ESSAYS ON UNEMPLOYMENT INSURANCE AND THE RESERVATION WAGE

by

Muhammad Usman Taj

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ABSTRACT

This dissertation comprises three research papers focusing on the effects of unemployment insurance and labor supply dynamics. In chapter one, I use new government Benefit Accuracy Measurement (BAM) survey data on unemployment insurance (UI) claimants to study the relationships between reservation wages and labor market conditions. The direction of most measures is in accordance with the theory. While the layoffs rate coefficient aligns with the theory, the total separation rate deviates from it, due to the role of quits in the job separation rate. Among the main indicators, workers are most responsive to the employment-to-population ratio. Results also show that the aggregate employment indicators matter more than worker's group-specific measures, indicating that workers focus more on the aggregate market conditions. To introduce exogeneity, I include shift share measures in my specifications and find similar positive relationships between the reservation wage and the shift share measures. All results are robust to different sub-sample selections and specifications.

In chapter two, I investigate the impact of unemployment insurance extension on labor market outcomes. In August 2020, the US government introduced the Lost Wages Assistance Program, the purpose was to provide relief to the unemployed workers. Under the program, $300 additional payments were provided in addition to regular UI benefits. Using the Household Pulse Survey, this paper attempts to study the moral hazard effect of the program. I find that a 1% increase in the replacement rate due to LWA was associated with a 4% decrease in the probability of working. The effect is similarly significant among the subgroups as well.

In chapter three, I study the impact of the withdrawal of unemployment insurance extensions on housing outcomes. In June 2021, 23 states decided to end the pandemic-era UI extensions. In this paper, I exploit state level variation to examine the impact of early withdrawal from FPUC (Federal Pandemic Unemployment Compensation) on housing outcomes. In the TWFE specifications, I find a negative impact of the UI extensions on home-owners, with foreclosure rates going up. I find no significant effect on the renters. To address treatment heterogeneity, I include the event study results. My event study findings indicate that the eviction rates go down significantly, foreclosure rates go down in the short run only, and mortgage confidence rises in the post period. These findings imply that the UI termination had a positive impact on the housing market outcomes.

Chapter 1

RESERVATION WAGES AND MACROECONOMIC CONDITIONS: EVIDENCE FROM BENEFIT ACCURACY MEASUREMENT DATA

1.1 Introduction

The reservation wage is defined as the wage at which a worker is indifferent between accepting or rejecting a job offer. It is highly important in the context of the labor market, as unemployed workers continue their search on the basis of it. How do reservation wages react to varying labor market conditions? It is an essential question when studying the dynamics of any given labor market. Despite the substantial literature on job search models, including theoretical predictions in Pissarides (1994), Jolivet et al. (2006), Bontemps et al. (2000), Cahuc et al. (2006) and Yamaguchi (2010), only a few papers examine the reservation wage explicitly. In most of these existing studies, the reservation wage is unobserved, mainly because of data constraint.

This paper fills the gap in the literature by focusing on the reservation wage. I use self reported data on reservation wages to understand how they react to local labor market shocks. Specifically, I investigate the reservation wage's response to various market indicators such as the unemployment rate, employment-to-population ratio and market tightness. I also evaluate the theoretical predictions of the search model and find most of my empirical results consistent with the theory.[1]

From a policy perspective, UI is a crucial tool for regulating the labor market. According to Blumkin et al. (2005), a declining UI amount with unemployment

[1] I use the Mortensen search model, presented in Blien et al. (2012).

duration results in voluntary unemployment for the temporarily unemployed individuals but induces improved matching. Hence, optimal unemployment insurance policy suggest that UI should vary over time and implies a declining benefit schedule over the spell of unemployment.[2] Similarly, Landais et al. (2018) states that the optimal UI policy is counter-cyclical using Bailey-Chetty formula. This means that the UI generosity is higher in downturns and lower otherwise. As UI generosity varies, reservation wages are expected to change as well for the UI claimant indicating a direct relation of macroeconomic conditions and reservation wages.[3] Theoretically, this further highlights the existence of the association between the reservation wage and the macroeconomic conditions. But, the empirical evidence on the connection is still scarce.

There is considerable evidence in the literature that establishes how individual characteristics affect the reservation wage.[4] However, there is a dearth of literature on the causal effect of macroeconomic factors on the reservation wage. For macroeconomic indicators, Blien et al. (2012) investigated the impact of local unemployment rates on the reservation wage. There was evidence that the local unemployment rates affected the reservation wage. Haurin & Sridhar (2003) and Prasad (2003) also included the relationship of unemployment rate and the reservation wage and found insignificant results. In my analysis, I use a larger sample of unemployed individuals while using additional macroeconomic indicators such as market tightness and employment-to-population ratio.[5] In contrast to the existing papers, I use data covering the extensive period from 2016-2019, containing regular business cycles which provides evidence of the reservation

[2] See Shavell & Weiss (1979) for more detail.

[3] Arni (2017), Huang (2021), Le Barbanchon et al. (2019) and many others found positive impact of UI generosity on the reservation wage.

[4] Christensen (2001), Bloemen & Stancanelli (2001), Addison et al. (2009) and Deschacht & Vansteenkiste (2021) studied the relation of reservation wages with micro variables.

[5] The sample size in Haurin & Sridhar (2003) was only 250, while it was around 10,000 in Blien et al. (2012). My sample size varies around 50,000-80,000.

wage behavior in normal economic conditions. Secondly, I present the reservation wage analysis by using a more recent time period.[6] I also add the pandemic period, to investigate how workers alter their behavior in lockdown restrictions.[7] Moreover, it is also important to understand how the welfare of unemployed workers fluctuate with changes in job market conditions. Shimer & Werning (2007) find that the reservation wage is welfare improving if it is highly elastic with respect to UI benefits. Apart from UI benefits, it is also important to study the relation of reservation wages with other market conditions. So, I analyze the same relation of reservation wages with the market indicators to observe how welfare of unemployed workers vary with the altering market conditions. The results show that the reservation wage is elastic to the main measures such as the unemployment rate and employment-to-population ratio. This means that the changing market conditions have a welfare impact on the unemployed workers. For instance, if unemployment rate increases, reservation wages will drop down, reducing the welfare of the job seekers.

Most of the existing papers on reservation wages only focus on micro variables such as the amount of unemployment benefits a worker receive, unemployment duration and search intensity. And while there is evidence on the relation of market wage and labor market conditions, there is limited work on the same relation for the reservation wage.[8] I address this gap in the literature by reporting the reservation wage behavior in relation to macroeconomic conditions, while controlling for the relevant micro-variables. Most of the current literature is focused on the market wage of employed workers and how it changes with the market conditions. But we can not overlook the significance of reservation wages as they are an important factor for understanding reemployment and search

[6] Hobijn & Şahin (2013) documented a shift in the Beveridge Curve in the United States since the Great Recession.

[7] Blien et al. (2012) used the period between 2006 and 2007, Prasad (2003) restricted the survey waves to years (1987-89, 1992-94, and 1996-97) that contained the reservation wage question, while Haurin & Sridhar (2003) used PSID data from 1984-87.

[8] Cheron & Langot (2004), Babeckỳ et al. (2010), Klein (2012)

models of the unemployed.

Using Benefit Accuracy Measurement data, I explore the relationship between the reservation wage and the local labor market conditions.[9] Most existing search models assume exogenous nature of the reservation wage while solving for the equilibrium wages and firms profit.[10] I provide evidence of how the reservation wage varies with the changing labor market conditions and present the mechanism of job seeker's reaction to different macro level shocks. I employ a labor market matching model introduced by D. Mortensen & Pissarides (1992), presented in Blien et al. (2012). The model includes a wage negotiation approach through Nash bargaining between firms and workers.

I test the theoretical predictions of the search model, which is one of the main contributions of this study as it connects the theoretical model with data. The direction of all coefficients is in accordance with the theory except for the job separation rate. The data shows a significant positive relation between the reservation wage and the job separation rate which is opposite to the predicted negative association between the two variables in the model. The opposite relation in the data is mainly driven by the quits rate while the model focuses on the involuntary separations (layoffs). I provide more detail on this in the results section. My results suggest that the reservation wage is more responsive to the employment to population ratio as compared to the other main factors such as the unemployment rate and market tightness. Secondly, I introduce the relationship between the reservation wage and multiple labor market indicators. Unlike most previous studies that only focus on the unemployment rate, I provide an analysis considering various macroeconomic measures.[11] Mostly, economic indicators

[9] BAM Data is a randomized survey that includes information on UI claimants from all states. The information is further used for accountability of state offices. More information is given in the data section.

[10] McCall (1970), Lippman & McCall (1976), D. T. Mortensen (1977) are one of the first papers on Job Search models. Later on, Rothstein (2011), Paserman (2008), Lentz (2009) also studied job search models.

[11] Blien et al. (2012) only used the unemployment rate, I investigate further by including other important macroeconomic indicators such as market tightness, employment to population ratio, job separation rate, etc.

such as the unemployment rate, market tightness and employment-to-population ratio depict the same labor market picture, but in theory, they can be independent of each other.[12] Hence, it is important to find out the reservation wage relation with other macroeconomic indicators as well. Moreover, this study is one of the first to provide detailed analysis on the reservation wage within the context of the US market. In the current literature, Addison et al. (2013), Pannenberg (2010), Le Barbanchon et al. (2019) and numerous others have studied the reservation wage using non-US datasets.

The relationship between the reservation wage and main economic measures is important, as it demonstrates the worker's preference towards different market indicators. But, these results might be biased due to simultaneity issue. To address this, I include the Bartik or Shift measure in my specification. The shift measure removes reverse causality by isolating the labor demand effect from the supply effect. It also reduces endogeneity concerns by measuring the local employment shock through the national employment level. This paper is one of the first to include such a relationship as most studies use Bartik instrument for the employment or wage growth.[13] The findings validate the significance of the shift measure when considering the reservation wage. I also compare the overall measures with the age-specific indicators. Blien et al. (2012) presented a comparison restricted to unemployment rate, while I extend the analysis by including additional indicators such as the age-specific market tightness and the age-specific employment-to-population ratio. Lastly, I estimate the model parameters and find a higher value of leisure as compared to past studies. This higher value indicates that unemployed workers receiving UI have a stronger preference for leisure and derive greater utility from it. This result is distinctive from other studies because the sample only includes job seekers as compared to data sources comprising both types of workers (employed and unemployed).

[12] According to Pissarides (2000), market tightness is independent of the unemployment rate, in the steady-state equilibrium. More information is provided in the model.

[13] T. J. Bartik (1991), Maestas et al. (2013), Wozniak (2010).

The rest of the paper proceeds as follows. Section 2 describes all of the relevant papers in the literature. In section 3, I provide details of BAM and other datasets. Section 4 shows the main theoretical results from the model. Section 5 includes the empirical strategy. Section 6 encompasses all of the relevant results. Turning to estimation, section 7 explains the parameter estimation of the model. Section 8 presents the robustness checks, while section 9 concludes.

1.2 Literature Review

Kiefer & Neumann (1979) is one of the first papers to study the reservation wage behavior over the spell of unemployment. The sample consisted of workers who were laid off from the production plant in US. The data followed the individuals over the period of their unemployment. The empirical model suggested that reservation wages decline over the spell of unemployment. This result is mostly consisted in other studies comprising different data sets as well. The model controlled for relevant variables such as last wage, income level, etc to avoid omitted variable bias. In my paper, I study the relation on a macro level while controlling for all of the relevant personal characteristics.

Majority of the literature is focused on the micro level variables for the determination of the reservation wage. I discuss those papers first before shifting to the papers focusing on the macro level. Feldstein & Poterba (1984) studied the reservation wage of unemployed workers in US. The data consisted of around 5,000 persons in the Current Population Survey that were asked to fill out additional survey on past earnings, reservation wages and future job opportunities, around May 1976. Majority of the workers reported the reservation wage which was as high as their last wage, which depicted that the last wage is an important factor to shape the reservation wage. Results also showed that a 10 percent increase in the UI replacement ratio increases the reservation wage by about 4 percent for people who lost their job recently and by considerably less for other unemployment groups.

Falk et al. (2006) designed a lab experiment involving random matches of firms and workers. The purpose was to study the impact of minimum wage laws on the reservation wage. Some firms were facing minimum wage law while others were free from it. Using random matching of workers and firms, the experiment indicated that the temporary introduction of minimum wage law increased the reservation wage of the workers as compared to the scenario where there was no law placed. This in turn, means that firms pay higher wages once they are exposed to the minimum wage law, even after the removal of those laws. Hence, this paper is an important evidence of how minimum wage law change the reservation wage over time. I attempt to present a similar evidence for the case of other labor market conditions.

In another study, Addison et al. (2013) explored the relationship of reservation wages and unemployment duration. With data from six waves of European Community Household Panel, the authors provided evidence on the basis of more than one country's economy. The study was unique because the sample consisted of individuals from contrasting regions such as Luxembourg, Sweden, etc. The results presented the elapsed duration coefficient of -1.5% and completed duration coefficient of 2.4%. However, elapsed duration alone did not matter significantly for the reservation wage.[14] This indicated that the completed duration is an important factor to determine the reservation wage behavior and it should always be included in the model specification. In the US context, Barron & Gilley (1979) focused on the relationship of unemployment duration and job search intensity, while using unique Bureau of Labor Statistics (BLS) data that contains information on unemployment duration and the reservation wage. According to the findings, an increase by one month in time left to receive benefits or the equivalent change in UI benefit rates reduced search intensity by 6.5 percent.

Most economists argue that job seekers are risk averse and select the reservation wage level which does not exceed the wage distribution of an optimal risk neutral worker. But, there is little empirical evidence on it. Pannenberg (2010)

[14] Authors divided the unemployment duration into two categories; elapsed duration and completed duration. Elapsed duration was defined as the period between the job loss up-to the point of the interview. Completed duration was the time interval between the two jobs.

took a different route and tried to explain the reservation wage behavior using risk preferences. The data came from German Socio-Economic panel survey that asked questions on reservation wages and measured risk aversion through the following question "Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?" Participants answered the question on a scale of 0 to 11 where 0 meant complete unwillingness to take risks while higher score indicated some level of risk taking ability among the individuals. The results showed that risk aversion was prevalent among the unemployed workers with a significant magnitude of -2%. This indicated a negative relation between risk aversion and the reservation wage. This also confirms the previous lab results in studies where more risk averse workers reported lower reservation wages for the next job.

Among the recent papers, Le Barbanchon et al. (2019) studied the reservation wage and unemployment insurance of the unemployed workers in France. Using administrative data, the paper exploited the variation of a UI reform rule to estimate the effect of potential benefit duration on reservation wages. The results showed that the relation holds and it is statistically non zero with an elasticity of 0.006. Similarly, Marinescu & Skandalis (2021) also focused on France and studied the job search behavior in light of UI payment schedule. The French administrative data was linked with an online job search platform containing over 400,000 job seekers. All those individuals were followed as long as they were unemployed. Results showed that the search intensity increased by 50% during the year preceding benefits exhaustion and remained high thereafter. The reservation wage went down by 2.4% during the year preceding benefit exhaustion. Schmieder et al. (2013) is another piece of evidence on the determination of the reservation wage, using German labor market. While exploiting the UI extensions as an IV for unemployment duration, authors presented the causal relation. With social security data from 1975-2008, the authors showed that each additional month of non-employment would decrease wage offers by around 0.8%. Indirectly, this also validated the point that reservation wages do decline over the unemployment period as workers only accept the wage offer if it is at least as high as their reservation wage.

Klepinger et al. (2002) used the employer search requirement treatment effect on UI and reemployment. In 1994, Maryland updated the job search requirement for UI claimants requiring additional employer contacts for further benefits. As a result of this, UI receipt reduced by one week and $115 per claimant. This can be taken as a non-monetary cost for the workers because of additional hassle of searching for a job and applying for it. Krueger & Mueller (2016) also studied the reservation wage phenomenon in US.[15] Mainly, the focus was on the reservation wage evolution over the time of unemployment duration. Their findings suggested that reservation wages decline at a modest rate over the spell of unemployment, and that the decline was driven by older individuals and those with non-negligible savings. Specifically, workers with more than $10,000 in liquid assets were more likely to lower their reservation wage over the course of their spell of unemployment, as compared to those with less savings to start with.

Prasad (2003) is one of the few papers that connected the reservation wage theory to the macroeconomic conditions. Using German Socio-Economic data set, the authors presented new empirical evidence on the relationship between reservation wages of unemployed workers and macroeconomic factors - including aggregate and local unemployment rates, generosity of the unemployment compensation system and characteristics of the wage structure - as well as individual-specific determinants, including proxies for general and specific human capital, length of unemployment spell and alternative income sources. The coefficient with unemployment rate was insignificant while personal characteristics such as vocational training and university degree were significant in most regressions. I

[15]For US, there is no standard survey containing questions on the reservation wage due to which there are fewer empirical papers and focus is mostly on the theoretical framework. In this paper, authors interviewed unemployed workers in New Jersey and kept following them for a period of 24 weeks. The strata consisted of 8 intervals of duration of unemployment (0–2 weeks, 10–12 weeks, 20–22 weeks, 30–32 weeks, 40–42 weeks, 50–53 weeks, 60–69 weeks, and 70 plus weeks at the end of September 2009). Only through this, they were able to perform the analysis.

present the same evidence for US economy and also focus on overall labor market conditions by including other indicators such as employment to population ratio, market tightness, labor productivity, etc. The US labor market differs from the German market for various reasons, including factors such as stronger labor unions in Germany and more generous UI payments. Hence, my results are different from the ones found in Prasad (2003).[16] By using all of the related variables, I provide a more comprehensive analysis of the reservation wage relation with labor market conditions.

Blien et al. (2012) also focused on the reservation wage and how it reacts to regional unemployment in Germany. Using the labor market theory on wage efficiency, the analysis was done using data from "Labor Market and Social Security", which is a new large-scale panel study in Germany conducted by the Institute for Employment Research (IAB). The results confirmed the matching model prediction with a significant coefficient of -0.03 for the regional unemployment rate and -0.052 for the gender-related unemployment rate. The coefficient was similar in magnitude for gender related unemployment rate as well. The coefficient was further compared with the coefficient of unemployment rate for market wages.[17] The conclusion predicted that the market wage and the reservation wage move in line with the unemployment rate. In another study, Jones (1989) also found significant coefficient of unemployment rate for the reservation wage. The study was based on a British survey conducted by the Economist Intelligence Unit in September 1982. After controlling for relevant individual characteristics, such as education, UI benefit, age, marital status, authors found a significant coefficient of -0.016 for the unemployment rate. In this paper, I also test the same hypothesis using US economy and compare the overall measures with the group-specific indicators. The result could be different because following recession, workers increased their working elasticity to unemployment benefit

[16] The coefficient of unemployment rate is insignificant in Prasad (2003) but significant at 1% in my results.

[17] Baltagi et al. (2009) showed the wage curve response to unemployment rate and found a significant coefficient of around -0.4.

which might hamper the reservation wage elasticity as well.[18] Secondly, workers in US have different work preferences which also have an impact on the reservation wage behavior.[19]

In the US context, Haurin & Sridhar (2003) studied the impact of local unemployment rate on the reservation wage and duration of job search. Authors utilized the data from the 1984-87 Panel Study of Income Dynamics (PSID) to test the relationship of unemployment rate with the reservation wage and job search. The main explanatory variable was the local unemployment rate at the county level. Results showed that the coefficient of unemployment rate was 0.01 for the reservation wage and 0.03 for the search duration. However, both coefficients were insignificant which indicated that the unemployment rate had no effect on the dependent variables (reservation wage and job search). As the sample size was only 247, there was no power in their findings. My analysis is based on a larger sample with a longer time period, which provides concrete evidence on the association of the reservation wage and other market indicators.

Domash & Summers (2022) showed different labor market indicators are sending different signals about the degree of slack in the US market, using the post pandemic period. While the supply side indicators, such as the prime-age employment-to-population ratio, suggested that there is still some slack in the labor market, the demand side ones such as the job vacancy rate and the quits rate, implied that the labor market is already very tight. Because of these divergent signals, authors compared alternative labor market indicators as predictors of wage inflation. Results showed that unemployment rate is a better predictor of wage inflation than non-employment and vacancy rates; quit rates have substantial predictive power for wage inflation. Using BAM, I also investigate if those indicators (employment to population ratio, market tightness, unemployment rate)

[18] Card et al. (2015) found that UI durations were more responsive to benefit levels during the recession and its aftermath, with an elasticity between 0.65 and 0.9 as compared to about 0.35 pre-recession.

[19] Bell & Freeman (1995) documented that Americans work 10-15% more hours than Germans. These differences could be due to low social safety net in US, lack of job security or earnings inequality across the two countries.

have different impact on the reservation wage during the pandemic period. The reservation wage and market wage move in the same directions, so we should expect similar trends as found by Domash & Summers (2022) in the reservation wage curve as well.

Overall, the literature is mostly using micro level variables to explain the variation in the reservation wage behavior. The evidence with respect to macro indicators is still scarce. I contribute towards the literature by presenting new evidence on the reservation wage elasticity to labor market indicators. So far, there is evidence on unemployment rate and its impact on the wage curve. I extend this analysis and test the hypothesis with other variables such as market tightness, labor productivity, employment to population ratio, etc. The results would have great significance as they present new evidence on the reservation wage sensitivity. For policy implications, it would also provide insight to how workers react when the local labor markets vary around them. If the reservation wage reacts to labor market indicators, policymakers should consider that while designing the optimal UI policy for the future.

1.3 Data

Labor search theory predicts the relationship between the reservation wage and various important economic measures. However, there is limited empirical evidence because of lack of data. Most empirical literature modelled the reservation wage using data from European markets such as Germany and France. I use unique US administrative data from the Benefit Accuracy Measurement (BAM) program, which includes information on the reservation wage as well as various other important individual variables such as the last wage, UI benefit, UI duration, etc. The data on economic measures comes from different sources, such as Job Openings and Labor Turn over Survey (JOLTS), Local Area Unemployment Statistics (LAUS), Office of Productivity and Technology (OPT), and Quarterly Workforce Indicator (QWI). Section A provides details on BAM, while section B contains additional information on economic indicator's data sources.

A. Benefit Accuracy Measurement

Benefit Accuracy Measurement (BAM) is a program used by federal and state UI agencies to measure the accuracy of UI payments over time. This data set is unique as it contains information on the reservation wage of individual workers which is mostly unobserved. It includes representative samples of UI payments in each state, which are drawn randomly to assess the payment structure. For every state, ongoing claims are sampled and selected randomly for almost every week.[20] The variable "keyweek" indicates the selected week information. Most of the individual variables such as age, gender, race, education, highest quarter earnings, maximum UI benefit received, wage of the last job, are obtained from the UI database of each state. I use UI related variables in my specification such as the unemployment duration, the replacement rate, last wage of the job, etc. The duration variable indicates the number of weeks since entering unemployment. I calculate the replacement rate by using the ratio of maximum UI benefit over last job wage, both set of variables are given in the BAM. Other variables are collected through survey from the claimant that also includes the main variable of interest "reservation wage". Specifically, the survey asks the following question *"What is the lowest hourly wage that you are willing to accept during this week?".* After the state UI offices compile the data, federal agencies investigate and match the information at their end. This leads to two different versions of UI variables such as "UI benefit received before" and "UI benefit received after" where "after" indicates the period after investigation. Most of the variables have the same observations but I still use variables after the investigation to avoid any discrepancy. In the absence of unique personal ID's, BAM is a repeated cross-section of people receiving UI payments all across US. I use the period between 2014-2021.

B. Economic Measures Data

Using Benefit Accuracy Measurement data, I use information of unemployed insurance claimants while merging it with various data sources from Bureau of

[20]There are some missing weeks in between for couple of states.

Labor Statistics (BLS). I use labor market indicators from different data sources such as Job Openings and Labor Turn Over Survey (JOLTS), Local Area Unemployment Statistics (LAUS), Office of Productivity and Technology (OPT), and Quarterly Workforce Indicators (QWI) from LEHD. JOLTS contains labor market performance indicators such as the number of vacancies created, total separations, number of quits, etc. It is state level monthly data. LAUS data contains employment measures such as total labor force, unemployment rate, employment-to-population ratio, etc. All of these measures are state-by-month level. The OPT includes labor productivity which measures the total output produced per hour of labor. It is state level annual data where 2012 is the reference year. This means that the productivity is 100 for all states in 2012, while rest of the years are then compared to 2012.[21] QWI contains employment levels of various industries for each state and quarter.[22] Figure 1.1 shows how the main measures of labor market evolve over time. As labor market expanded before the pandemic, all of them follow the same trend with unemployment rates going down and employment-to-population ratio on the rise. Market tightness and labor productivity are also on the rise as markets continued to become tighter with stronger competition and more productive labor. After the pandemic, lockdown measures were in place, resulting in a decline in economic activity. This has been exhibited by the main indicators with economy back on the recovery path in 2021.

For group specific measures, I use two sources of data.[23] Firstly, I use monthly current population survey (CPS) to calculate group specific employment measures such as the unemployment rate and employment-to-population ratio. For

[21]For my main indicators, I use unemployment rate and employment-to-population ratio from LAUS, while labor productivity from OPT data. For market tightness (ratio of vacancies over unemployment rate), JOLTS provides vacancies data while LAUS contains the unemployment rate. For separation rate, JOLTS provides the monthly separate rate for each state.

[22]I use QWI data to calculate the shift share measure at the industry level, described in the next section.

[23]BLS includes age and gender-specific employment measures at the annual level. For group-related monthly and quarterly indicators, I use CPS and LEHD data.

each month, I generated the employment measures across different groups.[24] Figures 1.2-1.4 show the comparison of BLS and CPS raw measures. Although, both measures follow the same trend, CPS measures are more noisy and inconstant. To address this, I apply Hodrick-Prescott (HP) filter to the CPS measures. The filter involves smoothing parameter, which is important in identifying the patterns that were initially unknown due to short term noise. Figures 1.5-1.6 depict the CPS measures after applying the hp filter command.[25]

Secondly, I use Quarterly Workforce Indicators (QWI) data under Longitudinal Employer-Household Dynamics (LEHD), which contains details of industry specific employment on the basis of demographics. The main purpose of using QWI is to generate group specific shift measures at each industry level with NAICS codes.[26] Although, LAUS contains employment data on the basis of demographics but the data is only available at an annual level. Further, CPS also contains employment measures and the industry information but the data is more noisy at the industry level and it does not match most industries with BAM.[27] So, I use QWI to obtain the group-specific employment measures for each industry.

Using all of the mentioned data sets with BAM, I am able to study the behavior of workers when they are outside the labor market and searching for a job. Table 1.1 presents the summary statistics of the main variables of interest.

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[24] I divide the workers on the basis of age and sex. The 3 different age specific groups are 20-30, 30-50 and 50-65. I also use cps weights to make the measures more representative.

[25] Hp filter is only applied to unemployment rate and employment to population ratio. As market tightness is defined as the ratio of vacancies over unemployment rate, the numerator remains the same for both CPS and BLS measure. Hence, the hp filter does not have a significant impact on market tightness.

[26] I provide more detail on the group specific shift measures in the empirical strategy section.

[27] CPS does not contain NAICS codes for industries. There is a separate cross walk for the matching, which also does not include most of the industries present in BAM.

1.4 Search Model

I use a theoretical Search model similar to Burdett & Mortensen (1998). The model presents a unique equilibrium solution to a game where identical workers search for jobs and firms employ those workers through wage offers.[28] The purpose of the model is to find out the theoretical predictions regarding the reservation wage and test those relations using the given data. Almost all of the job search models characterize the reservation wage in the same way and make similar predictions about the relationship between the reservation wage and labor market conditions. For instance, McCall (1970) is one of the early papers to present the job search model. Later on, D. Mortensen & Pissarides (1992) and Pissarides (1994) also cover the theoretical foundations comprising job creation and destruction. I apply the Mortensen search model given in Blien et al. (2012), as it solves for the reservation wage explicitly and produces the following equation:

$$R = rU = z + \frac{\beta}{1-\beta} c\left(\frac{v}{u}\right) \tag{1.1}$$

Equation 1.1 provides the following important relations:

- Reservation wage and unemployment rate are negatively related
- Reservation wage and market tightness are positively related
- Reservation wage and vacancies are positively related
- Reservation wage and job separation rate are negatively related

1.5 Empirical Strategy

I evaluate the search model predictions between the reservation wage and the market indicators through the empirical model of the following form:

$$R_{ijt} = \alpha + \beta_1 E_{jt} + \beta_2 Duration_{ijt} + \beta_3 lastwage_{ijt} + \beta_4 Rate_{ijt} + X'_{ijt}\gamma + \delta_j + \omega_t + \epsilon_{ijt}$$

[28] The model is attached in the appendix

where R_{ijt} is the reservation wage of any person i living in state j at time period t. The main independent variable of interest is E_{jt}, which measures the economic conditions. $Duration$ contains the unemployment spell, $lastwage$ is the wage of the last job, $Rate$ is the replacement rate, X_{ijt} is a vector of individual characteristics. δ_j and ω_t are state and time fixed effects. Main coefficient of interest is β_1, which captures the relationship between the reservation wage and other local economic conditions. For the economic conditions, I focus on unemployment rate, market tightness, employment-to-population ratio and labor productivity. These variables give different insights to the reservation wage behavior. The model gives different results when one of these variables change. Using the data, I test if the reservation wage behavior alter differently with respect to these variables. It might be the case that people focus more on one measure as compared to the other measures.

According to the existing literature, variables such as the duration of the unemployment spell, the wage associated with the last job and the replacement rate are all important determinants of the reservation wage. Secondly, they are also strongly correlated with labor market conditions. I am controlling for all of these relevant variables to avoid omitted variable bias.

One of the biggest threats to the identification of the effects of labor market conditions on reservation wages is the direction of the causal relationship. That is, in equilibrium, reservation wages impact the unemployment rate and the value of job creation. Thus, ordinary least square might not reveal whether the reservation wage is impacting the macro conditions or the other way around. In the existing literature, there is considerable evidence in support of the argument that labor market conditions influence the reservation wage behavior and not the other way around. Rothstein (2011), Tatsiramos & Van Ours (2014), Farber & Valletta (2015), and many others studied the impact of UI policy as a result of "The Great Recession". This further insinuates that UI policy is normally designed according to the economic conditions which further causes changes in other UI related variables such as the replacement rate, the duration of UI and thus, the reservation wage.

There might be still some evidence in favor of the other direction of causality where the reservation wage impacts the unemployment rate and other economic conditions. As a result, OLS results might be biased. To overcome this issue, I use a shift share measure that focuses on the labor demand effect through the employment growth.

The shift share measure captures variations in local employment growth due to differential impact of national employment trends on local states. This differential impact is captured by the state's distinct industrial structure. The first term represents the industrial structure through each industry's weight in the state's employment whereas the second term computes the national employment growth.[29] In this way, the shift share focuses on the local employment growth because of the changes in the national employment. While, removing the variation in the local employment due to state level wages (reservation wage or market wage). Similarly, the shift share does not vary with other local factors such as technological shocks or UI generosity, which further removes the role of local market changes. Hence, it is a valid assumption that the local market variables such as the reservation wage has no impact on the shift share. I calculate the industry specific shift share in the following equation:

$$Shift\ measure_{st} = \sum_{j} w_{jsb} \frac{L_{jt} - L_{jb}}{L_{jb}} \tag{1.2}$$

where w_{jsb} denotes the employment share of industry j in state s in the baseline period, which I define as January of 2016. L_{jt} denotes the national employment level of industry j in period t and L_{jb} is the national employment level of industry j at the baseline period. I use QWI quarterly employment data for the estimation. For each industry with NAICS code, it provides employment measures

[29] Breuer (2022) provides more technical details on Bartik instrument. I use the initial industry weights for my analysis. Some papers used past period weights but we should not expect the industry weights to differ much from January 2015 to January 2016.

at the state as well as at the national level. Using the industry level employment, I calculate the shift measure for each state and quarter. Then, I merge the measure with BAM using the NAICS codes as BAM provides the industry codes for the unemployed workers.

I also calculate the group specific shift measure to perform the heterogeneous analysis. The group-specific shift measure is given below:

$$Shift\ measure_{sgt} = \sum_j w_{gjsb} \frac{L_{gjt} - L_{gjb}}{L_{gjb}} \tag{1.3}$$

where w_{gjsb} denotes the employment share of group g of industry j within state s in the baseline period, which I define as January of 2016. L_{gjt} denotes the national employment level of group g within industry j in period t and L_{gjb} is the national employment level of group g within industry j at the baseline period.

For the group-specific shift measure, I need additional information on the worker's age. Under LEHD, Quarterly Workforce Indicator (QWI) includes data on employment measures of various industries on the basis of demographics.[30] So, I use QWI to generate the group-specific shift measure. First of all, I divide the sample into 3 age groups. Group 1 is between 20-30 years, group 2 is between 30-50 and group 3 is 50-65 years old workers. For the three mentioned age-groups, I calculate the shift measure and collapse the quarterly data by state-industry level. Lastly, I combine it with BAM using the industry, groups, and state identifiers.[31]

Then, I consider the shift measure with only group specific share, which is defined as follows:

$$Shift\ measure_{st} = \sum_g w_{gsb} \frac{L_{gt} - L_{gb}}{L_{gb}} \tag{1.4}$$

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[30] QWI includes employment levels of workers on the basis of age and sex. The data is available for each industry within the state and quarter.

[31] Both data sets include NAICS industry codes.

where w_{gsb} denotes the employment share of group g within state s in the baseline period, which I define as January of 2016. L_{gt} denotes the national employment level of group g in period t and L_{gb} is the national employment level of group g at the baseline period.

