ESSAYS ON MAJOR CHOICE, EMPLOYMENT, AND HOUSING PRICE

by

Yiran Duan

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

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ABSTRACT

This study examines three key areas where economic policy intersects with development: the influence of international student enrollments on the academic major choices of domestic students in the U.S., the effects of high-speed railroad infrastructure on employment in China, and the influence of monetary policy on housing prices in China. Each area provides insight into the broader effects of economic policies in a globally interconnected environment.

The first section of the dissertation assesses how international student enrollment in higher education institutions affects the choice of majors by domestic students. As a leading destination for international students, the U.S. relies heavily on the tuition fees they provide, which becomes crucial for maintaining university operations, particularly when financial resources are constrained. The study specifically investigates the aftermath of the 2008 financial crisis and its impact on domestic students' choice of majors. Data reveals an associated increase in domestic student enrollment with the rise of international student numbers, which is align with other research in this area. This paper revealed that the distribution of this impact is not uniform across all fields of study, majors such as Engineering, Business, and Physical/Life Sciences see a positive correlation, whereas Mathematics displays a decline, suggesting a crowding-out effect possibly due to increased competition. A further analysis of this trend through demographic lenses, such as ethnicity and gender. This study associates a thorough understanding of how international student presence within U.S. higher education influences domestic students' academic preferences. The study contributes to the discussion on the role of international students in U.S. education, with a focus on undergraduate levels as opposed to the graduate levels, which is more frequently

studied. It seeks to clarify the influence of international students on domestic students' selection of majors within U.S. universities.

The second topic investigates the transformative role of high-speed railroad (HSR) infrastructure on employment in China, a country that has rapidly expanded its HSR network to be the largest in the world. This paper studies the impact of high-speed-railway (HSR) on employment in China by utilizing data from the China Regional Employment Statistics Yearbooks (2005-2017) and the Chinese Research Data Services Platform (CNRDS). Employing the CSDID method developed by Callaway and Sant'Anna (2020), we identify the treatment effect of HSR on local employment and find that HSR on average increases employment by 6.8%. This paper further shows heterogeneity in the impact of HSR on different types of employment. HSR on average contributes to 14% rise in self-employment and employment in private businesses, whereas the impact of HSR on employment in public sector or state-owned firms is insignificant. Our interpretation suggests that HSR stimulates industries like retail, catering, travel, and hospitality, where private employment is concentrated where the more pronounced impact on private employment. This is supported by empirical evidence within the retail industry.

Lastly, this study examines the relationship between monetary policy and housing prices in China. China's house-to-income ratio ranks among the top ten globally, with several of its tier one cities positions in the top ranking in international comparisons. The elevated levels of housing costs are associated with significant economic and sociological effects, including increased rates of divorce, decreased fertility rates, and reduced marriage rates. The macroeconomic literatures suggests that one potential drive for escalated housing prices may be attributed to the excessive issuance of M2, indicative of a heightened money supply. Through the application of an exclusion restriction, the impact of different monetary policies on housing prices is shown to be consistent with the established economic principles. This analysis reveals that expansionary monetary policies are correlated with a surge in housing prices. Moreover, the response to monetary policy shocks exhibits regional variance within China:

in the eastern region, such shocks influence the demand aspect of the housing market, whereas in the mid-region, the supply side is more significantly affected. This differentiation provide evidence for policymakers to craft and implement strategies aimed at tempering housing prices, informed by these regional dynamics.

Chapter 1

EFFECT OF UNDERGRADUATE INTERNATIONAL ENROLLMENT INCREASE ON DOMESTIC MAJOR CHOICE

1.1 Introduction

A detailed report by the U.S. Department of Commerce's Bureau of Economic Analysis show that in the year 2018, the export of educational services ranked the 5th position among service exports. In the academic year of 2017/2018 shows that the U.S. welcomed over one million international students. This influx of students contributed significantly to the economy, with the reported revenue from education exports of $45.3 billion. This economic contribution, as highlighted by the US Department of Commerce's Bureau, played a crucial role in employment sector, endorsing over $455,000$ U.S. jobs (US Department of Commerce, 2016.export.gov/industry/education). The financial contributions of these international students, primarily through tuition fees, serve as a lifeline for numerous educational institutions, particularly when they are confronted with fiscal challenges. After the 2008 financial crisis, which severely affected funding, many institutions started recruiting more international students as a financial strategy. This move exploits the countercyclical nature of tuition fees, where countries with growing economies can afford to send more students abroad, often to prestigious U.S. universities. This countercyclical trend presents nations experiencing an uptrend in their Gross Domestic Product (GDP) with an opportunity to seek quality education from American institutions. As these countries get wealthier, they're better able to support and motivate their people to go to college in the United States, for the better education in those globally well-known universities.

Majority international students cannot access the usual financing options or scholarships available to domestic or in-state students, they typically pay "sticker price" tuition fees, which can be more than double the in-state rates. This situation is more sever in the undergraduate level. Many of these international students come from countries where local institutions are not highly ranked globally, making U.S. education an attractive alternative because of its diversity and high-ranking universities. Normally such institutions require much higher competition to get into in their country of origin. In this context, pursuing of American education, with its diverse range of highly ranked universities, becomes an attractive alternative for these students. It is reflecting both the perceived quality and international prestige associated with American higher education. An illustrative data point from the National Center for Enrollment Statistics (2018) highlights this trend: "Between 1980 and 2017, the total number of foreign students enrolling in U.S. educational institutions surged, witnessing a more than threefold increase from 305,000 to over one million students in 2017". In the realm of recent international student inflows, China emerges as a dominant player. Shen (2016) illuminated a dramatic surge in Chinese student enrollment over a decade. Specifically, the issuance of F1 visas for Chinese students witnessed a tenfold increment, soaring from $25,635$ in 2005 to a staggering $278,992$ in 2015, 10 times growth in 10 years. Presently, Chinese students constitute more than a third of the total international student body in the U.S., firmly establishing China as the principal source nation for both undergraduate and graduate international students seeking American education (see Figure 1.1).

Higher education institutions operating under a non-profit framework, they maintain an equilibrium between revenue generation and expenditure. The higher education institutions primary objectives are increasing educational standards, attracting academically superior students, and achieving higher institutional rankings. As these rankings improve, institutions become more attractive, they will be able to enroll both higher quantity and quality of students. Chen (2021) claims that "a public university's strategic considerations encompass both in-state enrollment and overall educational quality, all the while balancing capacity and budgetary constraints. An upward trend in international student enrollment at these public universities not only augments tuition revenue but also has implications for the dual objectives of student quality and educational excellence."

Higher education institutions often confront a dilemma: choosing between domestic and international student enrollments, with international students generate more revenue to achieve the goals. An increase in international enrollments could potentially boost institutional revenues, which can be strategically channeled either towards subsidizing domestic student costs or enhancing overall educational quality. Many literatures in this area examining the dynamics of international enrollment, suggests that an increase in international students doesn't necessarily "crowed out" domestic students. Instead, it provides a form of cross-subsidization, meaning increased international enrollment often enhances the institution's financial capacity, thereby indirectly promoting domestic student enrollment. As Shih (2017) pointed, "Foreign students, through their substantial tuition contributions, indirectly finance the enrollment of additional domestic students." Chen (2021) further supported this point, stating, "Institutions witnessing pronounced growth in international students have managed to augment in-state enrollment. Every additional international freshman indirectly catalyzes the enrollment of 2.2 in-state freshmen at US public universities."

