.858175	.0592669
black	.2118407	.682915	0.31	0.758	-1.159835	1.583516
asian	1.053788	.9883378	1.07	0.291	-.9313472	3.038923
hispanic	-.6116686	.6550984	-0.93	0.355	-1.927472	.7041351
years_sinc~l	.0115013	.0070747	1.63	0.110	-.0027086	.0257111
rural	1.477262	.3005742	4.91	0.000	.8735409	2.080983
year	-26.20685	12.9614	-2.02	0.049	-52.2406	-.1731077
year_sq	.0065005	.0032298	2.01	0.050	.0000132	.0129879
_cons	26451.9	13003.73	2.03	0.047	333.1388	52570.66

Specification (2), Endogenous-wage, Method 2, Full sample

Linear regression

Number of obs	=	1,375,615
F(18, 50)	=	.
Prob > F	=	.
R-squared	=	0.2753
Root MSE	=	.62088

(Std. Err. adjusted for 51 clusters in state)

lnwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	-.0623209	.0151934	-4.10	0.000	-.0928376	-.0318041
post911entry	-.0862458	.0053663	-16.07	0.000	-.0970244	-.0754672
post911entr~t	.0207717	.0070256	2.96	0.005	.0066603	.0348831
highmigrant~c	-.2716472	.0095386	-28.48	0.000	-.290806	-.2524883
hig~c_migrant	.1802458	.0237833	7.58	0.000	.1324756	.2280159
highmigra~911	.0927578	.0197777	4.69	0.000	.0530331	.1324824
hig~1_migrant	-.0736413	.02322	-3.17	0.003	-.12028	-.0270026
yearseduc	.1041151	.0023464	44.37	0.000	.0994022	.1088281
exp	.0400238	.0006845	58.47	0.000	.038649	.0413987
exp_sq	-.0006263	.0000128	-48.92	0.000	-.0006521	-.0006006
female	-.2421259	.0048517	-49.91	0.000	-.2518708	-.2323809
white	.1057486	.0122118	8.66	0.000	.0812206	.1302767
black	-.0496444	.016026	-3.10	0.003	-.0818336	-.0174551
asian	.1044022	.0203415	5.13	0.000	.063545	.1452593
hispanic	.0181706	.0198456	0.92	0.364	-.0216905	.0580318

years_since~l	.0022615	.0002522	8.97	0.000	.001755	.002768
rural	-.1655988	.0139581	-11.86	0.000	-.1936344	-.1375631
year	2.401222	.3204142	7.49	0.000	1.757651	3.044793
year_sq	-.0005986	.0000799	-7.50	0.000	-.000759	-.0004382
_cons	-2407.009	321.5774	-7.49	0.000	-3052.916	-1761.102

Linear regression

Number of obs	=	1,376,334
F(18, 50)	=	.
Prob > F	=	.
R-squared	=	0.1151
Root MSE	=	9.8977

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	-.0945098	.0906129	-1.04	0.302	-.2765112	.0874915
post911entry	-1.280977	.0738255	-17.35	0.000	-1.42926	-1.132694
post911entr~t	.7926711	.1432124	5.53	0.000	.5050204	1.080322
highmigrant~c	-1.341418	.1451981	-9.24	0.000	-1.633057	-1.049779
hig~c_migrant	2.153704	.4832743	4.46	0.000	1.183019	3.124389
highmigra~911	1.303296	.3751602	3.47	0.001	.5497649	2.056828
hig~1_migrant	-.9268069	.5489595	-1.69	0.098	-2.029425	.1758108
yearseduc	.5105604	.0248608	20.54	0.000	.460626	.5604947
exp	.5613621	.010326	54.36	0.000	.5406217	.5821025
exp_sq	-.0105493	.0001899	-55.55	0.000	-.0109307	-.0101678
female	-4.770746	.1160254	-41.12	0.000	-5.00379	-4.537702
white	-.0435309	.1645726	-0.26	0.792	-.3740846	.2870228
black	-.2198922	.1640606	-1.34	0.186	-.5494175	.1096332
asian	-.7006128	.1868897	-3.75	0.000	-1.075992	-.3252337
hispanic	.0833369	.2178077	0.38	0.704	-.3541428	.5208166
years_since~l	.0054272	.0027552	1.97	0.054	-.0001068	.0109612
rural	.1962171	.0771057	2.54	0.014	.0413457	.3510885
year	-8.40149	3.908698	-2.15	0.036	-16.25234	-.5506385
year_sq	.0020847	.0009746	2.14	0.037	.0001271	.0040423
_cons	8494.049	3920.099	2.17	0.035	620.2983	16367.8

Specification (3), Endogenous-wage, Method 2, Restricted sample

Linear regression

Number of obs	=	36,851
F(34, 50)	=	551.93
Prob > F	=	0.0000
R-squared	=	0.0547
Root MSE	=	.62115

(Std. Err. adjusted for 51 clusters in state)

lnwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	-.0822095	.0295162	-2.79	0.008	-.1414945	-.0229244
post911entry	-.1131754	.0284198	-3.98	0.000	-.1702582	-.0560926
post911ent~t	.0932894	.0330696	2.82	0.007	.026867	.1597117
hsgrad	.1694994	.0105626	16.05	0.000	.1482838	.1907151

```
   assocgrad |    .249549   .0177106    14.09   0.000     .2139761    .2851219
    bachgrad |   .3135239   .0284377    11.02   0.000     .2564051    .3706427
    mastgrad |   .3324521   .0668539     4.97   0.000     .1981721    .4667322
  doctorgrad |   .3370471   .0814635     4.14   0.000     .1734229    .5006714
         exp |    .013547   .0014497     9.34   0.000     .0106351    .0164588
      exp_sq |   -.000208   .0000244    -8.54   0.000     -.000257   -.0001591
      female |  -.1538154    .009715   -15.83   0.000    -.1733286   -.1343022
       white |   .0977272   .0391862     2.49   0.016     .0190195    .1764349
       black |   .0379729   .0459345     0.83   0.412    -.0542893    .1302352
       asian |   .0504783   .0467755     1.08   0.286    -.0434731    .1444296
    hispanic |  -.0035929   .0438004    -0.08   0.935    -.0915686    .0843827
years_sinc~l |   .0047957   .0007847     6.11   0.000     .0032197    .0063717
       rural |  -.1120643   .0133743    -8.38   0.000    -.1389274   -.0852012
             |
        year |
       1999  |   .0317069   .0224895     1.41   0.165    -.0134646    .0768783
       2000  |   .0123568    .020638     0.60   0.552    -.0290958    .0538094
       2001  |    .090844   .0186081     4.88   0.000     .0534686    .1282194
       2002  |   .0914135   .0167699     5.45   0.000     .0577303    .1250968
       2003  |   .0575518   .0339077     1.70   0.096    -.0105537    .1256574
       2004  |   .0115038    .032148     0.36   0.722    -.0530674    .0760749
       2005  |   .0094302   .0342787     0.28   0.784    -.0594206     .078281
       2006  |    .031719   .0285452     1.11   0.272    -.0256156    .0890537
       2007  |  -.0038211   .0267597    -0.14   0.887    -.0575696    .0499273
       2008  |  -.0042735   .0308604    -0.14   0.890    -.0662585    .0577115
       2009  |   .0164669   .0303446     0.54   0.590     -.044482    .0774159
       2010  |   .0538301    .040279     1.34   0.187    -.0270726    .1347328
       2011  |   .0378062   .0343854     1.10   0.277    -.0312589    .1068714
       2012  |   .0056506   .0344774     0.16   0.870    -.0635992    .0749004
       2013  |  -.0035041   .0391893    -0.09   0.929    -.0822181    .0752098
       2014  |   .0177971   .0368768     0.48   0.631    -.0562721    .0918662
       2015  |   .0335985   .0248717     1.35   0.183    -.0163577    .0835547
             |
       _cons |   2.132132    .050366    42.33   0.000     2.030969    2.233295
------------------------------------------------------------------------------

Linear regression                               Number of obs     =     36,948
                                                F(34, 50)         =     256.29
                                                Prob > F          =     0.0000
                                                R-squared         =     0.0918
                                                Root MSE          =     10.968

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   .4507701     .18055     2.50   0.016     .0881248    .8134154
post911entry |  -.8696309   .4492676    -1.94   0.059    -1.772012    .0327497
post911ent~t |   1.192093   .5257941     2.27   0.028     .1360044    2.248182
      hsgrad |   .3262916    .259108     1.26   0.214    -.1941422    .8467254
   assocgrad |   .8957787   .6000752     1.49   0.142    -.3095078    2.101065
    bachgrad |   .4059345   .5043658     0.80   0.425     -.607114    1.418983
    mastgrad |   .8899609   .9611208     0.93   0.359    -1.040507    2.820429
  doctorgrad |   .1246882   1.553576     0.08   0.936    -2.995761    3.245138
         exp |   .2917645   .0265938    10.97   0.000     .2383494    .3451797
      exp_sq |  -.0053295   .0005602    -9.51   0.000    -.0064546   -.0042043
      female |  -6.715329   .3437279   -19.54   0.000    -7.405727   -6.024931
       white |  -1.390183   .7199984    -1.93   0.059    -2.836342    .0559761
       black |    .262762   .6835377     0.38   0.702    -1.110164    1.635688
```

	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
asian	1.056812	.9888999	1.07	0.290	-.9294521	3.043076
hispanic	-.3638526	.6535496	-0.56	0.580	-1.676546	.9488403
years_sinc~l	.0099077	.0068207	1.45	0.153	-.0037921	.0236075
rural	1.489209	.3031431	4.91	0.000	.8803281	2.09809
year						
1999	-.1851593	.3672475	-0.50	0.616	-.9227975	.552479
2000	.1958949	.3943758	0.50	0.622	-.5962323	.9880221
2001	-.0922329	.3339674	-0.28	0.784	-.7630262	.5785603
2002	-.4421782	.3540519	-1.25	0.218	-1.153312	.2689561
2003	-.5888704	.3845211	-1.53	0.132	-1.361204	.1834631
2004	-.7437227	.3933634	-1.89	0.064	-1.533816	.0463708
2005	-1.105396	.3967843	-2.79	0.008	-1.902361	-.3084313
2006	-1.054915	.3641718	-2.90	0.006	-1.786376	-.3234545
2007	-1.086345	.3408416	-3.19	0.002	-1.770946	-.4017446
2008	-.6770606	.3509266	-1.93	0.059	-1.381917	.0277961
2009	-1.4998	.4081665	-3.67	0.001	-2.319627	-.6799736
2010	-2.74435	.3810494	-7.20	0.000	-3.509711	-1.97899
2011	-2.267348	.4541843	-4.99	0.000	-3.179604	-1.355092
2012	-1.393441	.4468537	-3.12	0.003	-2.290973	-.4959089
2013	-2.128462	.3946056	-5.39	0.000	-2.921051	-1.335874
2014	-1.936934	.3921879	-4.94	0.000	-2.724667	-1.149202
2015	-1.059244	.3004142	-3.53	0.001	-1.662643	-.455844
_cons	39.42841	.8211697	48.01	0.000	37.77904	41.07777

<u>Specification (3), Endogenous-wage, Method 2, Full sample</u>

Linear regression

Number of obs	=	1,375,615
F(38, 50)	=	5688.42
Prob > F	=	0.0000
R-squared	=	0.2889
Root MSE	=	.61503