1.6 Results

In this section, I explain my results in detail. In all my specifications, I use log of reservation wage as a dependent variable and cluster my standard errors at the state level. In panel A, I explain the relationship between the reservation wage and my main economic measures, including the shift or Bartik measure. Then, I perform the heterogeneous analysis on the basis of gender and college education. Lastly, I focus on the group specific measures where I replace the overall measures with the age-specific or gender-related indicator. For instance, I replace the state-level unemployment rate with the gender-specific and age-specific unemployment rate respectively.

A. Main Measures

First, I focus on the main measures of the labor market. Table 1.2 presents the initial results including employment-to-population ratio as the main measure. Overall, the data suggests a positive relationship between the employment-to-population ratio and the reservation wage, which is consistent with the predictions of the search model presented above. Column 1 includes the regular period 2016-2019 while column 2 adds data from 2020 and 2021. These years are excluded from column 1 because of the substantial disruptions caused by the COVID-19 pandemic. The column 1 estimates suggest that a 1 percent increase in the employment-to-population ratio is associated with a 2.49 percentage point increase in reservation wages. Column 2 also presents a positive relationship between reservation wages and the employment-to-population ratio after the pandemic. I specifically allow the effect to differ in the pandemic period by including the interaction of the employment ratio with an indicator for years 2020 and 2021. The coefficient for the interaction is negative and insignificant, which means that the reservation wage response to employment-to-population ratio remains unchanged after the pandemic. Replacement rate variable is not significant, the duration of unemployment is negative and significant with a magnitude of around -0.009% in both columns. This confirms a common result found in other studies: workers lower their expectation of future job offers as they continue to be unemployed. Last wage coefficient is significant with a higher magnitude of 0.66% which shows that most people are defining their reservation wage on the basis of the last wage they were receiving. Lastly, education level is also positive and significant.

Table 1.3 includes unemployment rate as the main variable of interest. In both columns, it is statistically significant and negative with a magnitude of -0.035% pre-pandemic and -0.02% for the overall period. This coefficient is slightly higher than the regional unemployment rate coefficient (-0.03) in Blien et al. (2012). This explains the difference in the work related preferences among the workers in US and Germany. Due to better social safety net and higher UI payments in Germany, workers are more responsive to labor shocks in US as compared to Germany.[32] The pandemic dummy is positive and the interaction is significant. This could happen due to unprecedented disruptions in the unemployment rate, which made it less reliable when it comes to the reservation wage determination. Most of the other variables such as duration, last wage and education are similar to table 2.

In Table 1.4, I focus on the market tightness which is the ratio of vacancies to the unemployment rate in a given period. The coefficient is positive and significant in both columns with a magnitude of 0.001 for regular period and 0.0008 for the pandemic era. The pandemic dummy is positive and significant but the interaction term is not significant which shows that the market tightness coefficient did not change significantly after the pandemic. The demographic variables are similar to the earlier results.

[32]See https://www.washingtonpost.com/business/2020/10/13/germany-unemployment/ for more details.

Table 1.5 shows the relationship between the labor productivity and the reservation wage. The coefficient is positive and significant with a magnitude of 0.008 before pandemic, and 0.006 including the covid time period. The interaction with covid dummy is also negative and significant which underscores the fact that workers alter their behavior at the onset of the pandemic. Under BLS, labor productivity is measured at the annual level while above measures are presented at the monthly level. This means there is less variation for the productivity indicator. So, we should not give too much importance to the coefficients associated with it.

I also include the job separation rate in my specification to study its impact on the reservation wage. Table 1.6 presents the results. In columns 1 and 2, job separation rate coefficient is 0.01 in the normal period and 0.007 after including the pandemic period. The direction of the relation is opposite to the theoretical prediction. This means that when unemployed workers observe an increase in the separation rate, they adjust their reservation wage at a higher rate. In the model, separation rate is closely related to the unemployment rate, implying that an increase in separation rate would decrease the expectation of the job seekers and they would lower down their expectation. However, the data shows an opposite relation. This also means that the model is focusing on the involuntary separations or layoffs because they move closely with the unemployment rate. In JOLTS, total separations are further divided into layoffs and quits.[33]

I use the layoffs rate as my main variable of interest. In column 3, the coefficient is -0.005 but insignificant. For column 4, the overall coefficient of layoffs is negative and significant. For column 5 and 6, I include the quits rate and find a positive significant coefficient for both specifications. This highlights the fact that the opposite coefficient in the separation rate is mainly driven by the quits rate. The reservation wage is also more sensitive to the quits rate, with a coefficient of around 0.03 as compared to the lower coefficient of -0.005 for layoffs. In general, quits rate rise when the economy is expanding while the layoffs are

[33]For JOLTS, *Total Separations = Layoffs+Quits+Other Separations.*

increasing in bad times. As a result, there is an opposite relation of these measures with the reservation wage.

In Table 1.7, I include all of the main measures in one regression. Only unemployment rate and labor productivity are significant, while other indicators are insignificant. In terms of magnitude, employment-to-population ratio has the highest coefficient of 0.193 but it lacks statistical significance due to the presence of multicollinearity. While including all of the main measures provide evidence on worker's preferences towards the market conditions, it also comes with the cost of over-fitting the model. Almost all of these measures move together and are closely related to each other, which reduces the accuracy of the model. Due to this issue, I use these measures separately in Table 1.2-Table 1.6.

So far, the results include the relationship between the reservation wage and the main economic indicators. However, these results might be biased due to simultaneity issue. To overcome this problem, I use a shift share measure for the employment growth, given in equation 1.2. I exploit the QWI industry level employment data, by state-quarter level. Most of the existing papers use shift measure as an instrument for employment.[34] I use different economic indicators in my analysis, so I include shift measure in the reduced form equation instead of the instrument variable approach. I also provide IV results in the robustness checks section. Table 1.8 shows the regression results after using the employment growth measure. In column 1, I use the pre-pandemic period while column 2 includes the whole sample till 2021. The results show that column 1 has a stronger impact as compared to the overall period with the pandemic. With a one percent increase in shift measure, the reservation wage goes up by 1.90 percentage points. The coefficient is slightly lower (1.76) in column 2. Overall, the shift measure coefficient is higher as compared to other studies. Maestas et al. (2013) found coefficient of around 0.5-0.9 for the wage growth. Bound &

[34] Wozniak (2010), T. J. Bartik (1991), Kahn (2010).

Holzer (2000) constructed the shift share instrument for the growth of the number of hours worked and estimated the coefficient to be around 0.4-0.6. My coefficient is higher due to a variety of reasons. Both studies used MSA level annual data, while my results are at the state-month level. I am using a more recent time period with different model specifications. My sample only includes unemployed individuals which is vastly different from those studies. Maestas et al. (2013) focused on older workers with age 55-74, whereas Bound & Holzer (2000) divided the sample into various worker-groups by education and work experience.[35] A higher shift measure coefficient for the reservation wage might also be attributed to a greater response among the unemployed workers for the varying market conditions. I find the interaction of shift measure with covid to be negative and significant, which means the reservation wage response was affected during pandemic. It also confirms the normal Bartik instrument relevance in the literature.[36]

B. Heterogeneity

For heterogeneous analysis, I focus on gender and education. As educated workers have higher reservation wage, they are expected to respond differently to labor market conditions. Similarly, females have different work preferences as compared to male workers.[37] To allow for these differences, I interact the macroeconomic indicators with female and college dummies. In Table 1.9, I include the interaction with college dummy, which is equal to 1 for individuals with college

[35] Bound & Holzer (2000) used Public Use Micro Samples (PUMS) of the Census of Population in 1980 and 1990. Maestas et al. (2013) used 2009-2011 ACS samples along with 5% Census samples. Both studies also included wage growth as a dependent variable instead of the reservation wage in my analysis. Secondly, Bound & Holzer (2000) studied the impact of growth of working hours while I focus on the employment level shock. Lastly, Bound & Holzer (2000) included 132 largest MSAs in the sample whereas Maestas et al. (2013) could identify 287 MSAs across different years.

[36] See David et al. (2013) and similar papers for more details.

[37] In the existing literature, Bloemen & Stancanelli (2001), Chernozhukov et al. (2018) and many others have studied the heterogeneity of wages with respect to gender and education. Similarly, Chen et al. (2020) found out that the worker's labor supply response vary by gender and age.

degree or higher and 0 otherwise. The results show that only interaction of market tightness is significant and positive. This means that more educated individuals would not alter their reservation wage significantly in response to the changing market conditions.

Table 1.10 includes interaction of indicators with female dummy variable. Only the interaction with unemployment rate and employment-to-population ratio are significant. The employment-to-population interaction is negative and significant with a magnitude of -0.167. Similarly, unemployment rate interaction is positive with a coefficient of 0.009. Both interactions have opposite signs to the main indicator measure. This indicates that in response to a labor market shock, female workers are less likely to alter their reservation wages as compared to the male workers. For reference, let's focus on the unemployment rate indicator. The main results show that a 1 percent change in unemployment rate will decrease the reservation wage by 0.03% points. However, the interaction term of unemployment rate with female dummy is positive. So, when unemployment rate goes up, workers would decrease their reservation wage. But, female workers would decrease their reservation wages at a lower rate as compared to the male workers. Similarly, when markets are tight and employment goes up, female workers would increase the reservation wages but at a lower rate than male workers. Overall, this means that male workers are more responsive to the labor market changes. One of the reasons behind this could be the job security. If male workers are confident about their job perspective, they would change their reservation wages more aggressively and at a higher rate as compared to less confident female workers. This result is similar to the findings in Baltagi & Blien (1998), where the wage of male workers was more responsive than the female workers to the local unemployment rate, with a coefficient of -0.07 as compared to -0.06.

In Table 1.11, I repeat the same exercise with the CPS data, where I interact the main measures with female dummy, to study the heterogeneous effects. The results are slightly different from the BLS data. The interaction term is insignificant throughout, which means that the reservation wage response to the labor market shocks does not vary by gender. The female dummy is negative and significant. This means that the female workers have a lower reservation wage as compared to their male counterparts. CPS data is more noisy and there is possibility of measurement error, due to which the estimates are different from Table 1.10.

C. Group Specific Measures

So far, I have focused on the overall labor market indicators and their relation with the reservation wage. Now, I shift to the heterogeneous indicators to study how people react to their own market measures. It might be the case that people react differently to their own group specific measure as compared to the overall indicator.[38] To answer this, I present the reservation wage sensitivity to various group-specific indicators on the basis of age and gender. Through an extensive analysis, I compare the worker's behavior to numerous group-level market indicators. By doing this, I am able to investigate worker's preferences towards diverse market measures under the dynamics of the labor market. Under BLS, LAUS (Local Area Unemployment Statistics) provides information on employment measures on the basis of sex, race and age. The information is given annually for each state.[39] I focus on the age-groups (16-19, 20-24, 25-34, 35-44, 45-54, 55-64) for each index. I divide my sample into the same age-groups, before combining the LAUS with Benefit Accuracy data. Table 1.12 shows the results where column 1 includes the same overall measures which I presented above, while column 2 has the same measures for each specific age-group. In panel A, employment-to-population ratio for the specific group is insignificant. In panel B, unemployment rate is significant with a lower magnitude of -0.012 as

[38] Blien et al. (2012) found similar coefficients of overall unemployment rate and the gender-related unemployment rate, for the reservation wage equation.

[39] https://www.bls.gov/lau/ex14tables.htm

compared to the overall measure of -0.03. Similarly, market tightness is also significant with a relatively lower magnitude of 0.0005.[40] One of the drawbacks of this comparison is the low frequency among the age-specific measures, all of the main measures are at monthly level, while LAUS only includes annual averages of the age-specific indicators.

To address this concern, I use monthly CPS data and generate measures at 3 different age groups. For each month, I divide the workers into early (20-30), medium (30-50) and senior (50-65) experience levels. Then, I calculate the employment measures (labor force, unemployment rate, employment-to-population ratio) for each group in each state. I also calculate the measures for each gender, to analyze if workers change their behavior with respect to their gender specific indicators.

In Table 1.13, I compare the BLS and CPS employment-to-population measure for each state and month level. Column 1 shows the same overall measure from BLS, explained before in table 2. Column 2 has the same measure while using the CPS data. The coefficient is positive and significant, but the estimate is lower (0.46) than column 1 (2.45). One of the reasons could be the noisy nature of CPS measures, as shown in Figures 1.2-1.4.[41] As a result, column 1 coefficient shows a stronger relation. In column 3-4, I use the age-specific and gender-specific employment-to-population ratio measures. Both coefficients are at a lower level as compared to column 2, while gender specific measure is slightly greater than the age measure. This indicates that workers give more attention to the overall measure as compared to their group specific measure. Similarly, they are more concerned about the gender specific measure as compared to the measure for their age group.

Table 1.14 shows the same results for the unemployment rate. Column 1 and

[40]Market tightness has the same numerator of vacancies due to which the coefficient only goes down with the lower frequency at annual level in column 2, as compared to monthly measure in column 1.

[41]BLS data is more smooth as compared to the CPS measures. For CPS, I apply the hp filter to mitigate the measurement error, but it still exhibits less steadiness as compared to BLS.

2 indicates the overall measures from BLS and CPS separately, while 3 and 4 includes the age-specific and gender related indicator. The trend is similar to the employment-to-population ratio case. Column 2 coefficient (-0.0125) is lower than column 1 coefficient (-0.036), mainly because of the existence of disruptions in CPS raw data. Coefficients associated with the group specific measures are also lower than the overall measure, where both coefficients are almost the same in magnitude. Specifically, I find the coefficient of gender-related unemployment rate to be -0.006, which is way lower than the coefficient (-0.05) in Blien et al. (2012). This further highlights the difference in the dynamics of US and German labor markets.

In Table 1.15, I focus on the market tightness. The results are similar to the previous cases, where CPS measures are lower in magnitude as compared to the BLS measure. I defined market tightness as the ratio of vacancies over unemployment rate. As the vacancies are the same in all measures, the only difference is arising from the unemployment rates.[42] As a result, the coefficients are closer to each other as compared to the unemployment rate and employment-to-population ratio. Figure 1.8 includes the associated coefficient plots of these comparisons.

So far, the results show that the reservation wage elasticity to overall indicators vary significantly by gender (Table 1.10). Now, I test the same hypothesis with the gender specific measure. In Table 1.16, I include the gender specific (unemployment rate and employment-to-population ratio) measures, with the interaction of female dummy. The results show that females are more responsive to the employment-to-population ratio as compared to their male counterparts. For unemployment rate, the interaction coefficient is insignificant. This result illustrates that workers behave differently to their gender specific outcome as compared to the overall economic indicator.[43]

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[42] I could not find any publicly available data on vacancies with respect to demographics. The only source is JOLTS that includes information on the number of new jobs for each state, at a monthly level.

[43] In Table 1.10, I find that female workers are significantly less responsive to the overall

One of the main contributions of this paper is to present the relationship between the shift measure and the reservation wage. In Table 1.8, I used the industry specific shift measure from QWI to study the employment growth effect on the reservation wage. Further, I use the pre-pandemic QWI data to measure the quarterly shift share on the basis of the age groups. In Table 1.17, different shift measures from QWI are included. Column 1 includes the overall shift measure with the industry specific share, similar to Table 1.8. In column 2, I include the shift measure on the basis of industry and age group, given in equation 1.3. Through this measure, I am able to study how workers alter their reservation wage with respect to the employment change in their industry and group. The coefficient is significant with a magnitude of 0.81. By comparing both columns, it means that the reservation wage is more elastic to the industry measure as compared to the industry and group measure. One of the reasons is the available information to them. Most people might know the industry growth rate in which they are working, but they would not know the industry and group specific growth rate. In column 3, I only focus on the group specific measure, removing the industry component.[44] It is also significant with the highest magnitude of 1.83. This further highlights the fact that individuals focus more on the overall shift share measures at industry or group level, but not so much on the specific employment levels of their group within the industry.

1.7 Estimation

The existing literature estimate the job search model using information on unemployment duration and employment wages. For instance, García Pérez (1998), Paserman (2008), Cockx et al. (2018) and many others estimated the model parameters in the job search environment. While leveraging the data from BAM, I also estimate the search model using Bayesian analysis. While most studies

measures of unemployment rate and employment-to-population ratio, while Table 1.16 shows that they are relatively more responsive to the gender-specific employment-to-population ratio indicator.

[44]The group specific measure is defined in equation 1.4.

used data containing both (employed and unemployed) types of workers, my estimation varies from the existing studies as the data only includes information on unemployed individuals. I apply Bayesian estimation to estimate the model parameters that are not present in the data. In the context of search models, there are some variables that are not explicitly available such as the value of leisure z and the bargaining power of the worker β. I use prior values of these variables from the literature to predict their estimate while using equation (1.1) in my model. To implement the estimation, I apply normal likelihood function of the observable variables (reservation wage, market tightness) along with the prior estimates of model parameters to obtain posterior values. Using those values, I calculate posterior distributions through random-walk Metropolis-Hastings algorithm.[45]

Prior Estimates

I estimate the bargaining power of the workers β and the leisure value z. For the prior estimates, β is assumed to have a uniform distribution around a unit interval with mean 0.5. The prior leisure value is selected using calibration results given in Hagedorn et al. (2016).[46]

Posterior Estimates

Table 1.18 shows the posterior estimates of the parameters with the 95% confidence interval. β is closer to the prior estimate with a mean of almost 0.5. This is consistent with most of the studies where β is found to be around the same range. The case of z is interesting. The posterior value is 2.75, which is way above than the prior mean and the distribution. It means that the data is informative and it pushes the value away from the prior mean. The BAM data only

[45] Lubik (2009) used a Bayesian analysis technique to estimate the search model. The authors used system of equations to estimate the model parameters, while I am only predicting a closed form single equation (A.8) in the model.

[46] Hagedorn et al. (2016) found $z_H = 0.813$ and $z_L = 0.929$, where H and L are for high skilled and low skilled workers. For my prior estimate, I multiply these values with the frequency of both groups in my data set.

includes unemployed workers who are still looking for a job. All of these workers are receiving UI benefits, so they assign higher value to leisure as compared to the workers who are transitioning into employment without these benefits. Hagedorn et al. (2016) used CPS monthly data in which people are entering or leaving the labor market with some of them not receiving the UI benefits. As a result, the value of z is lower in their analysis in comparison to the UI receiving unemployed workers in BAM.

1.8 Robustness Checks

In this section, I explore the robustness of the relationship of the reservation wage with macroeconomic conditions. In BAM data, UI recipients are randomly selected for the given week. Figure 1.7 shows the distribution of the UI duration. Although, 90% of the individuals have unemployment duration within 30 weeks, there is still possibility of people with longer duration driving the results. When a worker is unemployed for longer than usual, the individual preferences change drastically as compared to the usual worker who gets back into the labor market within a short span of time.[47] To address this concern, I restrict my sample to people with 20 or lower weeks of UI duration. Table 1.19 shows the results with the main labor market indicators where the coefficients are almost similar to the ones I present in Table 1.2-Table 1.5. This confirms that the sample is representative of the normal UI recipient worker. I repeat the same exercise for the different levels of shift measures. In Table 1.20, the results show that the coefficients are slightly different as compared to the full sample estimates in Table 1.17. Overall, they follow the same trend and do not vary significantly. Another possible source of sample bias could arise from the different sizes of labor markets at the state level. In bigger urban states, competition is higher and it is more difficult to re-enter into the job market as compared to smaller rural markets. At the same time, urban states offer more job openings with higher profits and better security. If the BAM data is skewed in either direction of the

[47] According to BLS, the average UI duration is 19-20 weeks. So, we should expect most workers to get back to the labor market within that time.

two types of markets, this could attenuate my estimates. To overcome this, I divide my sample into 15 largest and smallest states in terms of urban population.[48]

Table 1.21 shows the results with the main measures of labor markets. Panel A includes the employment-to-population ratio, where the coefficient for the urban states is higher (3.11) as compared to the one with smallest rural states (1.72) which is closer to the full sample estimate. Panel B shows the unemployment rate, the effect is similar where the urban states have a higher coefficient of -0.0438 while the rural states have an estimate of -0.0236. Combining these two results, we can say that the unemployed workers are more responsive to the changing market conditions in the dense urban markets. The case of market tightness is opposite, where the coefficient is significantly higher for the rural states. As market tightness includes the ratio of vacancies over unemployment rate, the smaller coefficient in the urban states is mainly due to the inverse of the unemployment rate term.[49] Panel D shows the labor productivity measure, which also follows the same trend where the estimate is slightly higher for the urban states. As labor productivity is measured at the annual level, there is less variation in the measure.

In Table 1.22, I use industry specific shift measure while dividing the sample on the basis of the labor market size. Column 1 shows the same overall measure, defined in column 1 of Table 1.17.[50] In column 2 and 3, I divide the sample into 15 biggest and smallest states on the basis of urban population. Both coefficients are statistically significant with smallest states having a slightly lower coefficient of 1.46 while the biggest states have a coefficient of 2.26. These findings

[48]I rank the states on the basis of 2023 urban population, with 1 being the state with highest urban population.
See https://worldpopulationreview.com/states for more details.

[49]Market tightness includes the unemployment rate in the denominator, due to which the estimate is higher for smaller states.

[50]Column 1 of Table 1.22 and Table 1.17 have the same specification with slightly different number of observations. In Table 1.17, I restrict the sample to have the same number of observations across columns. As a result, the observations are lower and both coefficients are slightly different.

show the same trend that workers react more towards the employment measures in urban states but they are relatively less informed in the smaller rural states.

I also divide my sample into different age-groups, to measure the sensitivity of the shift share estimate. Table 1.23 includes the results where all of the coefficients are statistically significant. I column 1, the coefficient is the highest with magnitude of 2.19 for the youngest (20-30) group, while it is slightly lower (1.91) for the middle one (31-50). The oldest group (51-65) has the lowest coefficient (1.68). Overall, the estimate is going down with age. This means that the younger workers give more value to the current macroeconomic conditions as compared to the experienced workers. It might be the case that younger workers follow the news or market trends closely so they can update their wage offers more frequently.

In Table 1.24, I include the interaction of the age-groups with shift measure. This shows if the shift measure vary significantly across the groups. Results indicate that only the interaction with the oldest (51-65) group is significant and negative. The negative coefficient means that the oldest group is slightly less responsive as compared to other groups. This is similar to the result in Table 1.23. Overall, the shift measure is going down with age but only the interaction of oldest group is statistically significant.

To examine the robustness of the shift measure, I use an alternative formula where the second term is the log of total employment instead of the national growth rate.[51] By doing this, I am able to investigate the effect of total employment combined with exogenous weights on the reservation wage. I reproduce the results shown in Table 1.17, by using the alternate shift measures. In Table 1.25, we can see that the alternate shift measures have significantly lower coefficients. For instance, industry specific measure had a coefficient of 1.9 before, whereas the alternate industry specific measure now has a coefficient of 0.11. The same thing happens with the other two measures (Industry-group specific and group specific). This illustrates that the reservation wage is strongly connected to the

[51] See Appendix for more details.

growth rate of employment as compared to the log of employment. As growth rate is a stronger predictor of labor market employment, we should expect this relation to hold in most of the cases. Importantly, all measures are still significant and the association still holds which confirms the validity of the shift measure.

So far, I used shift measure in the reduced form specification. But, most papers exploit the shift measure as an instrument variable for employment.[52] In Table 1.26, I employ the industry specific shift measure from equation 1.2 as an instrument for the log of employment. I also use aggregate weights for the IV regression, as given in Borusyak et al. (2020). The higher F-stats shows the relevance of the instrument, as shown in the literature as well. The coefficient estimate of 1.56 is higher than the Bartik instrument coefficient of 0.42 found in Bound & Holzer (2000). This means that the unemployed workers are more responsive to the market conditions and in general, workers value employment growth more than the expansion of working hours.[53] This further confirms the shift measure relevance in the case of reservation wages.

1.9 Conclusion

The reservation wage is an important element in solving the labor market equilibrium. Most of the existing job search models assume the exogenous nature of the reservation wage, while interpreting the labor market environment. In this paper, I present evidence of various relationships between the reservation wage and labor market factors.

I also connect the empirical findings with the theoretical model, presented in Blien et al. (2012). The overall results are in accordance with the theory except for the job separation rate. The theory predicts a negative relation between the reservation wage and the job separation rate, while the data depicts a positive

[52] T. J. Bartik (1991), Wozniak (2010), Kahn (2010).

[53] Bound & Holzer (2000) included the growth of working hours as an instrument for local labor demand shock.

coefficient. The model connects the exogenous job separation rate with the unemployment rate, meaning that as the separation rate goes up, it increases the unemployment rate as well. This is only true, in case of involuntary separations or layoffs. I further show that the positive relation between the reservation wage and the job separation rate in the data is mainly driven by the quits rate which goes up during the expansion of the labor market. Hence, quits rate have a positive coefficient with a higher magnitude as compared to the lower negative coefficient for the layoffs rate.

In the current literature, Prasad (2003) and Haurin & Sridhar (2003) found no evidence of the relationship between the reservation wage and the unemployment rate. The unemployment rate coefficient was around -.0005 in Prasad (2003) and -.01 in Haurin & Sridhar (2003). On the other hand, Blien et al. (2012) also included unemployment rate in the specification while investigating the determinants of the reservation wage in Germany. The coefficient was -0.03 but significant. Similarly, Jones (1989) used a British sample and found a significant coefficient of 0.016 for the unemployment rate. In my results, the coefficient of unemployment rate is -0.036, which is higher than the coefficients in Blien et al. (2012) and Jones (1989). One of the reasons is the different data structure in Blien et al. (2012) and Jones (1989). Blien et al. (2012) used a panel data from Germany where they followed each person over time while Jones (1989) analysis was based on a one time survey of British unemployed persons.

In my results, BAM is a repeated cross-section including different individuals at different time periods. In all of these studies, the sample size was not large enough.[54] I use an extensive larger sample of BAM over a prolonged time period. Secondly, I focus on the US labor market while Blien et al. (2012), Jones (1989), and Prasad (2003) studied the European market conditions. With better job security and higher unemployment benefits, workers react differently to macroeconomic shocks in Europe as opposed to job-seekers in US. Only Haurin & Sridhar (2003) analyzed the US market with PSID data but the sample

[54]The sample size was 10,000 in Blien et al. (2012), 572 in Jones (1989), 247 in Haurin & Sridhar (2003), and around 2,300 in Prasad (2003).

size is small and time period is too short. As a result, my findings are different from the existing literature. Lastly, I include other main market indicators such as the employment-to-population ratio, market tightness, and labor productivity. Most of these indicators move together, but it is still important to know the reservation wage elasticity to market measures other than the unemployment rate. Among the main indicators, the reservation wage is most sensitive to employment-to-population ratio with a coefficient of 2.49. Additionally, I compare the reservation wage response of overall market indicators to the age and gender specific indicators. According to the results, the reservation wage is more elastic to the overall market measures as compared to the group specific measures.

To control the simultaneity problem, I employ a shift share technique using the QWI data. The shift share reduces the endogeneity concerns by separating the labor demand effect from the labor supply effect. I also compare the overall shift share with the group-specific shift measure. The results are similar to the main indicators, where the reservation wage is more responsive to the overall shift share. This further solidifies the assumption that workers put more emphasis on the comprehensive market indicators. I also apply shift measure as an IV for the employment and find positive significant coefficient.

Lastly, I estimate the model parameters using the Bayesian analysis. While using the prior values from the literature, the estimated parameters are almost similar to the ones calculated in the literature, except the value of leisure z. It is slightly higher in BAM, suggesting that the unemployed workers receiving UI assign more value to their leisure time while looking for a new job offer. The results are robust to various sub-samples and model specifications.

My results have important implications from the policy point of view. In all of the findings, reservation wage is cyclical, meaning that job seekers are more confident when the economy is growing and lower their expectations in downturns. This is inline with the existing literature that shows real wages are cyclical.[55] My findings also support that the optimal UI policy should be counter-cyclical.[56] When the economy is growing, labor market is tight and reservation wages are higher. In that case, UI benefit amount should be lower to motivate workers to participate in the labor market. Similarly, for downturns, when the reservation wage is lower and workers are struggling to find a job, UI should act as an automatic stabilizer by providing assistance to the unemployed workers for better matching. Hence, my results further provide evidence in support of the counter-cyclical nature of optimal UI policy.

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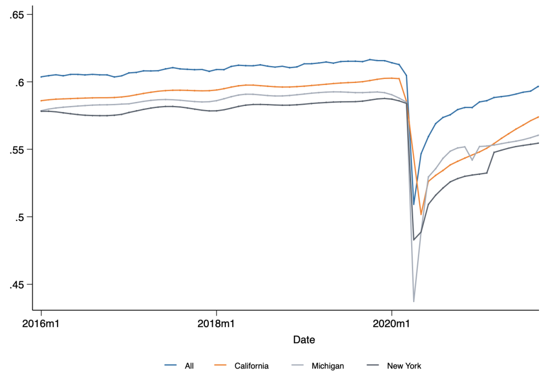
[55]Liu (2003), Devereux (2001), and many others discussed the cyclical nature of wages.

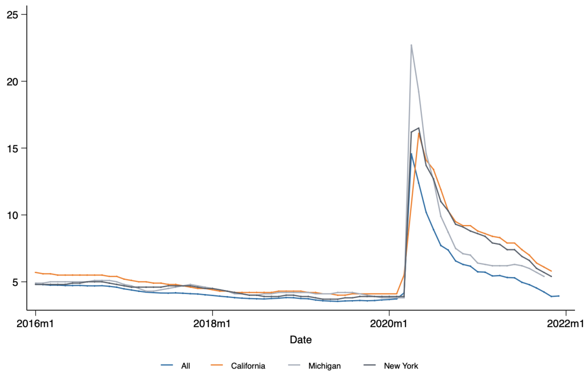
[56]Blumkin et al. (2005), Shavell & Weiss (1979), and Landais et al. (2018)

Figures

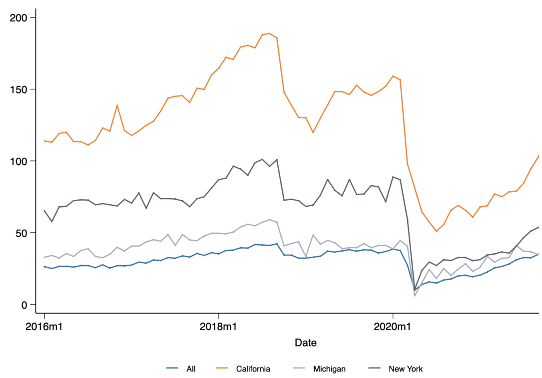
Figure 1.1: Main Economic Measures



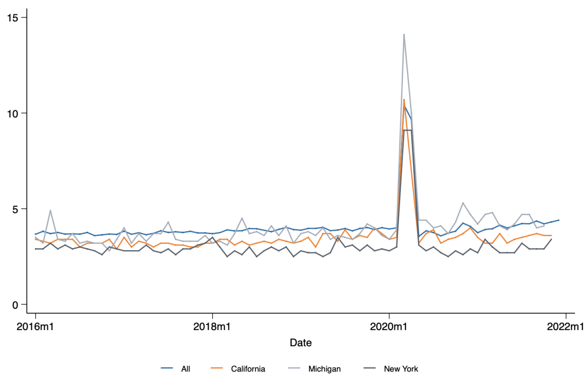
(a) Employment-to-Population Ratio



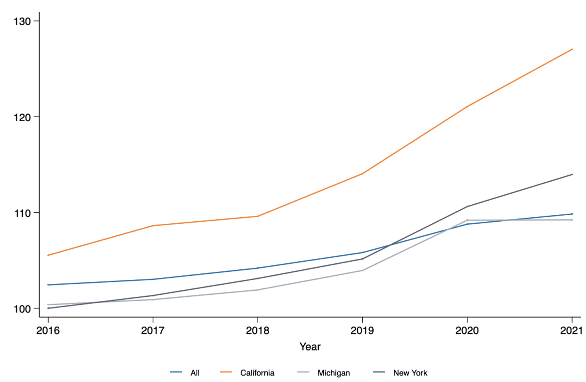
(b) Unemployment Rate



(c) Market Tightness



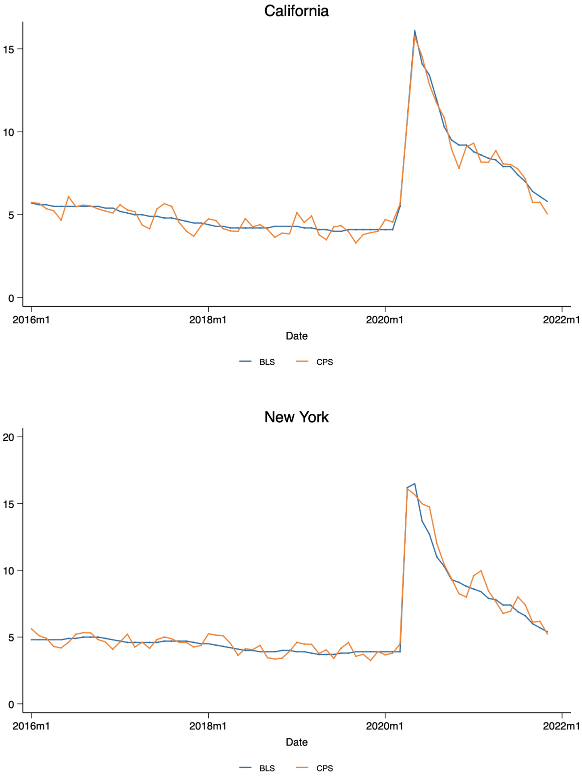
(d) Separation Rate



(e) Labor Productivity

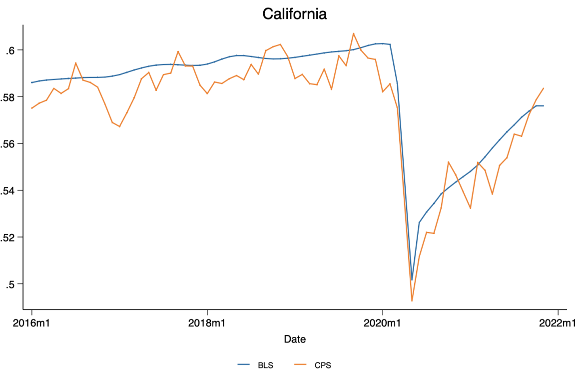
Source: BLS / JOLTS. In this figure, I include all of the main economic measures. Panel (a) shows the employment-to-population ratio, panel (b) includes the unemployment rate while the rest of the panels show the market tightness, separation rate, and the labor productivity measure. BLS includes the employment measures, JOLTS provides the separation rate and the vacancies for market tightness. Lastly, OPT includes the annual labor productivity indicator. In all panels, I combine the overall measure with the measure in various major states such as California, New York, and Michigan.