For the enrollment prospect, certain academic disciplines are more attractive to international students than others. These preferences often arise from different factors, most importantly the labor market prospects in both the host and home countries, and the academic proficiency of the students themselves. Data reveals that a significant 52% of international students gravitate towards STEM disciplines. This inclination towards STEM could be attributed to the extended Optional Practical Training (OPT) period it offers, enhancing their chances in the H1B lottery upon employment. The GAO highlights that international students constitute approximately one-third of the STEM master's and doctoral cohorts in the U.S., significantly supporting the U.S. STEM workforce. The NAS (2007) further sheds light on this trend, noting that more than 67% of engineering doctorates from U.S. institutions are awarded to non-U.S.

citizens. Moakler Jr and Kim (2014) suggest another perspective, positing that international students have to go through a very competitive admission processes, this might have strengthened their academic self-confidence, making them more inclined towards challenging disciplines like STEM. "Analyses revealed that students were more likely to choose STEM majors if they had strong confidence in mathematics and academic areas and had parents with STEM occupations."

Given the pronounced concentration of international students in specific fields, we could hypothesize potential potential "crowd-out" effect due to surging international enrollments if: 1) universities fail to swiftly adapt to the heightened demand in popular majors owing to capacity limitations, and/or 2) the increased competition both academically and professionally for domestic students without an increase in benefits. Consequently, domestic students might choose away from fields favored by international counterparts, opting for alternate majors instead of leaving education altogether. However, a silver lining emerges in the form of a potential "crowd-in" effect, wherein institutions might invest more resources, such as faculty, equipment, or infrastructural enhancements, in these high-demand disciplines, yielding long-term benefits for domestic students. Given the non-profit nature of higher education establishments, their revenue reinvestment is often geared towards enhancing educational quality, aiming to climb institutional rankings and thereby attract a more diverse and academically superior student cohort.

The structure of this paper is delineated as follows: Section 1.2 delves into a comprehensive review of literatures, highlighting the unique contributions and complexities embedded within this study. Section 1.3 states the research methodology employed and details the data sources utilized. The findings of the research are presented in Section 1.4, accompanied by discussion and potential extensions. Finally, Section 1.5 offers concluding remarks of the paper.

1.2 Related Literature

In the aftermath of economic recessions, the decision-making process of students regarding their choice of college majors becomes considerably multifaceted. They not only assess their innate capabilities and individual attributes but also give paramount importance to anticipated salary, potential job prospects, and job stability. A study conducted by Bailey et al. (2012) employing "A multinomial logit empirical technique strongly suggests that after economic downturns, those who declare intended majors are more likely to choose ones that offer higher wages and provide more job security, like Technology, Business, Engineering and Health." The allure of certain disciplines waxes and wanes in relation to their perceived job security and employment opportunities. In a post-2009 recession survey, Carnevale et al. (2013) discerned that recent college graduates from Architecture, Humanities, Social Sciences, and Arts faced the most daunting unemployment challenges, with the latter three also reporting the least earnings. Contrastingly, majors like Health and Education presented graduates with the most favorable employment landscape. Another study by Goulas and Megalokonomou (2015) further elucidated these patterns, noting an augmented student preference for fields such as Military, Mathematics and Statistics, Humanities, Nursing, Veterinary Science, Medicine, Psychology, Journalism, Biology, and Law following economic downturns. On the other hand, majors like Business, Agriculture, Education, Languages, History, Physical Education, Engineering, and Computer Science witnessed a decline in their appeal amidst crises.

Ethnicity and gender play an undeniable role in shaping these academic inclinations. As evidenced by Bailey et al. (2012), Asian students exhibited a pronounced preference for majors like Biology, Health, Engineering, Technology, Physical Sciences, and Math. In contrast, Black students showcased a greater propensity for Technology, Health, Social Sciences, Biology, and Business, while their white counterparts leaned towards disciplines like Education, English, Humanities, Mathematics, Physical Sciences, History, and Business. Moakler Jr and Kim (2014) research affirmed that the likelihood of students opting for STEM fields amplified if they possessed unwavering confidence in their mathematical and academic prowess and hailed from households where STEM careers prevailed. They also found that while female students generally displayed a hesitancy towards STEM, African American and Latino students exhibited a parity in their inclination for STEM with their White or Asian American peers.

Furthermore, Bailey et al. (2012) highlighted the undeniable link between a student's academic performance in high school and their subsequent choice of major, with high achievers frequently gravitating towards technically rigorous fields like Math, Physical Sciences, Biology, and Engineering. Students' self-perceived abilities, gauged on a scale of 1-6 across various disciplines, also weighed heavily on their academic decisions. Moreover, in light of the dot-com crash's repercussions on labor markets, Calkins (2020) revealed a distinctive gender-based pattern: women exhibited a marked retreat from computer science majors but not from engineering. Her findings emphasized that academic grades play an instrumental role in retaining female students within computer science curricula.

1.2.1 Contribution

The primary emphasis of this research paper revolves around revealing the potential implications of increased international student enrollments on the major choices of domestic students in the undergraduate level. This paper is focused on the undergraduate level is because of these two observations: firstly, the post-2008 era has witnessed an exponential surge in international enrollments in the undergraduate level, and secondly, the share of this increase can be attributed to students coming from China, as showed in Figure 1.3 and Figure 1.4.

While existing literature, as represented by scholars like Shih and Chen, majorly studied on the influence of international student enrollment increase on domestic student enrollment at school level, this study took one step deeper, it is seeking to unpack the impacts across various academic disciplines or majors. This in-depth examination goes beyond than the conventional metrics of anticipated salary, employment prospects, and job stability that typically shape domestic students' major choices, particularly during economic downturns. Instead, the research expands its scope to estimate whether the pronounced influx of international students, primarily concentrated in specific majors, could potentially cause a 'crowding-out' effect within these disciplines. The 'crowding-out' effect suggests that a high volume and concentrated number of international student enrollments focusing on certain majors might potentially displacing or discouraging domestic students from those fields. Such effect could happen if colleges can't quickly increase their capacity in response to the escalating demand within these majors. Furthermore, the increased competition could escalate the marginal costs for domestic students to pursue these majors, particularly if the perceived benefits remain static. Another dimension worth exploring is the subjective comfort level of domestic students in environments dominated by international cohorts.

To provide further clarity, this research is trying to hypothesize and empirically validate whether domestic students, considering the swelling numbers of international peers, are more likely choose towards alternative fields of study, diverging from those preferred by international students. This shift could be indicative of students electing different academic trajectories instead of giving up higher education altogether. The study's findings target to gain a comprehensive understanding of the dynamic of domestic students' behavior when facing increased international enrollment, ensuring informed decision-making in academic and administrative realms.

1.2.2 Complications

Evaluating the impact of international student enrollments on domestic students' major choices, particularly during periods of economic crisis, is a complex situation. The complication arises not only from the interplay between international and domestic student populations but also from the macroeconomic forces that affecting academic and career decisions. These multifaceted influences make the task of isolating the specific effect of international student influx on domestic students' academic major choices a challenging one.

Within the broader framework of the business cycle, rational students normally would recalibrate their academic decisions in alignment with anticipated economic conditions. This decision-making for college major selection, students seek to maximize future economic returns and job security. As stated by Bailey et al. (2012), "Economic fluctuations affect human capital investment including college enrollment". Furthermore, economic downturns, characterized by uncertain job markets and diminished opportunities, naturally prompt a reconsideration of academic durations. The behavioral response observed during such recessions is the propensity of students to extend their educational tenure. This deliberate behavior can be understood as a strategic deferment of entry into an unfavorable job market. There's an underlying rationale to this trend; recessions, apart from the immediate adversities they present, have been shown to exert long-term consequences on an individual's economic trajectory. Specifically, embarking on a professional journey during an economic downturn can precipitate enduring wage deficits, a phenomenon underscored by Mahajan et al. (2022), "Workers who enter the labor market during recessions experience lasting wage losses."