(Std. Err. adjusted for 51 clusters in state)

lnwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	-.1436699	.014939	-9.62	0.000	-.1736757	-.1136641
post911entry	-.0916843	.0069006	-13.29	0.000	-.1055446	-.077824
post911entr~t	.0192442	.0073034	2.63	0.011	.004575	.0339135
highmigrant~c	-.2697632	.0079482	-33.94	0.000	-.2857276	-.2537988
hig~c_migrant	.0734052	.0119369	6.15	0.000	.0494292	.0973812
highmigra~911	.1161664	.0199261	5.83	0.000	.0761437	.1561891
hig~1_migrant	-.0757035	.0218403	-3.47	0.001	-.119571	-.0318361
hsgrad	.2819434	.0058888	47.88	0.000	.2701154	.2937715
assocgrad	.4691319	.0072825	64.42	0.000	.4545045	.4837594
bachgrad	.7413101	.010137	73.13	0.000	.7209493	.7616709
mastgrad	.9341375	.0150708	61.98	0.000	.9038669	.9644082
doctorgrad	1.177804	.0131233	89.75	0.000	1.151445	1.204163
exp	.0378014	.0005904	64.03	0.000	.0366155	.0389873
exp_sq	-.0006141	.0000119	-51.70	0.000	-.0006379	-.0005902
female	-.2365107	.0051758	-45.70	0.000	-.2469067	-.2261148
white	.0862591	.0117317	7.35	0.000	.0626952	.1098229
black	-.0478775	.0163722	-2.92	0.005	-.0807622	-.0149929
asian	.0977062	.020192	4.84	0.000	.0571494	.1382631

```
     hispanic |  -.0242047   .0190214    -1.27   0.209    -.0624103    .0140009
years_since~l |   .0030405   .0002693    11.29   0.000     .0024997    .0035813
        rural |   -.162212   .0124868   -12.99   0.000    -.1872924   -.1371316
              |
         year |
        1999  |   .0298448   .0044208     6.75   0.000     .0209654    .0387242
        2000  |   .0440483   .0041785    10.54   0.000     .0356555     .052441
        2001  |   .0613969   .0050136    12.25   0.000     .0513267     .071467
        2002  |   .0692715   .0042645    16.24   0.000     .0607059     .077837
        2003  |     .07101   .0051706    13.73   0.000     .0606245    .0813954
        2004  |   .0642178      .0052    12.35   0.000     .0537733    .0746623
        2005  |   .0540079     .00498    10.84   0.000     .0440052    .0640105
        2006  |   .0487448   .0061076     7.98   0.000     .0364774    .0610123
        2007  |   .0517202   .0090353     5.72   0.000     .0335723     .069868
        2008  |   .0587724   .0076821     7.65   0.000     .0433423    .0742024
        2009  |   .0416958   .0072105     5.78   0.000     .0272131    .0561785
        2010  |   .0595186   .0069489     8.57   0.000     .0455614    .0734758
        2011  |   .0443135   .0073385     6.04   0.000     .0295737    .0590532
        2012  |   .0312329    .008213     3.80   0.000     .0147365    .0477292
        2013  |    .018162   .0081014     2.24   0.029     .0018899    .0344342
        2014  |   .0220241    .009725     2.26   0.028     .0024908    .0415574
        2015  |   .0237566   .0090797     2.62   0.012     .0055195    .0419937
              |
        _cons |   2.107187   .0135732   155.25   0.000     2.079924     2.13445
------------------------------------------------------------------------------

Linear regression                               Number of obs     =  1,376,334
                                                F(38, 50)         =    3497.64
                                                Prob > F          =     0.0000
                                                R-squared         =     0.1230
                                                Root MSE          =     9.8536

                                   (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
              |               Robust
  hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
      migrant |  -.4706548   .0994531    -4.73   0.000    -.6704123   -.2708973
 post911entry |  -1.302445   .0764487   -17.04   0.000    -1.455996   -1.148893
post911entr~t |   .7779186   .1460036     5.33   0.000     .4846617    1.071175
highmigrant~c |  -1.258448   .1404129    -8.96   0.000    -1.540476   -.9764206
hig~c_migrant |   1.689885   .3632855     4.65   0.000     .9602043    2.419565
highmigra~911 |   1.421097   .3667333     3.88   0.000      .684491    2.157702
hig~1_migrant |  -.9303469   .5364768    -1.73   0.089    -2.007892    .1471985
       hsgrad |   1.750331   .1845077     9.49   0.000     1.379737    2.120926
    assocgrad |   2.368865   .1835573    12.91   0.000      2.00018    2.737551
     bachgrad |   4.049553   .1511371    26.79   0.000     3.745985     4.35312
     mastgrad |   4.955088    .180207    27.50   0.000     4.593132    5.317045
   doctorgrad |   8.318324   .2891185    28.77   0.000     7.737612    8.899035
          exp |   .5462914   .0095871    56.98   0.000     .5270351    .5655477
       exp_sq |  -.0103562    .000172   -60.22   0.000    -.0107017   -.0100108
       female |  -4.730674   .1165487   -40.59   0.000    -4.964769   -4.496579
        white |  -.1961247    .156774    -1.25   0.217    -.5110145    .1187652
        black |  -.2143942   .1586338    -1.35   0.183    -.5330195    .1042311
        asian |  -.8707192   .1801755    -4.83   0.000    -1.232612    -.508826
     hispanic |  -.0429688   .2210941    -0.19   0.847    -.4870494    .4011117
years_since~l |   .0081135   .0025474     3.18   0.002     .0029969    .0132302
        rural |   .2709048   .0836764     3.24   0.002     .1028357    .4389738
              |
         year |
```

1999	.1131979	.0590344	1.92	0.061	-.0053761	.231772
2000	.1441715	.0882968	1.63	0.109	-.0331778	.3215208
2001	.1009582	.0922091	1.09	0.279	-.0842492	.2861657
2002	-.1276565	.0689248	-1.85	0.070	-.2660961	.0107832
2003	-.3188535	.084859	-3.76	0.000	-.4892979	-.1484091
2004	-.352767	.1043172	-3.38	0.001	-.5622943	-.1432398
2005	-.2354284	.086352	-2.73	0.009	-.4088715	-.0619853
2006	-.0619203	.0952928	-0.65	0.519	-.2533216	.129481
2007	-.0070162	.0841212	-0.08	0.934	-.1759786	.1619462
2008	-.0427265	.0835723	-0.51	0.611	-.2105863	.1251334
2009	-.3951084	.0797324	-4.96	0.000	-.5552556	-.2349613
2010	-.7765719	.0834637	-9.30	0.000	-.9442137	-.6089302
2011	-.7570006	.0818932	-9.24	0.000	-.9214879	-.5925133
2012	-.6024774	.0860395	-7.00	0.000	-.7752929	-.4296619
2013	-.4778583	.1002955	-4.76	0.000	-.6793077	-.2764089
2014	-.429195	.10073	-4.26	0.000	-.6315172	-.2268728
2015	-.224511	.0921502	-2.44	0.018	-.4096001	-.039422
_cons	34.82721	.2273862	153.16	0.000	34.37049	35.28392

Specification (4), Endogenous-wage, Method 2, Restricted sample

```
Linear regression                               Number of obs     =     36,851
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.0572
                                                Root MSE          =     .62051

                                  (Std. Err. adjusted for 51 clusters in state)
```

lnwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	.3810519	.0601692	6.33	0.000	.2601986	.5019052
post911entry	-.0958992	.0273624	-3.50	0.001	-.1508582	-.0409403
post911ent~t	.0658257	.0326389	2.02	0.049	.0002685	.1313828
yearseduc	.0495218	.0031524	15.71	0.000	.04319	.0558537
migrantyea~c	-.0292503	.0032568	-8.98	0.000	-.0357919	-.0227087
exp	.0177544	.0023442	7.57	0.000	.013046	.0224629
migrantexp	-.0095443	.002615	-3.65	0.001	-.0147967	-.0042918
exp_sq	-.00027	.0000479	-5.64	0.000	-.0003661	-.0001738
migrantexp~q	.0001738	.0000527	3.30	0.002	.000068	.0002796
female	-.1518044	.0120671	-12.58	0.000	-.1760418	-.127567
migrantfem~e	-.0086177	.0157131	-0.55	0.586	-.0401784	.022943
1.migrant	0	(omitted)				
wbhao						
Black	-.0868054	.0150987	-5.75	0.000	-.1171321	-.0564788
Hispanic	-.0495363	.0180126	-2.75	0.008	-.0857157	-.0133568
Asian	-.001132	.0467323	-0.02	0.981	-.0949965	.0927325
Other	-.0946647	.042075	-2.25	0.029	-.1791747	-.0101547
migrant#wbhao						
1#Black	.102475	.0323293	3.17	0.003	.0375397	.1674103
1#Hispanic	-.0863726	.0255445	-3.38	0.001	-.1376803	-.035065
1#Asian	-.0551083	.0610639	-0.90	0.371	-.1777588	.0675422

```
     1#Other  |  -.0709129   .1156578    -0.61   0.543    -.3032184    .1613925
              |
years_sinc~l  |   .0043838    .000752     5.83   0.000     .0028733    .0058943
       rural  |   -.113864    .015977    -7.13   0.000    -.1459548   -.0817732
migrantrural  |   .0344283   .0261305     1.32   0.194    -.0180562    .0869129
              |
        year  |
        1999  |    .054762   .0262587     2.09   0.042     .0020198    .1075041
        2000  |   .0030766   .0274326     0.11   0.911    -.0520235    .0581766
        2001  |   .0954979   .0283353     3.37   0.001     .0385847     .152411
        2002  |   .0946599   .0237111     3.99   0.000     .0470347    .1422851
        2003  |   .0411215   .0386688     1.06   0.293     -.036547    .1187899
        2004  |  -.0049962   .0446665    -0.11   0.911    -.0947114     .084719
        2005  |  -.0393633   .0293684    -1.34   0.186    -.0983515    .0196248
        2006  |   .0070074   .0342554     0.20   0.839    -.0617966    .0758115
        2007  |  -.0410075   .0353525    -1.16   0.252    -.1120151    .0300002
        2008  |  -.0069402   .0382841    -0.18   0.857    -.0838362    .0699558
        2009  |   .0031503   .0499834     0.06   0.950    -.0972442    .1035449
        2010  |   .0556874   .0476613     1.17   0.248    -.0400432     .151418
        2011  |     .01363   .0361665     0.38   0.708    -.0590125    .0862726
        2012  |  -.0085021   .0305578    -0.28   0.782    -.0698793     .052875
        2013  |  -.0305916   .0386754    -0.79   0.433    -.1082735    .0470902
        2014  |  -.0078505   .0440599    -0.18   0.859    -.0963475    .0806464
        2015  |   .0495666   .0318604     1.56   0.126    -.0144269    .1135601
              |
migrant#year  |
      1 1999  |  -.0734375    .037613    -1.95   0.056    -.1489855    .0021104
      1 2000  |   .0374507   .0361467     1.04   0.305    -.0351522    .1100535
      1 2001  |  -.0215725   .0498569    -0.43   0.667    -.1217129     .078568
      1 2002  |  -.0136095   .0391356    -0.35   0.729    -.0922158    .0649967
      1 2003  |   .0446445   .0450545     0.99   0.327    -.0458502    .1351392
      1 2004  |   .0439334   .0466064     0.94   0.350    -.0496782    .1375451
      1 2005  |   .1161578   .0289787     4.01   0.000     .0579525    .1743632
      1 2006  |   .0539142   .0521219     1.03   0.306    -.0507756     .158604
      1 2007  |   .0788837   .0399203     1.98   0.054    -.0012986    .1590659
      1 2008  |   .0073086   .0354022     0.21   0.837    -.0637988    .0784159
      1 2009  |   .0349751    .062492     0.56   0.578    -.0905437    .1604939
      1 2010  |   .0065036   .0444738     0.15   0.884    -.0828246    .0958318
      1 2011  |    .053353   .0337586     1.58   0.120    -.0144531    .1211591
      1 2012  |   .0363192   .0410099     0.89   0.380    -.0460517    .1186901
      1 2013  |    .053106   .0402334     1.32   0.193    -.0277051    .1339172
      1 2014  |    .049818   .0472972     1.05   0.297    -.0451813    .1448172
      1 2015  |  -.0330336   .0381476    -0.87   0.391    -.1096554    .0435882
              |
       _cons  |   1.724482   .0525784    32.80   0.000     1.618875    1.830088
------------------------------------------------------------------------------

Linear regression                               Number of obs     =     36,948
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.0953
                                                Root MSE          =      10.95

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   3.327339   1.334185     2.49   0.016     .6475486    6.007129
post911entry |  -.6816984    .548691    -1.24   0.220    -1.783777    .4203798
```

```
post911ent~t |   .9773788    .697146     1.40   0.167    -.4228801    2.377638
  yearseduc |   .0439771   .0686242     0.64   0.525    -.0938586    .1818129
migrantyea~c |  -.1323038   .0678492    -1.95   0.057     -.268583    .0039753
        exp |   .4127769   .0276679    14.92   0.000     .3572042    .4683496
 migrantexp |   -.262143   .0301449    -8.70   0.000    -.3226909   -.2015952
     exp_sq |   -.008174   .0005327   -15.35   0.000    -.0092438   -.0071041
migrantexp~q |   .0055405   .0005881     9.42   0.000     .0043593    .0067216
     female |  -7.293653   .4176515   -17.46   0.000    -8.132531   -6.454775
migrantfem~e |    1.48198   .5163888     2.87   0.006     .4447827    2.519178
  1.migrant |          0  (omitted)
             |
      wbhao |
      Black  |   1.668777   .3570803     4.67   0.000     .9515597    2.385993
   Hispanic  |   1.382217   .4034324     3.43   0.001      .571899    2.192535
      Asian  |    1.26859   .8326339     1.52   0.134    -.4038047    2.940984
      Other  |   1.290942   .7265666     1.78   0.082    -.1684102    2.750294
             |
    migrant#|
      wbhao |
    1#Black  |  -.3754775   .8001249    -0.47   0.641    -1.982576    1.231621
 1#Hispanic  |  -1.030777     .73951    -1.39   0.170    -2.516127    .4545721
    1#Asian  |   1.016922   1.232383     0.83   0.413    -1.458392    3.492236
    1#Other  |   1.171102    2.69153     0.44   0.665    -4.234995      6.5772
             |
years_sinc~l |   .0033976   .0082137     0.41   0.681    -.0131001    .0198953
      rural |   1.338834   .3388088     3.95   0.000     .6583169    2.019352
migrantrural |   .8017164   .6750881     1.19   0.241    -.5542378    2.157671
             |
       year |
       1999  |  -.3042129    .505523    -0.60   0.550    -1.319586    .7111598
       2000  |   .2663334   .5610317     0.47   0.637    -.8605318    1.393199
       2001  |  -.0763441   .5444836    -0.14   0.889    -1.169972    1.017283
       2002  |   -.373407   .5482407    -0.68   0.499    -1.474581    .7277668
       2003  |   -.756436   .6181928    -1.22   0.227    -1.998113    .4852409
       2004  |  -1.042737   .5947052    -1.75   0.086    -2.237237    .1517639
       2005  |  -1.360843   .6920977    -1.97   0.055    -2.750962    .0292758
       2006  |  -1.269664    .658178    -1.93   0.059    -2.591653    .0523254
       2007  |  -1.714559   .5096306    -3.36   0.001    -2.738182   -.6909356
       2008  |  -.6308964   .6007379    -1.05   0.299    -1.837514    .5757212
       2009  |  -1.212394   .6540818    -1.85   0.070    -2.526156    .1013682
       2010  |  -2.509016   .7231534    -3.47   0.001    -3.961512    -1.05652
       2011  |  -1.728143   .7767725    -2.22   0.031    -3.288336   -.1679492
       2012  |  -1.292933   .6043919    -2.14   0.037     -2.50689   -.0789763
       2013  |  -2.213918   .6643842    -3.33   0.002    -3.548373   -.8794634
       2014  |  -2.157928   .5723533    -3.77   0.000    -3.307533   -1.008322
       2015  |  -1.390095    .624961    -2.22   0.031    -2.645366   -.1348241
             |
migrant#year |
     1 1999  |   .4831417   .7540138     0.64   0.525     -1.03134    1.997623
     1 2000  |  -.0687086   .8303522    -0.08   0.934     -1.73652    1.599103
     1 2001  |   .0991324   .9938978     0.10   0.921     -1.89717    2.095435
     1 2002  |  -.1150596    .796002    -0.14   0.886    -1.713877    1.483758
     1 2003  |   .3305871   .9540807     0.35   0.730     -1.58574    2.246915
     1 2004  |   .5316058   .8623515     0.62   0.540    -1.200478     2.26369
     1 2005  |   .5137986   .9578155     0.54   0.594     -1.41003    2.437628
     1 2006  |   .4946235   1.023159     0.48   0.631    -1.560451    2.549698
     1 2007  |   1.424113   .7271589     1.96   0.056     -.036429    2.884654
     1 2008  |   .0286236   .8591874     0.03   0.974    -1.697105    1.754352
     1 2009  |  -.4511041   1.063429    -0.42   0.673    -2.587065    1.684857
     1 2010  |  -.3015596   1.118411    -0.27   0.789    -2.547955    1.944836
```

1 2011	-.8783884	1.023781	-0.86	0.395	-2.934714	1.177937
1 2012	-.084563	.9672577	-0.09	0.931	-2.027357	1.858231
1 2013	.2288075	.9292169	0.25	0.807	-1.637579	2.095195
1 2014	.5256625	.8295531	0.63	0.529	-1.140544	2.191869
1 2015	.6773333	1.097983	0.62	0.540	-1.52803	2.882697
_cons	37.47839	1.008254	37.17	0.000	35.45325	39.50353

Specification (4), Endogenous-wage, Method 2, Full sample

```
Linear regression                               Number of obs     =  1,375,615
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.2818
                                                Root MSE          =     .61809

                                   (Std. Err. adjusted for 51 clusters in state)
```

lnwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	.7609561	.0483632	15.73	0.000	.6638157	.8580965
post911entry	-.0712993	.0039114	-18.23	0.000	-.0791555	-.0634431
post911entr~t	-.0110275	.0069692	-1.58	0.120	-.0250255	.0029705
highmigrant~c	-.2465751	.0068518	-35.99	0.000	-.2603374	-.2328128
hig~c_migrant	.0696029	.0159657	4.36	0.000	.0375348	.101671
highmigra~911	.0872686	.0194549	4.49	0.000	.0481923	.126345
hig~1_migrant	-.0567076	.0215229	-2.63	0.011	-.0999377	-.0134776
yearseduc	.1178192	.0016621	70.89	0.000	.1144809	.1211576
migrantyear~c	-.0474308	.0031097	-15.25	0.000	-.0536768	-.0411849
exp	.0428061	.0009611	44.54	0.000	.0408758	.0447365
migrantexp	-.0176581	.00105	-16.82	0.000	-.0197672	-.015549
exp_sq	-.0006845	.0000189	-36.22	0.000	-.0007224	-.0006465
migrantexp_sq	.000318	.000021	15.14	0.000	.0002758	.0003602
female	-.2462759	.004685	-52.57	0.000	-.2556861	-.2368657
migrantfemale	.0276116	.0076029	3.63	0.001	.0123408	.0428825
1.migrant	0	(omitted)				
wbhao						
Black	-.1486745	.0089176	-16.67	0.000	-.1665862	-.1307629
Hispanic	-.075883	.0196642	-3.86	0.000	-.1153797	-.0363863
Asian	.0162391	.0144877	1.12	0.268	-.0128603	.0453384
Other	-.0971776	.011921	-8.15	0.000	-.1211217	-.0732335
migrant#wbhao						
1#Black	-.0132745	.0205121	-0.65	0.520	-.0544743	.0279254
1#Hispanic	-.1410835	.0219754	-6.42	0.000	-.1852223	-.0969446
1#Asian	-.0199381	.0183643	-1.09	0.283	-.0568239	.0169477
1#Other	.0064975	.0472285	0.14	0.891	-.0883636	.1013587
years_since~l	.0029509	.0003376	8.74	0.000	.0022728	.0036291
rural	-.1608498	.0121347	-13.26	0.000	-.1852231	-.1364764
migrantrural	.0866052	.0211331	4.10	0.000	.0441581	.1290523
year						
1999	.0302148	.0048599	6.22	0.000	.0204533	.0399762
2000	.0409993	.0045636	8.98	0.000	.0318331	.0501655

2001	.0561158	.0054013	10.39	0.000	.0452669	.0669647
2002	.0626273	.0043786	14.30	0.000	.0538325	.071422
2003	.0658763	.0048313	13.64	0.000	.0561722	.0755803
2004	.0598298	.00468	12.78	0.000	.0504299	.0692298
2005	.0471764	.0039987	11.80	0.000	.0391448	.0552081
2006	.0384742	.0052883	7.28	0.000	.0278524	.0490961
2007	.0424226	.0082187	5.16	0.000	.025915	.0589303
2008	.0485314	.0067597	7.18	0.000	.0349541	.0621086
2009	.0329316	.0068351	4.82	0.000	.0192029	.0466603
2010	.0491737	.0062783	7.83	0.000	.0365634	.061784
2011	.0325722	.0061359	5.31	0.000	.020248	.0448965
2012	.0191996	.0075122	2.56	0.014	.004111	.0342882
2013	.0035159	.0071744	0.49	0.626	-.0108943	.0179262
2014	.0081959	.0094907	0.86	0.392	-.0108666	.0272585
2015	.0110272	.0082614	1.33	0.188	-.0055662	.0276206
migrant#year						
1 1999	-.0170808	.0089211	-1.91	0.061	-.0349993	.0008377
1 2000	.0094481	.01056	0.89	0.375	-.0117624	.0306585
1 2001	.0247821	.0121758	2.04	0.047	.0003263	.0492379
1 2002	.0287159	.0070098	4.10	0.000	.0146363	.0427955
1 2003	.0113783	.0127302	0.89	0.376	-.0141911	.0369477
1 2004	.0096506	.0128919	0.75	0.458	-.0162434	.0355447
1 2005	.0279097	.0120767	2.31	0.025	.0036529	.0521665
1 2006	.04306	.0105528	4.08	0.000	.021864	.064256
1 2007	.0375621	.0083532	4.50	0.000	.0207842	.05434
1 2008	.0342319	.0099422	3.44	0.001	.0142625	.0542013
1 2009	.0292538	.013114	2.23	0.030	.0029135	.0555942
1 2010	.0361533	.0105328	3.43	0.001	.0149974	.0573091
1 2011	.0346094	.0115391	3.00	0.004	.0114325	.0577863
1 2012	.0388471	.0116919	3.32	0.002	.0153633	.062331
1 2013	.0513485	.012583	4.08	0.000	.0260748	.0766221
1 2014	.0526997	.0131087	4.02	0.000	.0263701	.0790293
1 2015	.0439137	.0160181	2.74	0.008	.0117405	.0760869
_cons	.9405077	.0229208	41.03	0.000	.8944699	.9865454