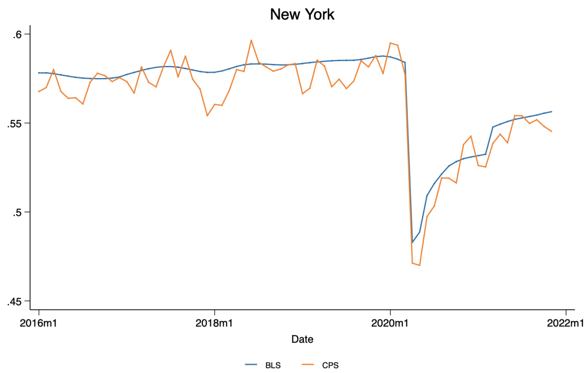
Figure 1.2: Unemployment Rate CPS vs BLS



Source: BLS / CPS. These graph show the comparison of unemployment rates calculated from various data sources. Blue line indicates BLS, while orange line represents CPS. Both lines coincide with each other but there is more noise in CPS. I showed the comparison for two major states of California and New York. The relationship is somewhat similar in other states as well.

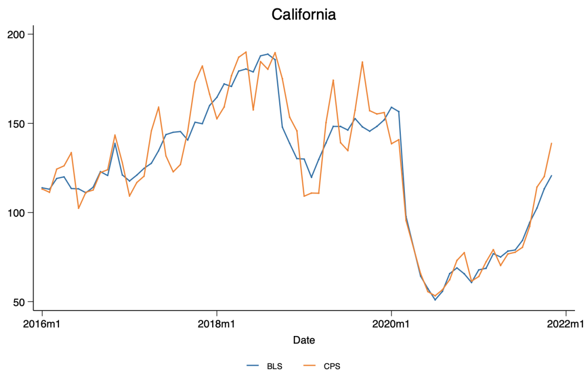
Figure 1.3: Emp to pop ratio CPS vs BLS

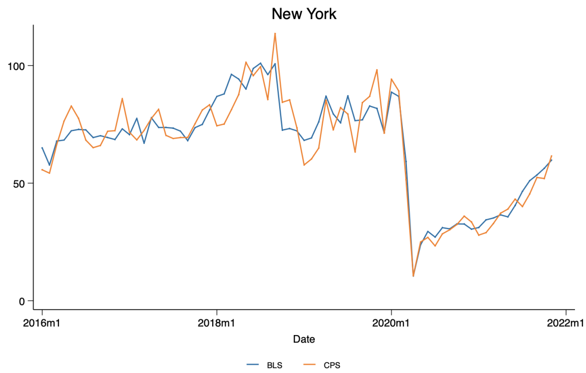




Source: BLS / CPS. These graph show the comparison of employment-to-population ratio calculated from various data sources. Blue line indicates BLS, while orange line represents CPS. Both lines coincide with each other but there is more noise in CPS. I showed the comparison for two major states of California and New York. The relationship holds in other states as well.

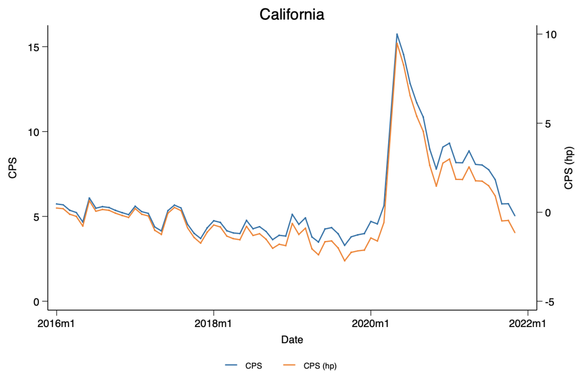
Figure 1.4: Market tightness CPS vs BLS

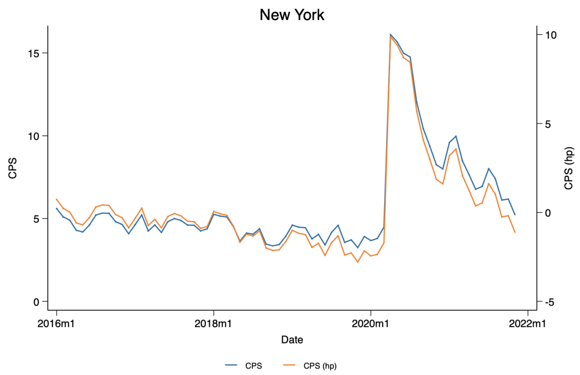




Source: BLS / CPS. These graph display the comparison of market tightness calculated from various data sources. Blue line indicates BLS, while orange line represents CPS. I defined market tightness as follows: $Market\ tightness = \frac{Vacancies}{Unemployment\ Rate}$. Both measures only differ in terms of unemployment rate as the vacancies are the same from JOLTS. I showed the comparison for two major states of California and New York. The relationship holds in other states as well.

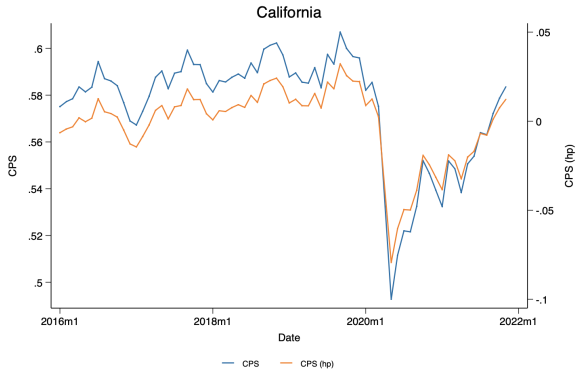
Figure 1.5: Unemployment Rate (Raw vs hp filter)

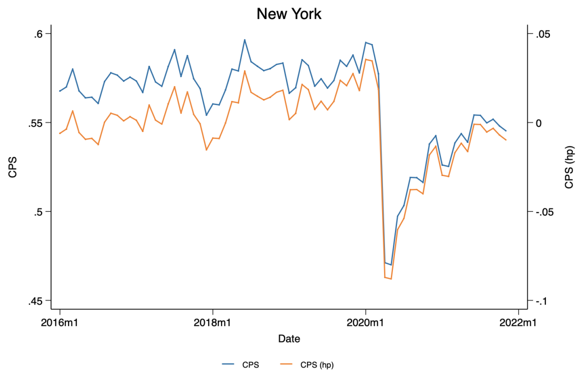




Source: CPS. These graphs depict the CPS raw measures of unemployment rate before and after applying the hp filter. After the filter, the unemployment rate goes down, while following the same distribution. I included the measures for two major states of California and New York.

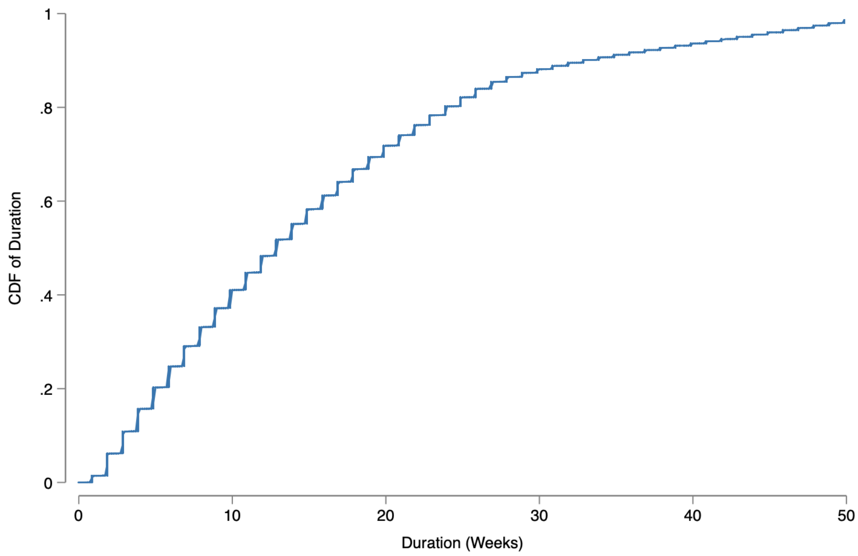
Figure 1.6: Emp to pop ratio (Raw vs hp filter)





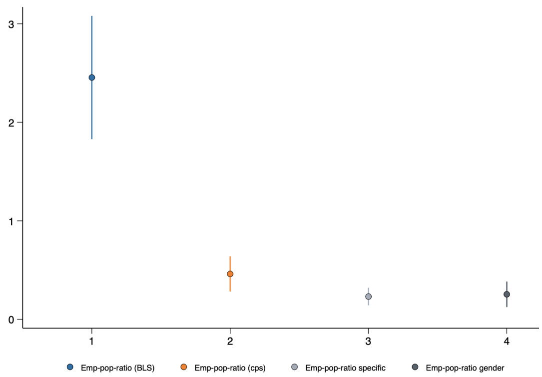
Source: CPS. These graphs depict the CPS raw measures of employment-to-population ratio before and after applying the hp filter. After the filter, the ratio shifts downward, while following the same distribution. I included the measures for two major states of California and New York.

Figure 1.7: CDF of UI Duration

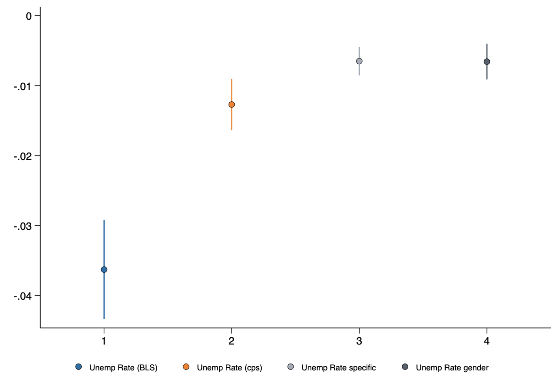


Source: Benefit Accuracy Measurement (BAM). In this graph, I plot the cumulative distribution function of unemployment insurance duration variable. The graph depicts that the major part of data (90%) lies within 30 weeks of duration. This rules out the possibility of workers with longer UI duration influencing the main results.

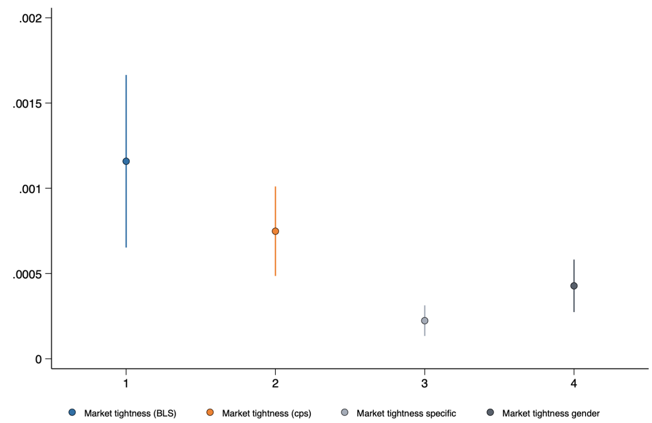
Figure 1.8: Coefficient Plots



(a) Employment-to-Population Ratio



(b) Unemployment Rate



(c) Market Tightness

These graphs include the coefficients of the main measures from different regressions, given in Table 1.13-Table 1.15. In all panels, Coefficient 1 shows the measure from the BLS data, while the rest of the coefficients are from CPS. Moreover, the first two coefficients are for the overall measures while the last two are for the age-specific and gender-related indicators. The coefficient is higher for the overall measures, where the coefficient of BLS measure has a greater magnitude in all cases.

Tables

Table 1.1: Summary Statistics

	Mean	SD	Min	Max	N
Panel A: Individual Characteristics					
Reservation Wage	18.01	14.20	5.00	992.63	113709
Education	13.35	2.53	0.00	20.00	113709
Age	44.74	11.96	18.00	65.00	113709
Replacement Rate	0.45	0.18	0.00	4.35	113709
Last Wage	21.33	15.30	5.00	999.99	113709
Unemployment Duration	15.66	12.01	0.00	59.14	113709
Unemployment Insurance	339.26	144.11	0.00	7131.00	113709
Base Period Wage	19.84	18.81	0.00	520.83	113709
Panel B: Economic Measures					
Labor Productivity	105.37	5.73	91.68	130.32	113709
Unemp Rate (BLS)	4.56	1.67	1.90	28.50	113709
Unemp Rate (CPS)	4.66	1.80	1.17	30.45	113709
Unemp Rate$_{specific}$ (CPS)	4.11	2.49	0.27	37.56	113709
Unemp Rate$_{gender}$ (CPS)	4.72	1.99	0.42	32.99	113709
Emp to pop ratio (BLS)	0.60	0.04	0.42	0.69	113709
Emp to pop ratio (CPS)	0.60	0.04	0.41	0.72	113709
Emp to pop ratio$_{specific}$ (CPS)	0.73	0.08	0.41	0.92	113709
Emp to pop ratio$_{gender}$ (CPS)	0.60	0.07	0.36	0.77	113709
Market Tightness (BLS)	31.30	31.44	0.42	188.81	113709
Market Tightness (CPS)	31.57	32.46	0.43	218.79	113709
Market Tightness$_{specific}$ (CPS)	41.74	45.81	0.36	427.29	113709
Market Tightness$_{gender}$ (CPS)	32.13	33.46	0.40	348.71	113709

Note: This table shows the summary statistics of the main variables. In panel A, I list all of the individual level characteristics including the demographics and UI related variables. Panel B includes the economic measures at state-level. All of the main economic measures are at the monthly level, except the labor productivity. I restrict my sample to 18-65 years old individuals who have full information on UI related variables.

Table 1.2: Estimated effect of employment-to-population ratio on the reservation wage

	Log Reservation Wage	
	2016-2019	2016-2021
Emp to pop ratio	2.491***	1.173***
	(0.325)	(0.181)
Replacement Rate	0.0141	0.0218
	(0.0158)	(0.0148)
Log (Duration)	-0.00930***	-0.00974***
	(0.00165)	(0.00174)
Last Wage	0.666***	0.678***
	(0.0132)	(0.0135)
Educ (Years)	0.00335***	0.00231***
	(0.000649)	(0.000593)
Covid		0.0940
		(0.0628)
Emp∗Covid		-0.0183
		(0.101)
N	84068	116083
adj. R^2	0.777	0.774

Note: This table shows the relationship between the reservation wage and the employment-to-population ratio. Each regression also includes age, age squared, gender, citizenship status, base period wages, occupation, state, and time fixed effects.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.3: Estimated effect of unemployment rate on the reservation wage

	Log Reservation Wage	
	2016-2019	2016-2021
Unemp Rate	-0.0357***	-0.0236***
	(0.00371)	(0.00323)
Replacement Rate	0.0126	0.0205
	(0.0158)	(0.0148)
Log (Duration)	-0.00914***	-0.00977***
	(0.00166)	(0.00173)
Last Wage	0.663***	0.676***
	(0.0132)	(0.0134)
Educ (Years)	0.00336***	0.00236***
	(0.000645)	(0.000586)
Covid		0.0203
		(0.0143)
Unemp*Covid		0.0134***
		(0.00327)
N	84068	116083
adj. R^2	0.778	0.774

Note: This table shows the relationship between the reservation wage and the unemployment rate. Each regression also includes age, age squared, gender, citizenship status, base period wages, occupation, state, and time fixed effects.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.4: Estimated effect of market tightness on the reservation wage

	Log Reservation Wage	
	2016-2019	2016-2021
Market Tightness	0.00115***	0.000880***
	(0.000247)	(0.000239)
Replacement Rate	0.0162	0.0224
	(0.0158)	(0.0148)
Log (Duration)	-0.00928***	-0.00961***
	(0.00165)	(0.00172)
Last Wage	0.668***	0.679***
	(0.0131)	(0.0134)
Educ (Years)	0.00336***	0.00233***
	(0.000645)	(0.000595)
Covid		0.0580***
		(0.00799)
Tightness∗Covid		0.000170
		(0.000320)
N	84068	116083
adj. R^2	0.777	0.774

Note: This table shows the relationship between the reservation wage and the market tightness. Each regression also includes age, age squared, gender, citizenship status, base period wages, occupation, state, and time fixed effects.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.5: Estimated effect of labor productivity on the reservation wage

	Log Reservation Wage	
	2016-2019	2016-2021
Labor Productivity	0.00857***	0.00638***
	(0.00128)	(0.000988)
Replacement Rate	0.0133	0.0206
	(0.0162)	(0.0150)
Log (Duration)	-0.00924***	-0.00949***
	(0.00165)	(0.00172)
Last Wage	0.665***	0.676***
	(0.0134)	(0.0136)
Educ (Years)	0.00338***	0.00234***
	(0.000646)	(0.000589)
Covid		0.267***
		(0.0637)
Productivity∗Covid		-0.00223***
		(0.000606)
N	84068	116083
adj. R^2	0.777	0.774

Note: This table shows the relationship between the reservation wage and the labor productivity. Each regression also includes age, age squared, gender, citizenship status, base period wages, occupation, state, and time fixed effects.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.6: Estimated effect of job separation rate on the reservation wage

	Log Reservation Wage					
	2016-2019	2016-2021	2016-2019	2016-2021	2016-2019	2016-2021
Job Separation Rate	0.0102***	0.00786***				
	(0.00332)	(0.00123)				
Separation*Covid		-0.00220				
		(0.00270)				
Layoff Rate			-0.00514	0.00483***		
			(0.00458)	(0.00123)		
Layoff*Covid				-0.0150***		
				(0.00277)		
Quits Rate					0.0340***	0.0350***
					(0.00424)	(0.00365)
Quit*Covid						-0.00376
						(0.00499)
Covid		0.0652***		0.0755***		0.0548***
		(0.0108)		(0.00534)		(0.0124)
N	84068	116083	84068	116083	84068	116083
adj. R^2	0.776	0.773	0.776	0.773	0.777	0.774

Note: This table shows the relationship between the reservation wage and the job separation rate. In column 3-6, I further divide the separation rate into layoffs and quits rate. Each regression also includes age, age squared, gender, citizenship status, base period wages, occupation, state, and time fixed effects.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.7: Estimated effect of all main measures on the reservation wage

	Log Reservation Wage
	(2016 - 2019)
Emp to pop ratio	0.193
	(0.324)
Unemp Rate	-0.0282***
	(0.00490)
Market Tightness	-0.000248
	(0.000167)
Labor Productivity	0.00487***
	(0.00119)
Job Separation Rate	-0.000286
	(0.00241)
Replacement Rate	0.0114
	(0.0159)
Log (Duration)	-0.00913***
	(0.00165)
Last Wage	0.662***
	(0.0133)
Educ (Years)	0.00338***
	(0.000647)
N	84068
adj. R^2	0.778

In this table, I include all of the main measures in one regression. I also control for age, age squared, gender, occupation, citizenship status, state, and time fixed effects.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.8: Effect of shift measure on the reservation wage

	Log Reservation Wage	
	2016-2019	2016-2021
Shift Measure$_{Industry\ Specific}$	1.906***	1.762***
	(0.110)	(0.108)
Shift Measure∗Covid		-0.370**
		(0.147)
Covid		0.128***
		(0.00684)
Replacement Rate	0.0230	0.0212
	(0.0156)	(0.0148)
Educ (Years)	0.00380***	0.00223***
	(0.000610)	(0.000581)
Log(Duration)	-0.00961***	-0.00930***
	(0.00163)	(0.00175)
Last Wage	0.692***	0.677***
	(0.0125)	(0.0121)
N	81269	111152
adj. R^2	0.778	0.778

This table includes the shift share measure from QWI. Each regression also includes age, age squared, citizenship status, gender, base period wages, occupation, state, and time fixed effects.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.9: Heterogeneous Analysis (Education) - BLS

	Log Reservation Wage			
	(1)	(2)	(3)	(4)
Emp to pop ratio	2.444***			
	(0.349)			
Emp∗College	-0.0312			
	(0.0852)			
Unemp Rate		-0.0365***		
		(0.00493)		
Unemp∗College		0.00214		
		(0.00374)		
Market Tightness			0.00102***	
			(0.000282)	
Tight∗College			0.000134**	
			(0.0000608)	
Labor Productivity				0.00718***
				(0.00133)
Productivity∗College				0.000720
				(0.000680)
College	0.0379	0.0103	0.0146***	-0.0550
	(0.0516)	(0.0164)	(0.00372)	(0.0694)
N	73460	73460	73460	73460
adj. R^2	0.773	0.774	0.773	0.773

Each regression also includes replacement rate, education, UI duration, last wage, age, age squared, citizenship status, gender, base period wages, occupation, state, and time fixed effects.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.10: Heterogeneous Analysis (Gender) - BLS

	Log Reservation Wage			
	(1)	(2)	(3)	(4)
Emp to pop ratio	2.492***			
	(0.351)			
Emp∗female	-0.167*			
	(0.0901)			
Unemp Rate		-0.0390***		
		(0.00407)		
Unemp∗female		0.00963***		
		(0.00346)		
Market Tightness			0.00111***	
			(0.000291)	
Tightness∗female			0.0000860	
			(0.0000772)	
Labor Productivity				0.00768***
				(0.00138)
Productivity∗female				0.000457
				(0.000639)
Female	0.0902	-0.0515***	-0.0141***	-0.0588
	(0.0543)	(0.0149)	(0.00396)	(0.0654)
N	74222	74222	74222	74222
adj. R^2	0.773	0.774	0.773	0.773

Each regression also includes replacement rate, education, UI duration, last wage, age, age squared, citizenship status, gender, base period wages, occupation, state, and time fixed effects.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.11: Heterogeneous Analysis (Gender) - CPS

	Log Reservation Wage		
	(1)	(2)	(3)
Unemp Rate (CPS)	-0.0112***		
	(0.00210)		
Unemp Rate (CPS)∗female	-0.000778		
	(0.00205)		
Emp to pop ratio (CPS)		0.351***	
		(0.109)	
Emp to pop ratio (CPS)∗female		0.117	
		(0.120)	
Market tightness (CPS)			0.000672***
			(0.000155)
Market tightness (CPS)∗female			0.0000902
			(0.0000769)
Female	-0.0114***	-0.0116***	-0.0142***
	(0.00288)	(0.00267)	(0.00400)
Replacement Rate	0.00289	0.00391	0.00435
	(0.0260)	(0.0259)	(0.0258)
Log (Duration)	-0.00891***	-0.00896***	-0.00887***
	(0.00182)	(0.00183)	(0.00183)
Last Wage	0.660***	0.661***	0.661***
	(0.0181)	(0.0180)	(0.0181)
Educ (Years)	0.00298***	0.00297***	0.00298***
	(0.000664)	(0.000670)	(0.000667)
N	74222	74222	74222
adj. R^2	0.773	0.773	0.773

This table shows the interaction of overall measures from CPS with female dummy. Each regression also includes age, age squared, citizenship status, gender, occupation, state, and time fixed effects.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.12: Main measures vs group level measures - BLS

	Log Reservation Wage	
	(1)	(2)
Panel A		
Emp to pop ratio	2.493***	
	(0.324)	
Emp to pop ratio$_{specific}$		0.0110
		(0.0107)
Replacement Rate	0.0140	0.0172
	(0.0158)	(0.0159)
Educ (Years)	0.00334***	0.00333***
	(0.000649)	(0.000644)
Log (Duration)	-0.00931***	-0.00936***
	(0.00165)	(0.00165)
Last Wage	0.666***	0.669***
	(0.0132)	(0.0131)
Panel B		
Unemp Rate	-0.0358***	
	(0.00371)	
Unemp Rate$_{specific}$		-0.0126***
		(0.00194)
Panel C		
Market Tightness	0.00115***	
	(0.000247)	
Market tightness$_{specific}$		0.000574***
		(0.000135)
N	84004	84004
adj. R^2	0.777	0.776

Source: BLS. This table shows the comparison of overall measures and age specific measures, for employment-to-population ratio, unemployment rate, and market tightness. The regressions are run separately for each measure. The controls do not change significantly across specifications. This table only shows the controls for employment measure. Each regression also includes age, age squared, gender, citizenship status, base period wages, occupation, state, and time
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.13: Employment to population ratio (overall vs group) - BLS and CPS

	Log Reservation Wage			
	(1)	(2)	(3)	(4)
Emp to pop ratio (BLS)	2.491***			
	(0.325)			
Emp to pop ratio (CPS)		0.460***		
		(0.0896)		
Emp to pop ratio$_{specific}$			0.227***	
			(0.0448)	
Emp to pop ratio$_{gender}$				0.255***
				(0.0647)
Replacement Rate	0.0141	0.0166	0.0169	0.0168
	(0.0158)	(0.0159)	(0.0159)	(0.0159)
Educ (Years)	0.00335***	0.00334***	0.00334***	0.00334***
	(0.000649)	(0.000647)	(0.000646)	(0.000646)
Log (Duration)	-0.00930***	-0.00941***	-0.00938***	-0.00939***
	(0.00165)	(0.00165)	(0.00165)	(0.00165)
Last Wage	0.666***	0.669***	0.669***	0.669***
	(0.0132)	(0.0132)	(0.0132)	(0.0131)
N	84068	84068	84068	84068
adj. R^2	0.777	0.777	0.777	0.776

Source: BLS & CPS. This table includes the comparison of employment-to-population from different sources. It also compares the overall CPS measure with the group-specific measure. Each regression also includes age, age squared, gender, citizenship status, occupation, state, and time fixed effects.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.14: Unemployment rate (overall vs group) - BLS and CPS

	Log Reservation Wage			
	(1)	(2)	(3)	(4)
Unemp Rate (BLS)	-0.0357***			
	(0.00371)			
Unemp Rate (CPS)		-0.0125***		
		(0.00183)		
Unemp Rate$_{specific}$			-0.00639***	
			(0.00101)	
Unemp Rate$_{gender}$				-0.00646***
				(0.00127)
Replacement Rate	0.0126	0.0158	0.0166	0.0167
	(0.0158)	(0.0159)	(0.0159)	(0.0159)
Educ (Years)	0.00336***	0.00336***	0.00337***	0.00333***
	(0.000645)	(0.000642)	(0.000642)	(0.000644)
Log (Duration)	-0.00914***	-0.00933***	-0.00932***	-0.00940***
	(0.00166)	(0.00165)	(0.00165)	(0.00165)
Last Wage	0.663***	0.668***	0.669***	0.669***
	(0.0132)	(0.0131)	(0.0132)	(0.0131)
N	84068	84068	84068	84068
adj. R^2	0.778	0.777	0.777	0.777

Source: BLS & CPS. This table includes the comparison of unemployment rate from different sources. It also compares the overall CPS measure with the group-specific measure. Each regression also includes age, age squared, gender, citizenship status, occupation, state, and time fixed effects.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.15: Market tightness (overall vs group) - BLS and CPS

	Log Reservation Wage			
	(1)	(2)	(3)	(4)
Market tightness (BLS)	0.00115***			
	(0.000247)			
Market tightness (CPS)		0.000732***		
		(0.000127)		
Market tightness$_{specific}$			0.000215***	
			(0.0000441)	
Market tightness$_{gender}$				0.000418***
				(0.0000755)
Replacement Rate	0.0162	0.0167	0.0170	0.0170
	(0.0158)	(0.0159)	(0.0158)	(0.0159)
Educ (Years)	0.00336***	0.00335***	0.00333***	0.00333***
	(0.000645)	(0.000644)	(0.000641)	(0.000644)
Log (Duration)	-0.00928***	-0.00928***	-0.00926***	-0.00933***
	(0.00165)	(0.00165)	(0.00166)	(0.00165)
Last Wage	0.668***	0.668***	0.669***	0.669***
	(0.0131)	(0.0132)	(0.0132)	(0.0132)
N	84068	84068	83942	84068
adj. R^2	0.777	0.777	0.777	0.777

Source: BLS & CPS. This table includes the comparison of market tightness from different sources. It also compares the overall CPS measure with the group-specific measure. Each regression also includes age, age squared, gender, citizenship status, occupation, state, and time fixed effects.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.16: Heterogeneous analysis with group level measures (Gender) - CPS

	Log Reservation Wage	
	(1)	(2)
Emp to pop ratio$_{gender}$	0.175**	
	(0.0765)	
Emp to pop ratio$_{gender}$*female	0.190*	
	(0.101)	
Unemp Rate$_{gender}$		-0.00583***
		(0.00148)
Unemp Rate$_{gender}$*female		-0.00150
		(0.00176)
Female	-0.0122***	-0.0122***
	(0.00249)	(0.00258)
Replacement Rate	0.0166	0.0165
	(0.0159)	(0.0159)
Educ (Years)	0.00333***	0.00333***
	(0.000645)	(0.000642)
Log (Duration)	-0.00938***	-0.00940***
	(0.00166)	(0.00165)
Last Wage	0.669***	0.669***
	(0.0132)	(0.0132)
N	84068	84068
adj. R^2	0.777	0.777

In this table, I interacted the CPS gender measures with female dummy. Each regression also controls for age, age squared, citizenship status, occupation, state, and time fixed effects.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.17: Effect of different shift measures on the reservation wage

	Log Reservation Wage		
	(1)	(2)	(3)
	Industry Specific	Industry and Group Specific	Group Specific
Shift Measure	1.909***	0.815***	1.835***
	(0.112)	(0.0684)	(0.116)
Replacement Rate	0.0233	0.0273*	0.0312*
	(0.0155)	(0.0155)	(0.0158)
Log (Duration)	-0.00944***	-0.00959***	-0.00891***
	(0.00162)	(0.00161)	(0.00166)
Last Wage	0.691***	0.696***	0.722***
	(0.0126)	(0.0125)	(0.0125)
Educ (Years)	0.00380***	0.00377***	0.00279***
	(0.000628)	(0.000627)	(0.000598)
N	79396	79396	79396
adj. R^2	0.778	0.777	0.774

Source: QWI. This table includes various shift measures at the industry and group level. Each regression also includes other demographic controls along with the state and time fixed effects.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.18: Parameter Estimation

Parameter	**Prior Distribution**	**Prior Value**	**Posterior**	**95% Interval**
z	Normal(0.5, 2)	0.86	2.75	[2.755, 2.761]
β	Unifrom(0, 1)	0.5	0.497	[0.027, 0.976]

This table shows the estimation of job search model parameters. I focused on the leisure value z and the bargaining parameter β.