In summary, while the primary focus of this study is to reveal the influence of international student populations on the academic choices of domestic students during economic downturns, it is important and unavoidable to consider the broader macroeconomic landscape. To fully understand this issue, we need to consider all the different factors involved.

1.3 Methodology

In this research I utilize the shift-share instrumental variable technique, a methodological approach that has increasingly been recognized for its capability to address issues related to identification. The principal motivation behind the adoption of this approach is to avoid potential endogeneity concerns and thereby accurately measure the causal implications of variations in international enrollments on the academic decisions of domestic students. The shift-share instrumental variable technique, in this context, is appropriate as it allows for a more rigorous and less biased estimation. By leveraging this method, I aim to construct instruments that isolate exogenous variations in international enrollments, thereby enabling a clearer disentanglement of the causal pathways influencing domestic students' major choices. The purpose of this study is to understand the changing of these international student enrollments on the major selection preferences of domestic students.

Covering a time span from 2008 to 2018, this study is estimation around a crucial decade that witnessed notable dynamics of higher education, especially in relation to international student mobility. The selected time period is especially relevant because it includes years marked by social, economic, and geopolitical changes. This provides a rich background for examining how these shifts might influence the academic choices of domestic students.

This research dedicates to contribute to the academic discourse by employing a robust methodological framework, ensuring that the derived insights regarding the relationship between international enrollments increase and domestic major preferences are both rigorously and academically important.

1.3.1 Data

The foundational dataset of this research was sourced from the Integrated Postsecondary Education Data System (IPEDS), specifically, the document titled "File documentation for enrollment in selected major fields of study, by race/ethnicity, gender, attendance status, and level of student: from Fall 2008 to Fall 2018." This dataset is the result of a biennial survey and includes detailed enrollment figures recorded in the fall of each survey year. This data categorizes students based on a wide range of criteria, such as race/ethnicity, gender, attendance regime (whether full-time or part-time), and student level, and it spans several major fields of study, including but not limited to Education, Engineering, Biological Sciences/Life Sciences, Mathematics, Physical Sciences, Business Management and Administrative Services, Law, Dentistry, and Medicine.

The data set exclusively captures enrollment trends in institutions offering 4-year degree programs. For the purposes of this research, I specifically utilized data corresponding to 'line = 1', which pertains to first-time, first-year full-time degree-seeking students. To maintain consistency and ensure the relevancy of data, I omitted the majors of law, dentistry, and medicine, given the disparate prerequisites that these fields entail across different countries. This strategic omission results in a focus on five major fields of study: Education, Engineering, Physical/Life Sciences, Mathematics, and Business Management and Administrative Services. To ensure the integrity of analysis, only institutions consistently offering all five majors over the six surveyed years (2008-2018, biennial data collection) were incorporated, yielding a balanced panel derived from 173 institutions.

To supplement and enrich the research, additional datasets were integrated: the Average Annual Unemployment Rates by State from the U.S. Bureau of Labor Statistics, the college-aged (18-24) population metrics by state to serve as state controls, and GDP metrics of countries of origin as obtained from the World Bank. Furthermore, data on International Students' Fields of Study for selected countries of origin was extracted from the 2020 report of the Institute of International Education. To engineer the 'share' component of the instrumental variable, I analyzed the proportion of international students hailing from a specific country of origin 'o' and enrolled in major 'm' relative to the total international student population from the same country. This analysis revolved around the top 23 countries of origin (namely Brazil, Canada, China, Colombia, Germany, France, Hong Kong SAR, Indonesia, India, Japan, Mexico, Kenya, Malaysia, Nigeria, Nepal, Pakistan, Russia, Saudi Arabia, Thailand, Turkiye, United Kingdom, South Korea, Vietnam). These countries collectively account for 94% of the total international student populace in the U.S. as per the 2020 report by the Institute of International Education.

1.3.2 Identification Strategy

For school level analysis, I used the following specification to estimate the causal effect of international enrollment on domestic enrollment at school level (base-line model):

$$\Delta N_{it} = \beta \Delta I_{it} + \gamma W_{st} + \alpha_s + \alpha_t + \epsilon_{it}$$

Herein, $\Delta N_{it} = N_{it} - N_{it-1}$ represents the change in domestic (native) student numbers at institution i during year t, and $\Delta I_{it} = I_{it} - I_{it-1}$ symbolizes the variation in international student enrollments at the same institution and time frame. Wst stands for state-level controls, which include variables such as the unemployment rate within state s and the natural logarithm of the college-aged (18-24) population count for the corresponding state and year. The terms α_s and α_t denote fixed effects for state and year, respectively. The parameter β is of primary interest as it quantifies the causal effect, interpretable as the incremental change in domestic student enrollment resulting from each additional international student enrolled. In conducting this analysis, I employed a first-difference methodology for both the dependent variable and independent variable, a methodological choice rooted in its capability to control for institution specific attributes that remain consistent over time. The rationale behind selecting unemployment rates and college-aged population counts as state-level controls is their hypothesized impact on native enrollment rates. Additionally, the application of fixed effects for years is intended to normalize for the general trends in college enrollment that transpire over time.

It is critical to understand, as previously emphasized, that domestic students' decision-making processes concerning their choice of major are complex and influenced by a variety of factors. These include, but are not limited to, the broader economic environment, labor market conditions, as well as personal academic self-confidence and proficiency. The principal aim of this study is to estimate and quantify the causal relationship between an increase in international student enrollments and the corresponding impact on native student numbers, evaluated both at the institutional level and across various academic disciplines. A simple ordinary least squares (OLS) regression may not be suitable for a reliable estimate of this causal relationship. There is possible a “crowding-out” effect that rising international enrollments might have on domestic students. This effect could be pronounced if there are constraints such as limited availability of seats in courses, or if increased international students in those majors brings in higher competition both in school and in the job market, which could increase the marginal costs for native students while marginal benefit remains the same. There could also be a “crowding-in” effect if higher education institutions can quickly adjust to a spike in international student enrollment and if they invest in the academic fields preferred by these international students. This could mean a greater advantage for domestic students in picking these majors because they’d get a better-quality education. The choices of majors by domestic students might also be influenced by the economic conditions during the time this study looks at. Lastly, OLS estimation is not suitable for this analysis because OLS estimates can be biased due to endogeneity in the model, as previously discussed. This endogeneity may arise from factors such as seating limitations, cross-subsidization, or unobserved time-varying changes at the institutional level, such as policy changes and funding granted.

To navigate this complexity causation, I have designed a shift-share instrumental variable. From the endogenous variable ΔI_{it}, which represents the variation in the international student body at institution i between time $t-1$ and t. First, note that this can be decomposed into the cumulative changes across all countries of origin:

$$\Delta I_{it} = \sum_{o} \Delta I_{oit}$$

Then, factoring out:

$$
\begin{aligned}
\Delta I_{it} &= \sum_o \Delta I_{oit} \\
&= \sum_o I_{oi,t-1} \frac{I_{oit} - I_{oi,t-1}}{I_{oi,t-1}} \\
&\equiv \sum_o I_{oi,t-1} g_{oit}
\end{aligned}
$$

where g_{oit}, the growth rate in international students from origin o in institution i between time $t-1$ and t. Where g_{oit} is obviously endogenous since students are attracted to institution i for many reasons.