Linear regression

Number of obs	=	1,376,334
F(49, 50)	=	.
Prob > F	=	.
R-squared	=	0.1186
Root MSE	=	9.8783

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	6.634293	.6192901	10.71	0.000	5.390412	7.878174
post911entry	-1.217184	.0702233	-17.33	0.000	-1.358232	-1.076136
post911entr~t	.9967676	.14478	6.88	0.000	.7059683	1.287567
highmigrant~c	-1.077857	.14782	-7.29	0.000	-1.374762	-.7809514
hig~c_migrant	.9109544	.4024786	2.26	0.028	.1025524	1.719356
highmigra~911	1.214106	.3774599	3.22	0.002	.4559552	1.972256
hig~1_migrant	-.6161134	.5301246	-1.16	0.251	-1.6809	.4486732
yearseduc	.626742	.0175807	35.65	0.000	.5914302	.6620538
migrantyear~c	-.3555975	.0282269	-12.60	0.000	-.4122929	-.298902
exp	.6014072	.0109743	54.80	0.000	.5793647	.6234498
migrantexp	-.2409964	.0146567	-16.44	0.000	-.2704352	-.2115575

```
     exp_sq |  -.0115207   .0002049   -56.22   0.000    -.0119323   -.0111091
migrantexp_sq |   .0053528   .0002825    18.95   0.000     .0047854    .0059202
     female |  -4.874432   .1129979   -43.14   0.000    -5.101395   -4.647469
migrantfemale |   .7570503   .1021912     7.41   0.000     .5517932    .9623074
  1.migrant |          0  (omitted)
            |
      wbhao |
      Black  |  -.0642801   .0773573    -0.83   0.410    -.2196567    .0910966
   Hispanic  |   .0353578   .2365028     0.15   0.882     -.439672    .5103876
      Asian  |  -.3181228   .2873987    -1.11   0.274    -.8953801    .2591344
      Other  |   .1245308   .1583459     0.79   0.435    -.1935164    .4425779
            |
migrant#wbhao |
    1#Black  |  -.5728624   .1421213    -4.03   0.000    -.8583214   -.2874035
 1#Hispanic  |   -.515706   .1533333    -3.36   0.001    -.8236849   -.2077271
    1#Asian  |  -.3427015   .2649227    -1.29   0.202    -.8748145    .1894114
    1#Other  |  -.7416278   .4355162    -1.70   0.095    -1.616388    .1331321
            |
years_since~l |   .0082828   .0025815     3.21   0.002     .0030977    .0134679
      rural |   .2416044   .0875235     2.76   0.008     .0658084    .4174005
migrantrural |   .8174308   .2765286     2.96   0.005     .2620067    1.372855
            |
       year |
       1999  |   .0991676   .0652845     1.52   0.135    -.0319601    .2302954
       2000  |   .1121859   .0910094     1.23   0.223    -.0706119    .2949838
       2001  |   .0522307   .0982834     0.53   0.597    -.1451774    .2496388
       2002  |  -.1477471   .0781558    -1.89   0.065    -.3047276    .0092335
       2003  |  -.3552388   .0871936    -4.07   0.000    -.5303723   -.1801054
       2004  |  -.3677569   .1072756    -3.43   0.001    -.5832263   -.1522875
       2005  |  -.2417767   .0937537    -2.58   0.013    -.4300865   -.0534668
       2006  |  -.1268299   .1074646    -1.18   0.244    -.3426789     .089019
       2007  |  -.0256552   .0902453    -0.28   0.777    -.2069181    .1556077
       2008  |  -.0600974   .0963012    -0.62   0.535    -.2535241    .1333293
       2009  |  -.3574561   .0927715    -3.85   0.000    -.5437931   -.1711191
       2010  |  -.6855042   .0987585    -6.94   0.000    -.8838664    -.487142
       2011  |  -.6874588   .0913579    -7.52   0.000    -.8709566    -.503961
       2012  |  -.5199289   .0974465    -5.34   0.000    -.7156559    -.324202
       2013  |  -.3961702   .1156294    -3.43   0.001    -.6284186   -.1639217
       2014  |  -.3572653   .1105537    -3.23   0.002     -.579319   -.1352116
       2015  |   -.147928   .1008292    -1.47   0.149    -.3504493    .0545934
            |
migrant#year |
     1 1999  |   .0641633   .1605316     0.40   0.691    -.2582739    .3866004
     1 2000  |   .2034969    .211716     0.96   0.341    -.2217473     .628741
     1 2001  |   .3131775    .163502     1.92   0.061    -.0152259    .6415809
     1 2002  |   .0610561   .1679327     0.36   0.718    -.2762467    .3983589
     1 2003  |   .1564367   .1719983     0.91   0.367    -.1890321    .5019055
     1 2004  |   .0408251    .205352     0.20   0.843    -.3716366    .4532867
     1 2005  |  -.0277599   .1213933    -0.23   0.820    -.2715856    .2160658
     1 2006  |   .3317038   .1697794     1.95   0.056    -.0093082    .6727157
     1 2007  |   .0448119   .1183493     0.38   0.707    -.1928998    .2825235
     1 2008  |   -.004769   .1757396    -0.03   0.978    -.3577524    .3482145
     1 2009  |  -.3222885   .1627904    -1.98   0.053    -.6492627    .0046856
     1 2010  |  -.6572506   .1555553    -4.23   0.000    -.9696926   -.3448086
     1 2011  |  -.6036574   .1363005    -4.43   0.000    -.8774251   -.3298898
     1 2012  |  -.6385416   .1532089    -4.17   0.000    -.9462707   -.3308124
     1 2013  |  -.6374584   .1563724    -4.08   0.000    -.9515417   -.3233751
     1 2014  |  -.5046679   .1662916    -3.03   0.004    -.8386745   -.1706614
     1 2015  |  -.5365162   .1391718    -3.86   0.000    -.8160511   -.2569813
            |
```

```
       _cons |   28.03497   .4122601    68.00   0.000     27.20692    28.86302
------------------------------------------------------------------------------
```

Specification (5), Endogenous-wage, Method 2, Restricted sample

```
Linear regression                               Number of obs     =     36,851
                                                F(50, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.0589
                                                Root MSE          =     .62003

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   .1195325   .0815367     1.47   0.149    -.0442389    .2833039
post911entry |  -.0882083   .0274936    -3.21   0.002    -.1434308   -.0329857
post911ent~t |   .0603024   .0345978     1.74   0.087    -.0091894    .1297941
      hsgrad |   .2069812   .0146377    14.14   0.000     .1775805    .2363818
   assocgrad |   .2898713   .0222959    13.00   0.000     .2450886     .334654
    bachgrad |   .4269001   .0499356     8.55   0.000     .3266014    .5271987
    mastgrad |   .3434952   .1068892     3.21   0.002      .128802    .5581885
  doctorgrad |   .3849842   .0671681     5.73   0.000     .2500731    .5198952
migranthsg~d |  -.0862374   .0207331    -4.16   0.000    -.1278811   -.0445938
migrantass~d |  -.1032234     .04536    -2.28   0.027    -.1943316   -.0121152
migrantbac~d |  -.2332028   .0434013    -5.37   0.000    -.3203769   -.1460287
migrantmas~d |  -.0147502   .1256901    -0.12   0.907    -.2672062    .2377059
migrantdoc~d |  -.0851249   .1454752    -0.59   0.561    -.3773204    .2070706
         exp |   .0174868    .002153     8.12   0.000     .0131624    .0218113
  migrantexp |  -.0096844   .0024986    -3.88   0.000     -.014703   -.0046659
      exp_sq |  -.0002799   .0000439    -6.38   0.000    -.0003681   -.0001918
migrantexp~q |   .0001608   .0000498     3.23   0.002     .0000608    .0002608
      female |  -.1480165   .0118775   -12.46   0.000    -.1718731   -.1241598
migrantfem~e |  -.0060903   .0162896    -0.37   0.710     -.038809    .0266283
   1.migrant |          0  (omitted)
             |
      wbhao |
      Black  |   -.077848   .0149785    -5.20   0.000    -.1079332   -.0477627
   Hispanic  |  -.0530243   .0186495    -2.84   0.006    -.0904829   -.0155656
      Asian  |  -.0075838   .0494232    -0.15   0.879    -.1068534    .0916857
      Other  |  -.0870498   .0396153    -2.20   0.033    -.1666195   -.0074802
             |
     migrant#|
       wbhao |
     1#Black |   .1007591    .029502     3.42   0.001     .0415026    .1600156
  1#Hispanic |  -.0866426   .0256911    -3.37   0.001    -.1382447   -.0350405
     1#Asian |  -.0447606   .0611433    -0.73   0.468    -.1675705    .0780493
     1#Other |  -.0933013   .1041459    -0.90   0.375    -.3024845    .1158818
             |
years_sinc~l |   .0022884   .0046425     0.49   0.624    -.0070364    .0116132
       rural |  -.1165104   .0154121    -7.56   0.000    -.1474665   -.0855543
migrantrural |   .0373017   .0273283     1.36   0.178    -.0175888    .0921922
             |
        year |
       1999  |   .0527784     .02618     2.02   0.049     .0001943    .1053624
```

```
        2000  |    .000591   .0276918     0.02   0.983    -.0550295    .0562116
        2001  |   .0981571   .0273564     3.59   0.001     .0432103     .153104
        2002  |   .0947925   .0224644     4.22   0.000     .0496715    .1399135
        2003  |   .0413859   .0380652     1.09   0.282    -.0350704    .1178421
        2004  |  -.0070164   .0447725    -0.16   0.876    -.0969446    .0829118
        2005  |  -.0429601   .0295474    -1.45   0.152    -.1023078    .0163875
        2006  |   .0075511   .0331959     0.23   0.821    -.0591249    .0742271
        2007  |   -.038858   .0356698    -1.09   0.281    -.1105029    .0327868
        2008  |  -.0010505   .0397171    -0.03   0.979    -.0808246    .0787237
        2009  |   .0042295   .0503024     0.08   0.933    -.0968058    .1052648
        2010  |   .0534742   .0476435     1.12   0.267    -.0422205    .1491689
        2011  |   .0158595   .0367825     0.43   0.668    -.0580203    .0897393
        2012  |  -.0100044   .0299405    -0.33   0.740    -.0701418    .0501329
        2013  |  -.0273351   .0374523    -0.73   0.469    -.1025602      .04789
        2014  |  -.0060556   .0452494    -0.13   0.894    -.0969416    .0848305
        2015  |   .0553569   .0336183     1.65   0.106    -.0121675    .1228813
              |
 migrant#year |
      1 1999  |  -.0718813   .0387493    -1.86   0.069    -.1497115     .005949
      1 2000  |    .043237   .0380958     1.13   0.262    -.0332807    .1197548
      1 2001  |  -.0197004   .0512593    -0.38   0.702    -.1226578     .083257
      1 2002  |   -.006447   .0400206    -0.16   0.873    -.0868307    .0739367
      1 2003  |   .0561124   .0554877     1.01   0.317    -.0553379    .1675627
      1 2004  |   .0626264   .0568496     1.10   0.276    -.0515595    .1768122
      1 2005  |   .1373538   .0504251     2.72   0.009     .0360721    .2386356
      1 2006  |   .0790538   .0759457     1.04   0.303    -.0734877    .2315952
      1 2007  |   .1068136   .0643576     1.66   0.103    -.0224524    .2360796
      1 2008  |   .0335561    .059778     0.56   0.577    -.0865115    .1536238
      1 2009  |   .0663969   .0763569     0.87   0.389    -.0869704    .2197642
      1 2010  |   .0492883   .0823871     0.60   0.552     -.116191    .2147675
      1 2011  |   .0928043    .076509     1.21   0.231    -.0608686    .2464771
      1 2012  |   .0809722   .0954477     0.85   0.400    -.1107401    .2726844
      1 2013  |   .0956756   .0935614     1.02   0.311    -.0922479    .2835991
      1 2014  |   .0957277   .0945879     1.01   0.316    -.0942577    .2857132
      1 2015  |   .0086683   .0938312     0.09   0.927    -.1797973    .1971338
              |
   entry_year |   .0031133   .0050163     0.62   0.538    -.0069622    .0131888
 entry_year~q |  -1.57e-06   2.50e-06    -0.63   0.534    -6.59e-06    3.46e-06
        _cons |   2.160223   .0299497    72.13   0.000     2.100067    2.220379
------------------------------------------------------------------------------

Linear regression                               Number of obs     =     36,948
                                                F(50, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.0960
                                                Root MSE          =     10.947

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   3.880628   1.318605     2.94   0.005     1.232131    6.529125
post911entry |  -.6718858   .5443526    -1.23   0.223     -1.76525    .4214787
post911ent~t |   1.022616   .6829329     1.50   0.141    -.3490954    2.394327
      hsgrad |   .8962576   .3081085     2.91   0.005     .2774034    1.515112
   assocgrad |   1.601585   .6429451     2.49   0.016     .3101914    2.892978
    bachgrad |   .8637816   .7951232     1.09   0.283    -.7332704    2.460834
    mastgrad |   1.040776   1.365341     0.76   0.449    -1.701591    3.783144
  doctorgrad |   3.802423   3.049954     1.25   0.218    -2.323589    9.928435
```