Table 1.19: Effect of main measures on the reservation wage - Restricted sample

	Log Reservation Wage			
	(1)	(2)	(3)	(4)
Emp to pop ratio	2.448***			
	(0.312)			
Unemp Rate		-0.0350***		
		(0.00369)		
Market Tightness			0.00115***	
			(0.000190)	
Labor Productivity				0.00827***
				(0.00134)
Replacement Rate	0.0210	0.0193	0.0231	0.0206
	(0.0180)	(0.0181)	(0.0182)	(0.0184)
Log (Duration)	-0.0125***	-0.0122***	-0.0124***	-0.0124***
	(0.00190)	(0.00191)	(0.00190)	(0.00189)
Last Wage	0.671***	0.668***	0.673***	0.670***
	(0.0135)	(0.0135)	(0.0134)	(0.0137)
Educ (Years)	0.00402***	0.00405***	0.00403***	0.00406***
	(0.000713)	(0.000711)	(0.000712)	(0.000711)
N	62144	62144	62144	62144
adj. R^2	0.784	0.784	0.783	0.784

This table includes the main market indicators, after restricting the sample to 20 weeks or less UI duration. Each regression also includes other demographic controls along with the state and time fixed effects.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.20: Effect of different shift measures on the reservation wage - Restricted sample

	Log Reservation Wage		
	(1)	(2)	(3)
	Industry Specific	Industry and Group Specific	Group Specific
Shift Measure	1.882***	0.844***	1.797***
	(0.112)	(0.0693)	(0.117)
Replacement Rate	0.0304*	0.0343*	0.0375**
	(0.0173)	(0.0174)	(0.0175)
Log (Duration)	-0.0125***	-0.0126***	-0.0120***
	(0.00190)	(0.00189)	(0.00192)
Last Wage	0.698***	0.703***	0.727***
	(0.0126)	(0.0125)	(0.0124)
Educ (Years)	0.00456***	0.00451***	0.00368***
	(0.000703)	(0.000704)	(0.000667)
N	58853	58853	58853
adj. R^2	0.784	0.783	0.781

This table includes the various shift measures, after restricting the sample to 20 weeks or less UI duration. Each regression also includes other demographic controls along with the state and time fixed effects.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.21: Effect of main measures on the reservation wage - Urban vs Rural

	Log Reservation Wage		
	(1) Full Sample	(2) Urban	(3) Rural
Panel A			
Emp to pop ratio	2.491***	3.119***	1.724***
	(0.325)	(0.671)	(0.361)
Replacement Rate	0.0141	0.0309	0.00123
	(0.0158)	(0.0283)	(0.0273)
Log (Duration)	-0.00930***	-0.00706***	-0.00763**
	(0.00165)	(0.00216)	(0.00335)
Last Wage	0.666***	0.667***	0.651***
	(0.0132)	(0.0275)	(0.0271)
Educ (Years)	0.00335***	0.00317***	0.00348**
	(0.000649)	(0.000976)	(0.00150)
Panel B			
Unemp Rate	-0.0357***	-0.0438***	-0.0236***
	(0.00371)	(0.00457)	(0.00583)
Panel C			
Market Tightness	0.00115***	0.000962**	0.00169***
	(0.000247)	(0.000385)	(0.000500)
Panel D			
Labor Productivity	0.00857***	0.0122***	0.00580**
	(0.00128)	(0.00160)	(0.00246)
N	84068	22530	25409
adj. R^2	0.777	0.795	0.768

In this table, I divide the sample into 15 biggest and smallest states in terms of urban population. The main individual controls are similar for each model. Each regression also includes other demographic controls along with the state and time fixed effects.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.22: Effect of different shift measures on the reservation wage - Urban vs Rural

	Log Reservation Wage		
	(1) Full Sample	(2) Urban	(3) Rural
Shift Measure	1.896***	2.263***	1.462***
	(0.119)	(0.150)	(0.185)
Replacement Rate	0.0229	0.0328	0.0258
	(0.0155)	(0.0291)	(0.0258)
Log (Duration)	-0.00959***	-0.00791***	-0.00849**
	(0.00162)	(0.00232)	(0.00330)
Last Wage	0.692***	0.692***	0.698***
	(0.0125)	(0.0290)	(0.0187)
Educ (Years)	0.00378***	0.00334***	0.00395**
	(0.000610)	(0.000811)	(0.00149)
N	81269	22543	22598
adj. R^2	0.778	0.793	0.777

In this table, I focus on the industry-specific shift measure while dividing the sample into biggest and smallest states in terms of urban population. Each regression also includes other demographic controls along with the state and time fixed effects.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.23: Effect of shift measure on the reservation wage - Comparison between cohorts

	Log Reservation Wage		
	(1)	(2)	(3)
	20-30	31-50	51-65
Shift Measure	2.198***	1.912***	1.688***
	(0.191)	(0.161)	(0.166)
Replacement Rate	0.0728***	-0.00602	0.0185
	(0.0244)	(0.0145)	(0.0218)
Log (Duration)	-0.00384*	-0.00935***	-0.0139***
	(0.00196)	(0.00203)	(0.00230)
Last Wage	0.655***	0.685***	0.714***
	(0.0179)	(0.0142)	(0.0152)
Educ (Years)	0.00222**	0.00386***	0.00480***
	(0.000880)	(0.000735)	(0.000947)
N	16662	40946	21786
adj. R^2	0.718	0.770	0.795

In this table, I focus on the industry-specific shift measure while dividing the sample into different age cohorts. Each regression also includes other demographic controls along with the state and time fixed effects.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.24: Effect of shift measure on the reservation wage - Interaction with cohort dummies

	Log Reservation Wage		
	(1)	(2)	(3)
	20-30	31-50	51-65
Shift Measure	1.881***	1.813***	1.974***
	(0.119)	(0.137)	(0.136)
I_{20-30}	-0.00369		
	(0.00444)		
Shift Measure*I_{20-30}	0.0787		
	(0.123)		
I_{31-50}		-0.00569	
		(0.00407)	
Shift Measure*I_{31-50}		0.164	
		(0.143)	
I_{51-65}			0.0119**
			(0.00515)
Shift Measure*I_{51-65}			-0.274*
			(0.160)
Replacement Rate	0.0232	0.0232	0.0230
	(0.0155)	(0.0155)	(0.0155)
Log (Duration)	-0.00942***	-0.00943***	-0.00944***
	(0.00162)	(0.00162)	(0.00162)
Last Wage	0.691***	0.691***	0.691***
	(0.0126)	(0.0126)	(0.0126)
Educ (Years)	0.00378***	0.00378***	0.00379***
	(0.000629)	(0.000628)	(0.000629)
N	79396	79396	79396
adj. R^2	0.778	0.778	0.778

In this table, I interacted the industry specific shift measure with cohort dummies. Each regression also includes other demographic controls along with the state and time fixed effects.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.25: Effect of alternate shift measures on the reservation wage

	Log Reservation Wage		
	(1)	(2)	(3)
	Industry Specific	Industry and Group Specific	Group Specific
Shift Measure	0.112***	0.0560***	0.0987***
	(0.00658)	(0.00466)	(0.00623)
Replacement Rate	0.0233	0.0273*	0.0312*
	(0.0155)	(0.0155)	(0.0158)
Log (Duration)	-0.00944***	-0.00959***	-0.00891***
	(0.00162)	(0.00161)	(0.00166)
Last Wage	0.691***	0.696***	0.722***
	(0.0126)	(0.0125)	(0.0125)
Educ (Years)	0.00380***	0.00377***	0.00279***
	(0.000628)	(0.000627)	(0.000598)
N	79396	79396	79396
adj. R^2	0.778	0.777	0.774

This table consists of alternate shift measures with the log of employment as compared to the employment growth. Each regression also includes demographic controls along with the state and time fixed effects.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 1.26: Effect of shift measure on the reservation wage - IV results

	(1) Log Reservation Wage
Employment	1.562***
	(0.145)
Replacement Rate	0.0200
	(0.0155)
Log (Duration)	-0.00944***
	(0.00164)
Lastwage	0.703***
	(0.0118)
Educ (Years)	0.00343***
	(0.000631)
N	63722
adj. R^2	0.743
F-Stat	228.5

In this table, I use industry shift measure as an IV for log of employment. I also control for age, age squared, gender, occupation, citizenship status, state, and time fixed effects.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Chapter 2

UNEMPLOYMENT INSURANCE AND EMPLOYMENT: EVIDENCE FROM THE LWA PROGRAM

2.1 Introduction

Unemployment insurance is provided to give aid to the unemployed workers. However, it also brings unintended consequences at the macro and micro level. This paper focuses on the micro elasticity of working with respect to an increase in replacement rate. During pandemic, US government introduced various assistance programs for the unemployed people. In the presence of those programs, replacement rates rose to a record high level with people having extra cash at hand. With such additional amount of money given to those people, it would be interesting to study the impact of UI extension programs in the pandemic context. Usually, there are papers written on moral hazard effect of UI under normal circumstances but this paper studies the effect of UI extensions when there are structural changes happening in the labor market. Hence, the behavior of workers should alter when labor demand was low and most workers were hesitant to get back into the labor market.

An important question arises here is "Why do we care about the moral hazard effect of UI?" If the UI is too high, it will make the replacement rates go up and induces disincentive effects among the workers. In the long run, it will increase unemployment rate and slow down the recovery of the labor market which is exactly opposite to the true planned effect of the UI. We should focus more on the economic growth and not on the unemployment when it comes to UI. As UI is associated with higher replacement rates, the link between replacement rates and unemployment is the outcome of a large number of different relationships, some of which favor growth and some impede growth. Therefore, UI has the potential to impede or accelerate the pace of economic growth Levin & Wright (2001).

As the country was hit by the coronavirus pandemic, most businesses and organizations were shut down due to social distancing measures taken at the federal as well as at the state level. These circumstances forced employers to lay off a lot of workers, resulting in a record decrease in employment. Total civilian employment, as measured by the Current Population Survey (CPS), fell by 21.0 million from the fourth quarter of 2019 to the second quarter of 2020, while the unemployment rate more than tripled, from 3.6 percent to 13.0 percent. This was the highest quarterly average unemployment rate in the history of the CPS "Unemployment rises in 2020, as the country battles the COVID-19 pandemic" (2021).

US government launched various assistance programs to cater the needs of the struggling economy. One of those programs was FPUC (Federal Pandemic Unemployment Compensation) which provided $600 weekly payments to the unemployed workers. Due to the additional payments made under FPUC, replacement rates rose over 100% for most workers Ganong et al. (2020). A replacement rate over 100% meant that people were receiving more benefits by not going to work as compared to the wages they were getting before the pandemic. This could cause serious issues to the recovery of the labor market. One should think that people would have an incentive to not go to work as they were already getting more than what they would earn in the labor market.

In July 2020, FPUC program was ended but most of the states were still struggling to get back to the pre-pandemic unemployment level. So, LWA (Lost Wages Assistance) program was introduced under which unemployed workers received $300 weekly payments addition to their UI benefits. This paper investigates whether there are moral hazard effects of the payments made under LWA. Initially, the program was introduced to support the people who suffered job losses and to provide them more leverage so that they could come back into the labor market on time. But, in the presence of the moral hazard effects, it could go the opposite way. So, I focus on the LWA benefits and its impact on the recipients. I control for the pandemic job loss and pandemic related controls such as number of covid cases, number of deaths per-capita and lockdown restrictions in my specification. The existing literature only focuses on the labor market side but in my opinion, pandemic related controls should also have an important role when it comes to the decision of going to work.

Petrosky-Nadeau & Valletta (2021) studied the labor force transitions after the $600 pandemic benefit given to individuals who suffered job loss. For data, monthly CPS data is linked with annual earnings data from CPS Annual Social and Economic Supplement. The results showed that a typical worker earning $1000 per week need at least $1550 reservation benefits to reject the same wage offer attached to the previous job. This indicates the workers preference towards long term employment spell as compared to short term UI benefits. The same result was found in a dynamic value function framework where each worker optimally chooses the decision of either going to work or remain in leisure during the same period.

In another study, A. W. Bartik et al. (2020) analyzed the impact of UI benefit extension using Homebase data. The data is maintained by a private firm and contained detailed information on hourly work schedule of workers which was absent in CPS. The firms in the data were not ideally representative of the whole US labor market but they did present a reasonable picture of the trends faced by the workers. The specification used variation in UI benefits across states to examine its impact on workers. Results showed that higher UI replacement rate was not associated with job loss and slower rehiring. In fact, states with higher UI consisted of workers with faster rehiring. This highlighted that the moral hazard effects of higher UI were overstated and labor demand was the more important determinant of employment thus far. However, the paper only used the first few months of pandemic which were already chaotic and far from normal. My topic analyzes the impact of extra payments when things were relatively less drastic in the later half of 2020.

Contrary to this, there are pieces of evidence to show that higher UI would slow down the recovery of the labor market. Specially, low income workers would definitely not prefer to go into the labor market after a substantial increase in their replacement rates. Using a bellman equation model, Boar & Mongey (2020) showed that a worker with a lower previous wage and a nearly certain return-to-work offer, would turn down his old employer and remain unemployed under the CARES Act. This confirms that in the absence of wage loss and search frictions, most of the workers would be likely to return to their old jobs even after receiving higher UI except those low wage earners. This proposition is backed up by the theoretical model but still requires more analytical evidence. Dube (2021) used a DID to compare pre and post period of FPUC in various states, there was little impact of job gains from the benefit reduction, especially when the focus groups were non-college graduates, and those from non-high-income households that comprise of most UI recipients. The estimates ruled out job gains implied by much of the micro UI duration elasticities from the existing literature. An absence of job gain could be explained by the adverse labor market conditions after the FPUC. The first extension ended in July 2020 when most states were still struggling to get back to the normal working conditions. Cases were still high and most of the contact service industries were still shut down. My paper uses a different time period as it focuses on the period when things were coming back to the new normal.

Using the first extension of FPUC from March to July 2020, a higher UI was only associated with small disincentive effects Altonji et al. (2020). Using an event study design, findings showed that the workers who experienced larger increases in UI generosity did not experience larger declines in employment when the benefits expansion went into effect. Also, there were workers who returned to their old jobs as some businesses look to reopen. One of the possible reasons of early openings could be PPP loans which required small business to retain their workers. As the paper states "In future research, it will be important to assess whether the same results hold when states move to reopen, and to analyze". My paper aim to solve this missing piece of the puzzle and look to study the UI benefit analysis during the later period of the pandemic.

There are couple of papers that measured the elasticity of UI extensions with work using duration of unemployment or other related variables. Eugster (2015) found that a change in replacement rate increased unemployment duration by 3.1% for the unemployed. On the other hand, Coombs et al. (2021) found that states that ended pandemic era UI experienced an increase of 4.4% in employment. One of the reasons could be that early half of 2020 was so much different than any other regular period that's why there were no significant disincentive effects of UI in Dube (2021). Card et al. (2015) compared the pre and post recession period and found that UI durations are more responsive to benefit levels during the recession and its aftermath, with an elasticity between 0.65 and 0.9 as compared to about 0.35 pre-recession. My topic is measuring the elasticity with respect to the working probability so the magnitude is quite different in that aspect. Lalive et al. (2006) found that an increase in replacement rate of 4.6% points leads to an increase of 0.4 weeks of unemployment. Similarly, Card et al. (2007) used administrative data of Austria to show that an increase in duration of UI benefits lowers the job finding rate by 5-9% points. Overall, most of the existing literature contains elasticity with the duration spells while this paper examines the relationship of increase in replacement rate on working probability. The results in the later section shows that the coefficient associated with the change in replacement rate is slightly higher then the existing literature.

There are moral hazard effects studied in other parts of the world as well. Hall & Hartman (2010) studied the moral hazard effect of sickness insurance (SI). Moral hazard could arise from the structure of the benefit levels as for some unemployed persons benefits from the SI were higher than benefits from the UI. Using a reform of the SI system that came into force on 1 July 2003, they tried to identify the effect of economic incentives arising from the different benefit levels. The purpose of the reform was to eliminate the difference in benefits between the two social insurance systems. The results from a duration analysis showed clearly that the higher the sickness benefits, the higher the probability of reporting sick. This could lead to the possibility of people reporting sickness even when they were not actually sick. Overall, the UI system has two unintentional effects. A more expensive UI system hurts employment due to the burden of the UI contribution fees required to finance the program. Also, a more generous UI system aggravates the moral hazard problem since the improved outside option induces more workers engaged in the low-productivity matches to quit their jobs and more workers paired up with bad jobs to turn down offers as long as they are entitled to UI Zhang et al. (2010).

This paper explores the role of UI extensions in a pandemic setting. It is different in a way that pandemic caused most of the industries to shut down which does not happen in normal circumstances. So, one might be compelled to think that workers would be less likely to work in the presence of high UI benefits. Additionally, to the best of my knowledge I could not find any paper that studied the LWA effects on the labor market. Most of them focused on the extensions of federal pandemic program. As shown in Figure 2.1, the share of people not working due to covid was going down during the period which might be an indicator that people were not working because of other non-covid reasons such as additional UI benefits.[1] Secondly, I include deaths per capita, job vacancies, to measure how each state had been affected by the pandemic. Most of the papers only include pandemic variables but labor demand side is also crucial as it shows the opportunities available for each worker during that specific time.

2.2 Lost Wages Assistance Program

After the first extension of FPUC program which ended in July 2020, US federal government announced the Lost Wages Assistance Program under which each

[1] Petrosky-Nadeau & Valletta (2021) found small disincentive effects for the early period of pandemic as Covid was the driving force. The LWA period (Aug-Nov 2020) is different as people are not working now because of non-covid reasons.

UI claimant would receive additional $300 to $400 per week. With the expiration of the CARES Act, LWA was designed to provide further support to the states. On the announcement, Assistant Secretary of Labor for Employment and Training John Pallasch said "Without federal pandemic unemployment compensation, LWA will provide further assistance to the people who need it". The program was expected to run from Aug 1 2020 to Dec 27 2020 but it got ended early (Sept 5 2020) due to depleted funding. Although, the funding was announced for weeks starting in August but states had to apply before the release of funding from the federal government. As a result of this, funding released later than expected from the federal government. Some states even received it as late as November. Table 2.1 shows the LWA tracker with different timings for various states.[2] As we can see in the table, almost every state applied and received the funding except South Dakota. I will be using the variation in timing of these payments to construct a causal model.

Table 2.1: LWA Tracker

States	Date	States	Date	States	Date
AL	9/3/20	ME	9/12/20	PA	9/17/20
AK	Unknown	MD	9/12/20	RI	9/3/2020
AZ	8/24/20	MA	9/1/20	SC	9/24/20
AR	9/12/20	MI	9/18/20	SD	N/A
CA	10/22/20	MN	9/4/20	TN	8/27/20
CO	9/18/20	MS	9/27/20	TX	8/24/20
CT	9/17/20	MO	8/26/20	UT	9/11/20
DE	9/20/20	MT	8/24/20	VT	9/24/20
DC	9/24/20	NE	10/6/20	VA	10/16/20
FL	9/8/20	NV	10/21/20	WA	9/22/20
GA	9/11/20	NH	9/10/20	WV	9/16/20
HI	9/25/20	NJ	10/22/20	WI	10/31/20
ID	9/10/20	NM	9/9/20	WY	9/16/20
IL	9/9/20	NY	9/17/20		
IN	9/21/20	NC	9/3/20		
IA	9/9/20	ND	9/16/20		
KS	10/9/20	OH	9/15/20		
KY	9/13/20	OK	9/23/20		
LA	8/27/20	OR	10/1/20		

2.3 Data

For data, I use the weekly Census Household Pulse Survey, which collects data from an average of around 97,000 respondents per week using email and texts. The US census bureau designed the survey to assess and collect information on the coronavirus pandemic impact on households. There are a number of reasons why I use the HPS in this paper. First, and most importantly, the HPS provides high frequency measures of employment rates. This higher frequency measurement with fairly large sample size allows for a more compelling event study analysis, where I can study the dynamic effects of additional payments to the workers using an event study approach. Second, the HPS also asks several questions (including whether anyone in the household has experienced job loss since March 2020, and 2019 income) which are useful for constructing controls and defining likely treated subgroups for heterogeneous effects.

The first reported week was the week starting on April 23rd 2020. It was collected every week in Phase I between May 2020 and July 2020; there was a subsequent gap, followed by collection in every two weeks starting late August 2020 during Phase II. I use all survey rounds between August 2020 and November 2020 when the LWA payments were initiated for this analysis. Table 2.2 includes the summary statistics of the variables of interest. I focus on individuals between 25 and 60 years of age, producing a total of around 5 million observations in my sample. The reason of focusing on 25-60 aged people is early retirement of older workers and non-participation of young workers between 18-25. I also present the results with 18-65 years sample for robustness.

My main variable of interest comes from the following question in the survey "Did you do any work for pay or profit in the previous week?" I also control for other relevant variables such as age, gender, race, marital status, household size, number of people below 18 years in the family, education, etc.

I use state UI benefit level data from the Department of Labor. Figure 2.2 shows

[2]The table is constructed using the information on unemploymentpua.com. The website contains extensive details of various UI benefit programs.

the UI benefit level in different states after the introduction of LWA. Additional sources of data will be JOLTS (Job Openings and Labor Turnover) survey under Department of Labor which is an informative survey published monthly at the state level. It provides useful information on the labor market such as the number of new job vacancies, number of quits, number of people laid off, separation rate, etc. I need this information to measure how much impact the pandemic had on each state during that time. I also use USAFacts website to report daily number of covid cases and deaths. For lockdown and vaccine data, I use "Our World in Data" website that has recent data on states restrictions and stringency level in terms of lockdown and closure of outdoor activities. It is a public funded website that gathers information from the global community of researchers and compile it. The main idea is to provide free data around the world for research purposes to make this world a better place. It has different themes such as education, covid, health, war, etc.[3]

2.4 Empirical Strategy

For the empirical strategy, I will be using the timing variation in the start of the LWA program across states as shown by the LWA tracker. For the dynamic effect, I use an event study design using the following model:

$$\begin{aligned} \text{Y}_{ijt} = \alpha + \textstyle\sum_{\tau=-6}^{\tau=6} \Gamma_\tau (I_\tau \times LWA_{jt}) + \beta_2 Cases_{jt} + \beta_3 Stringency_{jt} + \\ \beta_4 free\_food_{ijt} + \beta_5 hhsize_{ijt} + \beta_6 Vacancies_{jt} + X'ijt\gamma + \delta_j + \Psi_t + u_{ijt} \end{aligned} \tag{2.1}$$

where Y_{ijt} is an indicator of working in the previous week for person i in state j at time t. I constructed this variable from the "ANYWORK" variable in the

[3] Visit https://ourworldindata.org/ for more details.

survey question which is equal to 1 only if a person has worked in the previous week, 0 for not working. I_τ is an indicator for each survey week which is interacted with LWA dummy; equal to 1 if LWA has started in that state. Then, I control for some pandemic related variables such as covid cases per capita in any state j at time t because people would not go to work if the state had been hit hard by the pandemic, lockdown restrictions are measured by using the stringency level, free food dummy indicates if anyone in that family has received free food voucher. This gives a better idea because there might be omitted variable bias if I do not control for these relevant variables in the specification. I also control for the number of newly created vacancies in each month for any state as different states followed different paths to recovery during the pandemic. I also control for individual characteristics in a vector X'ijt such as age, race, education, etc. Lastly, δ_j and Ψ_t are state and time fixed effects. Individual fixed effects are not included as it is a repeated cross-section. Coefficient of interest is Γ_τ which presents the dynamic effect of LWA in different states on the basis of timing variation. Moreover, regression includes the sampling weights provided by the survey data set and standard errors are clustered at the state level.
In addition to this, I also run the OLS regression using the following equation:

$$\text{Y}_{ijt} = \alpha_i + \beta_1 \Delta R_{ijt} + \beta_2 Cases_{jt} + \beta_3 Stringency_{jt} + \beta_4 free\_food_{jt} + \beta_5 hhsize_{ijt} + \beta_6 Vacancies_{jt} + X'ijt\gamma + \delta_j + \Psi_t + u_{ijt} \tag{2.2}$$

Here, β_1 measures the impact of change in replacement rate on work which was associated with the LWA program. The change in replacement rate is defined as follows:

$$\Delta R = \frac{UIBenefit_{jt} + \$300 - UIBenefit_{jt}}{Wage_{ij}} = \frac{\$300}{Wage_{ij}}$$

So, basically β_1 measures the effect of giving extra \$300 to workers during the LWA period.

2.5 Results

I use an event study design to predict the dynamic effects of LWA payments on workers. Using equation 2.1, I focus on individuals between age 25 and 60. Then, I repeat the same analysis on different sub-samples such as people belonging to specific race (Black), people without a Bachelor's degree and married people. Figure 2.3-Figure 2.6 shows the event studies that are associated with a clear significant drop in working probability after the introduction of LWA payments. For 25-60 (Black) sub-sample, the effect is similar but not significant at 5%. For married and non-bachelors sub-samples, there is negative significant effect of LWA on the working probabilities over time. Parallel trend assumption is satisfied in most of these event studies which confirms the validity of the specification.

In the regression results presented in Table 2.14, there are 5 leads and 6 lags. Most leads are either significantly positive or insignificant while lags are negative for everyone except black people. The reason behind choosing these sub-samples is the composition of UI recipients. According to Dube (2021), people with non-bachelors education comprise of 79% of the UI claimants data. Similarly, I choose people with specific races to trace out if there were any heterogeneous effects. I am including state fixed effect to address any state level differences in my specification as high income states might be following a different recovery path from pandemic as compared to low income states.

Table 2.3 presents the results of estimating equation 2.2. Dependent variable is a dummy for work. Main variable of interest is the change in replacement rate due to LWA payments. Column 1 includes sample of working age 25-60. Results show that for a 1% point increase in replacement rate, there is a decrease in working probability of 3.9% point. Similarly, I estimate the same equation for different sub-groups like the event study. The coefficient is only significant for non-bachelors and low income group. Another interesting result in this equation is the log of deaths per-capita variable in row 2. It is also negative and significant except in column 2 for the sample including black people. This shows that deaths are a more accurate measure of covid effect on labor market. Cases variable is insignificant throughout and even positive for black people. Stringency index is also either positive or insignificant. This shows that people did not care about the lockdown restrictions or covid cases during the LWA period. Similarly, household size and free food are significantly negative for most sub-samples.

Table 2.4 presents the same equation 2.2 while using the LWA dummy as a treatment variable. The LWA coefficient is insignificant which means the continuous treatment is more important and relevant as compared to the binary treatment. Most of the other coefficients are similar to Table 2.3. Covid cases and stringency index do not matter much, vacancies are also following the same trend while household size and free food are negative and significant.

In the HH Pulse Survey, the participants also report whether they are being paid for the leave. During pandemic, some people were still receiving the wages from their employers even after everything was shut down. For more accurate results of UI payments, I excluded individuals who reported that they were getting paid for the leave. Table 2.5 presents the same results as in Table 2.3 but without those individuals of paid leave. The coefficient of ΔR is slightly higher (-0.0426%) which is consistent with the argument that people who would get the payments from their own company are less likely to apply for the UI payments. From covid variables, only log of death is significant. Vacancies only matter for black people. Household size and free food are again mostly negative and significant across sub-samples.

I also compare states with different minimum wage levels. Table 2.6 shows the regression of states with less than \$10 and states with greater than \$10 minimum wage. Column 1 includes all states, while column 2 and 3 shows states with lower and slightly higher minimum wage. Column 2 has a higher negative coefficient because the opportunity cost of working would be higher in those states as workers would prefer to adopt leisure. All the remaining coefficients are similar to the previous specifications.

Table 2.7 shows the heterogeneity in terms of gender. Column 1 presents the full sample results while column 2 and 3 divides the sample into male and female respondents. The increase in change in replacement rate is associated with 8% less likelihood of working among males as compared to 0.5% among females. Usually, females have lower wages so we should expect a stronger relation. However, the results are showing an opposite relation. One of the reasons behind this could be the composition of workers in different industries. Male workers normally participate more in contact industries such as construction and manufacturing, that were affected the most in pandemic whereas female workers are absent in those places.[4] As a result of it, we see a larger effect in males as compared to females. However, I do not have industry information in the given data to further solidify this claim.

The change in replacement rate depends on the variation at individual level. To address variation across the states, I generated a new variable "Ratio" which is the ratio of extra \$300 payment to the maximum UI benefit in any state.

$$Ratio = \frac{\$300}{UIBenefit_j}$$

There are two advantages of using this variable. First of all, it separates the states with higher UI benefit with states of low UI benefit. Secondly, it introduces heterogeneity across states as \$300 extra payment will have a different effect on workers already receiving \$855 in Massachusetts as compared to workers receiving only \$275 in Alabama. Results are given in Table 2.8. A 1% increase in ratio is associated with a decrease in working probability by 28% points. Similar significant effect can be seen in the sub-groups except married individuals. The effect is the highest among black families because those people would be the

[4]See https://statusofwomendata.org/gender-differences-in-sectors-of-employment/ for reference.

most vulnerable during the pandemic. Log of deaths variable is also significant for the whole sample as well as for most sub-groups. Log of cases is insignificant throughout, except for black people where it is even positive. This could happen due to the log of deaths variable as it is driving the main covid effect. Income is positive and significant. Stringency index is significant but has a positive coefficient, opposite to what it should be. One of the reasons behind this is that the overall covid effect is already included in the deaths variable so lockdown restrictions did not matter much. Vacancies variable is again insignificant, similar to most previous results. This shows that labor demand was not the prime driving factor of working among workers. Household size and free food dummy is negative and significant as well.

Labor demand was more dominant in the earlier half of 2020 when everything shut down as compared to the later months. To test this, I present coefficient plots of my main variables using the time variation of the HH pulse surveys. I estimate equation 2.2 in different periods of 2020. The first two periods (April-May, June-July) are before LWA while the last two periods (Aug-Sept, Oct-Nov) are during LWA program. I start off with the covid variables of lncases and lndeaths which are log(cases per capita) and log(deaths per capita). In Figure 2.12, I plot the covid cases coefficient against different time periods. It is negative and significant in the early half of 2020 but indifferent from zero in the later half when LWA was in place. Similarly, Figure 2.13 shows the same results with lndeath variable. It is almost indifferent from zero in all periods except the June-July coefficient which might be due to the 2nd wave in US. Overall, these plots show that covid variables were insignificant during the end of 2020 as people were used to the new normal and social distancing was slowly becoming the norm. This confirms the hypothesis that covid was the main cause of people not working in the early half of 2020 while non-covid reasons were the source in the later period.

For the LWA payments, I use ΔR to show the dynamic effect over time. In Figure 2.14, coefficient plot shows that the estimate is negative and significant only in the later half of 2020. Another important thing to note here is that the ΔR in the first two time periods correspond to the FPUC payments while the later is for the LWA payments. As we know, under FPUC the unemployed workers received $600 extra weekly payments which is twice as high as the LWA payments. But, the responsiveness is at a lower level. The main reason behind is the covid effect which was larger in the earlier half of 2020 as compared to the later half. So, even with higher payments people could not work due to labor demand effect as compared to the supply effect which further provides evidence in support of the given hypothesis. Regression results are given in Table 2.9-Table 2.11.

2.6 Robustness Checks

For the event study graphs, so far I used individuals aged 25-60. Further, I perform the same analysis on a larger sample including people from 18-60 years old. The results are given in the left graph of Figure 2.7 for the whole sample and Figure 2.9-Figure 2.11 for sub-samples. As shown in the graphs, the trends are almost similar to the ones found in the restricted sample (25-60). The results are more pronounced in the sub-sample of married and non-bachelors degree individuals. The related regression results are given in Table 2.15. Most coefficients are almost similar to what I found in the main sample (25-60). Covid variables do not matter much and vacancies are insignificant. Most of the leads are positive while lags are negative and significant. In terms of magnitude, lags have a slightly higher coefficient as compared to the 25-60 sample. In the sub-samples, the coefficients are more or less the same.

According to the updated DiD literature, TWFE models might be biased. In the case of staggered treatment timing, generalized difference-in-difference analysis could be biased due to treatment heterogeneity Baker et al. (2022). Callaway & Sant'Anna (2021) proposed an alternative technique that would mitigate this concern in the case of multiple treatment timing. Using the Stata package for the Callaway and Sant'Anna, I replicated my event studies. In the right side graph of Figure 2.7, I focused on the same working age population 18-60 with the dependent variable as a dummy for work.[5] The event studies show similar results and parallel trend assumption holds as well. In Figure 2.8, I repeated the same exercise at an aggregate level. I collapsed all my variables at the state level to give my data a panel structure. The new dependent variable is the percentage change in total number of people working during that week, in a given state. The results show significant negative disincentive effect of LWA payments. In comparison to TWFE, CS estimators show a lagged effect after $t = 2$. This shows that the overall negative effect creeps in after the first two weeks. Possible explanation to this could be the delay in the payments at the individual level as some workers still received payments with 1 or 2 weeks delay as opposed to the regular schedule of LWA.

Table 2.16 contains the regression results associated with the CS estimator. Column 1 shows the working dummy as a dependent variable while column 2 includes log of total proportion of population not working. With CS estimator, the lag coefficients are smaller in magnitude as compared to column 1 of table 15 in TWFE. Post average is the total effect of all post periods, which has a coefficient of -1.3% as compared to -4% in the TWFE regression. This means that TWFE estimator was slightly overstating the overall effect.

I also reproduce my main results by adding state specific linear time trend. This would include state specific time variation in my model. Results are showed in Table 2.12 and Table 2.13. I only used the prior specification from Table 2.3 and Table 2.5 that represents the main results. After controlling for the time trend, the ΔR coefficient is almost similar which means timing variation was already incorporated in the main model and adding a time trend has close to no effect on the coefficient of interest.

[5] In CS estimator, the results for 25-60 and 18-60 are exactly the same after collapsing. So, I only present the 18-60 results here.

2.7 Conclusion

Lost Wages Assistance program was introduced to assist the struggling labor market condition of US. Each unemployed worker who was receiving UI benefits was provided with additional \$300 weekly payments. The payments started in Aug 2020 till late Nov 2020. Almost every state applied for the program and secured funding from the federal government at different weeks. Using timing variation across states, I showed an event study to investigate the effects of LWA. Results show significant disincentive effects of LWA, the effect is more clear among married and non-bachelor individuals.

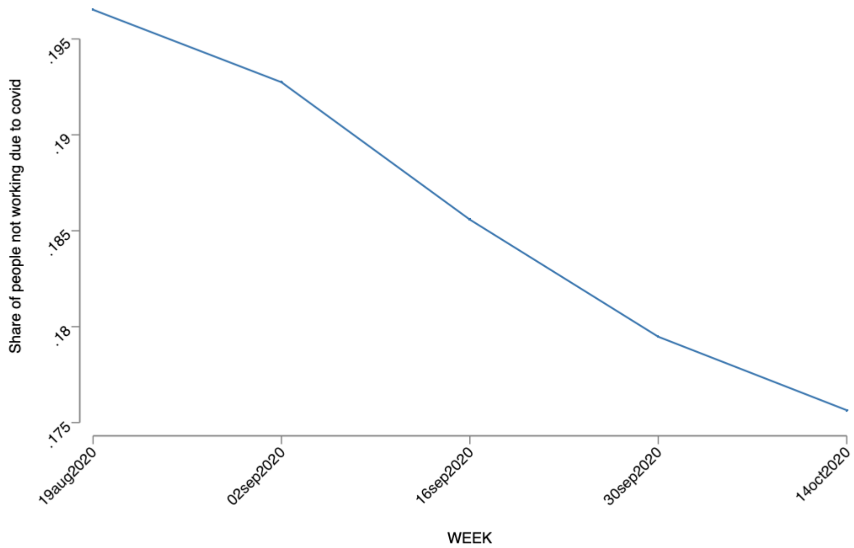
The existing literature uses FPUC programs to predict the causal impact of extra payments. Dube (2021) presents an event study using expiration of FPUC payments and found small to no employment effects of it. Similarly, Altonji et al. (2020), Petrosky-Nadeau & Valletta (2021) also found insignificant moral hazard effect in the earlier period of 2020. My coefficient estimates are significant in the full sample (25-60) as well as in some sub-samples of the data. In terms of magnitude, most of the existing papers report the elasticity of working with respect to the UI duration to be around -4-5.0%. In my results, the replacement rate change coefficient is 3.92% for the full sample, which is closer to the range of the existing studies.

In my specifications, I also include Callaway and Sant'Anna event studies, that provide better estimates in the presence of treatment heterogeneity. The event study results are robust and show a clear decline of working probability in the post period. Overall, my results provide evidence of providing UI generosity in the short run. More work is needed to investigate if there was a change in worker's preferences in the long term.