The concept underlying the shift-share instrument posits that, preserving the generality of the approach, we can separate g_{oit} into a segment exclusively influenced by exogenous 'push' factors from the country of origin o, and another segment indicative of endogenous 'pull' factors attracting students to institution i:

$$
g_{oit} \equiv \underbrace{g_{ot}}_{\text{exogenous push}} + \underbrace{u_{oit}}_{\text{endogenous pull}}
$$

The rationale of the shift-share instrument would be to substituting $I_{oi,t-1}$ with a baseline value that is more distanced from $I_{oi,t-1}$ to exclusively employ exogenous 'push' factors start from the country of origin, denoted as g_{ot}. So, the ideal instrument variable would be:

$$
\Delta Z_{it} = \sum_o I_{oib} \times g_{ot}
$$

Nevertheless, the international student enrollment from origin o at institution i in the base year: I_{oib} is not directly observable. Consequently, an estimation of I_{oib} is pursued, utilizing available data on academic majors. This is achieved by both multiplying and dividing by the observable variable I_{imb}, which correlates with the international student enrollment in institution i with specific major m:

$$
I_{oit} = \sum_m I_{oimb} = \sum_m \frac{I_{oimb}}{I_{imb}} I_{imb}
$$

The proportion denoting the share of international students majoring in subject m at institution i who originate from country o, remains unmeasured. To estimate this ratio, one might employ the national-level proportion of foreign-born students in major m hailing from country o:

$$\frac{I_{oimb}}{I_{imb}} \approx \frac{I_{omb}}{I_{mb}} = \frac{I_{omb}}{\sum_o I_{omb}}$$

Therefore, evolving from our ideal share, we now obtain the observed shares:

$$\underbrace{I_{oib}}_{\text{ideal shares}} = \sum_m I_{oimb} = \sum_m \frac{I_{oimb}}{I_{imb}} I_{imb} \approx \underbrace{\frac{I_{omb}}{\sum_o I_{omb}} I_{imb}}_{\text{observed shares}}$$

We approximate our conceptual shift, g_{ot}, by employing the variation in log GDP per capita, which reflects income growth in the country of origin and signifies the financial capacity to afford education in the United States:

$$\underbrace{\Delta \ln(\text{GDPPC}_{ot})}_{\text{observed shifts}}$$

Consequently, our instrument variable is articulated as follows:

$$\Delta Z_{it} = \sum_o \sum_m \frac{I_{omb}}{\sum_o I_{omb}} \times I_{imb} \times \Delta \ln(\text{GDPPC}_{ot})$$

where $\Delta Z_{it} = Z_{it} - Z_{it-1}$.

The 'share' component is represented by the initial ratio of international students from origin o enrolled in a base year b, majoring in m, relative to the national enrollment of international students in the same major. This is coupled with the number of international students at institution i majoring in m. The 'shift' element encapsulates the fiscal capability to finance education in the U.S. from the students' country of origin, o.

This paper is focused on estimate the causal relationship between international student enrollment and the major selection of domestic students. Within the analytical paradigm of this study, the focal point has been to estimate the causal relationship between international student enrollment and the major selection of domestic students. A predominant hypothesis within academic researchers in this area is that international student enrollment can serve as a catalyst for increased domestic student enrollment at the institutional level by cross-subsidizing. This potential relationship might be underpinned by various factors. Primarily, international students often strength the financial capacities of higher educational establishments, enhancing their overall operational budgets. This financial augmentation can facilitate institutions in diversifying and enhancing their academic offerings. For instance, they might invest in hiring a greater number of faculty members, procuring advanced equipment, expanding classroom spaces, among other infrastructural enhancements. The resultant elevated quality of education, supported by a richer budget, invariably stands to benefit domestic students in the long term. Yet, a good understanding of this dynamic of the specific majors that international students gravitate towards is needed. If international student enrollment predominantly converges on particular majors, the influx might not necessarily push out domestic students from the institution altogether. However, it could potentially impact domestic enrollment in those specific majors favored by international students. Such a scenario could happen if institutions are slow to adapt to the surging demand in those disciplines, perhaps due to constraints like limited seating capacities. Furthermore, the marginal costs associated with selecting those majors could escalate for native students. This could arise from heightened competition, both within the educational and the broader professional market, even as the potential benefits remain constant. Consequently, if these dynamics hold true, domestic students may change their academic preferences in response to the surge in international enrollments. This could entail a strategic shift in their field of study, moving away from disciplines favored by international students, rather than opting out of tertiary education altogether.

For the analysis at the level of academic majors, the subsequent specification was employed:

$$\Delta N_{it}^{\text{major}} = \beta^m \Delta I_{it} + \gamma W_{st} + \alpha_s + \alpha_t + \epsilon_{it}$$

As in the foundational model employed for this research, I incorporated the first difference for both domestic (native) and international enrollments. The variable W_{st} represents state-level controls. Specifically, I utilized the state unemployment rate combined with the logarithmically transformed college-age population within state s, for year t. The terms α_s and α_t function as state and year fixed effects, respectively. The coefficient β^m seeks to isolate the causal effect delineating the association between an uptick in international enrollment and the consequent effect on domestic enrollment across specific academic majors.

To explore the effect of escalating international enrollments, this study also quantifies the causal dynamics between the upsurge in international student numbers and its differential impacts across various gender and racial demographics. The specification adopted for this analysis is as follows:

$$\Delta N_{it}^{\text{gender/race}} = \beta^{g/r} \Delta I_{it} + \gamma W_{st} + \alpha_s + \alpha_t + \epsilon_{it}$$

Within the foundational framework of the study, designated as the baseline model, I implemented the first difference approach to simultaneously analyze domestic enrollments delineated by gender (male and female) as well as international enrollments. The variable W_{st} functions as a state-level control with the state unemployment rate alongside the logarithmically transformed college-age population for state s during year t. The components α_s and α_t serve as dedicated fixed effects for the state and the year respectively. Within this framework, the coefficient $\beta^{g/r}$ is of paramount significance, as it aims to quantify the causal effect, determining the way an upsurge in international student enrollment exerts an influence on the domestic enrollment bifurcated by gender (female/male) across distinct academic majors.

1.4 Results

1.4.1 Baseline results

This section presents the comprehensive empirical results derived from the estimation of the causal relationship between the increase in international student enrollments and the subsequent fluctuations in the enrollment of native students within higher education institutions. It also addresses the decision-making processes employed by domestic students in choosing their academic majors and examines the consequent implications of these processes. Furthermore, it considers the varying impacts these enrollment trends may have on students of different gender identities and racial backgrounds, thereby offering a deeper understanding of the dynamics at play within the educational landscape. This analysis aims to uncover the presence of international students influences the academic major choices of domestic students and institutional demographics, thereby contributing to the broader discussion on educational diversity and student body composition. The findings seek to provide a detailed discovers on how the demographic composition of student populations within higher education institutions is affected by the increasing international admissions and its intersection with domestic students' academic and social environments.

Goes to the detailed empirical outcomes, Table A.1 offers a comprehensive overview of the influence of international student admissions on domestic student registration at the institutional level. The first column introduces an identification strategy that employed year fixed effect with state level control, which are the state unemployment rate and the logarithmically transformed population of college-age individuals (18-24 years old) for each corresponding institution's geolocation by state. The second column shows the result from identification strategy that incorporates both year fixed effect and a state fixed effect, while the third column integrates a state-year fixed effect. The coefficients here are instructive, it is revealed the relationship of native student enrollment in response to the enrollment of each international student at the school level. A consistent result showing across all three specifications.

Referring to Table A.1, the 2SLS with SSIV showing that for every incremental increase in the enrollment of international students — characterized as first-time, first-year, full-time, degree-seeking individuals — there is a corresponding increase of 4 domestic students fitting the same demographic description. This observed trend aligns well with the findings from extant literature. Specifically, Shih (2017) posits that for every international student added, there's a corresponding influx of a native student. Similarly, Chen (2021) suggesting the addition of approximately 2.8 students for every international student. The elevated numerical outcomes derived from our model specification may come from a focus on a limited subset of popular majors rather than an inclusive range across all disciplines.