migranthsg~d	-1.357695	.4007312	-3.39	0.001	-2.162588	-.5528032
migrantass~d	-2.199634	.7399172	-2.97	0.005	-3.685801	-.7134662
migrantbac~d	-.9951964	.800832	-1.24	0.220	-2.603715	.613322
migrantmas~d	-.3597483	1.697975	-0.21	0.833	-3.770231	3.050734
migrantdoc~d	-5.887226	3.227164	-1.82	0.074	-12.36917	.5947227
exp	.4062139	.0271607	14.96	0.000	.35166	.4607678
migrantexp	-.2535751	.0303791	-8.35	0.000	-.3145932	-.1925569
exp_sq	-.0079642	.0005262	-15.13	0.000	-.0090212	-.0069072
migrantexp~q	.0054309	.0005583	9.73	0.000	.0043095	.0065524
female	-7.317384	.4200617	-17.42	0.000	-8.161103	-6.473666
migrantfem~e	1.446202	.5295032	2.73	0.009	.3826633	2.50974
1.migrant	0	(omitted)				
wbhao						
Black	1.744183	.3643554	4.79	0.000	1.012354	2.476012
Hispanic	1.652754	.4135687	4.00	0.000	.8220764	2.483431
Asian	1.375668	.8804854	1.56	0.125	-.3928392	3.144175
Other	1.371378	.7252478	1.89	0.064	-.0853247	2.828082
migrant#wbhao						
1#Black	-.4063141	.7925395	-0.51	0.610	-1.998176	1.185548
1#Hispanic	-1.174212	.722415	-1.63	0.110	-2.625226	.276801
1#Asian	.9206855	1.279466	0.72	0.475	-1.649197	3.490568
1#Other	1.044826	2.767725	0.38	0.707	-4.514313	6.603965
years_sinc~l	.0952914	.0690192	1.38	0.174	-.0433378	.2339205
rural	1.344168	.3346119	4.02	0.000	.6720798	2.016256
migrantrural	.8084106	.6771868	1.19	0.238	-.551759	2.16858
year						
1999	-.2992005	.5053862	-0.59	0.557	-1.314299	.7158976
2000	.2362094	.5535334	0.43	0.671	-.8755951	1.348014
2001	-.0954943	.540364	-0.18	0.860	-1.180847	.9898588
2002	-.4181179	.5433337	-0.77	0.445	-1.509436	.6732
2003	-.7177997	.6063426	-1.18	0.242	-1.935675	.5000754
2004	-1.017106	.5896679	-1.72	0.091	-2.201489	.1672764
2005	-1.329829	.7061379	-1.88	0.065	-2.748148	.0884912
2006	-1.262093	.6520033	-1.94	0.059	-2.57168	.0474941
2007	-1.68617	.5036655	-3.35	0.002	-2.697812	-.6745282
2008	-.6298742	.5994405	-1.05	0.298	-1.833886	.5741375
2009	-1.214362	.6531423	-1.86	0.069	-2.526237	.0975128
2010	-2.523161	.7278976	-3.47	0.001	-3.985187	-1.061136
2011	-1.788383	.7694104	-2.32	0.024	-3.333789	-.2429765
2012	-1.336486	.6043597	-2.21	0.032	-2.550378	-.1225939
2013	-2.268947	.6671568	-3.40	0.001	-3.60897	-.9289227
2014	-2.200748	.5853544	-3.76	0.000	-3.376467	-1.025029
2015	-1.465712	.6324155	-2.32	0.025	-2.735956	-.1954676
migrant#year						
1 1999	.4000483	.7574136	0.53	0.600	-1.121262	1.921358
1 2000	-.221978	.8360572	-0.27	0.792	-1.901248	1.457292
1 2001	-.133495	1.007095	-0.13	0.895	-2.156305	1.889315
1 2002	-.4338377	.8560551	-0.51	0.615	-2.153275	1.285599
1 2003	-.1498815	.9752915	-0.15	0.878	-2.108812	1.809049
1 2004	-.0322653	.8488547	-0.04	0.970	-1.73724	1.672709
1 2005	-.1430501	1.057161	-0.14	0.893	-2.266421	1.98032
1 2006	-.2481642	1.163639	-0.21	0.832	-2.585402	2.089074
1 2007	.5628061	.9045369	0.62	0.537	-1.25401	2.379622
1 2008	-.9085942	1.069111	-0.85	0.399	-3.055966	1.238778

```
     1 2009  |  -1.470136   1.320537    -1.11   0.271    -4.122513     1.18224
     1 2010  |  -1.416082   1.239298    -1.14   0.259    -3.905285    1.073122
     1 2011  |  -2.035893    1.28142    -1.59   0.118    -4.609702    .5379147
     1 2012  |  -1.349911   1.300936    -1.04   0.304    -3.962918    1.263095
     1 2013  |  -1.117381   1.367509    -0.82   0.418    -3.864103    1.629342
     1 2014  |   -.915642   1.302816    -0.70   0.485    -3.532425    1.701141
     1 2015  |  -.8250366   1.295941    -0.64   0.527    -3.428011    1.777938
             |
  entry_year |  -.0923368   .0700533    -1.32   0.193     -.233043    .0483693
entry_year~q |   .0000459   .0000349     1.31   0.195    -.0000242    .0001161
       _cons |   37.27066    .571213    65.25   0.000     36.12334    38.41797
------------------------------------------------------------------------------
```

Specification (5), Endogenous-wage, Method 2, Full sample

```
Linear regression                               Number of obs     =  1,375,615
                                                F(50, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.2916
                                                Root MSE          =     .61385

                                   (Std. Err. adjusted for 51 clusters in state)
--------------------------------------------------------------------------------
               |               Robust
        lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
       migrant |   .3423745   .0321237    10.66   0.000      .2778522    .4068968
  post911entry |  -.0643487   .0037415   -17.20   0.000     -.0718637   -.0568337
post911entr~t |    .019722   .0075756     2.60   0.012      .004506     .034938
highmigrant~c |  -.2672068   .0077514   -34.47   0.000     -.282776   -.2516375
hig~c_migrant |   .0836011   .0100412     8.33   0.000     .0634327    .1037694
highmigra~911 |   .1136943   .0200754     5.66   0.000     .0733717    .1540169
hig~1_migrant |  -.0738254   .0213326    -3.46   0.001    -.1166732   -.0309777
        hsgrad |   .2927065   .0059002    49.61   0.000     .2808556    .3045574
     assocgrad |    .476233   .0058043    82.05   0.000     .4645746    .4878913
      bachgrad |   .7506867   .0100854    74.43   0.000     .7304296    .7709438
      mastgrad |   .9231457   .0136421    67.67   0.000     .8957448    .9505465
    doctorgrad |   1.189727   .0129647    91.77   0.000     1.163686    1.215767
migranthsgrad |  -.1061327   .0059567   -17.82   0.000    -.1180971   -.0941682
migrantasso~d |  -.0906865     .01141    -7.95   0.000    -.1136042   -.0677688
migrantbach~d |  -.0987828   .0116677    -8.47   0.000    -.1222181   -.0753475
migrantmast~d |   .0213133   .0158138     1.35   0.184    -.0104496    .0530761
migrantdoct~d |  -.1249169    .014421    -8.66   0.000    -.1538823   -.0959515
           exp |   .0410501   .0009321    44.04   0.000     .0391779    .0429222
    migrantexp |   -.017868   .0010052   -17.77   0.000    -.0198871   -.0158489
        exp_sq |  -.0006684   .0000183   -36.53   0.000    -.0007052   -.0006317
migrantexp_sq |   .0002523   .0000186    13.56   0.000     .0002149    .0002896
        female |  -.2414233   .0047428   -50.90   0.000    -.2509496    -.231897
 migrantfemale |   .0350407   .0068284     5.13   0.000     .0213256    .0487559
     1.migrant |          0  (omitted)
               |
         wbhao |
        Black  |   -.139208   .0091445   -15.22   0.000    -.1575754   -.1208407
     Hispanic  |   -.068584   .0242316    -2.83   0.007    -.1172547   -.0199134
        Asian  |   .0233588   .0161328     1.45   0.154    -.0090449    .0557624
        Other  |  -.0853508   .0120122    -7.11   0.000    -.1094781   -.0612235
               |
 migrant#wbhao |
```