My paper adds to the literature by studying the impact of UI extensions in the later period of the pandemic. In comparison to the studies that found no effect of the UI extensions on workers in the earlier 2020 period, I found significant negative coefficient for the replacement rate. This shows that in the earlier period of 2020, lockdown restrictions and lower labor demand were the main factors behind the lack of labor participation. Due to which, UI extensions had no impact on the working probability. However, in the later period of 2020, when LWA was initiated, economy was slowly recovering. As a result, labor supply effect was more prominent which decreased the working probability because of the UI extensions.

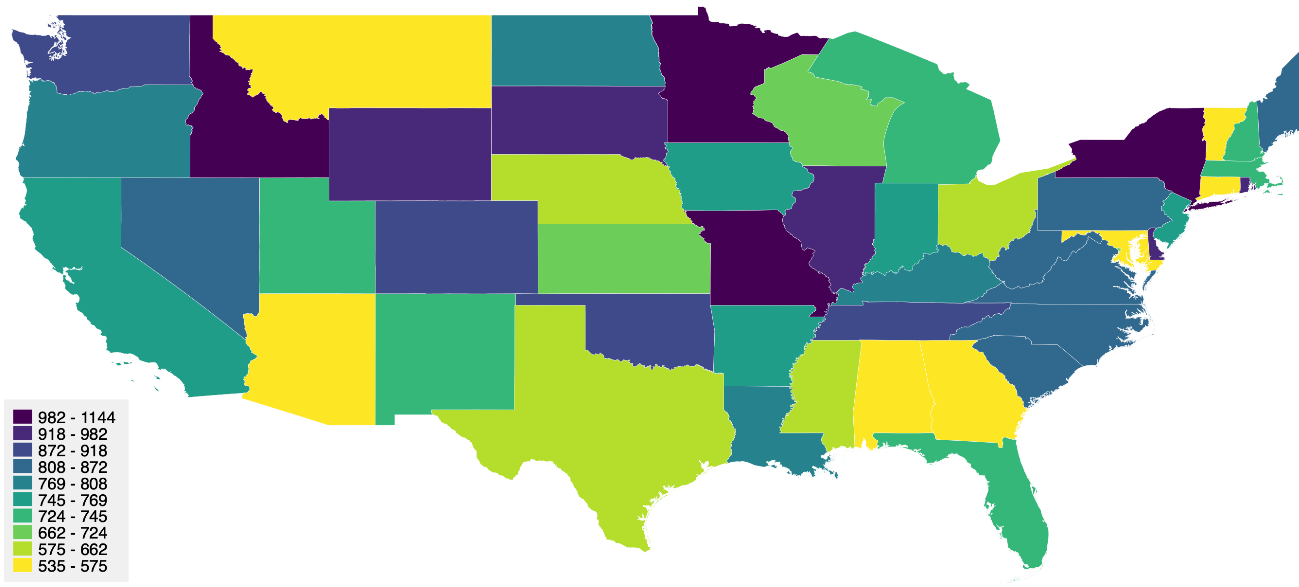
These findings have key implications for the optimal UI generosity, as they provide useful information for the role of UI generosity in the business cycle. My results highlight the important role of UI as a stabilizer for workers in the earlier half of 2020, when the economy was struggling and job market was significantly down. They also provide evidence for the negative effect of UI extensions in the later half when jobs were readily available and labor demand was slowly coming back to the pre-pandemic level. Overall, these set of results point out that the optimal UI policy should be counter-cyclical.

Figure 2.1: Why People are not working



Source: Household Pulse Survey. For each week, people report the reason of not working. I count Covid as a reason if someone is not working because of having Covid, due to fear of Covid, taking care of someone who has covid, etc. Covid share is the percentage of people reporting these reasons as compared to the whole sample in that specific week. The graph shows that there is a slight decrease in the proportion which means people are not working in that period due to non-Covid reasons such as higher UI benefits, etc.

Figure 2.2: UI Distribution



Source: https://fileunemployment.org/unemployment-benefits-comparison-by-state. The graph shows the maximum weekly UI benefit available in each state after the introduction of LWA. There is considerable variation with the lowest amount $540 in Arizona to the highest amount of $1144 in Washington.

Figure 2.3: Sample:25-60

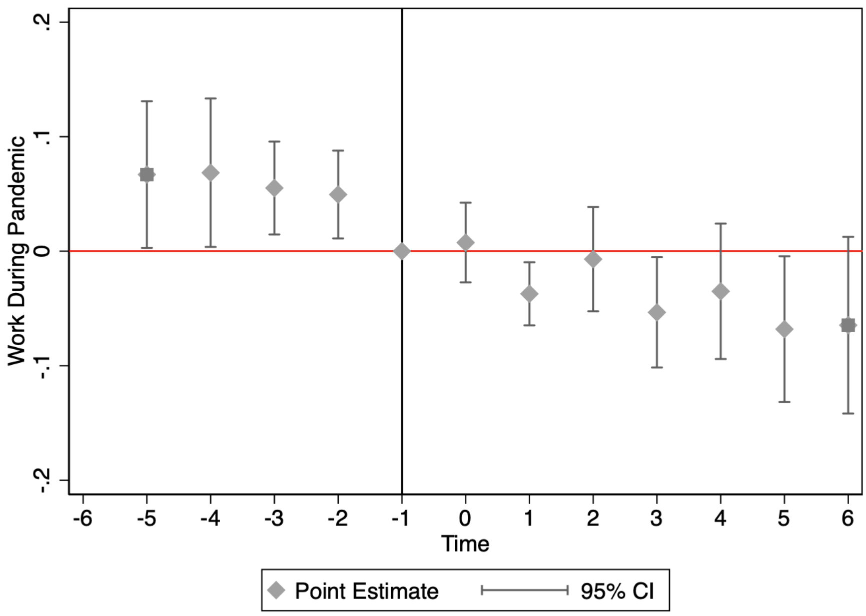


Figure 2.4: Sample: 25-60 (Black)

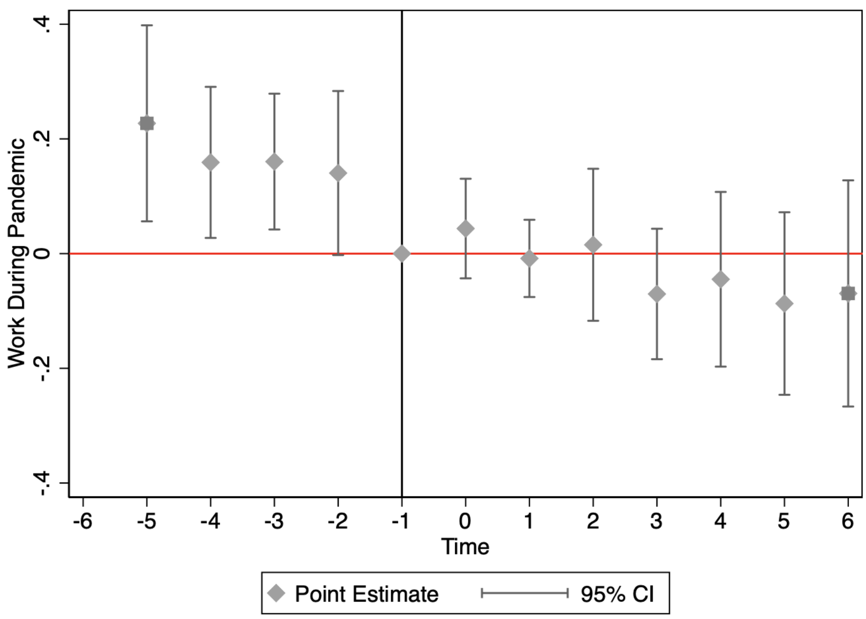


Figure 2.5: Sample 25-60 (Married)

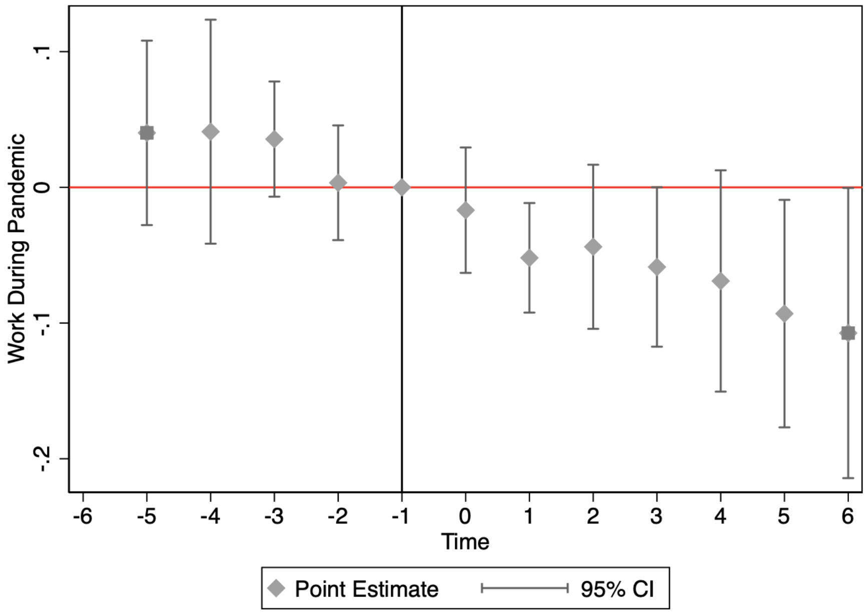


Figure 2.6: Sample: 25-60 (Non-Bachelors)

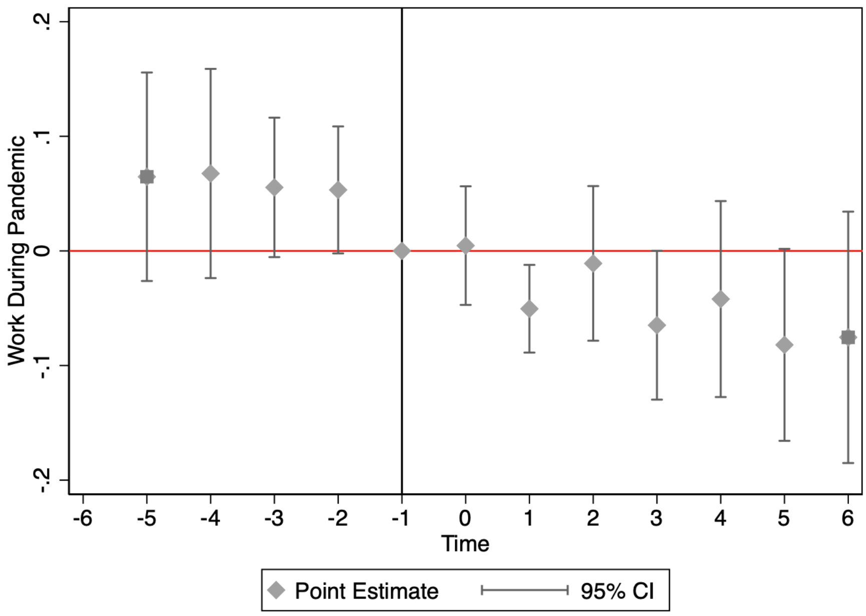


Figure 2.7: TWFE vs CS (Sample 18-60)

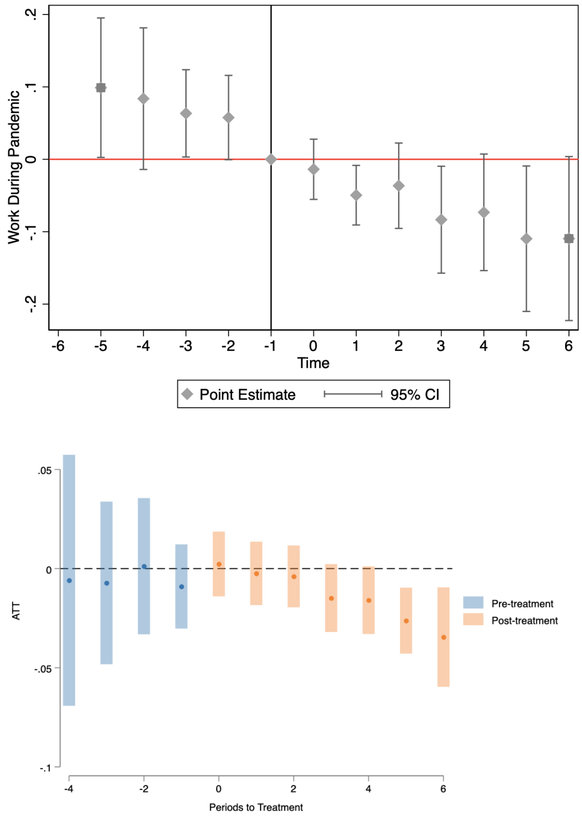


Figure 2.8: CS Estimator (Aggregate)

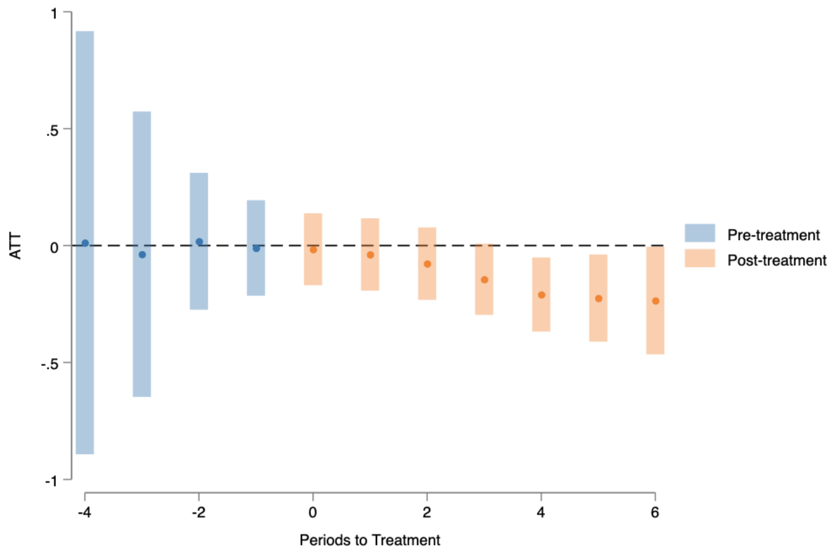


Figure 2.9: Sample 18-60 (Black)

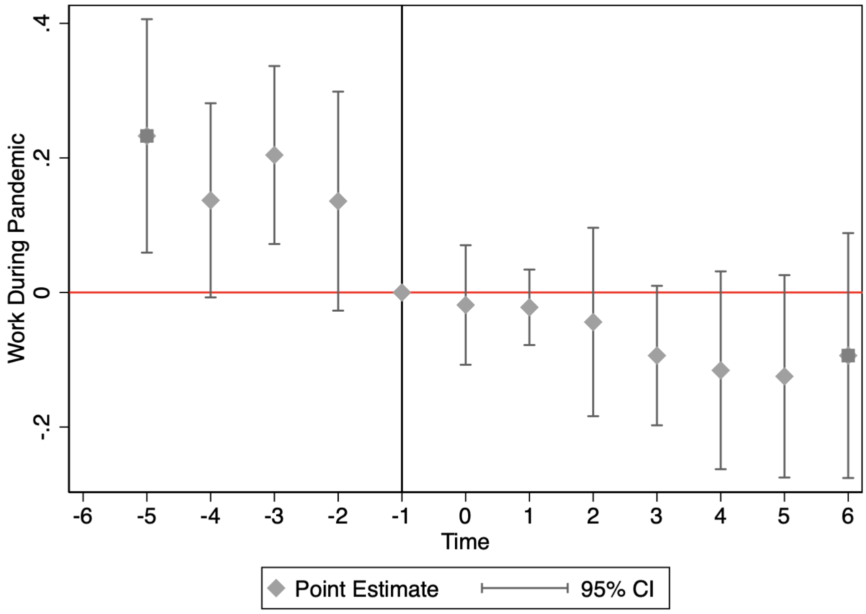


Figure 2.10: Sample 18-60 (Married)

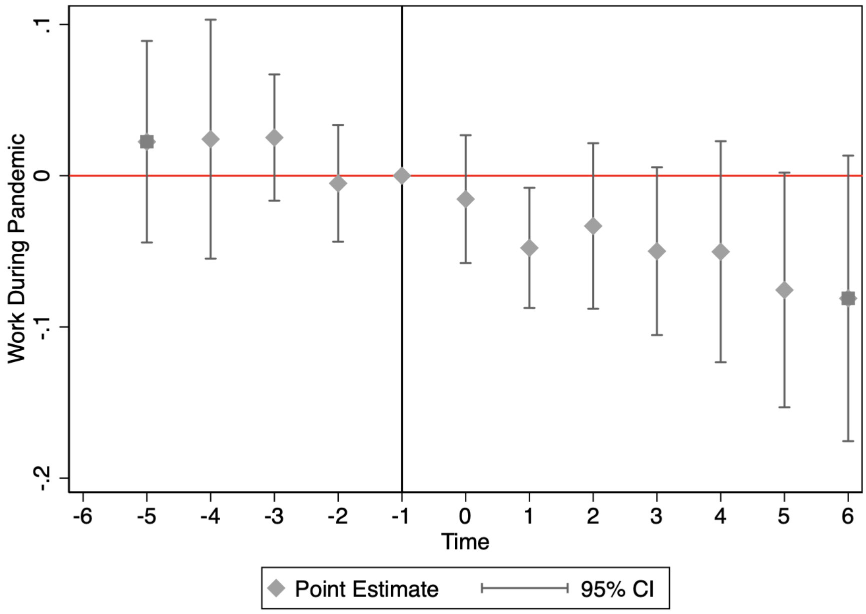


Figure 2.11: Sample 18-60 (Non-Bachelors)

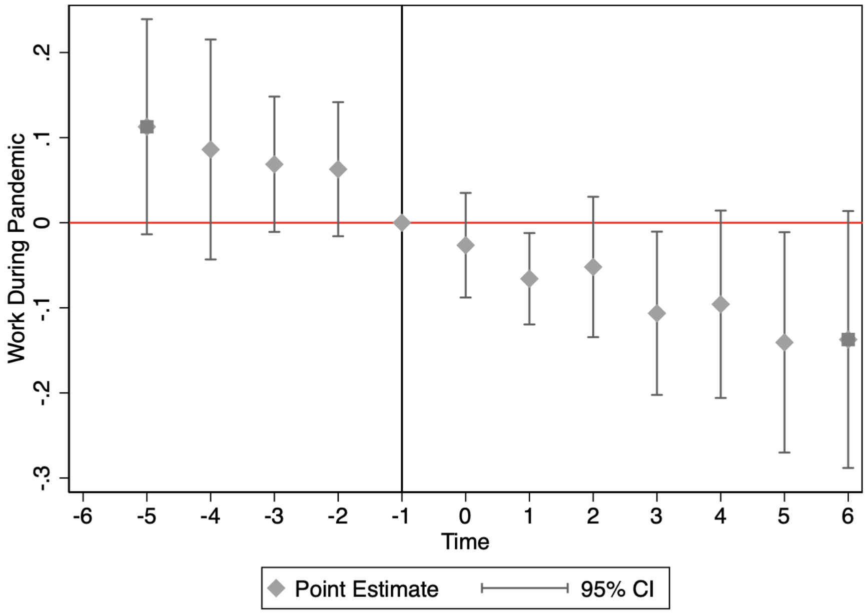


Figure 2.12: lncases Coefficient Plot

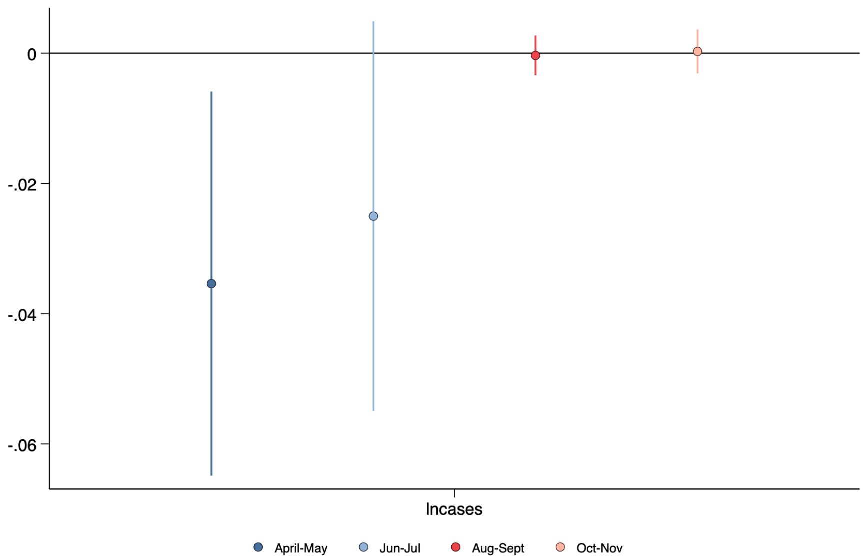


Figure 2.13: lndeaths Coefficient Plot

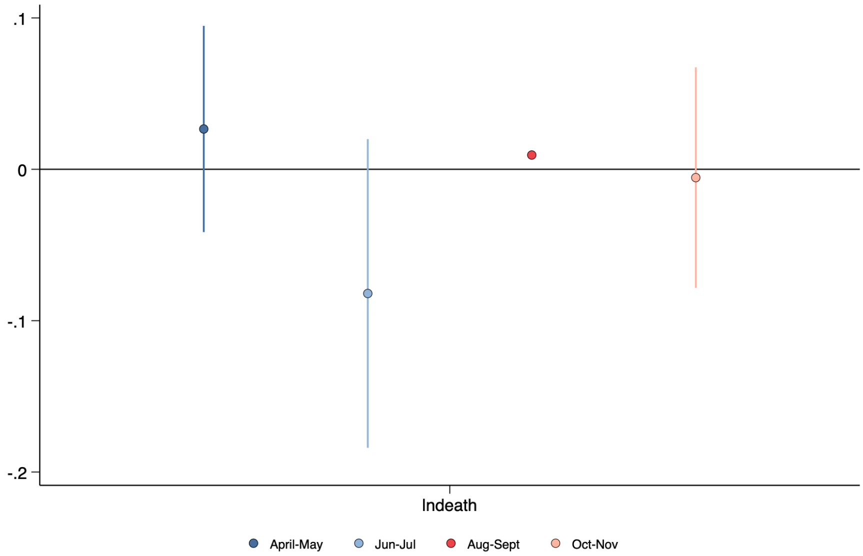


Figure 2.14: ΔR Coefficient Plot

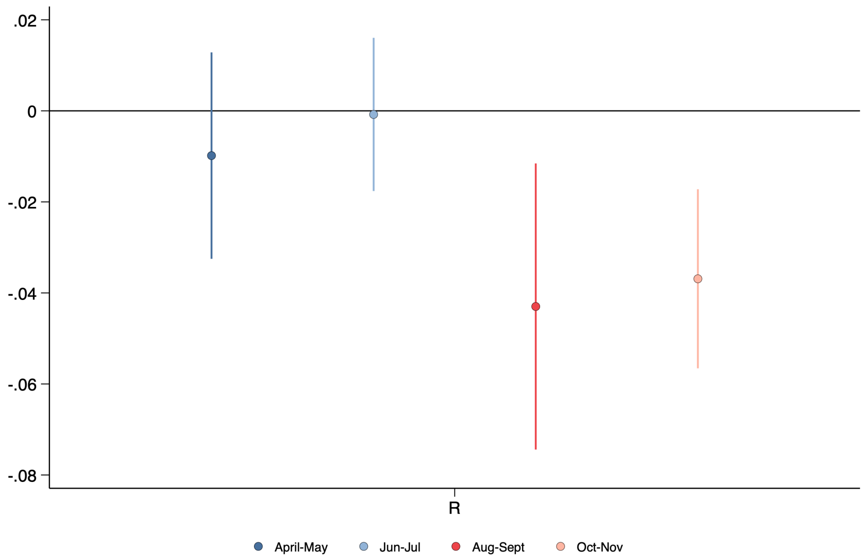


Table 2.2: Summary Statistics

	(1) All	(2) Male	(3) Female
Age	51.09	52.13	50.36
	(15.85)	(16.26)	(15.51)
HHsize	2.780	2.733	2.813
	(1.495)	(1.459)	(1.519)
Income	67687.4	73076.6	63889.0
	(39319.4)	(39934.8)	(38428.5)
Wage	1083.0	1154.3	1032.7
	(706.3)	(725.7)	(687.8)
ΔR	0.447	0.413	0.471
	(0.390)	(0.367)	(0.404)
Ratio	0.694	0.692	0.696
	(0.231)	(0.231)	(0.231)
Vacancies	197.7	202.0	194.7
	(198.6)	(201.8)	(196.3)
StringencyIndex	51.79	51.86	51.74
	(11.25)	(11.23)	(11.26)
Covid Deaths	5037.6	5100.1	4993.8
	(6090.6)	(6160.2)	(6041.0)
Covid Cases	203313.7	207408.2	200450.1
	(258638.3)	(263187.2)	(255370.1)
N	561421	231051	330370

Note: This table includes the summary statistics of the main variables Age variable is the age of the respondent. HHsize is the size of the household. Income includes annual income of the household. Wage represents the weekly wage. ΔR is the change in replacement rate. Ratio shows the ratio of LWA extra payment over maximum UI in every state. Vacancies is the number of vacancies created every month. Stringency index measures the lockdown restrictions. Last two variables are for covid deaths and covid cases for every week.
Mean coefficients; SD in parentheses

Table 2.3: Dependent variable is dummy for Work

	(1) 25-60	(2) Black	(3) Non-Bachelors	(4) Married	(5) Low-Income
ΔR	-0.0392***	-0.0210	-0.0204*	-0.0291	0.0309***
	(0.00924)	(0.0194)	(0.0117)	(0.0182)	(0.0104)
lndeath	-0.0856**	-0.110	-0.133**	-0.0841*	-0.129**
	(0.0374)	(0.0739)	(0.0503)	(0.0461)	(0.0584)
lncases	0.000301	0.0186***	0.00201	0.00132	0.00418
	(0.00233)	(0.00594)	(0.00264)	(0.00284)	(0.00362)
StringencyIndex	0.000580	0.00208**	0.000811*	0.000731*	0.00112
	(0.000373)	(0.000899)	(0.000431)	(0.000384)	(0.000678)
lnvacancies	-0.00457	0.171**	-0.0108	0.000179	0.0263
	(0.0306)	(0.0786)	(0.0416)	(0.0356)	(0.0520)
HHsize	-0.00600**	-0.00232	-0.00526	-0.00823**	-0.0154**
	(0.00284)	(0.00629)	(0.00403)	(0.00394)	(0.00592)
Free food	-0.0399***	-0.0267	-0.0427**	-0.0356**	-0.0239
	(0.0120)	(0.0358)	(0.0160)	(0.0170)	(0.0161)
N	142679	11105	59439	85275	36563
adj. R^2	0.111	0.125	0.088	0.098	0.089

Note: Column 1 includes individuals aged 25-60. The following columns include the same age group but with different sub-groups. Columns 2 includes Black race people. Column 3 includes individuals without a bachelors degree. Last two columns include sample with married people and low income group which is defined as people with below 40,000 annual 2019 household income. Each regression also includes age, age squared, marital status, state, and week FE.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.4: Dependent variable is Dummy for Work

	(1) 25-60	(2) Black	(3) Non-Bachelors	(4) Married	(5) Low-Income
LWA	-0.0426	-0.105	-0.0425	-0.0296	-0.0227
	(0.0261)	(0.0647)	(0.0400)	(0.0286)	(0.0418)
lndeath	-0.0534	-0.129	-0.0970*	-0.0586	-0.121*
	(0.0387)	(0.121)	(0.0536)	(0.0409)	(0.0625)
lncases	0.00160	0.0189***	0.00312	0.00261	0.00381
	(0.00169)	(0.00657)	(0.00228)	(0.00326)	(0.00396)
Income	0.000239***	0.000452**	0.000352***	0.000340***	0.134***
	(0.0000807)	(0.000171)	(0.0000633)	(0.0000444)	(0.00519)
StringencyIndex	0.000726**	0.00327**	0.000732	0.000368	0.00113
	(0.000315)	(0.00125)	(0.000500)	(0.000402)	(0.000677)
lnvacancies	-0.0282	0.0238	-0.0441	0.00108	0.0220
	(0.0266)	(0.0634)	(0.0330)	(0.0312)	(0.0545)
HHsize	-0.00972***	-0.00111	-0.00590	-0.0138***	-0.00775
	(0.00282)	(0.00474)	(0.00373)	(0.00279)	(0.00547)
Free food	-0.0699***	-0.0711**	-0.0792***	-0.0679***	-0.0264
	(0.00869)	(0.0306)	(0.0123)	(0.0130)	(0.0160)
N	181206	15904	79160	107485	36563
adj. R^2	0.067	0.057	0.028	0.067	0.088

Note: Column 1 includes individuals aged 25-60. The following columns include the same age group but with different sub-groups. Columns 2 includes black race people. Column 3 includes individuals without a bachelors degree. Last two columns include sample with married people and low income group which is defined as people with below 40,000 annual 2019 household income. Each regression also includes age, age squared, marital status, state, and week FE.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.5: Dependent variable is dummy for Work

	(1) 25-60	(2) Black	(3) Non-Bachelors	(4) Married	(5) Low-Income
ΔR	-0.0426***	-0.0234	-0.0237**	-0.0338*	0.0272**
	(0.00906)	(0.0194)	(0.0116)	(0.0178)	(0.0103)
lndeath	-0.0807**	-0.118	-0.127**	-0.0774	-0.134**
	(0.0374)	(0.0764)	(0.0509)	(0.0465)	(0.0579)
lncases	0.000476	0.0184**	0.00218	0.000763	0.00366
	(0.00258)	(0.00699)	(0.00291)	(0.00292)	(0.00366)
StringencyIndex	0.000581	0.00192*	0.000827*	0.000647	0.00118*
	(0.000412)	(0.00112)	(0.000471)	(0.000394)	(0.000680)
lnvacancies	0.000889	0.173**	-0.00567	0.00566	0.0311
	(0.0316)	(0.0827)	(0.0437)	(0.0369)	(0.0501)
HHsize	-0.00553*	-0.00274	-0.00484	-0.00717*	-0.0145**
	(0.00275)	(0.00606)	(0.00395)	(0.00383)	(0.00582)
Free food	-0.0405***	-0.0252	-0.0431***	-0.0363**	-0.0229
	(0.0120)	(0.0368)	(0.0161)	(0.0175)	(0.0164)
N	141980	10996	59057	84875	36357
adj. R^2	0.111	0.126	0.089	0.099	0.087

This table is similar to table 3 but excludes individuals receiving pay during non-working time. The replacement rate coefficient is slightly higher than table 3. Each regression includes age, age squared, marital status, state, and week FE.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.6: Dependent Variable is dummy for Work

	(1) Full Sample	(2) Min Wage < 10	(3) Min Wage>10
ΔR	-0.0392***	-0.0423***	-0.0334**
	(0.00924)	(0.0141)	(0.0116)
lndeath	-0.0856**	-0.0764*	-0.101
	(0.0374)	(0.0438)	(0.0837)
lncases	0.000301	0.000903	0.00186
	(0.00233)	(0.00339)	(0.00213)
StringencyIndex	0.000580	0.000217	0.00191*
	(0.000373)	(0.000312)	(0.000908)
lnvacancies	-0.00457	0.0128	-0.0248
	(0.0306)	(0.0363)	(0.0566)
HHsize	-0.00600**	-0.0108***	0.000609
	(0.00284)	(0.00324)	(0.00303)
Free food	-0.0399***	-0.0281*	-0.0638***
	(0.0120)	(0.0153)	(0.0146)
N	142679	78981	54758
adj. R^2	0.111	0.108	0.116

Note: Column 1 includes all states. Column 2 and 3 includes states with min wage less than 10 and greater than 10 separately. Each regression also includes age, age squared, marital status, state, and week FE.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.7: Dependent Variable is dummy for Work

	(1) Full Sample	(2) Male	(3) Female
ΔR	-0.0392***	-0.0810**	-0.00564
	(0.00924)	(0.0344)	(0.0225)
lndeath	-0.0856**	-0.101*	-0.0654
	(0.0374)	(0.0583)	(0.0416)
lncases	0.000301	-0.00116	0.00198
	(0.00233)	(0.00366)	(0.00372)
StringencyIndex	0.000580	0.000712	0.000423
	(0.000373)	(0.000649)	(0.000529)
lnvacancies	-0.00457	0.000620	-0.0147
	(0.0306)	(0.0417)	(0.0379)
HHsize	-0.00600**	0.0120***	-0.0220***
	(0.00284)	(0.00343)	(0.00418)
Free food	-0.0399***	-0.0264	-0.0474***
	(0.0120)	(0.0248)	(0.0123)
N	142679	55878	86801
adj. R^2	0.111	0.129	0.093

Note: Column 1 includes full sample. Column 2 and 3 includes only males and females respectively. Each regression also includes age, age squared, marital status, state, and week FE.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.8: Dependent variable is dummy for work

	(1) 25-60	(2) Black	(3) Non-Bachelors	(4) Married	(5) Low-Income
Ratio	-0.280*	-1.097**	-0.397**	-0.384	-0.738**
	(0.165)	(0.492)	(0.188)	(0.239)	(0.291)
lndeath	-0.0795**	-0.224**	-0.0670*	-0.118**	-0.155**
	(0.0321)	(0.104)	(0.0388)	(0.0480)	(0.0613)
lncases	0.00163	0.0173***	0.00304	0.00329	0.00242
	(0.00168)	(0.00584)	(0.00364)	(0.00206)	(0.00369)
Income	0.000339***	0.000454***	0.000340***	0.000352***	0.137***
	(0.0000450)	(0.000169)	(0.0000440)	(0.0000635)	(0.00548)
StringencyIndex	0.000750*	0.00346**	0.000376	0.000752	0.00120*
	(0.000401)	(0.00159)	(0.000437)	(0.000581)	(0.000691)
lnvacancies	-0.0347	-0.00851	0.00503	-0.0475	0.00422
	(0.0274)	(0.0646)	(0.0275)	(0.0291)	(0.0498)
HHsize	-0.00759***	-0.00122	-0.0138***	-0.00590	-0.00742
	(0.00281)	(0.00479)	(0.00279)	(0.00373)	(0.00540)
Free food	-0.0761***	-0.0705**	-0.0679***	-0.0793***	-0.0262
	(0.00929)	(0.0308)	(0.0130)	(0.0123)	(0.0164)
N	181206	15904	107485	79160	36563
adj. R^2	0.060	0.056	0.067	0.028	0.086