The data indicates a very small impact of increases in international student enrollment on domestic enrollment when using OLS estimation when compared to the results from 2SLS. This observed difference, could result from attenuation bias, where measurement error in the independent variable leads to underestimation. Our independent variable, international student enrollment, might contain measurement errors due to data limitations. Additionally, this difference could also result from reverse causality, as previously discussed, domestic enrollment could also affect international enrollment due to the limited number of students each institution can accommodate. Another reason for the difference in the IV result could be that the marginal school pushed by the instrument relies heavily on foreign students, resulting in significantly more crowd-in. Therefore, estimation using an instrumental variable would yield a more accurate result.

Table A.2 present the empirical results that explicate the causal relationships between the increase of international student enrollment and the preferences of domestic students in choosing their fields of study at higher education institutions. This inquiry specifically targets five distinguished majors, namely Education, Engineering, Mathematics, Physical and Life Sciences, and Business, chosen due to the data availability and their commonly preference among the international student cohort. This study systematically excludes an array of disciplines such as Law, Dentistry, Medicine, Fine Arts, History, and several other majors that do not resonate as strongly with the international student demographic. The notable dislike of international students in specialized majors such as Law and Medicine are likely linked to the unique legal and medical systems in place across various countries, which required specific qualifications that are typically country-specific for professional practices. Moreover, disciplines that have been characterized by a lack of popularity among international students were deliberately left out of this research, this exclusion is based on the hypothesis that these less-favored majors may not effectively facilitate job placement in their respective fields after graduation, potentially diminishing their attractiveness to students who are also weighing the employability outcomes of their educational investments. This examination into the major selection trends among domestic students relative to international enrollment patterns provides a layered understanding of how global flows of students can influence and possibly reshape academic offerings and pursuits within institutions of higher learning.

As initially expected, that the most substantial crowding-in effects are observed within majors that are highly favored by international students. Within the scope of the five evaluated majors, Engineering and Business are the disciplines most affected by the surge in international student enrollments, these majors are the most preferred among the international demographic. The domain of Physical and Life Sciences ranks next, showcasing a notable increase in domestic enrollment, consequent to the international student influx. As Bradley (2012) posits, "In economically challenging times, students declaring their intended majors exhibit a propensity to opt for disciplines promising lucrative remuneration and enhanced job security, such as Technology, Business, Engineering, and Health." This observed trend might be due to the premise that disciplines that require equipment and most favored in international students exhibit a pronounced crowding-in effect. Empirical evidence denotes that for every increment in international student admissions (enrolling for the first time, pursuing full-time undergraduate studies) there is an associated augmentation of domestic student enrollment by a factor of four. Analyzing this growth shows a strong preference for Engineering, as about half of the crowed-in effect is from this discipline. In close succession, Business attracts about 1.5 of these 4 domestic students that crowed-in from the increase of international student, with the Physical and Life Sciences drawing nearly one.

This crowding-in phenomenon, as discussed in prior discussions, is largely imputed to the financial leverage educational institutions gain from the higher tuition paid by international students. This influx of funding enables universities to increase their financial aid offerings to domestic students. Additionally, these earnings enable substantial improvements to programs that attract international students, including the acquisition of state-of-the-art scientific equipment, hiring of distinguished faculty members, and overall academic enrichment. These improvements serve to heighten the appeal of these disciplines among domestic students, thereby steering their academic preferences toward these globally favored majors. The differential crowding-in effects observed across Engineering, Physical/Life Sciences, and Business can be rationalized by distinct institutional priorities and strategies. The increase in the number of local students pursuing Business majors may suggest the introduction of a broader range of courses and programs, reflecting the school's increased financial capabilities. In contrast, the rise in popularity of Engineering and Physical/Life Sciences may be attributed to deliberate improvements in educational assets, such as the latest facilities and the hiring of renowned scholars and researchers, which enhance the learning environment and research possibilities for local students.

The mathematics major presents an interesting counterpoint, revealing a marginal but significant crowding-out effect. This might suggest resource constraints, such as a shortage of specialized faculty or a lack of funding allocated to the major, leading to a finite capacity to accommodate student interest. As Bradley (2012) suggests that academic administrators equipped with this data-driven model can customize their resource distribution approaches at the school level. Even with financial limitations, they can skillfully predict which fields will need increased resources and which can have resources redistributed to best meet student interests. The dynamics within academic selection processes could further be influenced by the level of academic confidence and the anticipated incremental advantages that are associated with the pursuit of specific disciplines. Moakler Jr and Kim (2014) shed light on another dimension, underscoring that the degree of confidence students have regarding their academic and mathematical competencies plays a pivotal role in shaping their preliminary choices within the STEM fields. International students who manage to navigate the competitive process of gaining admission to study in U.S. educational institutions typically exhibit a high degree of academic confidence. Particularly, those who choose to major in Mathematics are normally those individuals who have already demonstrated superior scholastic capabilities. This influx of academically adept international students into the U.S. education system introduces a heightened degree of competition, which happens both the educational environment and the broader professional market. Consequently, this intensification of competitive standards sets a higher academic requirement, because of that it possibly deterring native students from selecting such a demanding major. Especially if they seeing the competition as undermining their own academic self-assurance or if it seems to lessen the marginal benefit of their educational choices. In addition, native students will have the marginal benefits against the potential costs such as increased pressure to perform and the likelihood of facing tougher competition for career opportunities post-graduation into calculation. As a result, they may put their attention to alternative majors where the competitive field is less pronouced and where they feel their chances for academic and professional success are more promised. This scenario highlights the nuanced and complex considerations that native students might consider when making decisions about their educational choices, particularly in the context of an evolving and increasingly international academic environment. The presence of a highly concentrated international student population in demanding majors such as Mathematics could influence not only the academic composition of these programs but also have broader implications for domestic students' academic strategies and future career trajectories.

Education as a major remains relatively unaffected, not displaying significant statistical changes in domestic enrollment patterns. Moreover, the Education major experienced the minimal international student engagement. Like medical and law, Education professions have country-specific requirements for professional practice in these areas, coupled with potential language obstacles. This nature deters international students from pursuing these paths. This indicates a complex interaction of regulatory policies, cultural elements, and language proficiency, which together shaping the international education and influencing the distribution of academic preferences.

This analysis explores the complexities of demographic trends, examining the effects of increasing international student enrollment on native enrollment broken down by gender and race. Table A.3 in the research shows that male students are subject to a crowding-in effect that is nearly double that of their female counterparts, a phenomenon that is further elaborated upon in gender-specific effect analyses. Reflecting upon the insights of Zafar (2013), it is observed that while male and female students may have similar academic inclinations, there is a marked divergence in their career aspirations. Female students often give greater weight to non-monetary considerations such as familial approval and personal fulfillment from their work, in contrast to male students, who are more inclined towards the monetary benefits, prestige attached to certain careers, likelihood of job attainment, and future income potential. The empirical evidence gathered in this study seems to be in line with Zafar's observations, particularly regarding the differential impact on domestic enrollment in increased international student admissions. The analysis reveals that male students demonstrate a more significant crowding-in effect than their female peers.

Regarding racial demographics and their relation to the crowding-in effect, the data reveals disparate experiences among various ethnic cohorts. White students account for roughly half of the overall institutional-level crowding-in effect, while Black students witness a crowding-in effect that is only a fraction (approximately one-tenth) of that experienced by White students. Meanwhile, Asian and Hispanic student populations do not appear to experience the benefits from the cross-subsidy effect that from the increase in international enrollments. These results may be due to the distribution patterns of financial aid among different racial groups.