1#Black	.0346059	.0180769	1.91	0.061	-.0017026	.0709145
1#Hispanic	-.114804	.0203432	-5.64	0.000	-.1556645	-.0739435
1#Asian	-.0444345	.0144001	-3.09	0.003	-.0733579	-.0155111
1#Other	.0171033	.0497267	0.34	0.732	-.0827757	.1169824
years_since~l	.0092593	.00116	7.98	0.000	.0069294	.0115892
rural	-.1666642	.0127068	-13.12	0.000	-.1921865	-.1411419
migrantrural	.0858669	.0156049	5.50	0.000	.0545235	.1172103
year						
1999	.0312377	.0048809	6.40	0.000	.0214342	.0410413
2000	.0425573	.0045048	9.45	0.000	.0335092	.0516055
2001	.0580616	.0051814	11.21	0.000	.0476544	.0684688
2002	.0651742	.0044241	14.73	0.000	.0562882	.0740603
2003	.0690786	.0053115	13.01	0.000	.0584102	.0797471
2004	.0619051	.0050973	12.14	0.000	.0516669	.0721433
2005	.0481965	.0041737	11.55	0.000	.0398135	.0565796
2006	.0406221	.005434	7.48	0.000	.0297075	.0515367
2007	.042851	.0079338	5.40	0.000	.0269156	.0587864
2008	.0506464	.0068853	7.36	0.000	.0368169	.064476
2009	.0337982	.0068262	4.95	0.000	.0200874	.047509
2010	.0495056	.0058075	8.52	0.000	.0378409	.0611703
2011	.0335513	.0062029	5.41	0.000	.0210925	.0460101
2012	.0196331	.0078623	2.50	0.016	.0038412	.035425
2013	.0042841	.007269	0.59	0.558	-.0103161	.0188844
2014	.0067879	.0100419	0.68	0.502	-.0133819	.0269576
2015	.0093828	.00897	1.05	0.301	-.008634	.0273996
migrant#year						
1 1999	-.0169699	.0089248	-1.90	0.063	-.0348959	.000956
1 2000	.0095621	.0091771	1.04	0.302	-.0088706	.0279948
1 2001	.0226177	.0110268	2.05	0.046	.0004697	.0447656
1 2002	.0218894	.007176	3.05	0.004	.0074759	.0363028
1 2003	.0014459	.0128862	0.11	0.911	-.0244368	.0273285
1 2004	-.0032157	.0131868	-0.24	0.808	-.0297021	.0232707
1 2005	.0145015	.0135099	1.07	0.288	-.0126339	.0416369
1 2006	.0221094	.0109923	2.01	0.050	.0000307	.0441881
1 2007	.0186546	.0112248	1.66	0.103	-.0038911	.0412003
1 2008	.0077676	.0124489	0.62	0.535	-.0172368	.032772
1 2009	-.000316	.015655	-0.02	0.984	-.0317601	.031128
1 2010	.0079745	.0149642	0.53	0.596	-.0220821	.0380311
1 2011	.0058945	.0152674	0.39	0.701	-.0247711	.0365601
1 2012	.0043278	.0164941	0.26	0.794	-.0288015	.0374571
1 2013	.0108867	.0173189	0.63	0.532	-.0238993	.0456727
1 2014	.0030762	.0192039	0.16	0.873	-.035496	.0416483
1 2015	-.0137248	.0228169	-0.60	0.550	-.0595538	.0321042
entry_year	-.0017222	.0008995	-1.91	0.061	-.0035289	.0000846
entry_year_sq	7.95e-07	4.46e-07	1.78	0.081	-1.02e-07	1.69e-06
_cons	2.155603	.0078468	274.71	0.000	2.139842	2.171364

Linear regression

Number of obs	=	1,376,334
F(50, 50)	=	.
Prob > F	=	.
R-squared	=	0.1247
Root MSE	=	9.8437

(Std. Err. adjusted for 51 clusters in state)

hoursworked	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	2.955199	.3948085	7.49	0.000	2.162203	3.748195
post911entry	-1.193007	.0682564	-17.48	0.000	-1.330104	-1.05591
post911entr~t	.9576277	.1463626	6.54	0.000	.6636498	1.251606
highmigrant~c	-1.091024	.1424967	-7.66	0.000	-1.377237	-.8048112
hig~c_migrant	.8608812	.3495123	2.46	0.017	.1588652	1.562897
highmigra~911	1.350844	.3660381	3.69	0.001	.615635	2.086053
hig~1_migrant	-.6671878	.5177117	-1.29	0.203	-1.707042	.3726668
hsgrad	2.349165	.1234455	19.03	0.000	2.101218	2.597113
assocgrad	2.955268	.1341275	22.03	0.000	2.685865	3.224671
bachgrad	4.681419	.1347189	34.75	0.000	4.410828	4.95201
mastgrad	5.599368	.1744468	32.10	0.000	5.248981	5.949755
doctorgrad	8.869715	.2577262	34.42	0.000	8.352056	9.387373
migranthsgrad	-1.77537	.1369364	-12.96	0.000	-2.050415	-1.500325
migrantasso~d	-1.948278	.1961035	-9.93	0.000	-2.342163	-1.554392
migrantbach~d	-2.31304	.2133381	-10.84	0.000	-2.741542	-1.884538
migrantmast~d	-2.321362	.2992577	-7.76	0.000	-2.922439	-1.720285
migrantdoct~d	-1.744412	.2489585	-7.01	0.000	-2.24446	-1.244364
exp	.5860105	.0104717	55.96	0.000	.5649775	.6070436
migrantexp	-.2302471	.01431	-16.09	0.000	-.2589895	-.2015047
exp_sq	-.0112821	.0001954	-57.73	0.000	-.0116746	-.0108896
migrantexp_sq	.0049652	.0002658	18.68	0.000	.0044313	.0054991
female	-4.841172	.1129166	-42.87	0.000	-5.067972	-4.614372
migrantfemale	.8402935	.1084281	7.75	0.000	.6225093	1.058078
1.migrant	0	(omitted)				
wbhao						
Black	.0328795	.0779395	0.42	0.675	-.1236667	.1894257
Hispanic	.1108909	.227863	0.49	0.629	-.3467854	.5685671
Asian	-.3887332	.2704176	-1.44	0.157	-.9318829	.1544165
Other	.2401966	.1552552	1.55	0.128	-.0716427	.5520359
migrant#wbhao						
1#Black	-.3494768	.1465324	-2.38	0.021	-.6437957	-.0551579
1#Hispanic	-.3797982	.1695133	-2.24	0.030	-.7202758	-.0393207
1#Asian	-.360281	.2806691	-1.28	0.205	-.9240215	.2034596
1#Other	-.6973816	.4240076	-1.64	0.106	-1.549026	.1542628
years_since~l	-.0131114	.0128344	-1.02	0.312	-.0388901	.0126673
rural	.2587826	.0889998	2.91	0.005	.0800213	.4375439
migrantrural	.7478435	.2709041	2.76	0.008	.2037166	1.29197
year						
1999	.1019295	.0656363	1.55	0.127	-.0299048	.2337639
2000	.1159126	.0906884	1.28	0.207	-.0662405	.2980657
2001	.058583	.0966765	0.61	0.547	-.1355974	.2527634
2002	-.1398526	.0762777	-1.83	0.073	-.2930608	.0133556
2003	-.3445164	.0842676	-4.09	0.000	-.5137728	-.1752599
2004	-.3663769	.1051731	-3.48	0.001	-.5776234	-.1551305
2005	-.2433722	.0917556	-2.65	0.011	-.4276688	-.0590755
2006	-.1228409	.104577	-1.17	0.246	-.33289	.0872082
2007	-.0309208	.0869268	-0.36	0.724	-.2055184	.1436767
2008	-.0585947	.095007	-0.62	0.540	-.2494219	.1322326
2009	-.3659011	.0922504	-3.97	0.000	-.5511914	-.1806107
2010	-.697982	.0955096	-7.31	0.000	-.8898188	-.5061452
2011	-.6964367	.0902081	-7.72	0.000	-.877625	-.5152484
2012	-.5315175	.0957067	-5.55	0.000	-.72375	-.339285
2013	-.4076003	.1154386	-3.53	0.001	-.6394655	-.1757352

```
        2014  |  -.3835814   .1101971    -3.48   0.001    -.6049187    -.162244
        2015  |  -.1734517    .101061    -1.72   0.092    -.3764388    .0295354
              |
 migrant#year |
      1 1999  |   .1037441   .1566289     0.66   0.511    -.2108544    .4183425
      1 2000  |   .2839861   .2249484     1.26   0.213    -.1678361    .7358082
      1 2001  |   .4063498   .1614002     2.52   0.015      .082168    .7305316
      1 2002  |   .1809072   .1642932     1.10   0.276    -.1490855    .5108998
      1 2003  |   .2957157   .1718296     1.72   0.091    -.0494141    .6408455
      1 2004  |   .2116117   .2093017     1.01   0.317    -.2087832    .6320067
      1 2005  |   .1854673   .1518928     1.22   0.228    -.1196184     .490553
      1 2006  |    .545603   .1934972     2.82   0.007     .1569525    .9342535
      1 2007  |   .3214317    .165004     1.95   0.057    -.0099886     .652852
      1 2008  |   .2854388   .2115711     1.35   0.183    -.1395143    .7103919
      1 2009  |  -.0060408   .2077333    -0.03   0.977    -.4232854    .4112038
      1 2010  |  -.2842694   .2086885    -1.36   0.179    -.7034325    .1348937
      1 2011  |  -.1846454    .198798    -0.93   0.357     -.583943    .2146521
      1 2012  |  -.2073003   .2268387    -0.91   0.365    -.6629192    .2483186
      1 2013  |  -.1980301   .2451393    -0.81   0.423    -.6904069    .2943466
      1 2014  |   -.044571   .2621926    -0.17   0.866    -.5712004    .4820584
      1 2015  |  -.0626492   .2316472    -0.27   0.788    -.5279264     .402628
              |
   entry_year |   .0289566   .0135993     2.13   0.038     .0016415    .0562717
entry_year_sq |  -.0000145   6.79e-06    -2.14   0.038    -.0000281   -8.63e-07
        _cons |   33.80293   .2491935   135.65   0.000     33.30241    34.30345
------------------------------------------------------------------------------
```