Ratio is equal to 300/maxbenefit. Each regression also includes age, gender, race, stringency index, state, and week FE

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.9: Coefficient plot of lncases

	(1) April-May	(2) Jun-July	(3) Aug-Sept	(4) Oct-Nov
ΔR	-0.00381	0.00415	-0.0353**	-0.0376***
	(0.0103)	(0.00959)	(0.0171)	(0.00991)
lncases	-0.0347**	-0.0251*	-0.000412	0.0000448
	(0.0149)	(0.0147)	(0.00159)	(0.00163)
StringencyIndex	0.0312	-0.0700	0.000191	0.000181
	(0.0367)	(0.0557)	(0.000443)	(0.000570)
lnvacancies	-0.0129	0.0352	0.0163***	-0.0243
	(0.0287)	(0.0379)	(0.00363)	(0.0400)
HHsize	-0.00464	-0.00954***	-0.0129***	-0.00845***
	(0.00318)	(0.00300)	(0.00444)	(0.00253)
Free food	-0.0206	-0.00666	-0.0294**	-0.0119
	(0.0201)	(0.0128)	(0.0139)	(0.0121)
Bachelors	0.0969***	0.0579***	0.0609***	0.0694***
	(0.00967)	(0.00538)	(0.00482)	(0.00582)
N	266771	296030	89710	146510
adj. R^2	0.153	0.129	0.130	0.131

Note: This table compares the lncases coefficient over time through coefficient plot. Each column includes different months of 2020. Each regression also includes age, age squared, marital status, state, and week FE.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.10: Coefficient plot of lndeath

	(1) April-May	(2) Jun-July	(3) Aug-Sept	(4) Oct-Nov
lndeath	0.0266	-0.0820	0.00944***	-0.00550
	(0.0339)	(0.0508)	(0.00124)	(0.0363)
StringencyIndex	0.0240	-0.0411	0.000189	0.000181
	(0.0218)	(0.0317)	(0.000441)	(0.000571)
lnvacancies	-0.00881	0.0503	0.0267***	-0.0244
	(0.0299)	(0.0382)	(0.00364)	(0.0382)
HHsize	-0.00465	-0.00953***	-0.0129***	-0.00845***
	(0.00318)	(0.00301)	(0.00445)	(0.00253)
Free food	-0.0206	-0.00685	-0.0294**	-0.0119
	(0.0200)	(0.0127)	(0.0139)	(0.0120)
Bachelors	0.0969***	0.0579***	0.0609***	0.0694***
	(0.00967)	(0.00539)	(0.00481)	(0.00582)
N	266771	296030	89710	146510
adj. R^2	0.153	0.129	0.130	0.131

Note: This table compares the lndeath coefficient over time through coefficient plot. Each column includes different months of 2020. Each regression also includes age, age squared, marital status, state, and week FE.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.11: Coefficient plot of ΔR

	(1) April-May	(2) Jun-July	(3) Aug-Sept	(4) Oct-Nov
ΔR	-0.00983	-0.000789	-0.0430***	-0.0369***
	(0.0113)	(0.00838)	(0.0156)	(0.00979)
StringencyIndex	0.0470	-0.132*	0.000645*	0.000495
	(0.0473)	(0.0679)	(0.000365)	(0.000556)
lnvacancies	-0.0104	0.0834*	0.0122***	-0.0312
	(0.0364)	(0.0449)	(0.00355)	(0.0328)
HHsize	0.000333	-0.00616**	-0.0105***	-0.00538**
	(0.00260)	(0.00279)	(0.00374)	(0.00267)
Free food	-0.0281	-0.0177	-0.0287*	-0.0160
	(0.0189)	(0.0137)	(0.0155)	(0.0112)
Bachelors	0.0881***	0.0412***	0.0519***	0.0564***
	(0.00895)	(0.00538)	(0.00496)	(0.00542)
N	257027	284380	85858	140660
adj. R^2	0.163	0.139	0.137	0.136

Note: This table compares the ΔR coefficient over time through coefficient plot. Each column includes different months of 2020. Each regression also includes age, age squared, marital status, state, and week FE.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.12: Dependent variable is dummy for Work - Full Sample with Time Trend

	(1) 25-60	(2) Black	(3) Non-Bachelors	(4) Married	(5) Low-Income
ΔR	-0.0395***	-0.0199	-0.0207*	-0.0292	0.0311***
	(0.00925)	(0.0182)	(0.0117)	(0.0180)	(0.0104)
lndeath	-4.757**	-0.182*	-5.048	-6.858***	-2.036
	(2.259)	(0.102)	(3.466)	(2.195)	(4.470)
lncases	0.000176	0.0213***	0.00155	-0.0000898	0.00237
	(0.00231)	(0.00662)	(0.00271)	(0.00237)	(0.00378)
StringencyIndex	0.000476	0.00263**	0.000625	0.000665	-0.000913
	(0.000477)	(0.00115)	(0.000548)	(0.000455)	(0.00214)
lnvacancies	-0.0000891	0.0312	0.0147	-0.0959*	0.0939
	(0.0462)	(0.191)	(0.0750)	(0.0508)	(0.0983)
HHsize	-0.00596**	-0.00253	-0.00527	-0.00824**	-0.0156**
	(0.00284)	(0.00622)	(0.00403)	(0.00395)	(0.00592)
Free food	-0.0400***	-0.0269	-0.0426**	-0.0352**	-0.0237
	(0.0120)	(0.0353)	(0.0160)	(0.0171)	(0.0160)
N	142679	11105	59439	85275	36563
adj. R^2	0.111	0.129	0.088	0.099	0.089
State-Specific Linear time Trend	YES	YES	YES	YES	YES

Note:Column 1 includes individuals aged 25-60. The following columns include the same age group but with different sub-groups. Columns 2 includes black race people. Column 3 includes individuals without a bachelors degree. Last two columns include sample with married people and low income group. Low income group is defined as people with below 40,000 annual household income.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.13: Dependent variable is dummy for Work

	(1) 25-60	(2) Black	(3) Non-Bachelors	(4) Married	(5) Low-Income
ΔR	-0.0428***	-0.0220	-0.0239**	-0.0337*	0.0274**
	(0.00907)	(0.0181)	(0.0116)	(0.0177)	(0.0102)
lndeath	-0.0222	0.113	-0.161	0.132	-0.391
	(0.245)	(0.964)	(0.311)	(0.323)	(0.435)
lncases	0.000305	0.0214***	0.00176	-0.000806	0.00221
	(0.00256)	(0.00740)	(0.00291)	(0.00233)	(0.00375)
StringencyIndex	0.000520	0.00294**	0.000703	0.000591	0.000152
	(0.000514)	(0.00142)	(0.000606)	(0.000461)	(0.000889)
lnvacancies	-0.00890	-0.0390	0.00151	-0.0993*	0.0818
	(0.0505)	(0.211)	(0.0790)	(0.0542)	(0.0990)
HHsize	-0.00550*	-0.00305	-0.00485	-0.00722*	-0.0146**
	(0.00276)	(0.00596)	(0.00395)	(0.00383)	(0.00581)
Free food	-0.0405***	-0.0258	-0.0428**	-0.0359**	-0.0226
	(0.0120)	(0.0363)	(0.0161)	(0.0176)	(0.0164)
N	141980	10996	59057	84875	36357
adj. R^2	0.111	0.131	0.089	0.100	0.088
State-Specific linear time Trend	YES	YES	YES	YES	YES

This table is similar to table 12 but excludes people who were receiving pay during non-work period.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.14: Event Study (25-60)

	(1) 25-60	(2) Black	(3) Married	(4) Non-Bachelors
lead5	0.0671*	0.229**	0.0452	0.0660
	(0.0338)	(0.0909)	(0.0357)	(0.0502)
lead4	0.0715**	0.160**	0.0472	0.0763
	(0.0328)	(0.0680)	(0.0464)	(0.0486)
lead3	0.0538**	0.160**	0.0356	0.0553
	(0.0224)	(0.0678)	(0.0234)	(0.0356)
lead2	0.0500***	0.141*	0.00388	0.0564**
	(0.0180)	(0.0726)	(0.0228)	(0.0277)
lag0	0.00770	0.0350	-0.0175	0.00625
	(0.0183)	(0.0456)	(0.0248)	(0.0279)
lag1	-0.0345**	-0.00853	-0.0477**	-0.0458**
	(0.0144)	(0.0363)	(0.0202)	(0.0206)
lag2	-0.00999	-0.000381	-0.0530*	-0.0157
	(0.0240)	(0.0693)	(0.0315)	(0.0368)
lag3	-0.0523**	-0.0729	-0.0587*	-0.0631*
	(0.0256)	(0.0630)	(0.0298)	(0.0363)
lag4	-0.0391	-0.0638	-0.0809*	-0.0497
	(0.0313)	(0.0857)	(0.0413)	(0.0477)
lag5	-0.0674**	-0.0905	-0.0956**	-0.0819*
	(0.0327)	(0.0864)	(0.0413)	(0.0452)
lag6	-0.0676*	-0.0796	-0.118**	-0.0812
	(0.0396)	(0.105)	(0.0514)	(0.0577)
N	181206	15904	107485	79160
adj. R^2	0.067	0.063	0.072	0.037

Note: The table shows the regression results from the event study. Column 1 includes sample from 25-60 years. Column 2-4 includes sub samples of black people, married individuals, and non-bachelors.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.15: Event Study (18-60)

	(1) 18-60	(2) Black	(3) Married	(4) Non-Bachelors
lead5	0.0958*	0.226**	0.0263	0.108
	(0.0484)	(0.0912)	(0.0352)	(0.0653)
lead4	0.0816*	0.124*	0.0292	0.0872
	(0.0468)	(0.0732)	(0.0437)	(0.0633)
lead3	0.0584*	0.202***	0.0248	0.0625
	(0.0311)	(0.0745)	(0.0233)	(0.0426)
lead2	0.0553**	0.130	-0.00460	0.0623*
	(0.0263)	(0.0790)	(0.0206)	(0.0365)
lag0	-0.0138	-0.0282	-0.0159	-0.0241
	(0.0215)	(0.0485)	(0.0225)	(0.0321)
lag1	-0.0472**	-0.0245	-0.0442**	-0.0610**
	(0.0215)	(0.0328)	(0.0198)	(0.0284)
lag2	-0.0372	-0.0450	-0.0406	-0.0513
	(0.0303)	(0.0759)	(0.0285)	(0.0432)
lag3	-0.0810**	-0.0914	-0.0498*	-0.102**
	(0.0375)	(0.0593)	(0.0282)	(0.0499)
lag4	-0.0730*	-0.117	-0.0597	-0.0947
	(0.0408)	(0.0861)	(0.0370)	(0.0575)
lag5	-0.106**	-0.119	-0.0774*	-0.135**
	(0.0501)	(0.0834)	(0.0386)	(0.0657)
lag6	-0.109*	-0.0883	-0.0893*	-0.136*
	(0.0565)	(0.0993)	(0.0457)	(0.0765)
N	191367	16664	108694	86835
adj. R^2	0.068	0.067	0.072	0.035

Note: The table shows the regression results from the event study. Column 1 sample from 18-60 years. Column 2-4 includes sub samples of black people, married individuals, and non-bachelors.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 2.16: Callaway and Sant'anna Event Study

	(1) Work	(2) lnwork
Pre Avg	-0.00523	-0.00414
	(0.00722)	(0.0972)
Post Avg	-0.0137**	-0.135**
	(0.00626)	(0.0599)
Tm4	-0.00590	0.0124
	(0.0323)	(0.462)
Tm3	-0.00722	-0.0370
	(0.0209)	(0.311)
Tm2	0.00121	0.0183
	(0.0175)	(0.149)
Tm1	-0.00902	-0.0103
	(0.0108)	(0.104)
Tp0	0.00234	-0.0158
	(0.00833)	(0.0785)
Tp1	-0.00241	-0.0381
	(0.00816)	(0.0789)
Tp2	-0.00394	-0.0771
	(0.00796)	(0.0790)
Tp3	-0.0148*	-0.144*
	(0.00874)	(0.0776)
Tp4	-0.0159*	-0.209***
	(0.00871)	(0.0808)
Tp5	-0.0262***	-0.225**
	(0.00849)	(0.0951)
Tp6	-0.0345***	-0.235**
	(0.0128)	(0.117)
N	392	392

Note:This table shows the output from csdid command. Column 1 is for work dummy while column 2 includes log of total working proportion in that state in each week.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Chapter 3

HOW DOES THE EARLY WITHDRAWAL FROM PANDEMIC UI EXTENSIONS IMPACT HOUSING OUTCOMES?

3.1 Introduction

During pandemic, a lot of people suffered job losses and similar financial constraints. In the presence of lockdown, aggregate demand fell down sharply, which led to a record rise in unemployment rates.[1] According to Dixon (2023), around 23 million US workers were unemployed during the pandemic, the greatest job loss since the Great Depression. In the wake of this situation, US government introduced various social protection plans such as UI extensions, social protection security, SNAP benefits and similar cash transfer programs. The purpose of these programs was to assist the struggling families specially low income households that had limited financial savings at their disposal. In this topic, I focus on the unemployment insurance extension program and its impact on the housing market.

This paper examines the impact of early withdrawal from FPUC (Federal Pandemic Unemployment Compensation) on housing outcomes. Unemployment insurance is an important source of income for household, specially low income families as it provides them financial support. In the absence of the program, beneficiaries may experience difficulty in paying rents, mortgages, etc. Early withdrawal from these benefits will induce two possible scenarios. While on one hand, recipients may lose extra cash through the discontinuation of UI benefits, on the other hand, they can look for jobs and potentially earn more than the benefits they were previously receiving. So, the overall effect of the program on housing market is unknown.

[1] https://www.bls.gov/opub/mlr/2021/article/unemployment-rises-in-2020-as-the-country-battles-the-covid-19-pandemic.htm

There is considerable literature focusing on the UI policy design. For instance, Lentz (2009), Fredriksson & Holmlund (2006), and many others discussed the optimal UI policy and it's implications. Chodorow-Reich & Coglianese (2019), Di Maggio & Kermani (2017), Flamang & Kancherla (2022), highlighted the positive effects of UI as an automatic stabilizer in the economy. Chetty (2008), Larsson & Runeson (2007), Hall & Hartman (2010), studied the behavioral aspects of UI, as it generates moral hazard effect among the workers. Similarly, Hsu et al. (2018), Hurd & Rohwedder (2010), and Di Maggio & Kermani (2017), investigated the role of UI during the economic downturn and its impact on various economic outcomes, including the housing market. My paper adds to the literature by studying the role of UI in the housing market during the pandemic period. I provide extensive results using a variety of housing market variables, such as rent payment, mortgage confidence, foreclosure, etc.[2] Most of the existing studies mainly focus on home-owners or mortgage default. I perform detailed analysis focusing on renters and home-owners outcome.

FPUC (Federal Pandemic Unemployment Compensation) was one of the unemployment assistance programs, under which each unemployed worker received $300 additional weekly payment along with the regular UI benefit. The program was designed to give aid to people who lost their jobs during the pandemic and to offer support while they search for new opportunities of employment. In the first phase of FPUC, government provided $600 additional payments to the workers while I will focus on the second phase that granted $300 weekly payments in 2021.

There are couple of reasons of choosing phase II period. Firstly, it covers the 2021 period which was relatively more stable as compare to 2020 when the economy was extremely disrupted. Secondly, there is timing variation of withdrawal among the States which is critical for my specification. The first phase ended right away, with an introduction of LWA in 2020. Table 3.1 includes the timeline

[2] Hsu et al. (2018) is one of the first papers that analyzed the relationship between the UI payment and the housing market outcomes. The main dependent variable was mortgage default or delinquency.

of these unemployment assistance programs.

Table 3.1: UI Extension Programs

Programs	Date	Amount
FPUC I	Mar-July 2020	$600
LWA	Aug-Dec 2020	$300
FPUC II	Jan-Sept 2021	$300

Initially, FPUC was introduced for the period of January - September 2021. At the end of the first quarter of 2021, the economy was slowly recovering. Most people were getting vaccinated, cases were going down and job openings reached an all time high of 9.3 million in April, 2021.[3] A lot of people including US chamber of commerce argued that the extra UI benefits are enticing Americans to stay home and delaying the recovery of the labor market Thomas Franck (2021). As a result of this, 22 states decided to end the pandemic unemployment compensation program immediately, returning to the pre-pandemic UI benefit level. Table 3.2 shows the states with their FPUC ending dates. Figure 3.1 shows the unemployment rate comparison between the early states and the late states.[4] This confirms that the early states have better macroeconomic conditions as compared to the late states.

Figure 3.2 and Figure 3.3 show the eviction and foreclosure rates around the termination timing. There is a slight increase in the eviction and foreclosure rates at the time of UI expiration. The first dashed line indicates the time when early states started to end the program while at the second dashed line, every state returned to the pre-pandemic UI payments level. In Figure 3.4, I further divide the eviction and foreclosure rates into early and late states. The early states experience slightly higher eviction and foreclosure rates. Figure 3.5 and Figure 3.6 show the same effects in the case of mortgage and rent caught up. On average, respondents are more caught up with mortgage which shows that the

[3]https://www.ziprecruiter.com/blog/states-canceling-pandemic-unemployment-early/

[4]Early states are the states that ended the UI extensions around June 2021, whereas late states decided to continue the program till September 6th, 2021.

home-owners are slightly doing better. Across states, late states are doing better with higher share of people who are caught up with their housing payments.
To the best of my knowledge, there is no current literature that studies the impact of FPUC on housing outcomes. Using household pulse survey, I investigate the impact of termination of FPUC on housing payments. The event study results show that eviction goes down significantly after the FPUC. Similarly, the probability of foreclosure also goes down initially but then starts to increase after the first few weeks. Overall, the effect on foreclosure is insignificant. This happens due to the mortgage payments as households are more confident to pay their mortgage right after the FPUC ended. However, they are relatively less confident in the later periods. Hence, the increase in mortgage confidence was not enough to decrease the possibility of foreclosure significantly. These findings also highlight the difference in home-owners preferences. As UI payments ended, workers either found new jobs or used their savings. As a result, they were able to pay their rents on time and avoid eviction orders. But at the same time, those payments were not enough to decrease the foreclosure.[5]

[5]For post average in csdid, I find coefficient of -0.13** for eviction, while the coefficient for mortgage confidence is 0.014***. On the other hand, foreclosure coefficient is 0.014.

Table 3.2: FPUC Ending Dates

State	Ending Date	State	Ending Date
Alabama	6/19/21	Montana	6/27/21
Alaska	6/12/21	Nebraska	6/19/21
Arizona	7/10/21	Nevada	9/6/21
Arkansas	9/6/21	New Hampshire	6/19/21
California	9/6/21	New Jersey	9/6/21
Colorado	9/6/21	New Mexico	9/6/21
Connecticut	9/6/21	New York	9/6/21
Delaware	9/6/21	North Carolina	9/6/21
DC	9/6/21	North Dakota	6/19/21
Florida	6/26/21	Ohio	6/26/21
Georgia	6/26/21	Oklahoma	9/6/21
Hawaii	9/6/21	Oregon	9/6/21
Idaho	6/19/21	Pennsylvania	9/6/21
Illinois	9/6/21	Rhode Island	9/6/21
Indiana	9/6/21	South Carolina	6/30/21
Iowa	6/12/21	South Dakota	6/26/21
Kansas	9/6/21	Tennessee	7/3/21
Kentucky	9/6/21	Texas	6/26/21
Louisiana	7/31/21	Utah	6/26/21
Maine	9/6/21	Vermont	9/6/21
Maryland	9/6/21	Virginia	9/6/21
Massachusetts	9/6/21	Washington	9/6/21
Michigan	9/6/21	West Virginia	6/19/21
Minnesota	9/6/21	Wisconsin	9/6/21
Mississippi	6/12/21	Wyoming	6/19/21
Missouri	6/12/21		

3.2 Literature Review

This section provides evidence of the existing literature on UI benefits and its impact on the household outcomes. There are papers that investigated the impact of UI benefits on recipient's labor market outcomes. Some papers also highlighted the importance of UI policy in enhancing the economy activity and moderating the labor market crisis. Similarly, there are papers that focused on the pandemic period. My paper adds to the literature by focusing on the impact of UI termination policy on housing outcomes.

Coombs et al. (2022) studied the impact of early withdrawal from pandemic UI on employment and earnings. The data source was Earnin, a financial services company that provides early access to earnings for users who have connected their bank accounts. Using a difference-in-difference technique, authors compared the UI retained states with the UI withdrawal states. The results showed a major reduction in UI recipiency and income. For the employment effects, there was a slight increase in job finding rates for those who lost benefits. But, this increase was not significant in magnitude. By the first week of September (3 months after the expiration), they found a 6.8 percentage point causal increase in job finding rate in the withdrawal states. Holzer et al. (2021) performed similar analysis, where they investigated the employment effects of early termination of FPUC. Using CPS data, they showed that the flow of unemployed workers into employment increased by two-thirds following the early expiration of the program. In this paper, I use the same treatment effect and extend it to the housing market. With the expiration, the recipients lost the financial support which they had. This could impact their ability to pay housing expenses on time. There is already evidence of slight increase in employment after the termination of FPUC. I use the pulse survey, to consider the impact of FPUC on the housing outcomes.

In the literature, there are couple of papers that examined the generosity of UI and how it would affect the economic activity, through individual preferences. Hsu et al. (2018) is one of the primary papers that studied the impact of UI on the housing market. Empirical strategy exploited the exogenous variation in UI benefits among states and across different time periods. Using household level data from the Survey of Income and Participation Program (SIPP), authors studied the employed and unemployed homeowners by comparing their response to the state-level changes in UI benefits. While utilizing the timing variation of UI benefits between 1991 and 2010, results showed that the UI generosity alleviated mortgage default. For a $3600 increase in UI benefits, mortgage delinquency would reduce by 83 basis points. The effect was the strongest among the unmarried individuals or households without the permanent source of income. Additionally, authors also studied the effect of UI extensions during the

Great Recession, when the maximum duration of UI was extended to as high as 99 weeks as compare to the regular period of 26 weeks. The results were similar where a $3600 increase in UI benefits was associated with a decline in the mortgage delinquency by 108 basis points. I also perform similar analysis where I use a pandemic period which should be completely different from the normal times as it depicts the household preferences in disrupted times. I also focus on the UI benefit levels as compare to the UI duration levels during the Great Recession. This provides another piece of evidence on how people react to the UI termination programs, in the context of the housing market. I also focus on a variety of housing variables such as rent payments, confidence in paying mortgage, possibility of foreclosure, etc.

Di Maggio & Kermani (2017) is another paper that studied the impact of UI generosity on local economic activity, in the presence of local labor demand shock. The empirical strategy used an interaction of Bartik measure with unemployment insurance generosity.[6] The UI generosity is measured through the average replacement growth rate in each county. The authors used numerous data sources to measure UI generosity, such as Annual Social and Economic Supplement (ASEC) and Current Population Survey (CPS). Employment growth rate was the main dependent variable along with consumption and earnings. The results showed that in more generous counties, the employment growth was less sensitive to local labor demand shocks. With a one standard deviation increase in UI generosity, employment growth response went down by 7%. The results were similar in case of consumption and earnings growth, where a one standard deviation change in UI generosity was associated with a decrease in the effect of shock by 7-9%. More importantly, authors also studied the UI generosity in the context of housing market. The findings were consistent with Hsu et al. (2018). In regions with more generous UI, housing prices and mortgage delinquency were less sensitive to negative shocks in the local economy. This means that the UI is providing extra cushion to households, who lost their jobs in the

[6] The paper used a normal industry-level bartik measure with a product of industry weights and national employment of each industry.

past. With extra cash at hand through UI, households are more likely to make their housing payments on time. This paper provided evidence of how UI diminished the negative effect of local labor demand shock. I am exploring the same channel by using the UI pandemic program and its impact on the housing market.

One of the primary objectives of UI is to provide assistance to the unemployed workers. Chodorow-Reich & Coglianese (2019) studied the role of unemployment insurance as a macroeconomic stabilizer, while focusing on the recession period. The authors also proposed various changes to the UI system that would further increase the role of UI as an automatic stabilizer in a given economy. Some of the changes were expansion of UI take-ups and adding automatic extended benefits during an extremely high unemployment period. The authors argued that the low UI recipiency rate is one of the major hurdles, in making the UI system more efficient. According to the authors, only 28 to 35 percent unemployed individuals were receiving UI in 2018. This shows that the target population is not reached. In an ideal scenario, we should expect the UI take-up rate to be somewhere around 60-70%. In a similar study, Kekre (2021) performed analysis of UI extensions as a stabilizer. Using US economy over 2008-2014, authors studied the role of UI in general equilibrium, in the presence of normal rigidities and search frictions. The findings showed that the benefit extensions in UI raises the aggregate demand for consumption given a higher marginal propensity to consume (MPC) for unemployed workers. The results stated that with absent normal rigidities, UI extensions would raise the output multiplier by -0.5. However, in the presence of normal rigidities and fixed nominal interest rate under the monetary policy, the UI generosity would increase the output multiplier to a factor of 1.1. These papers provide evidence in support of UI acting as a stabilizer for the overall economy. In my paper, I also contribute to the literature by connecting the UI system with the housing market. If unemployed workers alter their consumption with an extra money available through UI, we should expect them to change their level of savings as well which would be used later for paying rents or mortgages.

Unemployment insurance gives financial stability to the individuals. Flamang & Kancherla (2022) measured the impact of UI on households through the financial channel. Using administrative data of credit records from California's Consumer Credit Panel (CCP), authors studied the overall sensitivity of various types of loans to the unemployment rate. They used an extensive period from 2017-2022, which provided detailed analysis over time. Initially, they used regression framework with average delinquency of each county as the main dependent variable and the unemployment rate as the main independent variable. They also divided the credit loans into different types such as auto loans, credit card loans, student loans and mortgages. Results suggested that the overall sensitivity of credit loans to unemployment rate went down, specially after the pandemic period. For credit cards, there was a 66% drop in sensitivity while a substantial 50% reduction happened for auto loans. Similarly, coefficient for mortgages was roughly around 0.4-0.6 in the pre-pandemic period, after going down to 0-0.1 after the pandemic. One of the possible channels of this drop is UI relief programs. To solidify this claim, they performed an event study by using the timing variation in the UI termination program. The findings were consistent with the previous results, where a significant increase in sensitivity of the credit loans to unemployment rate happened right after the termination of UI extension program. This further highlights the importance of UI assistance pandemic programs. With a lot of relief programs in place, such as UI extensions, child credit support program, stimulus payment program, households were not affected by the disruptions caused by the pandemic. Due to which, they did not experience the burden of the downfall of economic activity with UI being the most prominent channel. Through Household pulse survey, I also test the relationship between the UI payments and housing default. I perform the analysis at a micro level which provides further explanation to the association.[7]

[7]According to Ganong et al. (2020), 76% of workers eligible for regular Unemployment Compensation have statutory replacement rates above 100%. This is an unprecedented increase which is mostly uncommon.

There is a growing literature that studies the behavior of unemployed workers. Once the job loss occurs, it enhances the possibility of a default among the unemployed workers through reduction in income. Using employer-employee data with credit record, Braxton et al. (2020) showed that the displaced workers are 3.1 percentage points more likely to be delinquent as compare to the non-displaced individuals. Similarly, a displaced individual is more likely (0.9 percentage points) to have a debt charge-off than a non-displaced individual. Hurd & Rohwedder (2010) also investigated the impact of recession on households. Using an internet survey from American Life Panel, the paper studied the effects of financial crisis on households. The findings suggested that between 2008 and 2010, around 39% of households had either been unemployed, experienced negative equity in their house or missed housing payments. The authors also analyzed the coping mechanism of unemployed workers. Among the unemployed workers, 85% reduced their spending while 46% cut down their savings. Moreover, the paper also presented the home ownership status and housing payments timeline for the unemployed workers. For the whole population, the home ownership rate is 65% while it dropped down to 45% for the unemployed individuals. For mortgage, unemployed workers are more likely to delinquent (10% versus 3%) as compare to the employed ones. Similarly, 17% of unemployed workers faced negative home equity in comparison to 12% for the employed workers. All of these statistics showed the financial burden unemployed individuals faced during the recession period. During Covid-19, people faced similar consequences once they experienced job loss. Due to this, they should be more likely to default or miss payments in the absence of UI benefit extension program.

In a similar study, Keys (2018) examined the role of job displacement in the context of bankruptcy for the households. The data source is National Longitudinal Survey of Youth (NLSY), which is an annual survey till 1994 and biennial since then. The survey asks questions on education, health, family formation, employment, assets accumulation, etc. The author used extensive information on asset and debts to investigate the bankruptcy decisions among the households. The author also obtained restricted NLSY license data that includes information of individual's state of residence for bankruptcy. With an event-study design, results depicted that the households with a male worker facing job displacement were three times more likely to file for bankruptcy. The higher possibility of default was consisted in the first 2-3 years after job loss, while the following year were not different from zero. This highlights the prolonged effect of job-loss on default.

Gerardi et al. (2018) is another important paper that studied the relative importance of negative equity versus ability to pay, in the context of mortgage defaults that occurred between 2009-2013. Authors used Panel Study of Income Dynamics (PSID) supplements on housing, mortgage distress and wealth, to investigate the underlying comparison. The sample is restricted to borrowers with mortgage aged 24 to 65, with a labor force status. The initial OLS estimates suggested a negative significant relationship between the residual income and the mortgage default. Specifically, with a 10% increase in residual income is associated with a decrease in the default probability by 0.37 percentage points. Similarly, the interaction term of LTV ratio and income is also negative significant. This meant that with a higher LTV ratio (lower equity levels), the decrease in income would have a more pronounced effect on default. To overcome the endogeneity concerns, authors also presented the IV results. The instrument for LTV ratio was the cumulative growth in the housing price index at the state level. Similarly, involuntary job loss was used as an instrument for the residual income. The IV results included a higher coefficient in magnitude as compared to the OLS estimates. The residual income coefficient was -0.24 as compared to -0.025 in the OLS model. These findings supported the validity of the instruments.

In the ongoing literature, there is evidence of job loss being one of the primary reasons of default. Additionally, there is also support in favor of UI providing assistance to the households in avoiding default and making payments on time.

This paper contributes to the literature by extending this analysis, while examining the impact of UI benefit programs on housing default. I also provide the analysis by using information on mortgage, rent payments, as well as on mortgage confidence and eviction.

3.3 Data

My data source is Household Pulse Survey for this topic. It is a rich data source designed by US Census Bureau to measure the coronavirus impact on households. In the survey, there are questions on the household expenses, income sources, employment, payments, etc. The survey also includes basic demographic information such as age, gender, race, education and marital status. It is an individual repeated cross section. The collection of the survey started in March 2020 and it is still in process. Each survey round is published biweekly with an average of around 95,000 respondents. I use the period between April - Dec 2021 as it contains detailed information on the income sources and the housing default. Specifically, the survey asks "Is this household currently caught up on rent?", "Is this household currently caught up on mortgage payments?", "How confident are you that your household will be able to pay your next rent or mortgage payment on time?", "How likely is it that your household will have to leave this home within the next two months because of foreclosure?" Using these questions, I can check whether UI payments have made any difference in terms of on time mortgage or rent payments among the recipients. Table 3.3 shows the summary statistics of the main variables of interest.

I use state level controls in my specification, to avoid omitted variable bias. During mid 2021, most of the states were still recovering from the pandemic. To control for that, I use the number of COVID cases and deaths in my specification. For each state, I use "Our World in Data" website which provides pandemic controls such as the cases and deaths.[8] Secondly, I control for the unemployment rate to measure the labor market conditions in each state. Under BLS,

[8] https://ourworldindata.org/coronavirus

LAUS (Local Area Unemployment Statistics) publishes monthly state-level employment measures such as the unemployment rate, employment-to-population ratio, labor force, etc. So, I use state-level unemployment rate from LAUS.[9] I also use quarterly wages data from QCEW to construct the median replacement rate.[10]

3.4 Empirical Strategy

Similar to Dube (2021), I calculate the difference-in-differences estimate as follows:

$$Y_{ijt} = \alpha + \beta_{DID}(Post * Share_{s(i)}) + \beta_1 \Delta_{jt} + \beta_2 Moratorium_{jt} + X'ijt\gamma + \Psi_t + u_{ijt}$$

(3.1)

I define the share amount as the ratio of $300 over average mortgage or rent amount.[11] Share amount will be higher for states where $300 is a larger part of the housing payments, indicating that those states would be more vulnerable after the UI termination. Moratorium is a dummy, which is equal to 1 if the eviction protection program is still running in state j at time t.[12] I construct this dummy with the help of a novel data set developed by Zbiciak & Markiewicz (2023), which captured the temporal and substantive features of different renter-supportive measures.[13] The moratorium is equal to 1 if the overall eviction measures at the federal level are not expired at that time. Similarly, it is also equal

[9] https://www.bls.gov/lau/data.htm

[10] I calculate the replacement rate as the ratio of 300 over average wage, where average wage is the mean of state-level wage in 2019.

[11] I use the pre-pandemic rent and mortgage amounts for each state.
I use the rental rates from https://www.experian.com/blogs/ask-experian/research/median-rental-rates-for-an-apartment-by-state/. Mortgage amounts are listed here https://infogram.com/mortgage-payment-by-state-1hzj4onjgvkp2pw.