When these demographic differences are viewed through existing academic research, they provide crucial insights for policymakers and educational administrators. This detailed knowledge facilitates the development and execution of tailored strategies that cater to the varied requirements of a diverse student population. By incorporating these findings, there is an opportunity to foster an educational atmosphere that is not only more inclusive but also responsive to gender and ethnic considerations, ensuring equitable educational opportunities and support that reflect the diverse needs and aspirations of all student groups. By using these focused strategies, the higher education sector can more effectively meet the varying needs and expectations of its diverse student body, improving the educational experiences and achievements for students of all backgrounds.

1.4.2 Discussions and extensions

The contribution of this study lies in its clear analysis of how international student enrollment influences the choices of domestic students regarding their majors. The study's detailed approach uncovers a significant crowding-in effect at the institutional level, and especially in academic disciplines favored by international students. This crowed-in effect is coming from the financial benefits that universities receive from international tuition. This phenomenon is largely attributed to a cross-subsidization mechanism, where the additional financial resources generated from international tuition fees enable institutions to offer greater financial support to domestic students and to invest in the overall quality of education. This is particularly evident in majors that require extensive equipment and resources, which can now be supported by the influx funding from increasing of international students. For the major of Mathematics, a crowding-out effect has been observed, potentially due to heightened academic competition within the educational and professional job market. It's essential to examine how the presence of international students affects domestic students' decisions to enter particular majors. This research could reveal whether a higher number of international students deters domestic students, potentially due to intensified competition or a perceived saturation of the field by foreign-born students. Further exploration could unravel whether the shift in domestic students' major choices is a direct result of increased international numbers, or if it's due to a change in preferences. In other words, are domestic students being pushed away from certain majors because of the rise in international students, and does this result from competition or a bias against international students? Investigating these questions could provide important information on how domestic and international students interact academically and the complex factors domestic students consider when choosing their majors in a global educational environment. A deeper dive into the different effects by gender in discipline-specific data. This exercise would empower the assignment of differentiated scores across various dimensions, including family support, the inherent worth of professions, the social status of specific jobs, the likelihood of getting employed, and potential income growth over time.

$$\Delta N_{it}^{\text{major}} = \beta^m \Delta I_{it}^{\text{major}} + \alpha_s + \alpha_t + \epsilon_{it}$$

A detailed and varied analysis is crucial for revealing the complex factors that determine academic and career choices according to gender. A future study could undertake a detailed evaluation of the major specific impact on domestic enrollment as influenced by fluctuations in international student numbers going to those specific fields. This method offers a granular understanding of how institutional funding allocation and the presence of international peers within certain majors may sway the academic decisions of domestic students. As stated by Anelli et al. (2020), the presence of international students in STEM fields can act as a catalyst, prompting domestic students to gravitate toward other rewarding majors within the Social Sciences to safeguard their projected earnings. Therefore, comprehending how each gender and race is impacted by the escalation in international enrollments across various disciplines becomes vital, providing educational administrators with profound insights for student admission strategies in diverse fields.

$$\Delta N_{imt}^{\text{gender/race}} = \beta^{g/m} \Delta I_{it}^{\text{major}} + \alpha_s + \alpha_t + \epsilon_{it}$$

Moreover, the sudden move to online learning during the COVID-19 pandemic presents interesting possibilities for digital education to overcome the usual limitations of physical classroom space. With travel restrictions and changing views on the security of studying in the U.S., it's worth considering how these issues could reshape the preferences and enrollment trends of international students, and in turn, affect the enrollment choices and major selection of domestic students. Given the significant influx of Chinese students, a detailed analysis focusing on this group, distinct from the broad international student body, would prove illuminative. Moreover, with international students also representing a substantial presence in postgraduate programs, it is crucial to determine whether undergraduate-level trends mirror those at the graduate level. Finally, the landscape for international students is shaped by a confluence of factors, including visa policies like the H1B, prevailing job market conditions, the reputation of universities in their home countries, and diplomatic ties between their countries of origin and the U.S. An exploration into these aspects would undoubtedly add depth to the narrative of this research.

1.5 Conclusions

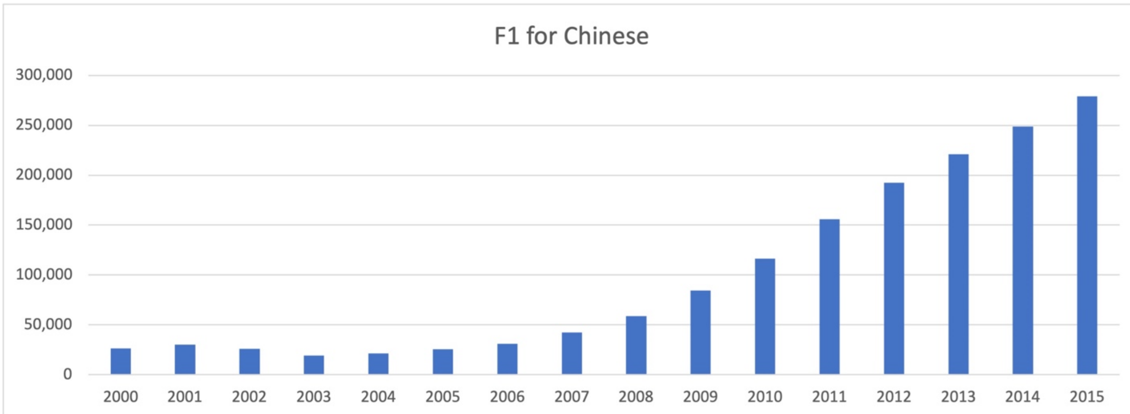
Upon an in-depth examination of the data, we observe a pronounced crowd-in effect. Across the range of majors including Education, Engineering, Physical/Life Sciences, Mathematics, and Business, the enrollment of each full-time, first-time, degree-seeking international student is associated with an increase of about four domestic students with similar demographic characteristics. This empirical finding aligns closely with earlier research by scholars such as Shih and Chen. In Shih's study, he carefully analyzed two separate phases: the growth period from 1995-2001, which he attributes to the ripple effect of a global surge in college-age population, and the decline from 2002-2005, predominantly due to visa constraints post the unfortunate 9/11 incident.

Shih discovered a crowd-in effect during the growth period, quantifying it at approximately positive 1 between international and domestic enrollments. He believes that this could be attributable to a cross-subsidy mechanism. On the other hand, Chen's analytical covered spanned the years 2005-2016, a period characterized by robust economic growth in several developing nations, thereby endowing their citizens with enhanced financial capacities to invest in U.S. education. Chen's conclusions similarly evince a positive correlation, approximating 2.2, between international and native enrollments.

This study is dedicated to revealing the nuances of international student enrollment expansion and its impacts on the enrollment of domestic students within different academic majors at the higher education institutions. The emphasis on the undergraduate segment is underpinned by the pronounced escalation witnessed in international admissions at this academic tier. Initial data analysis suggests a noticeable crowding-in effect in majors that are favored among international student populations. This effect can be grouped into two main channels: the first posits that preferred majors of international students receive augmented institutional investment, enhancing the financial aid capacity for domestic students; the second posits that with the increment in capital generated from international tuition, institutions are inclined to allocate funds to 'equipment-intensive' disciplines, thereby uplifting the educational quality for all students, which in turn escalates the marginal benefit for native students within these fields. Conversely, the Mathematics discipline exhibits a crowding-out effect, whereas other disciplines that traditionally lack appeal to international students show resistance to these enrollment shifts. Such patterns may be explicated by the restricted seating capacity within certain majors due to a finite faculty cohort and the amplified competition both in the education world and professional market wrought by the rising tide of international scholars.