Specification (6), Endogenous-wage, Method 2, Restricted sample

```
Linear regression                               Number of obs     =     36,513
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.0591
                                                Root MSE          =     .61984

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
      lnwage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   .0965106   .0402751     2.40   0.020     .0156158    .1774055
post911entry |  -.0874484   .0272023    -3.21   0.002    -.1420859   -.0328109
post911ent~t |    .048964   .0332257     1.47   0.147    -.0177717    .1156998
      hsgrad |   .2070756   .0147675    14.02   0.000     .1774142     .236737
   assocgrad |   .2895582   .0224515    12.90   0.000     .2444631    .3346533
    bachgrad |   .4270631   .0498811     8.56   0.000     .3268739    .5272522
    mastgrad |    .343307   .1067652     3.22   0.002     .1288629    .5577512
  doctorgrad |   .3823987   .0692435     5.52   0.000      .243319    .5214785
migranthsg~d |  -.0828242   .0204565    -4.05   0.000    -.1239123    -.041736
migrantass~d |  -.1016615   .0456989    -2.22   0.031    -.1934504   -.0098727
migrantbac~d |  -.2256163   .0431085    -5.23   0.000    -.3122023   -.1390304
migrantmas~d |  -.0207936   .1494726    -0.14   0.890    -.3210181    .2794308
migrantdoc~d |  -.0804451   .1527534    -0.53   0.601    -.3872593    .2263691
         exp |   .0174364   .0021277     8.20   0.000     .0131628      .02171
  migrantexp |  -.0106349   .0023976    -4.44   0.000    -.0154506   -.0058193
      exp_sq |  -.0002791   .0000436    -6.40   0.000    -.0003667   -.0001916
migrantexp~q |    .000179   .0000491     3.65   0.001     .0000804    .0002775
```

```
      female | -.1482061   .0119379   -12.41   0.000     -.172184   -.1242282
migrantfem~e | -.0053106   .0160461    -0.33   0.742    -.0375403     .026919
   1.migrant |         0  (omitted)
             |
       wbhao |
      Black  | -.0776062   .0149974    -5.17   0.000    -.1077294    -.047483
   Hispanic  | -.0588626   .0172218    -3.42   0.001    -.0934537   -.0242716
      Asian  | -.0227491   .0459885    -0.49   0.623    -.1151198    .0696216
      Other  | -.0871157   .0395941    -2.20   0.032    -.1666429   -.0075886
             |
    migrant#|
       wbhao |
    1#Black  |  .1080482    .028723     3.76   0.000     .0503562    .1657401
 1#Hispanic  | -.0748089   .0248485    -3.01   0.004    -.1247185   -.0248993
    1#Asian  | -.0240755   .0585951    -0.41   0.683    -.1417672    .0936162
    1#Other  | -.0862069   .1041758    -0.83   0.412    -.2954503    .1230364
             |
years_sinc~l |  .0048641   .0008469     5.74   0.000     .0031629    .0065652
       rural | -.1161789   .0154409    -7.52   0.000    -.1471929   -.0851648
migrantrural |  .0362934   .0261606     1.39   0.171    -.0162516    .0888385
             |
        year |
       1999  |  .0526894     .02619     2.01   0.050     .0000851    .1052936
       2000  |  .0005472   .0276157     0.02   0.984    -.0549205     .056015
       2001  |  .0983113   .0273942     3.59   0.001     .0432883    .1533342
       2002  |   .094772   .0223035     4.25   0.000      .049974    .1395699
       2003  |  .0414751   .0377272     1.10   0.277    -.0343023    .1172524
       2004  | -.0071448   .0444928    -0.16   0.873    -.0965112    .0822217
       2005  | -.0431835   .0293018    -1.47   0.147    -.1020379     .015671
       2006  |  .0075997   .0334484     0.23   0.821    -.0595835    .0747828
       2007  | -.0392653   .0355283    -1.11   0.274    -.1106259    .0320953
       2008  |   -.00151   .0392703    -0.04   0.969    -.0803867    .0773667
       2009  |  .0037854   .0498808     0.08   0.940    -.0964031    .1039739
       2010  |  .0528429   .0472346     1.12   0.269    -.0420305    .1477164
       2011  |  .0147225   .0359666     0.41   0.684    -.0575185    .0869635
       2012  |  -.010564   .0299041    -0.35   0.725    -.0706282    .0495002
       2013  | -.0288082   .0372143    -0.77   0.443    -.1035553    .0459389
       2014  | -.0062771   .0446225    -0.14   0.889    -.0959041    .0833499
       2015  |  .0542064   .0324136     1.67   0.101    -.0108983     .119311
             |
migrant#year |
     1 1999  | -.0739158   .0375542    -1.97   0.055    -.1493457     .001514
     1 2000  |  .0378371   .0362219     1.04   0.301    -.0349166    .1105909
     1 2001  | -.0287362   .0500749    -0.57   0.569    -.1293145    .0718421
     1 2002  | -.0175662   .0391934    -0.45   0.656    -.0962885     .061156
     1 2003  |   .041189   .0450955     0.91   0.365     -.049388    .1317659
     1 2004  |  .0449715   .0462921     0.97   0.336     -.048009     .137952
     1 2005  |  .1232248    .031716     3.89   0.000     .0595214    .1869283
     1 2006  |   .057148   .0535096     1.07   0.291    -.0503292    .1646252
     1 2007  |  .0831993    .040528     2.05   0.045     .0017965    .1646022
     1 2008  |  .0045783   .0359262     0.13   0.899    -.0675815    .0767382
     1 2009  |  .0407745   .0637033     0.64   0.525    -.0871773    .1687262
     1 2010  |  .0160969   .0427622     0.38   0.708    -.0697935    .1019874
     1 2011  |  .0629931   .0326877     1.93   0.060     -.002662    .1286482
     1 2012  |  .0438076   .0436388     1.00   0.320    -.0438435    .1314588
     1 2013  |  .0536223   .0415458     1.29   0.203     -.029825    .1370695
     1 2014  |  .0513936   .0456781     1.13   0.266    -.0403535    .1431407
     1 2015  | -.0330225   .0409167    -0.81   0.423    -.1152061    .0491611
             |
       _cons |  2.160678   .0304045    71.06   0.000     2.099609    2.221747
```

```
------------------------------------------------------------------------------

Linear regression                               Number of obs     =     36,609
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.0955
                                                Root MSE          =     10.955

                                   (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
             |               Robust
 hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     migrant |   2.885108   .8566363     3.37   0.001     1.164503    4.605712
post911entry |  -.6830696   .5437442    -1.26   0.215    -1.775212    .4090727
post911ent~t |   .9957908   .6829446     1.46   0.151    -.3759439    2.367525
      hsgrad |   .9024864   .3073284     2.94   0.005     .2851992    1.519774
   assocgrad |   1.609007   .6406285     2.51   0.015     .3222665    2.895747
    bachgrad |   .8634101   .7935331     1.09   0.282     -.730448    2.457268
    mastgrad |   1.026466   1.359271     0.76   0.454     -1.70371    3.756642
  doctorgrad |   3.799035   3.048483     1.25   0.218    -2.324023    9.922092
migranthsg~d |  -1.382249   .4080072    -3.39   0.001    -2.201755   -.5627424
migrantass~d |  -2.186587   .7261582    -3.01   0.004    -3.645119   -.7280555
migrantbac~d |  -1.165769   .7778876    -1.50   0.140    -2.728202    .3966647
migrantmas~d |   .0245567   1.757799     0.01   0.989    -3.506087      3.5552
migrantdoc~d |  -5.616671   3.207078    -1.75   0.086    -12.05828    .8249355
         exp |   .4053873   .0272254    14.89   0.000     .3507035    .4600711
  migrantexp |  -.2568821   .0357802    -7.18   0.000    -.3287487   -.1850155
      exp_sq |  -.0079507   .0005278   -15.06   0.000    -.0090108   -.0068906
migrantexp~q |   .0055243    .000648     8.53   0.000     .0042227    .0068258
      female |  -7.315596   .4197487   -17.43   0.000    -8.158686   -6.472506
migrantfem~e |    1.48466    .532293     2.79   0.007     .4155185    2.553802
   1.migrant |          0  (omitted)
             |
       wbhao |
      Black  |   1.746128   .3643069     4.79   0.000     1.014396     2.47786
   Hispanic  |   1.587909   .3816801     4.16   0.000     .8212816    2.354536
      Asian  |   1.303574   .8181352     1.59   0.117    -.3396985    2.946847
      Other  |   1.371205   .7258423     1.89   0.065    -.0866918    2.829102
             |
    migrant#|
       wbhao |
    1#Black  |  -.4866477    .777977    -0.63   0.534    -2.049261    1.075965
 1#Hispanic  |  -1.194334   .6904576    -1.73   0.090    -2.581159    .1924913
    1#Asian  |   .9168766   1.237855     0.74   0.462    -1.569429    3.403182
    1#Other  |   1.012655    2.75407     0.37   0.715    -4.519057    6.544368
             |
years_sinc~l |  -.0006234   .0077888    -0.08   0.937    -.0162677     .015021
       rural |   1.348646   .3348613     4.03   0.000     .6760576    2.021235
migrantrural |   .7496149   .6725501     1.11   0.270    -.6012417    2.100471
             |
        year |
       1999  |  -.3004432   .5054257    -0.59   0.555    -1.315621    .7147342
       2000  |   .2419812    .556314     0.43   0.665    -.8754084    1.359371
       2001  |  -.0799155   .5425221    -0.15   0.883    -1.169603    1.009772
       2002  |  -.4022266   .5472473    -0.73   0.466    -1.501405    .6969519
       2003  |  -.6980043   .6087141    -1.15   0.257    -1.920643     .524634
       2004  |  -.9955812    .588489    -1.69   0.097    -2.177596    .1864338
       2005  |  -1.306496    .702503    -1.86   0.069    -2.717515    .1045227
       2006  |  -1.232313   .6493207    -1.90   0.063    -2.536512    .0718862
```

	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
2007	-1.656889	.4990931	-3.32	0.002	-2.659347	-.6544308
2008	-.5981302	.5985903	-1.00	0.322	-1.800434	.6041738
2009	-1.178048	.6512329	-1.81	0.076	-2.486088	.129992
2010	-2.486965	.7196484	-3.46	0.001	-3.932421	-1.041509
2011	-1.744719	.7687301	-2.27	0.028	-3.288759	-.2006789
2012	-1.289766	.6037494	-2.14	0.038	-2.502432	-.0770993
2013	-2.218455	.6635705	-3.34	0.002	-3.551276	-.8856348
2014	-2.149141	.5776557	-3.72	0.001	-3.309397	-.9888858
2015	-1.401776	.6189213	-2.26	0.028	-2.644916	-.1586357
migrant#year						
1 1999	.4956559	.7600917	0.65	0.517	-1.031033	2.022345
1 2000	-.0378384	.8272206	-0.05	0.964	-1.69936	1.623683
1 2001	.1262974	.9938792	0.13	0.899	-1.869968	2.122562
1 2002	-.0810446	.7923485	-0.10	0.919	-1.672523	1.510434
1 2003	.2808346	.9509874	0.30	0.769	-1.62928	2.190949
1 2004	.4877479	.8619009	0.57	0.574	-1.243431	2.218927
1 2005	.4950196	.942876	0.53	0.602	-1.398803	2.388842
1 2006	.5377201	.9917668	0.54	0.590	-1.454302	2.529742
1 2007	1.353421	.7253844	1.87	0.068	-.1035565	2.810398
1 2008	-.0419054	.8728585	-0.05	0.962	-1.795093	1.711282
1 2009	-.4484182	1.064194	-0.42	0.675	-2.585914	1.689078
1 2010	-.2885923	1.091091	-0.26	0.792	-2.480114	1.902929
1 2011	-.8874743	1.013455	-0.88	0.385	-2.923059	1.14811
1 2012	-.1631687	.9712153	-0.17	0.867	-2.113912	1.787575
1 2013	.2114158	.9340944	0.23	0.822	-1.664768	2.0876
1 2014	.465383	.8416167	0.55	0.583	-1.225054	2.15582
1 2015	.5515435	1.057825	0.52	0.604	-1.57316	2.676247
_cons	37.24748	.5737297	64.92	0.000	36.09511	38.39985

Specification (6), Endogenous-wage, Method 2, Full sample

Linear regression

Number of obs	=	1,364,949
F(50, 50)	=	.
Prob > F	=	.
R-squared	=	0.2914
Root MSE	=	.61346