[12] I include moratorium for renters only, as it includes eviction orders and rent protection which are focused to assist renters.

[13] The details of the project can be found here.

to 1 in the presence of other state level protection against eviction orders, otherwise the dummy is set to 0.[14]

I use an event study approach, to capture the dynamic effects of early withdrawal from FPUC. I estimate the following equation:

$$Y_{ijt} = \alpha + \sum_{\tau=-6}^{\tau=6} \Gamma_\tau (I_\tau \times Withdrawal_{s(i)}) + \beta_1 \Delta_{jt} + X'ijt\gamma + \delta_j + \Psi_t + u_{ijt}$$

(3.2)

where Yijt is one of the housing outcomes. Withdrawal is a dummy equal to 1 if the FPUC program has been terminated in that state and zero otherwise. Δ_{jt} is a vector of state level time variant characteristics such as unemployment rate, number of covid cases, lockdown restrictions, etc. During pandemic, every state was recovering differently. I am including these state level variables to control for that inconsistent recovery path. X'ijt includes individual characteristics such as age, race, education, etc. Lastly, Ψ_t and δ_j are state and time fixed effects. Coefficient of interest is Γ_τ which presents the dynamic effect of early withdrawal in different states on the basis of timing variation.

There might be some potential identification issues, while estimating equation 3.1. In my empirical strategy, I exploit the sharp timing variation of UI termination program among states. In such an event study framework, the underlying assumption is the similarity in the treated and control group. This directly relates to the parallel trends assumption. Most of my event studies fulfill this assumption, which further provides validity to the results.

Secondly, there were numerous non-UI programs in place during the period. For instance, households received around \$500 and \$1400 per member through the

[14]In the data set developed by Zbiciak & Markiewicz (2023), there are numerous eviction protection measures for different states, such as the prohibition of eviction orders at the federal level, rent protection act at the state level, courts preventing landlords from filing eviction orders, etc. For the moratorium index, I only use the overall protection measures that includes information for almost all of the states. For the remaining measures, most of the state's information is missing.

Economic Impact Payment Program. The American Rescue Plan also provided an expanded and fully refundable Child Tax Credit of $3,600 per child under 6 and $3,000 per child between the ages of 6 and 17. The CARES Act also initiated the Paycheck Protection Program, a policy designed to provide small loans to the employers so that they could make payroll payments on time. In the presence of these programs, it is not easy to separate the UI policies impact on the housing market. Also, there is no feasible way to control for each and every mentioned policy in my specification. Following Flamang & Kancherla (2022) approach, I employ state and time fixed effect to control for the time varying state level changes in my event studies. By doing this, I can isolate the common changes in the housing payments due to non-UI policies.

3.5 Results

In this section, I explain the initial set of results. First, I study the impact of the program on the housing outcomes. To do this, I control for the post dummy which is 1 for states where program has been started and 0 otherwise. Table 3.4 shows the results for the home owners. I also control for different versions of unemployment rate in each of the panel A-C. The coefficient of post dummy is only significant for the "caught up with mortgage", indicating that the individuals are less likely to be caught up with mortgage after the program. Table 3.5 shows the same set of results for renters. The results are a little different. The effect is most evident for the eviction rate in column 3 and 4.[15] For all of the panels, post is positive and significant showing an increase in the eviction rates because of the unemployment insurance termination.

In Table 3.6, I use the interaction of mortgage share and post dummy. I define mortgage share as the ratio of $300 over average mortgage amount in each state. It measures the impact of $300 loss for each household in terms of mortgage. The results show that each outcome is significant except for the mortgage confidence. The interaction has a negative impact on the caught up mortgage and

[15]In column 3, I use the eviction rate for people who are not confident in paying the rent. In column 4, I use the full sample while including the confident renters as well.

positive impact on the foreclosure. This means that the states where $300 was a higher portion of the mortgage amount, experienced an increase in foreclosure rates.

In Table 3.7, I use the interaction of rent share and post dummy. I define rent share as the ratio of $300 over average rent amount in each state. It measures the impact of $300 loss for each household in terms of rent amount. The results show no effect on the housing outcomes for the renters.

I also use the median replacement rate change in my specification. I replace the share amount in equation 3.1 with the median replacement rate for each state. For Table 3.8 and Table 3.9 , I employ the interaction of median replacement rate with the post dummy. In Table 3.8, the interaction term is negative and significant for the mortgage confidence and positive for the foreclosure. This shows that states with higher replacement rate change, have lower mortgage confidence and experience higher rates of foreclosures. In Table 3.9, the effect is not significant for the renters. One of the reasons behind this is the presence of various renter protection programs, such as moratorium. These programs reduce the eviction rates and provide significant protection against the eviction.

Heterogeneity

In this section, I provide further heterogeneous analysis. In Table 3.10, I restricted my sample of unemployed individuals. Then, I run the specification similar to Table 3.6 (Panel B). The results are significant for foreclosure. The coefficient is similar in magnitude as well. This implies that the program had a similar effect on unemployed individuals. In Table 3.11, the specification is similar to Table 3.7 (Panel B) with the same restricted sample of unemployed individuals. The coefficient is non-significant for all of the outcomes, which is similar to the result found in the full sample (Table 3.7).

So far, the results include the full sample and the sub-sample of unemployed individuals. Further, I also study the potential sub-groups that might be affected by the UI policy. In Table 3.12, I include homeowner's outcome with people belonging to low income, married individuals, and non-bachelors.[16] The interaction term is significant for low income and non-bachelors with foreclosure, while the effect does not exist for married individuals. This shows that the policy has an impact on home-owners who were non-bachelors or people belonging to low income group. It could be possible that these people were not able to find jobs once the policy was terminated. As a result, foreclosure rates went up for these sub-groups. In Table 3.13, I repeat the same exercise for renters but there is no effect. Similar to the results presented in Table 3.7.

So far, I included unemployment rate to measure the varying market conditions across states. As a robustness check, I also control for the employment-to-population ratio instead of the unemployment rate. The logic behind this is that workers sometimes put more emphasis on one market indicator as compared to others. Table 3.14 and Table 3.15 show the results for home-owners and renters. The results are somewhat similar to the ones found in the case of unemployment rate. The employment-to-population ratio is positive and significant for the caught up with housing payments and mortgage / rent confidence, while it is negative and significant for foreclosure and eviction rates. The signs make sense because if the employment ratio is higher, workers are more likely to find jobs and they will be more confident in paying rents or mortgage amounts. As a result, foreclosure / eviction rates will go down.

Event Studies

The above mentioned regression analysis provide mixed findings. To provide further evidence, I also employ event study approach explained in equation 3.2. Through the event study, I am able to examine the dynamic effect of the intervention, allowing for a more detailed analysis of how treatment evolves over time. Initially, I provide the TWFE results. In Figure 3.7, I include the TWFE results of foreclosure. The results show that there is a slight negative effect in

[16] For low-income, I only consider individuals with annual family income of less than $30,000.

the post-period but it is not significant. In Figure 3.8, I include the eviction outcome and found similar results. Some of the post period coefficients are positive but insignificant. Overall, the TWFE results are not convincing and lack significance.

So far, the results use TWFE to investigate the impact of UI termination on housing outcomes. However, under treatment heterogeneity, TWFE could be biased. Due to which, the coefficient would not be able to capture the true effect. To solve this, I use Callaway and Sant'Anna estimator given in Callaway & Sant'Anna (2021). According to Callaway & Sant'Anna (2021), TWFE is more suitable in a canonical framework, where there are two groups (control and treatment) and two periods (pre and post). In the presence of multiple treatment timing, TWFE would not produce the desired results. Callaway & Sant'Anna (2021) propose an alternate estimator that takes care of the treatment heterogeneity and produces robust group-specific average treatment effect (ATT_g).[17] The csdid estimator verifies the parallel trend assumption and give different results than TWFE. In the case of multiple treatment timing, this also suggests that the csdid estimator provides meaningful results that could not be achieved through the TWFE methods.

In my results, the Callaway and Sant'anna estimator outperforms the TWFE in the case of multiple treatment timing while holding the parallel trend assumption. Figure 3.9-Figure 3.14 shows the event studies under the csdid estimator from stata.[18]

In Figure 3.9, I illustrate the impact of early UI termination on working probability. The results indicate a notable increase in working probability after the termination period, suggesting a recovering job market. This trend implies that individuals found jobs in the post-period. Such an outcome should positively impact housing outcomes, as individuals would likely have more savings from their earnings.

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[17] More technical details can be found in Callaway & Sant'Anna (2021).

[18] More details on csdid estimator can be found here.

To study the housing outcomes, I focus on the home-owners. In Figure 3.10, I present the event studies from the foreclosure outcome. In panel (a), I include the full sample. Panel (b)-(d) show various sub-samples. In all of the panels, the foreclosure rate goes down in the first few periods and then starts to increase from period 3 onwards. This shows that the UI termination had a short term positive impact on the foreclosure rates but could not change the possibility of foreclosure in the long run.

The effect of the policy is different in the case of renters. In Figure 3.11, I use the eviction as the dependent variable. Panel (a) includes the full sample, panel (b)-(d) show the sub-samples effect. In all of the panels, the eviction rate is going down after the policy. This shows a positive impact of the UI termination on renters. This result is in accordance with Figure 3.9. As people start to work in the post period, they are expected to have more disposable income, allowing them to pay rents on time.

I also observe the same result in the case of mortgage / rent confidence. In Figure 3.12, all of the panels have the same findings. After the UI termination, mortgage or rent confidence is going up showing that people have more savings due to which they are more confident in paying their housing payments.

Lastly, I study the dynamics of UI termination policy on the caught up on mortgage and rent outcomes. In Figure 3.13, I show the caught up on mortgage outcome. On average, more people are caught up on mortgage in the post period. Figure 3.14 includes the renters outcome where the trend is upward in the post period. This further validates the positive impact of the UI termination policy on households.

3.6 Conclusion

Covid-19 caused a lot of disruptions in the US economy. To overcome the difficulties attached to the pandemic, US government introduced various assistance programs. One of the programs was FPUC (Federal Pandemic Unemployment Compensation). Under FPUC, additional payments were provided apart from the regular unemployment insurance benefits. In the first round of FPUC (July

- Dec 2020), \$600 extra was given each week. At the start of 2021, second round of FPUC was initialized. Under the second round, \$300 extra payments were included in the weekly UI benefits. Although, the second round of FPUC was supposed to be till September 2021, some of the states decided to terminate the additional payments in June 2021.

This paper studies the impact of early withdrawal from FPUC (Federal Pandemic Unemployment Compensation) on housing outcomes. Unemployment insurance is an important source of income for job-seekers, specially low income families as it provides financial support. In the absence of the program, beneficiaries may experience difficulty in paying rents, mortgages, etc.

The existing literature includes evidence of UI as a financial stabilizer (Chodorow-Reich & Coglianese (2019), Di Maggio & Kermani (2017), Kekre (2021)). Among the current papers, Hsu et al. (2018) studied the direct impact of UI on the housing market. The results showed a positive impact of UI on the housing outcomes, with a decrease in mortgage delinquency.

In this paper, I provide similar analysis in the pandemic period. Using household pulse survey, I study the impact of early withdrawal from FPUC on the housing payments. In the TWFE model, I find a positive impact of the termination policy on foreclosure rates. A 1% increase in the mortgage share during the post period, increases the foreclosure rate by 60% (only less confident home-owners) in the restricted sample and 5% in the full sample (including confident home-owners). However, there is no significant effect on the renters side.

In the presence of treatment-effect heterogeneity, TWFE estimates could be biased. To address this concern, I employ Callaway and Sant'Anna estimator. The results show short run decline in the foreclosure rates and a more permanent decline in the eviction rate. In the post periods, I find that households are more likely to caught up on mortgage and rent, with an increase in their confidence to pay mortgage / rent payments.

My results provide positive impact of the UI termination on housing outcomes.

As UI extensions were ended, two possible scenarios could occur at the household level. On one hand, their weekly income reduced by $300 which they were receiving under the extension. But, on the other side, this would also motivate job seekers to participate in the labor market and start working. If the earned wages are higher than the lost $300, households savings would go up. With the positive impact of UI termination on housing outcomes, it seems that the wages are higher.[19] However, the data does not provide further information on wages or current income to prove this claim. Future work should focus on combining wages and studying the impact of UI termination on housing market through the employment channel.

[19]Figure 3.9 shows an increase in working probability after the UI termination. To find comparison between wages and the housing payments, we need more detail on the wages side.

Figure 3.1: Unemployment Rate (Early vs Late States)

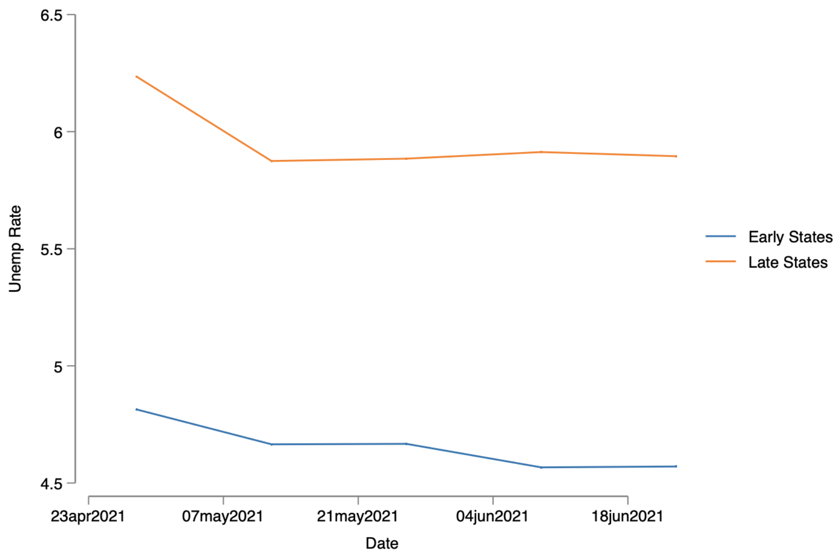


Figure 3.2: Eviction and Foreclosure Rates

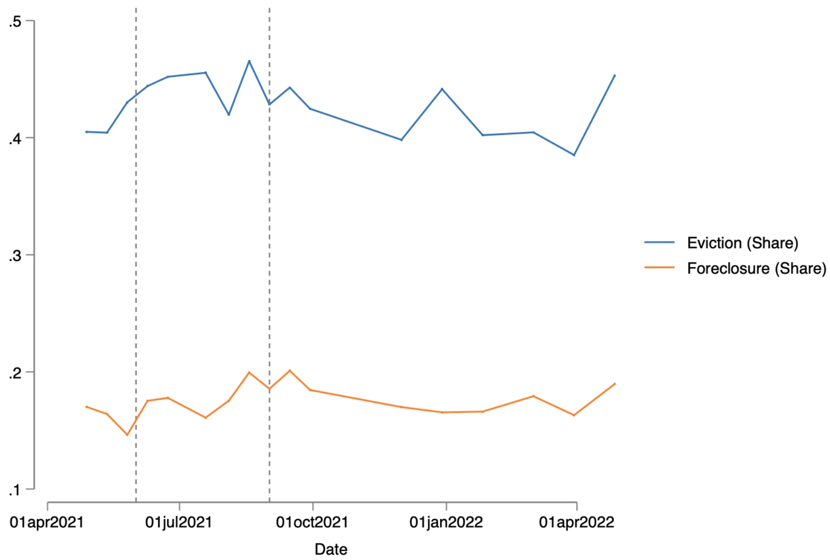


Figure 3.3: Eviction and Foreclosure Rates - Full Sample

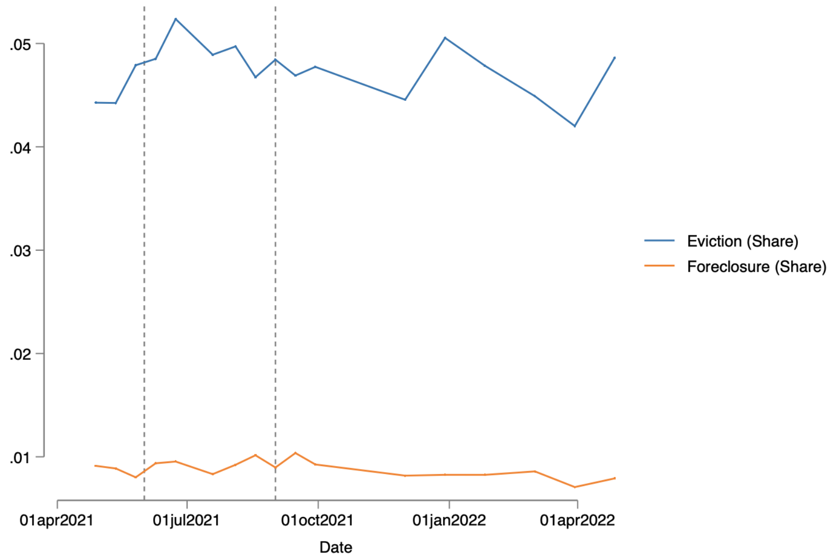


Figure 3.4: Eviction and Foreclosure Rates - Early vs Late States

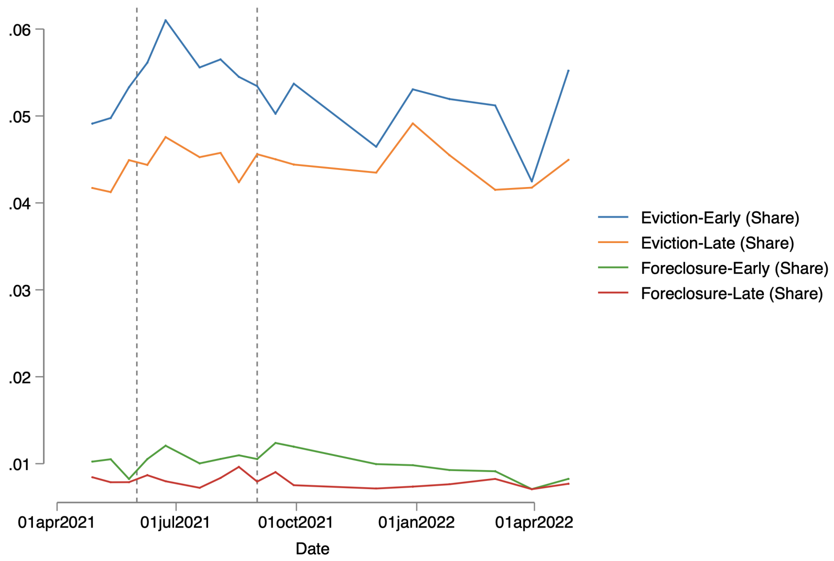


Figure 3.5: Caught up with Rent and Mortgage

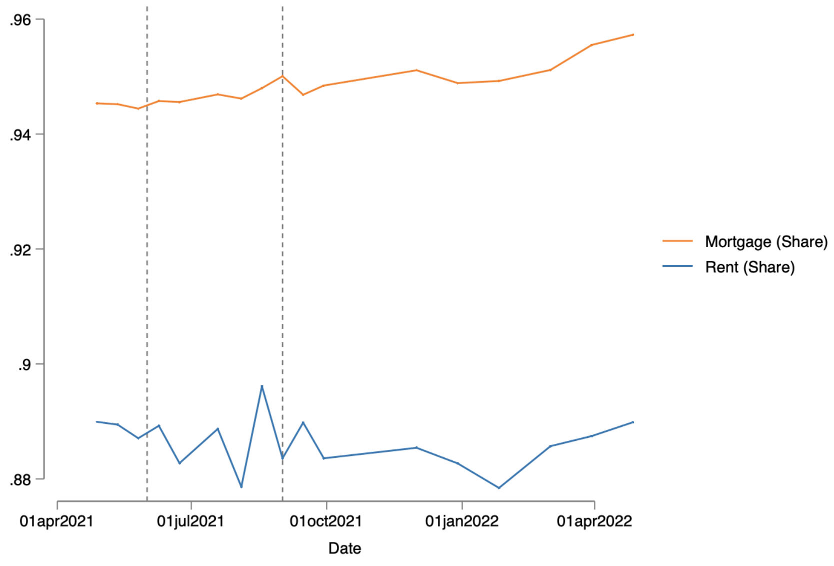


Figure 3.6: Caught up with Rent and Mortgage (Early vs Late States)

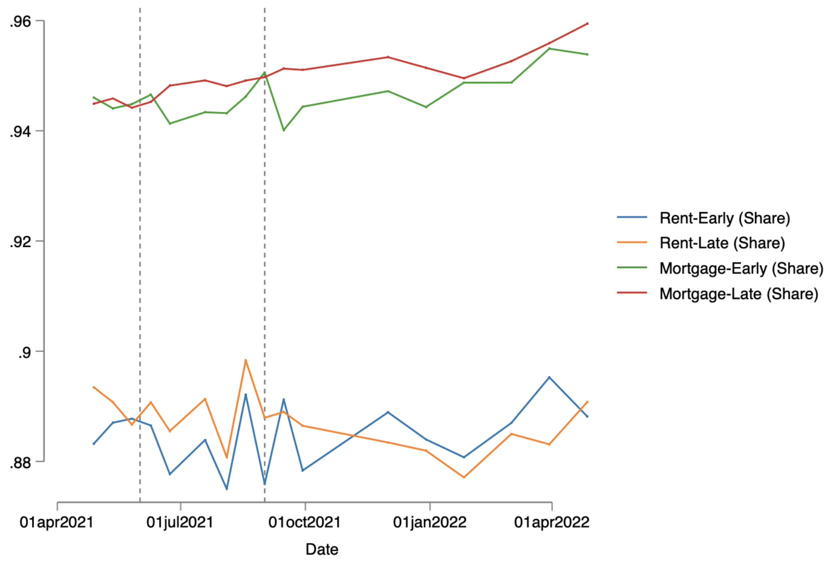
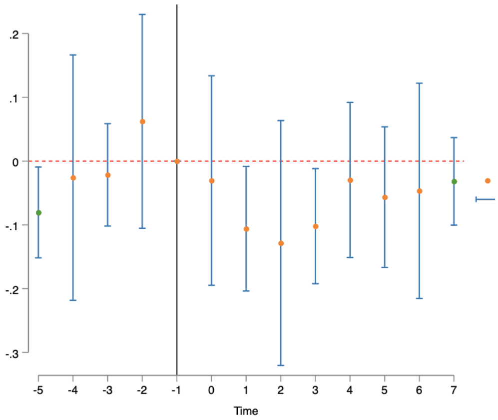
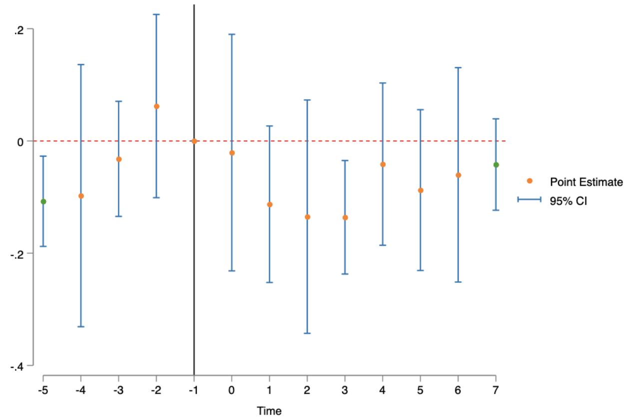


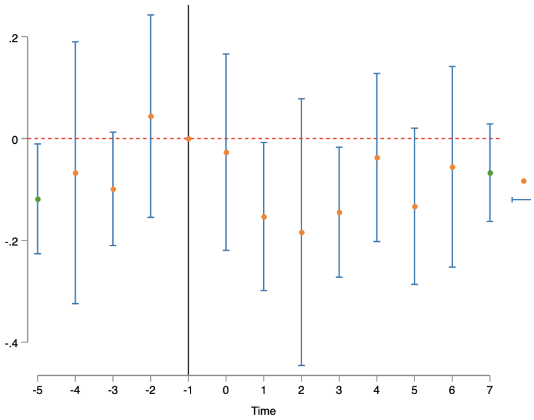
Figure 3.7: Foreclosure - TWFE



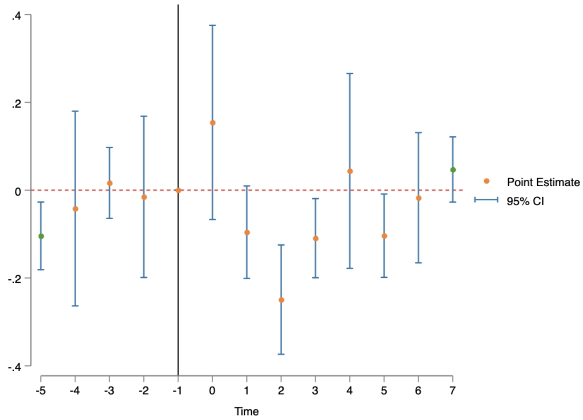
(a) Full Sample



(b) Non-Bachelors

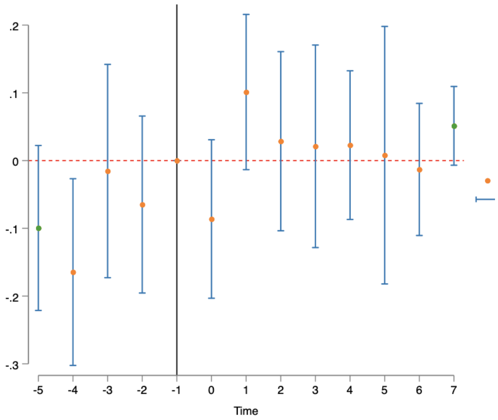


(c) Low Income

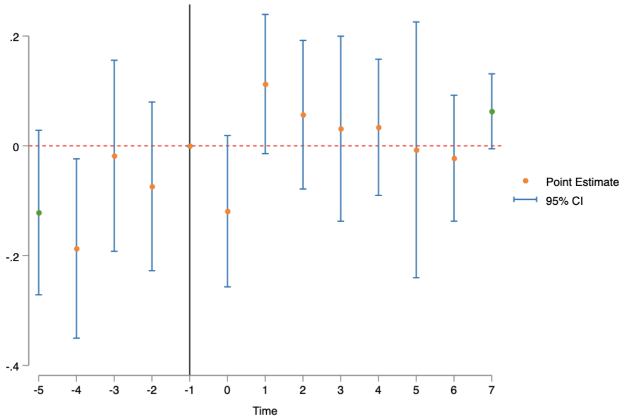


(d) Married

Figure 3.8: Eviction - TWFE



(a) Full Sample



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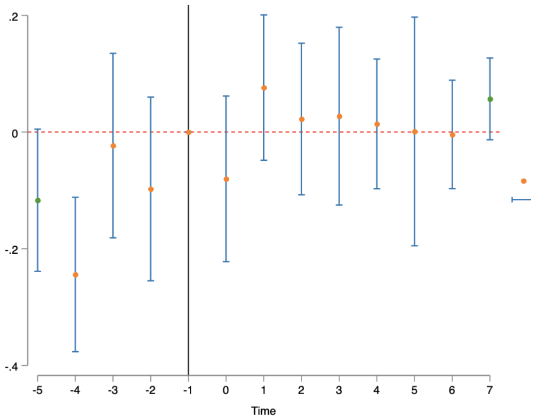

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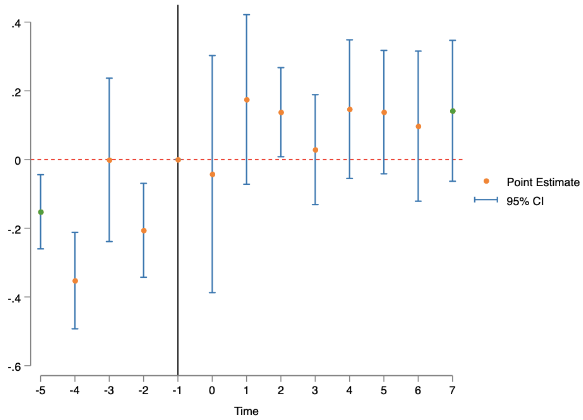


(d) Married

Figure 3.9: Work

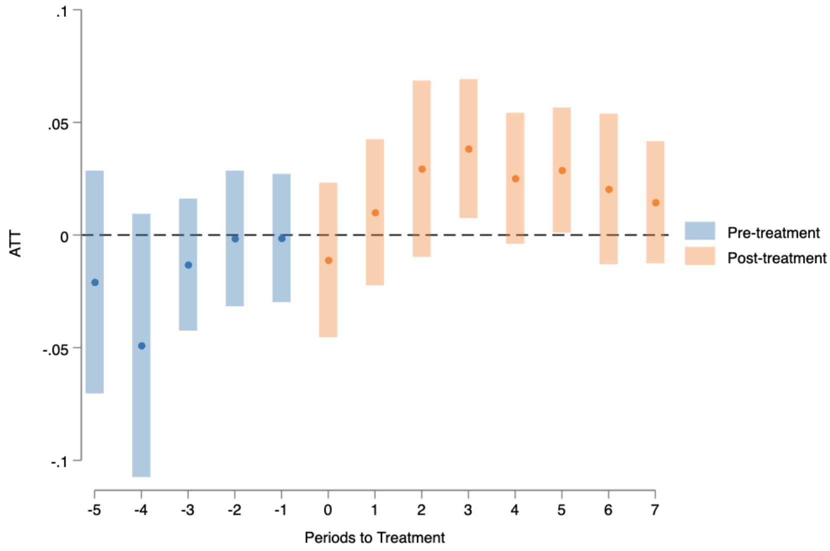
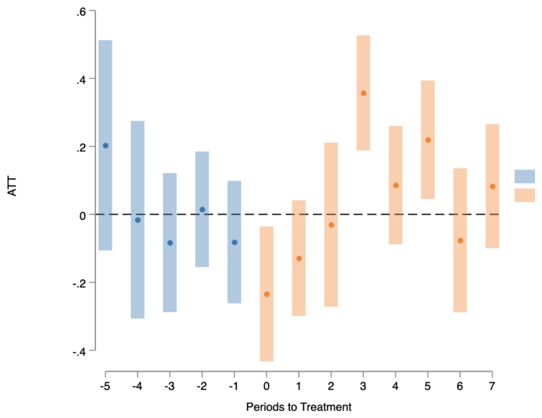
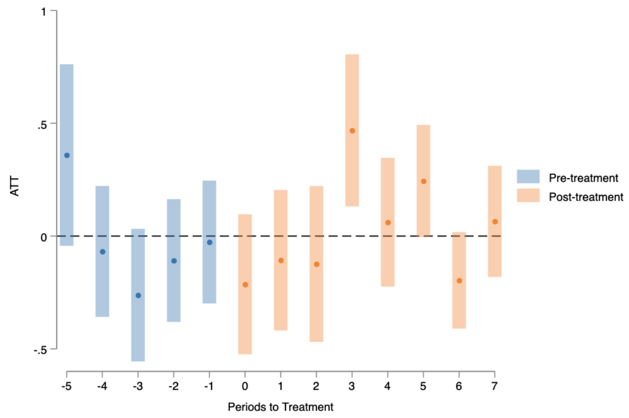