Furthermore, our research also discovered pronounced variations when the data was disaggregated based on racial and gender parameters. White students exhibited a statistically significant positive crowd-in effect. In contrast, the Asian and Hispanic cohorts seemed largely unaffected. From a gender perspective, while both male and female students reaped positive benefits from the trend, the magnitude was markedly disparate. Male students, intriguingly, manifested an effect nearly threefold compared to their female counterparts.

Figure 1.1: F1 visa issuance for Chinese from 2000-2015



Notes. F1 visa issuant data by country of origin from U.S. Department of State BUREAU of CONSULAR AFFAIRS, Table XVII (Part I) Nonimmigrant Visas Issued. Retrieved from https://travel.state.gov/.

Figure 1.2: International students' field of study distribution

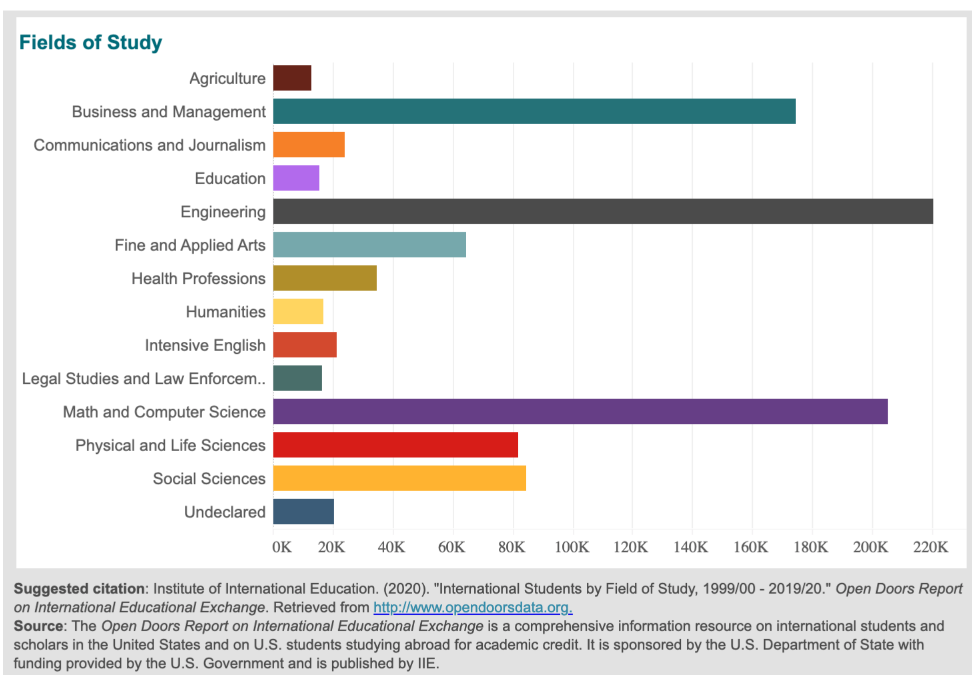
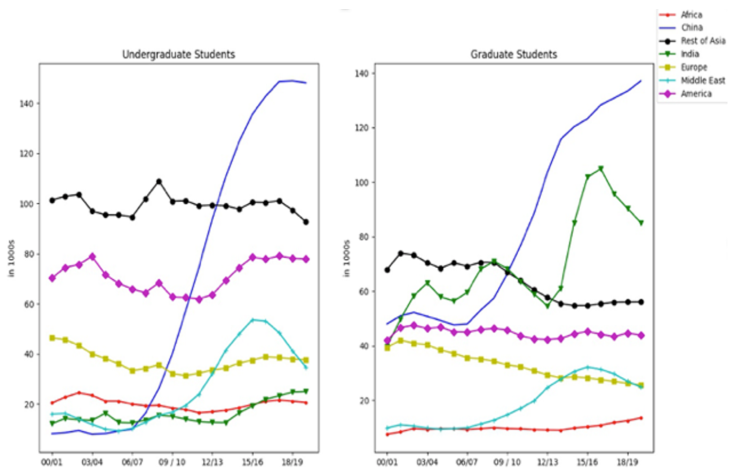
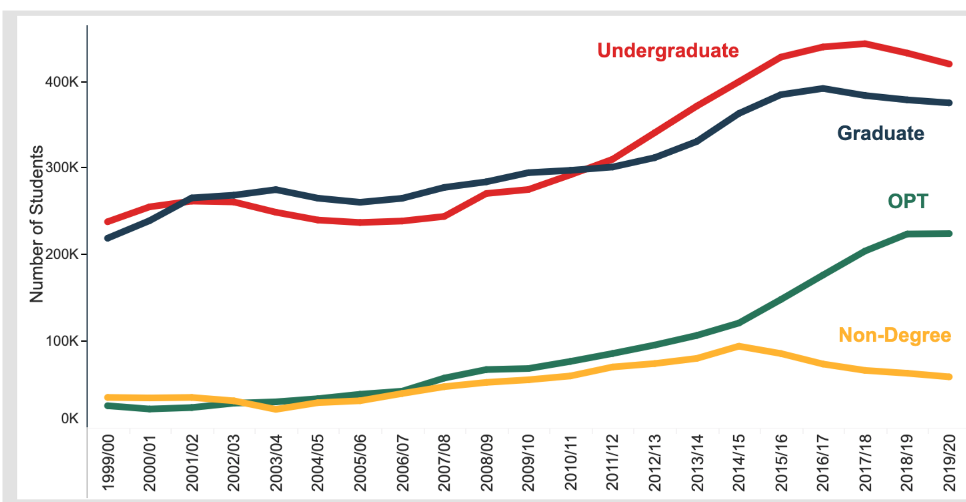


Figure 1.3: International enrollment by country of origin



Notes. picture constructed by data from Opendoors, “academic level and places of origin”. https://opendoorsdata.org/data/international-students/academic-level-and-places-of-origin/

Figure 1.4: International enrollment by academic level



Suggested citation: Institute of International Education. (2020). "International Students by Academic Level, 1999/00 - 2019/20." *Open Doors Report on International Educational Exchange*. Retrieved from http://www.opendoorsdata.org
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Chapter 2

IMPACT OF HIGH-SPEED-RAILWAY ON EMPLOYMENT IN CHINA

2.1 Introduction

China has the longest and most extensively used high-speed-rail (HSR) network in the world (total length 26,000 miles by the end of 2022)[1]. HSR network is designed for speed range from 200 km to 350 km (120 mph - 220 mph). The first HSR line in China started to operate in 2003[2]. In a strategic move to enhance inter-city connectivity, the Ministry of Railway in China, in 2008, amended the construction plan to establish a "four-vertical and four-horizontal" HSR network, linking major cities across the nation (Dai, 2020). The term "four-vertical"[3] signifies four major HSR networks connecting the north and south of China, while "four-horizontal"[4] denotes four major HSR networks connecting the east and west. Subsequently, China witnessed an exponential surge in HSR growth. By 2017, the HSR network seamlessly linked approximately 200 prefecture cities. As of the end of 2021, an impressive 93% of cities with populations exceeding half a million gained access to the HSR network.

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1 https://en.wikipedia.org/wiki/High-speed_rail_in_China

2 https://www.icauto.com.cn/chuxing/70/704168.html

3 The four vertical lines are HSR networks Beijing-Harbin (connecting Beijing to northeast major cities), Beijing-Shanghai (connecting Beijing and Shanghai as well as other major cities along the HSR line), Beijing-Guangzhou (connecting Beijing, Guangzhou, Shenzhen and other cities along the line), and Hangzhou-Fuzhou-Shenzhen (connecting major cities along southeast coast of China.