(Std. Err. adjusted for 51 clusters in state)

lnwage	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
migrant	.3929845	.0330659	11.88	0.000	.3265696	.4593993
post911entry	-.0644262	.0037365	-17.24	0.000	-.0719312	-.0569213
post911entr~t	.0019589	.0072695	0.27	0.789	-.0126424	.0165602
highmigrant~c	-.2671521	.0077491	-34.48	0.000	-.2827166	-.2515876
hig~c_migrant	.0832756	.0104903	7.94	0.000	.0622052	.104346
highmigra~911	.1136473	.0200815	5.66	0.000	.0733124	.1539822
hig~1_migrant	-.0663952	.021689	-3.06	0.004	-.1099588	-.0228317
hsgrad	.292672	.0058844	49.74	0.000	.2808528	.3044911
assocgrad	.4761971	.0057892	82.26	0.000	.4645692	.4878251
bachgrad	.7506654	.0100709	74.54	0.000	.7304373	.7708934
mastgrad	.9231255	.0136293	67.73	0.000	.8957502	.9505009
doctorgrad	1.189719	.0129542	91.84	0.000	1.1637	1.215739
migranthsgrad	-.1072426	.0055862	-19.20	0.000	-.1184627	-.0960224

migrantasso~d	-.0902774	.0118128	-7.64	0.000	-.1140041	-.0665506
migrantbach~d	-.1041223	.0111717	-9.32	0.000	-.1265614	-.0816832
migrantmast~d	.015103	.0162094	0.93	0.356	-.0174545	.0476605
migrantdoct~d	-.1379848	.0146771	-9.40	0.000	-.1674645	-.108505
exp	.041053	.0009324	44.03	0.000	.0391802	.0429259
migrantexp	-.0222454	.0010858	-20.49	0.000	-.0244263	-.0200646
exp_sq	-.0006685	.0000183	-36.53	0.000	-.0007053	-.0006317
migrantexp_sq	.0003216	.0000192	16.77	0.000	.0002831	.0003602
female	-.2414267	.0047449	-50.88	0.000	-.2509571	-.2318963
migrantfemale	.0295066	.0068461	4.31	0.000	.0157558	.0432573
1.migrant	0	(omitted)				
wbhao						
Black	-.139196	.0091458	-15.22	0.000	-.1575658	-.1208262
Hispanic	-.0678714	.0242876	-2.79	0.007	-.1166544	-.0190883
Asian	.0247675	.016165	1.53	0.132	-.0077008	.0572357
Other	-.0853787	.0120167	-7.10	0.000	-.1095151	-.0612424
migrant#wbhao						
1#Black	.0353948	.0196335	1.80	0.077	-.0040403	.0748299
1#Hispanic	-.1232537	.0208464	-5.91	0.000	-.1651249	-.0813825
1#Asian	-.0485639	.0149114	-3.26	0.002	-.0785143	-.0186135
1#Other	.0147211	.0548698	0.27	0.790	-.0954882	.1249303
years_since~l	.0071146	.0010925	6.51	0.000	.0049202	.009309
rural	-.1666931	.012703	-13.12	0.000	-.1922078	-.1411784
migrantrural	.0848547	.0156235	5.43	0.000	.0534739	.1162355
year						
1999	.0312703	.0048751	6.41	0.000	.0214784	.0410621
2000	.0426353	.0045036	9.47	0.000	.0335896	.051681
2001	.0581787	.0051817	11.23	0.000	.047771	.0685865
2002	.0653204	.0044196	14.78	0.000	.0564434	.0741974
2003	.0692521	.0053038	13.06	0.000	.0585992	.0799051
2004	.0621227	.0050904	12.20	0.000	.0518983	.0723471
2005	.0484536	.0041562	11.66	0.000	.0401057	.0568016
2006	.0409201	.0054265	7.54	0.000	.0300207	.0518195
2007	.0431851	.0079322	5.44	0.000	.0272529	.0591174
2008	.051027	.0068717	7.43	0.000	.0372247	.0648293
2009	.0342116	.0068153	5.02	0.000	.0205228	.0479005
2010	.0499551	.0058192	8.58	0.000	.038267	.0616432
2011	.034038	.0061834	5.50	0.000	.0216183	.0464577
2012	.0201577	.0078519	2.57	0.013	.0043867	.0359288
2013	.004857	.0072604	0.67	0.507	-.0097259	.01944
2014	.0073815	.0100289	0.74	0.465	-.0127621	.0275252
2015	.0100391	.0089568	1.12	0.268	-.0079512	.0280294
migrant#year						
1 1999	-.0148612	.0087781	-1.69	0.097	-.0324925	.0027701
1 2000	.014743	.009311	1.58	0.120	-.0039587	.0334446
1 2001	.0300901	.0108309	2.78	0.008	.0083356	.0518445
1 2002	.0325685	.0070511	4.62	0.000	.0184059	.0467311
1 2003	.0156534	.0130164	1.20	0.235	-.0104907	.0417976
1 2004	.01584	.0132831	1.19	0.239	-.0108399	.0425199
1 2005	.0396704	.0129253	3.07	0.003	.0137092	.0656316
1 2006	.0514366	.0099529	5.17	0.000	.0314456	.0714276
1 2007	.0537675	.0100707	5.34	0.000	.03354	.073995
1 2008	.0428842	.0106784	4.02	0.000	.021436	.0643325
1 2009	.0405367	.0143638	2.82	0.007	.0116861	.0693872
1 2010	.0494455	.0136946	3.61	0.001	.021939	.0769519

```
      1 2011  |    .051445   .0132423     3.88   0.000      .024847     .078043
      1 2012  |   .0515207   .0151765     3.39   0.001     .0210378    .0820036
      1 2013  |    .062867   .0155636     4.04   0.000     .0316066    .0941273
      1 2014  |   .0589002   .0168264     3.50   0.001     .0251034    .0926971
      1 2015  |   .0495219   .0204139     2.43   0.019     .0085194    .0905244
              |
   entry_year |   .0007101   .0008953     0.79   0.431    -.0010882    .0025084
entry_year_sq |  -4.21e-07   4.45e-07    -0.95   0.349    -1.32e-06    4.73e-07
        _cons |   2.155365   .0078498   274.57   0.000     2.139598    2.171132
------------------------------------------------------------------------------

Linear regression                               Number of obs     =  1,365,655
                                                F(49, 50)         =          .
                                                Prob > F          =          .
                                                R-squared         =     0.1244
                                                Root MSE          =     9.8377

                                  (Std. Err. adjusted for 51 clusters in state)
------------------------------------------------------------------------------
              |               Robust
  hoursworked |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
      migrant |   3.929985   .3989861     9.85   0.000     3.128598    4.731373
 post911entry |  -1.191927   .0682725   -17.46   0.000    -1.329057   -1.054798
post911entr~t |   .6526862   .1289243     5.06   0.000      .393734    .9116383
highmigrant~c |  -1.092017   .1429884    -7.64   0.000    -1.379217   -.8048158
hig~c_migrant |    .775959   .3490939     2.22   0.031     .0747833    1.477135
highmigra~911 |   1.351825   .3659522     3.69   0.001     .6167882    2.086861
hig~1_migrant |  -.5419607   .5188004    -1.04   0.301    -1.584002    .5000805
       hsgrad |   2.349978   .1233318    19.05   0.000     2.102259    2.597697
    assocgrad |   2.956081   .1339407    22.07   0.000     2.687053    3.225109
     bachgrad |   4.682014   .1346317    34.78   0.000     4.411598    4.952429
     mastgrad |   5.599965    .174443    32.10   0.000     5.249586    5.950344
   doctorgrad |   8.870182   .2574555    34.45   0.000     8.353068    9.387297
migranthsgrad |  -1.742631   .1386233   -12.57   0.000    -2.021064   -1.464198
migrantasso~d |  -2.081925   .2093953    -9.94   0.000    -2.502508   -1.661342
migrantbach~d |  -2.554132   .2330479   -10.96   0.000    -3.022222   -2.086041
migrantmast~d |  -2.649716   .2935332    -9.03   0.000    -3.239295   -2.060138
migrantdoct~d |  -2.277764   .2470458    -9.22   0.000     -2.77397   -1.781558
          exp |   .5859737   .0104651    55.99   0.000     .5649539    .6069934
   migrantexp |  -.2932192   .0174568   -16.80   0.000    -.3282823   -.2581561
       exp_sq |   -.011281   .0001953   -57.77   0.000    -.0116732   -.0108888
migrantexp_sq |   .0060303    .000309    19.52   0.000     .0054098    .0066509
       female |  -4.841116   .1129246   -42.87   0.000    -5.067932     -4.6143
migrantfemale |   .7876611   .1117622     7.05   0.000     .5631801    1.012142
    1.migrant |          0  (omitted)
              |
        wbhao |
       Black  |   .0327218   .0779304     0.42   0.676    -.1238061    .1892496
    Hispanic  |   .0996443   .2251951     0.44   0.660    -.3526734    .5519621
       Asian  |  -.4092265   .2714318    -1.51   0.138    -.9544133    .1359604
       Other  |   .2404928   .1552082     1.55   0.128     -.071252    .5522377
              |
migrant#wbhao |
     1#Black  |  -.4545912   .1333702    -3.41   0.001    -.7224731   -.1867093
  1#Hispanic  |  -.5724949   .1553929    -3.68   0.001    -.8846107    -.260379
     1#Asian  |  -.3558215   .2490332    -1.43   0.159    -.8560193    .1443764
     1#Other  |  -.7194345   .4546234    -1.58   0.120    -1.632573    .1937035
              |
years_since~l |   .0112408   .0025695     4.37   0.000     .0060799    .0164017
```

rural	.2592773	.0890174	2.91	0.005	.0804807	.438074
migrantrural	.747775	.2821711	2.65	0.011	.1810176	1.314532
year						
1999	.1015181	.0656216	1.55	0.128	-.0302866	.2333229
2000	.1150031	.0905952	1.27	0.210	-.0669627	.2969688
2001	.0572098	.0964002	0.59	0.556	-.1364157	.2508353
2002	-.141572	.0761328	-1.86	0.069	-.2944893	.0113453
2003	-.3465674	.0840856	-4.12	0.000	-.5154584	-.1776765
2004	-.3689725	.1049666	-3.52	0.001	-.5798041	-.1581409
2005	-.2463902	.0914701	-2.69	0.010	-.4301133	-.0626672
2006	-.1263443	.1043396	-1.21	0.232	-.3359167	.083228
2007	-.0348318	.0866382	-0.40	0.689	-.2088496	.1391861
2008	-.0630707	.0946415	-0.67	0.508	-.2531638	.1270225
2009	-.3707444	.0916871	-4.04	0.000	-.5549034	-.1865854
2010	-.7032383	.0955647	-7.36	0.000	-.8951856	-.511291
2011	-.7021312	.0897811	-7.82	0.000	-.8824618	-.5218005
2012	-.5376239	.0950419	-5.66	0.000	-.7285211	-.3467266
2013	-.4143019	.1151101	-3.60	0.001	-.6455072	-.1830965
2014	-.3904892	.1098194	-3.56	0.001	-.6110679	-.1699104
2015	-.1811044	.1002244	-1.81	0.077	-.3824111	.0202023
migrant#year						
1 1999	.0750184	.1589014	0.47	0.639	-.2441444	.3941812
1 2000	.2349827	.2175805	1.08	0.285	-.2020406	.672006
1 2001	.3289559	.1658075	1.98	0.053	-.0040782	.66199
1 2002	.115047	.1632095	0.70	0.484	-.2127688	.4428628
1 2003	.2667487	.1567782	1.70	0.095	-.0481496	.581647
1 2004	.2154757	.2016062	1.07	0.290	-.1894621	.6204136
1 2005	.2128391	.1286781	1.65	0.104	-.0456184	.4712966
1 2006	.5632315	.1726356	3.26	0.002	.2164827	.9099802
1 2007	.2794344	.1198365	2.33	0.024	.0387357	.5201331
1 2008	.1602811	.1617972	0.99	0.327	-.1646982	.4852604
1 2009	-.0756459	.1604426	-0.47	0.639	-.3979044	.2466126
1 2010	-.4525191	.151838	-2.98	0.004	-.7574946	-.1475436
1 2011	-.3551583	.1294616	-2.74	0.008	-.6151897	-.095127
1 2012	-.4412577	.1472078	-3.00	0.004	-.7369332	-.1455821
1 2013	-.4615555	.1705144	-2.71	0.009	-.8040438	-.1190672
1 2014	-.2606241	.17154	-1.52	0.135	-.6051723	.0839242
1 2015	-.2538709	.1451515	-1.75	0.086	-.5454163	.0376744
_cons	33.80503	.2489439	135.79	0.000	33.30502	34.30505