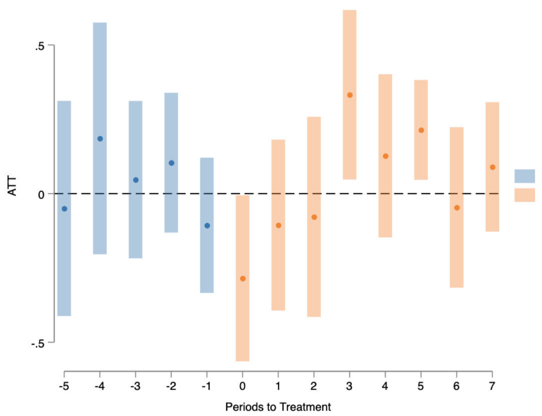
Figure 3.10: Foreclosure



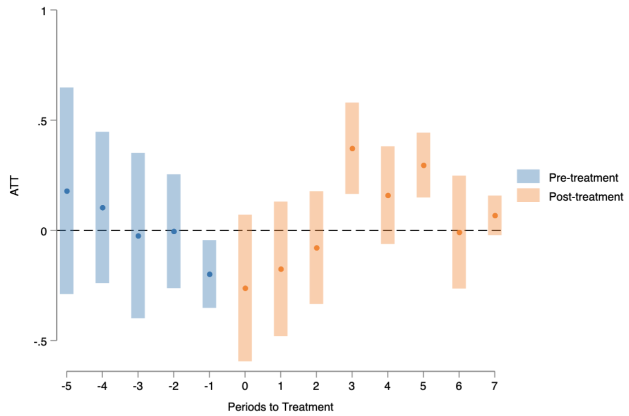
(a) Full Sample



(b) Non-Bachelors

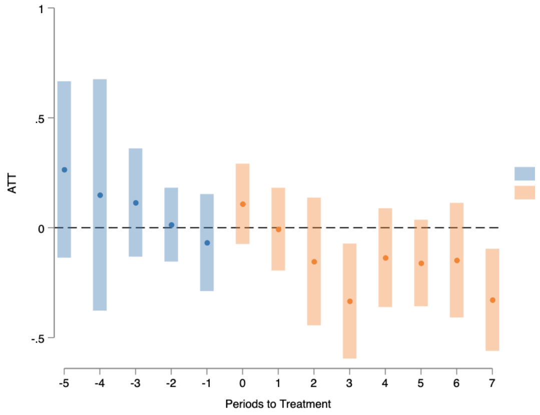


(c) Low Income

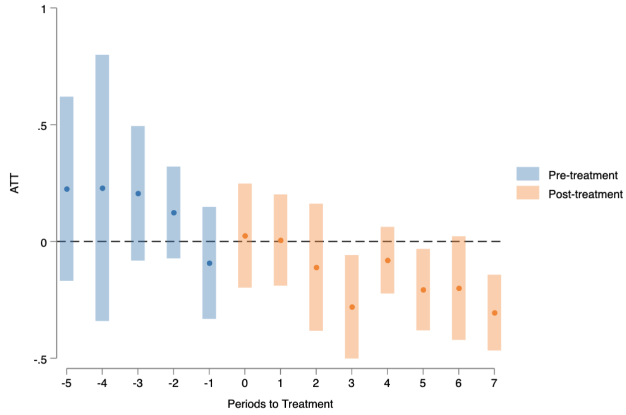


(d) Married

Figure 3.11: Eviction



(a) Full Sample



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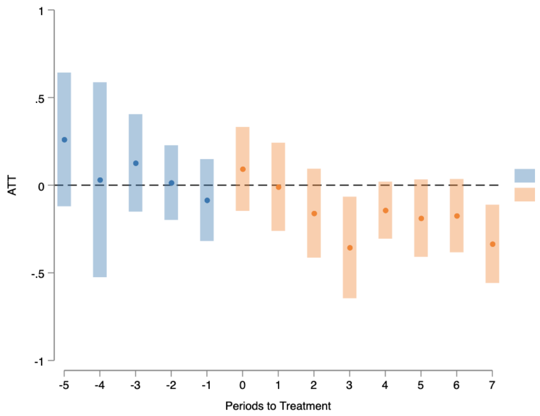
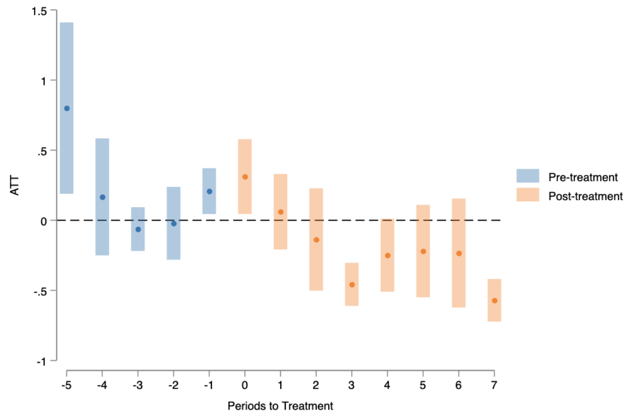
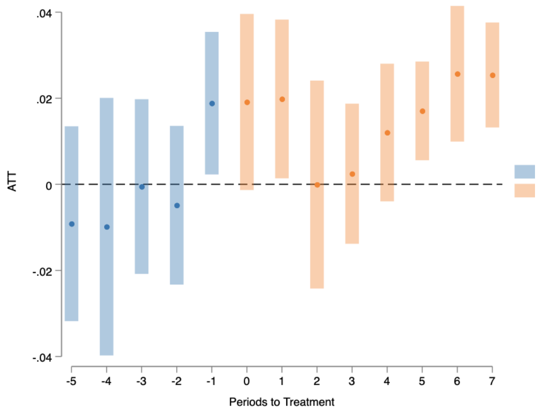


(c) Low Income



(d) Married

Figure 3.12: Mortgage / Rent Confidence



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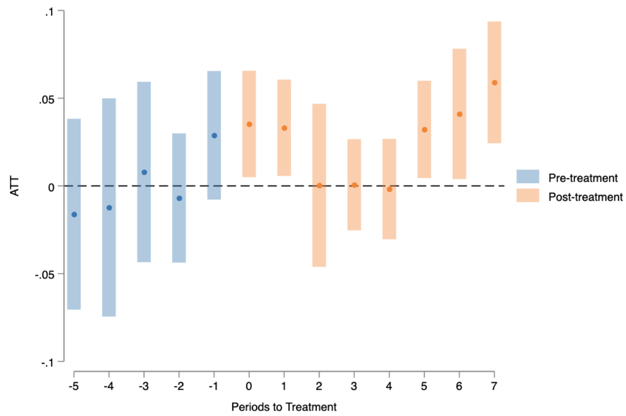

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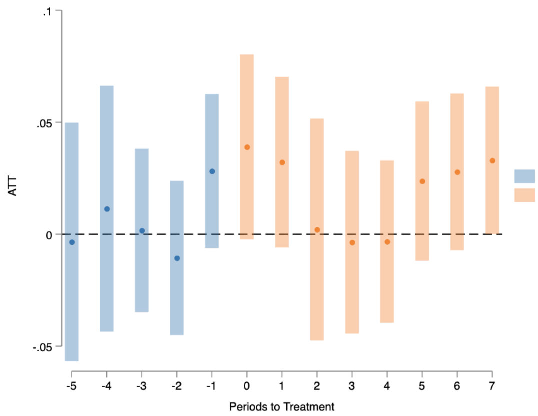

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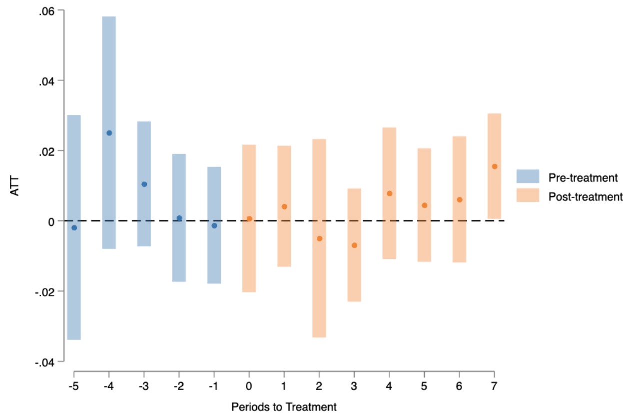
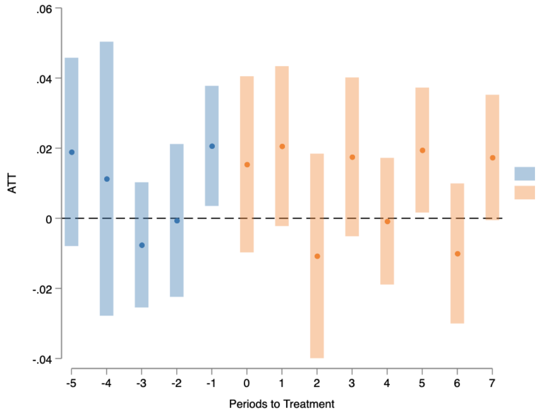
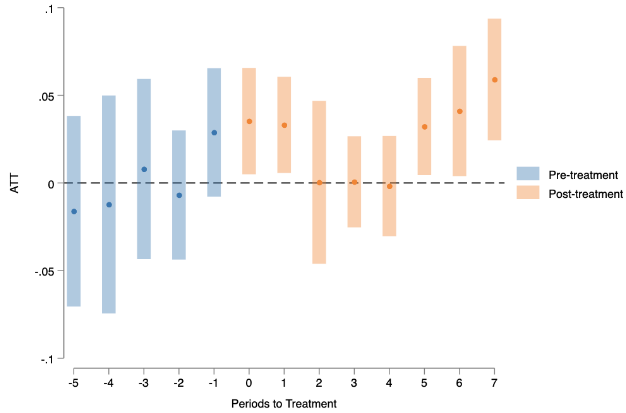


(d) Married

Figure 3.13: Caught up on Mortgage



(a) Full Sample



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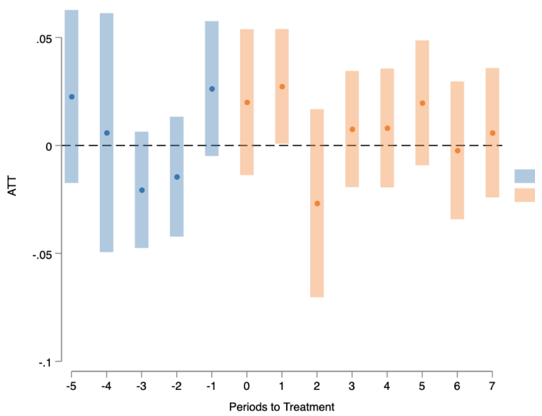
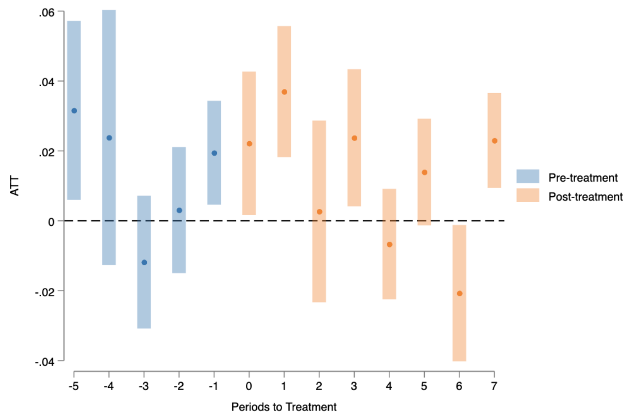
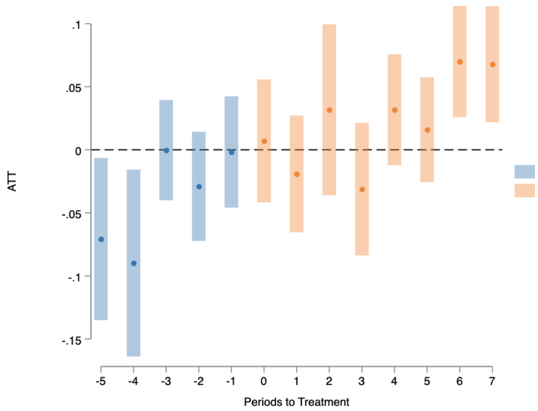


(c) Low Income

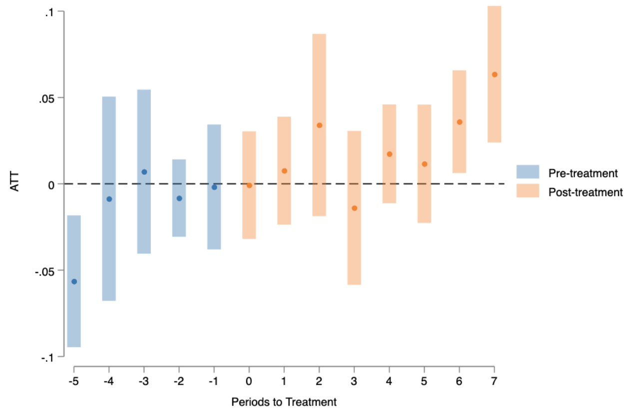


(d) Married

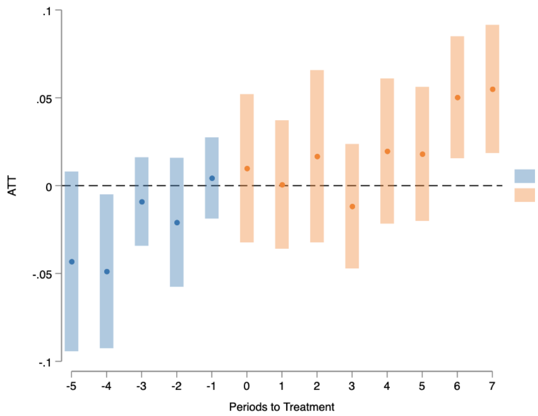
Figure 3.14: Caught up on Rent



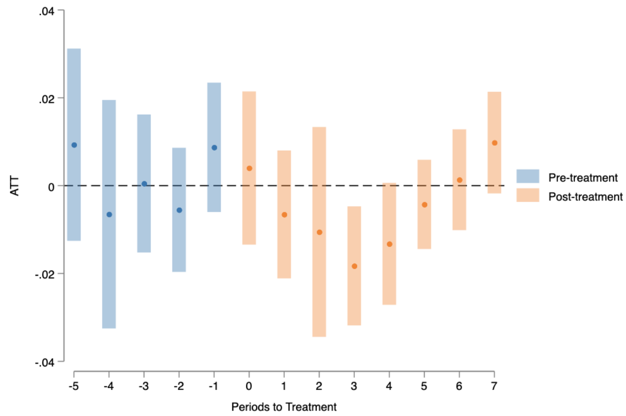
(a) Full Sample



(b) Non-Bachelors



(c) Low Income



(d) Married

Table 3.3: Summary Statistics

	Mean	SD	N
UI Benefit	851.56	322.30	331794
Replacement Rate	1.59	1.73	331794
Weekly Wage	23.18	16.70	331794
Unemp Rate	4.50	0.91	331794
Covid Deaths	5047.82	6006.65	331794
Household Size	2.65	1.45	331794
Age	53.58	15.58	331794
Bachelors (%)	58.57	49.52	331794
Mortgage / Rent Confidence (%)	95.41	1.34	331794
Caught up on Mortgage (%)	94.76	1.67	229003
Caught up on Rent (%)	88.73	3.14	102295
Eviction (%)	4.72	1.89	102082
$\text{Eviction}_{Restricted}$ (%)	42.91	11.18	9,201
Foreclosure (%)	0.88	0.49	228847
$\text{Foreclosure}_{Restricted}$ (%)	17.19	7.68	8,802

Note: This table includes the summary statistics of the main variables of interest. I include all of the individual characteristics along with the housing outcomes. All of the housing outcomes are in percentages.

Table 3.4: Home Owners

	(1) Caught up with Mortgage	(2) Mortgage / Rent Confidence	(3) Foreclosure (Restricted sample)	(4) Foreclosure (Full sample)
Panel A: No Unemployment				
Post	-0.00651	0.00160	-0.00191	0.00197
	(0.00683)	(0.00535)	(0.0205)	(0.00171)
Panel B: Unemployment as control				
Post	-0.0126**	-0.00269	-0.0144	0.00200
	(0.00586)	(0.00446)	(0.0196)	(0.00193)
Panel C: Unemployment as polynomial				
Post	-0.0122**	-0.00245	-0.0131	0.00194
	(0.00550)	(0.00425)	(0.0192)	(0.00192)
N	223849	339862	12782	223785
adj. R^2	0.060	0.076	0.055	0.027

This table shows the impact of UI termination on home-owners. Each regression controls for age, age squared, income, household size, marital status, race, education, and time fixed effect.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 3.5: Renters

	(1)	(2)	(3)	(4)
	Caught up with Rent	Mortgage / Rent Confidence	Eviction (Restricted sample)	Eviction (Full sample)
Panel A: No Unemployment				
Post	0.00496	0.00239	0.153***	0.0259***
	(0.0143)	(0.00657)	(0.0345)	(0.00453)
Panel B: Unemployment as control				
Post	0.00648	-0.00260	0.142***	0.0224***
	(0.0102)	(0.00560)	(0.0241)	(0.00482)
Panel C: Unemployment as polynomial				
Post	0.00256	-0.00472	0.162***	0.0268***
	(0.0104)	(0.00496)	(0.0178)	(0.00438)
N	61747	161564	7425	61705
adj. R^2	0.075	0.075	0.046	0.048

This table shows the impact of UI termination on renters. Each regression controls for age, age squared, income, household size, marital status, race, education, and time fixed effect.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 3.6: Home Owners

	(1)	(2)	(3)	(4)
	Caught up with Mortgage	Mortgage / Rent Confidence	Foreclosure (Restricted sample)	Foreclosure (Full sample)
Panel A: No Unemployment				
Mortgage Share*Post	-0.119*	-0.0188	0.608**	0.0555**
	(0.0680)	(0.0346)	(0.299)	(0.0270)
Panel B: Unemployment as control				
Mortgage Share*Post	-0.102	-0.0101	0.689**	0.0574**
	(0.0760)	(0.0366)	(0.287)	(0.0275)
Panel C: Unemployment as polynomial				
Mortgage Share*Post	-0.209**	-0.0750	0.548*	0.0719**
	(0.102)	(0.0459)	(0.279)	(0.0305)
N	221105	334704	12676	221041
adj. R^2	0.061	0.077	0.057	0.027

This table includes the interaction of post with mortgage share. Each regression controls for age, age squared, income, household size, marital status, education, and time fixed effect.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 3.7: Renters

	(1) Caught up with Rent	(2) Mortgage / Rent Confidence	(3) Eviction (Restricted sample)	(4) Eviction (Full sample)
Panel A: No Unemployment				
Rent Share*Post	-0.0435	0.0225	-0.247	-0.0214
	(0.0473)	(0.0236)	(0.193)	(0.0416)
Panel B: Unemployment as control				
Rent Share*Post	-0.0403	0.0307	-0.249	-0.0224
	(0.0430)	(0.0251)	(0.204)	(0.0394)
Panel C: Unemployment as polynomial				
Rent Share*Post	-0.0957*	0.000733	-0.160	0.0154
	(0.0561)	(0.0338)	(0.202)	(0.0424)
N	119671	339862	14622	119598
adj. R^2	0.082	0.077	0.044	0.054

This table includes the interaction of post with rent share. Each regression controls for age, age squared, income, household size, marital status, education, and time fixed effect.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 3.8: Home Owners

	(1) Caught up with Mortgage	(2) Mortgage / Rent Confidence	(3) Foreclosure (Restricted sample)	(4) Foreclosure (Full sample)
R_{median}	0.271**	0.132***	-0.0489	-0.0449*
	(0.105)	(0.0468)	(0.235)	(0.0241)
Post	0.0204	0.0299	-0.244***	-0.0177
	(0.0258)	(0.0179)	(0.0829)	(0.0111)
R_{median}*Post	-0.125*	-0.129**	0.851***	0.0727*
	(0.0726)	(0.0603)	(0.304)	(0.0366)
Unemp Rate	0.00192	0.000331	-0.00564	-0.00105
	(0.00345)	(0.00161)	(0.00678)	(0.000770)
N	160194	158288	9676	160148
adj. R^2	0.063	0.054	0.061	0.029

This table includes the interaction of post and median replacement rate change in each state. Each regression controls for age, age squared, income, race, household size, marital status, education, and time fixed effect.
Standard errors in parentheses
* $p < .10$, ** $p < .05$, *** $p < .01$

Table 3.9: Renters

	(1) Caught up with Rent	(2) Mortgage / Rent Confidence	(3) Eviction (Restricted sample)	(4) Eviction (Full sample)
R_{median}	0.375	0.183**	1.526***	0.0855
	(0.218)	(0.0730)	(0.381)	(0.0689)
Post	0.0476	-0.0145	0.345	0.0374
	(0.0442)	(0.0253)	(0.209)	(0.0228)
R_{median}*Post	-0.154	0.0331	-0.770	-0.0568
	(0.149)	(0.0908)	(0.739)	(0.0823)
Moratorium	0.00323	0.0106*	-0.0535***	-0.00929*
	(0.0142)	(0.00547)	(0.0169)	(0.00499)
Unemp Rate	0.00818*	0.00147	0.0227***	-0.000470
	(0.00419)	(0.00203)	(0.00650)	(0.00138)
N	54181	53595	6705	54143
adj. R^2	0.074	0.066	0.053	0.048

This table includes the interaction of post and median replacement rate change in each state. Each regression controls for age, age squared, income, race, household size, marital status, education, and time fixed effect.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Heterogeneous Analysis

Table 3.10: Home Owners - Unemployed Sample

	(1)	(2)	(3)	(4)
	Caught up with Mortgage	Mortgage / Rent Confidence	Foreclosure (Restricted sample)	Foreclosure (Full sample)
Mortgage Share*Post	-0.166	0.0309	0.634*	0.119*
	(0.181)	(0.0827)	(0.342)	(0.0646)
N	40197	71804	4318	40170
adj. R^2	0.054	0.070	0.062	0.034

This table includes the interaction of post and mortgage share, while only including the unemployed people. Each regression includes age, age squared, income, race, household size, marital status, education, and time fixed effects.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 3.11: Renters - Unemployed Sample

	(1)	(2)	(3)	(4)
	Caught up with Rent	Mortgage / Rent Confidence	Eviction (Restricted sample)	Eviction (Full sample)
Rent Share*Post	-0.115	-0.0506	-0.499	-0.0364
	(0.181)	(0.0644)	(0.316)	(0.0937)
N	17325	35741	3583	17304
adj. R^2	0.055	0.067	0.046	0.044

This table includes the interaction of post and rent share, while only including the unemployed people. Each regression includes age, age squared, income, race, household size, marital status, education, and time fixed effects.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 3.12: Home Owners - Subgroup Analysis

	(1) Caught up with Mortgage	(2) Mortgage / Rent Confidence	(3) Foreclosure (Restricted sample)	(4) Foreclosure (Full sample)
Panel A: Low Income				
Mortgage Share*Post	-0.149	0.0395	0.861***	0.127*
	(0.160)	(0.0586)	(0.272)	(0.0644)
N	65094	145622	7856	65055
adj. R^2	0.036	0.056	0.053	0.024
Panel B: Married				
Mortgage Share*Post	-0.0776	-0.00652	0.731	0.0390
	(0.105)	(0.0459)	(0.638)	(0.0265)
N	156252	193041	7448	156217
adj. R^2	0.066	0.074	0.054	0.028
Panel C: Non - Bachelors				
Mortgage Share*Post	-0.138	-0.00953	0.917**	0.0964**
	(0.128)	(0.0495)	(0.354)	(0.0447)
N	79724	139738	7082	79683
adj. R^2	0.053	0.065	0.047	0.024

This table includes the interaction of post and mortgage share, while focusing on the subgroups of married, non-bachelors, and low-income individuals. Each regression includes age, age squared, income, race, household size, marital status, education, and time fixed effects.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 3.13: Renters - Subgroup Analysis

	(1) Caught up with Rent	(2) Mortgage / Rent Confidence	(3) Eviction (Restricted sample)	(4) Eviction (Full sample)
Panel A: Low Income				
Rent Share*Post	-0.000899	-0.00566	-0.156	-0.0412
	(0.0868)	(0.0357)	(0.327)	(0.0585)
N	41054	68256	6505	41017
adj. R^2	0.058	0.051	0.045	0.041
Panel B: Married				
Rent Share*Post	-0.128	0.0258	0.683	0.132
	(0.118)	(0.0572)	(0.745)	(0.130)
N	20668	90655	2287	20650
adj. R^2	0.069	0.078	0.084	0.049
Panel C: Non - Bachelors				
Rent Share*Post	0.0177	-0.0366	-0.343	-0.0766
	(0.116)	(0.0409)	(0.384)	(0.0755)
N	31079	65885	5300	31049
adj. R^2	0.058	0.063	0.035	0.039

This table includes the interaction of post and rent share, while focusing on the subgroups of married, non-bachelors, and low-income individuals. Each regression includes age, age squared, income, race, household size, marital status, education, and time fixed effects.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 3.14: Home Owners

	(1) Caught up with Mortgage	(2) Mortgage / Rent Confidence	(3) Foreclosure (Restricted sample)	(4) Foreclosure (Full sample)
Mortgage Share*Post	-0.103	-0.0116	0.621**	0.0530*
	(0.0692)	(0.0344)	(0.304)	(0.0269)
Emp to pop ratio	0.208***	0.107**	0.0988	-0.0327*
	(0.0731)	(0.0481)	(0.180)	(0.0184)
N	221105	334704	12676	221041
adj. R^2	0.061	0.077	0.056	0.027

This table includes the interaction of post and mortgage share, while using employment-to-population ratio. Each regression controls for age, age squared, income, race, household size, marital status, education, and time fixed effect.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

Table 3.15: Renters

	(1)	(2)	(3)	(4)
	Caught up with Rent	Mortgage / Rent Confidence	Eviction (Restricted sample)	Eviction (Full sample)
Rent Share*Post	-0.0329	0.0260	-0.251	-0.0269
	(0.0477)	(0.0222)	(0.195)	(0.0419)
Emp to pop ratio	0.308**	0.102**	-0.155	-0.161***
	(0.119)	(0.0452)	(0.310)	(0.0462)
N	119671	339862	14622	119598
adj. R^2	0.082	0.077	0.043	0.054

This table includes the interaction of post and rent share, while using employment-to-population ratio. Each regression controls for age, age squared, income, race, household size, marital status, education, and time fixed effect.

Standard errors in parentheses

* $p < .10$, ** $p < .05$, *** $p < .01$

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Appendix A

SEARCH MODEL AND ALTERNATE SHIFT MEASURES

A.1 Search Model

I use the search model proposed by Mortensen and Pissarides, similar to the one used in Blien et al. (2012). In the model, firms and workers meet with each other where firms are maximizing their profits while workers search to maximize their lifetime utility. The match happens through Nash bargaining where surplus is divided between firms and workers.

Firms

Each firm decides to create a job in the economy in two ways. First, the decision to create an opening in the economy is defined by the following equations:

$$rV = -c + q(\frac{v}{u})(J - V) \tag{A.1}$$

Secondly, the occupied job will have the following form:

$$rJ = p - w - sJ \tag{A.2}$$

In these equations J is the capitalized value of an occupied job and V is the value of a vacancy, r is the interest rate, p the product of a single worker, w the wage, v the vacancy rate and u the unemployment rate. s is the separation rate, which is calculated for occupied jobs, c is the cost of search during the time a vacancy is open, q is a special form of the aggregate labor market matching function: $m(\frac{u}{v}, 1) = q(\frac{u}{v})$. The function m describes the matches formed in the economy.

Workers

The workers problem is defined by the following:

$$rW = w - s(W - U) \tag{A.3}$$

$$rU = z + (\frac{v}{u})q(\frac{v}{u})(W - U) \tag{A.4}$$

Here, W are the expected returns from holding a job and U those of being unemployed. z comprises unemployment assistance and the non-monetary aspects of leisure. In the matching approach, a single firm and an individual worker negotiate about the size of the wage. Since it is assumed that they meet each other pair-wise, they form a double-sided monopoly, which is described as a Nash bargaining problem:

$$w = max\Big[(W - U)^{\beta}(J - V)^{1-\beta}\Big] \tag{A.5}$$

The first order condition is:

$$W - U = \beta(J + W - V - U) \tag{A.6}$$

Equation (A.6) shows that the solution strongly depends on the parameter β which indicates the relative bargaining strength of the two parties.
Now, nearly all material is at our disposal to construct on the one hand a wage curve and on the other hand an expression for reservation wages. The latter one is already defined by equation (A.4), since this describes the lower threshold for wages. If wages are higher than rU, workers are available for working. To derive expressions for market wages and reservation wages, which could be estimated, a further assumption is needed. It is assumed that in (A.1) vacancy creation exhausts all available profits, therefore V is assumed to be zero. Then, (A.1) can be transformed to the so-called job creation condition:

$$\frac{p - w}{r + s} = \frac{c}{q(\frac{v}{u})} \tag{A.7}$$

(A.7) holds if $V = 0$. Now, I can write (A.4) to calculate the reservation wage R:

$$R = rU = z + \frac{\beta}{1-\beta} c(\frac{v}{u}) \tag{A.8}$$

Similarly, the market wage equation is follows:

$$w = (1-\beta)z + \beta\left(p + c(\frac{v}{u})\right) \tag{A.9}$$

Equation (A.8) and (A.9) are an increasing function of market tightness $\frac{v}{u}$ and a decreasing function of unemployment rate u. According to Pissarides (2000), the steady-state equilibrium equations are defined as follows:

$$u = \frac{s}{s + \theta q(\theta)} \tag{A.10}$$

$$p - w - \frac{(r+s)c}{q(\theta)} = 0 \tag{A.11}$$

$$w = (1-\beta)z + \beta\left(p + c(\frac{v}{u})\right) \tag{A.12}$$

Equation (A.11) is the job creation curve, while equation (A.12) is the wage curve. Figure (a) shows the unique equilibrium for wages and tightness, where higher wage rates induces less profitable job creation which leads to a lower ratio of jobs to workers. As a result, job creation slopes downward. Similarly, at higher market tightness, workers have more bargaining strength which makes the wage curve slopes upward. In combination, these two curves intersect to give the unique equilibrium (θ, w).

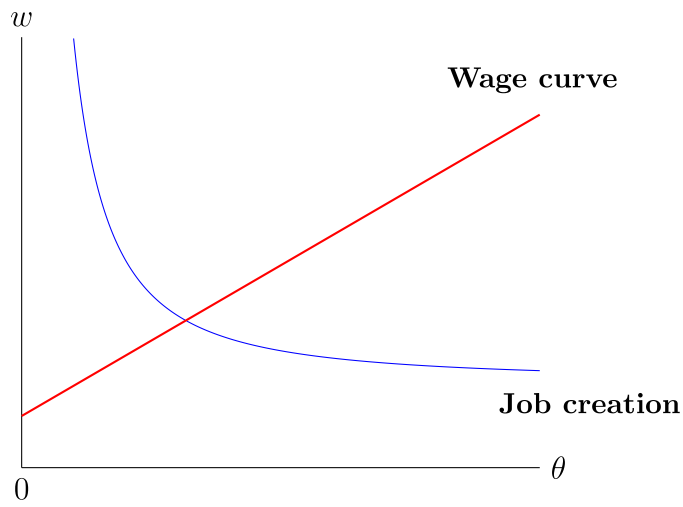

Figure (a): Equilibrium

wages and market tightness

In figure (a), the equilibrium θ is independent of the unemployment. We can solve for the θ by substituting wages from (A.12) into (A.11), which generates the following equation:

$$(1-\beta)(p-z) - \frac{\Big(b\theta q(\theta) + (r+s)\Big)c}{q(\theta)} = 0 \tag{A.13}$$

In the vacancy-unemployment space of figure (b), this is given by the line through the origin, with slope θ. The steady-state unemployment rate is given by equation (A.10), which is the Beveridge curve. It is convex to the origin because of the properties of the matching technology.

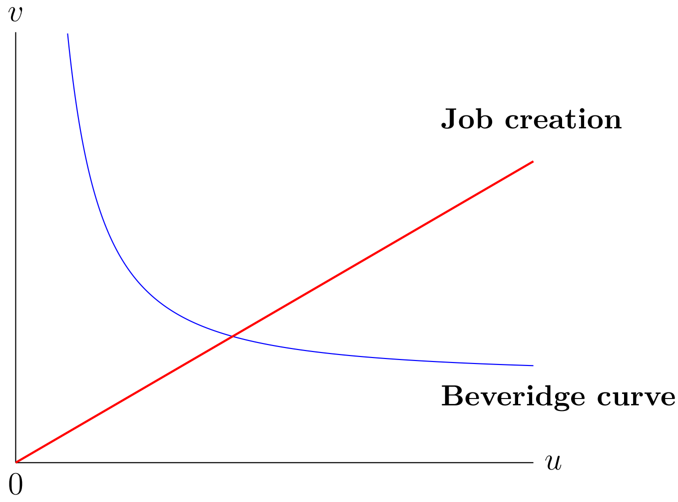

Figure (b): Equilibrium vacancies and unemployment

Important Relations

In an environment with exogenous job separation rate s, figures (a) and (b) show the unique equilibrium of θ and u. As exogenous job separate rate changes, the reservation wage will fluctuate as well, according to the equation given below:

$$\frac{\partial R}{\partial s} = rU = \frac{\beta}{1-\beta}c\left(\frac{\partial \theta}{\partial s}\right) \tag{A.14}$$

$$\frac{\partial R}{\partial s} = -\frac{(p-z)-\beta c\theta}{\gamma(r+s)} < 0 \tag{A.15}$$

In equation A.14, the direction of the relationship depends on the $\frac{\partial \theta}{\partial s}$ term. With $\frac{\partial \theta}{\partial s} < 0$, the whole equation is negative as well.[1] With unemployment closely related to separation rate in eq (A.10), it will also have a negative relation with

[1]In the model, $\theta = \frac{v}{u}$ and $q(\theta) = \theta^{1-\gamma}$. The sign of the relation depends on the numerator, which includes $\frac{\partial \theta}{\partial s}$. Using figure (a) and equation A.11, $\frac{\partial \theta}{\partial s} = -\frac{(1-\beta)(p-z)-\beta c\theta}{\gamma(r+s)c\beta} < 0$. In Pissarides (2000), job separation rate is denoted by λ, while in my model, s represents the job destruction rate.

the reservation wage. Using the same logic, job creation / vacancies will be positively related to the reservation wage. While, higher market tightness also increases the reservation wage.[2]

Apart from the steady-state solution, I can obtain the following relations using the close-form equation of the reservation wage from Blien et al. (2012):

$$\frac{\partial R}{\partial u} = -\frac{\beta}{1-\beta}c(\frac{v}{u^2}) < 0 \tag{A.16}$$

$$\frac{\partial R}{\partial \theta} = \frac{\beta}{1-\beta} * c > 0 \tag{A.17}$$

$$\frac{\partial R}{\partial v} = \frac{\beta}{1-\beta} * \frac{c}{u} > 0 \tag{A.18}$$

where $\theta = \frac{v}{u}$. These equations also confirm the earlier reservation wage relation with other macroeconomic indicators. Overall, the model has the following theoretical predictions:

- Reservation wage decrease with unemployment rate
- Reservation wage increase with market tightness
- Reservation wage increase with vacancies
- Reservation wage decrease with job separation rate

A.2 Alternate Shift Measures

For alternate shift measures, I use the log of employment compared to the national growth rate of employment. The industry specific measure is given below:

$$Shift\ measure_{st} = \sum_j w_{jsb} * log(L_{jt})$$

where w_{jsb} denotes the employment share of industry j in state s in the baseline period, which I define as January of 2016. L_{jt} denotes the national employment level of industry j in period t.

[2] Figure (a) demonstrates that job creation and market tightness move in the same direction, resulting in an upward shift in wages.

Similarly, the industry-group specific measure is defined as follows:

$$Shift\ measure_{sgt} = \sum_j w_{gjsb} * log(L_{gjt})$$

where w_{gjsb} denotes the employment share of group g of industry j within state s in the baseline period, which I define as January of 2016. L_{gjt} denotes the national employment level of group g within industry j in period t.
Lastly, the following equation define the group specific measure:

$$Shift\ measure_{st} = \sum_g w_{gsb} * log(L_{gt})$$

where w_{gsb} denotes the employment share of group g in state s in the baseline period, which I define as January of 2016. L_{gt} denotes the national employment level of group g in period t.