4 The four horizontal lines are Qindao-Taiyuan (connecting major cities in Shandong, Hebei, and Shanxi provinces), Xuzhou-Lanzhou (connecting major cities in central and west of China), Shanghai-Wuhan-Chengdu, and Shanghai-Kunming that connect major cities in southeast and southwest of China

Figure 2.1 shows HSR network growth over the period from 2005 to 2017. Data of accumulated HSR network (in KM) is sourced from Chinese Research Data Services Platform (CNRDS). As we can see from Figure 2.1, HSR network increased fast from 2008 to 2015. Figure 2.2 is a map of China that shows how HSR networks were distributed in China by the end of 2017. Most major cities in east and central area of China have joined HSR networks by 2017.

HSR networks serve not only as efficient transportation systems but are also regarded as environmentally friendly alternatives compared to traditional modes of transportation. Because of that, China has made substantial investments in research and development to propel the advancement of high-speed rail (HSR) technology and the construction of HSR networks. According to Dai (2020), the country allocated a significant sum of 1.875 trillion RMB (approximately 278 billion US dollars) to the HSR program from 2011 to 2015. The International Railway Journal reports that the typical infrastructure cost for China's HSR, boasting a maximum speed of 350 km/h, ranges from 100-125 million RMB (about 17-21 million US dollars) per kilometer. Undoubtedly, the HSR program is a substantial financial undertaking, with a prolonged timeline before reaching the breakeven point and turning a profit. As highlighted in the Disclosure of Financial Report for the Wuhan-Guangzhou HSR Line (2011), it is anticipated to take a considerable 12 years for the Wuhan-Guangzhou HSR line to achieve positive profitability. This underscores the substantial financial commitment and long-term perspective required for the HSR program to realize its economic viability and return on investment.

The substantial expenses associated with the construction and operation of HSR motivate researchers to study whether HSR brings any economic benefits to local economies. Existing literatures find that HSR boosts local economic growth and efficiency[5]. Apart from economic growth, it also worth exploring the impact of HSR on

[5] See examples in Wang and Dong (2022), Ke et al. (2017), Li et al. (2020), Diao (2018), Zhou and Zhang (2021).

local employment. According to American Public Transportation[6], 1 billion investment in HSR creates 24,000 jobs. Rail authority states that California's HSR not only add more temporary construction jobs, but also creates more long-term employment[7]. Duranton and Turner (2012) use instrument variable regression to find that 10% increase in interstate highway construction led to 1.5% growth in employment on average. The impact of transportation system on employment in the US motivates us to explore the impact of HSR on employment in China. Do HSR networks promote employment and is the impact transient or enduring? Furthermore, does HSR exert a uniform influence on employment across large organizations, encompassing government-related entities, state-owned enterprises, and publicly listed firms, compared to its effect on individual and private employment? It is a very important question, as promoting employment in large organizations may have different economic and social implications compared to promoting employment in small businesses. If HSR incentivizes skilled individuals to relocate from non-HSR cities to those connected by HSR, it may result in heightened employment within large organizations. Conversely, if the primary boost is within service industries linked to tourism, one might anticipate a substantial increase in individual employment and employment within small businesses following a city's access to HSR. This paper will address these questions using administrative data from China Regional Statistics Yearbook (2005-2017) and High-speed railway data from CNRDS.

One of the challenges to identify average treatment effect (ATT) of HSR is that treatment effect might depend on treatment timing. On one hand, cities that get access to HSR earlier might be different from cities get access to HSR later in size of population and scale of economy, which could lead to difference in treatment effect. On the other hand, early treated cohorts may only get access to single or a coupe of HSR lines, while later treated cohorts can enjoy better established HSR network, which could also result in difference in treatment effect. To solve this problem, this

[6] https://www.apta.com/research-technical-resources/high-speed-passenger-rail/benefits-of-high-speed-rail-for-the-united-states/

[7] https://www.naco.org/articles/high-speed-rail-delivers-jobs-counties

paper uses CSDID developed by Callaway and Sant'Anna (2021) to identify average treatment effect of HSR on local employment.

Among existing literatures that study the impact of HSR on local employment or various industries, some studies consider access to HSR as a policy change, and therefore employ difference-in-difference (DID) or two-way-fixed effect (TWFE) methodology to identify treatment effect. Dong and Zhu (2016) use propensity score matching (PSM-DID) to find that HSR network promote employment and labor mobility. Lin (2017) employs a TWFE model to identify the average impact of HSR on ridership of different type of transportation tool and employment. Furthermore, Lin's study uncovers heterogeneous impacts of HSR on employment across different industries. In a similar vein, Dong (2018) utilizes a TWFE model to investigate the impact of HSR on various industries, highlighting a more pronounced effect on the retail and wholesale industry compared to others.

We contribute to current literature in the two ways. First, based on our knowledge, we are the first to use CSDID to identify the impact of HSR on local employment in China[8]. Evidently, not all cities simultaneously operate high-speed rail (HSR), and thus access to HSR is considered as treatment at multi-time periods. TWFE method is appropriate only if treatment effect is homogenous across treated entities and remain fixed over time. In fact, most literatures published before 2022, such as Agarwal et al. (2021), use TWFE model to identify average treatment effect if treatment occurs at multi-time period. However, TWFE method would mis-specify average treatment effect, if entities receive treatment at different timing and treatment effect varies between early and later treated cohorts (Goodman-Bacon, 2021). HSR is not randomly assigned to each city. Some cities may be prioritized due to factors such as larger population, higher GDP, or other considerations. The impact of HSR on early treated cohorts might differ from the impact on later treated cohorts, due to difference in size of population or economic scale. Even if cities randomly get access to HSR, the impact

[8] More detailed discussion about CSDID will be given in the section of Empirical Strategy.

of HSR on employment of earlier treated cities would still be different from the impact of HSR on employment of later treated cities, because earlier treated cities only get access to single or several HSR lines, while later treated cities can enjoy the benefit of entire HSR network. Therefore, treatment effect of HSR is likely to be heterogenous across cities getting HSR at different time periods, and the results of previous research based on TWFE method could be biased. Unlike TWFE model, CSDID does not suffer from estimation bias caused by time-varying treatment effect. With CSDID, we find that HSR raises employment by 6.8% on average, which is much larger.

Second, in addition to identify treatment effect of HSR on overall employment, we further test the impacts of HSR on employment in large originations and on employment of small businesses and self-employment. Our research suggests that HSR primarily promote self-employment and employment in private firms (14% increase after HSR in operation), while impact of HSR on employment in state-owned originations and public listed companies are insignificant. One explanation is that HSR boosts employment in industries such as catering, hospitality, retail & whole sale and other services industries highly related to travel, where small private businesses are concentrated. Our findings regarding the estimated treatment effect on employment in the retail & wholesale industry lend support to this hypothesis.

This paper is divided into six sections. Section 2.2 describes the data used in the analysis. Section 2.3 discusses the identification and empirical strategy. The empirical results and robustness checks are in Section 2.4 and Section 2.5. Section 2.6 concludes the study.

2.2 Data

We collected annual data on prefecture city-level, including population, overall employment, employment in public organizations, self-employment & employment in private firms, employment in the retail & wholesale industry, real GDP, and government expenditures from the China Regional Statistics Yearbooks. These yearbooks source their data from the National Bureau of Statistics of China, providing comprehensive and authoritative statistical information on different regions, provinces, and prefecture cities across China. Information about the timing of each city gaining access to high-speed rail (HSR) is sourced from the Chinese Research Data Services Platform (CNRDS), which details when each HSR city begins to have HSR in operations and the specific HSR lines it is connected to.

There are over 280 prefecture cities in China. Our sample period spans from 2005 to 2017. The first cohort of cities obtained HSR in 2003, followed by the second cohort in 2008. As our empirical approach (CSDID) necessitates no treated observations in the first period, and there are more missing values in earlier periods, we excluded all six cities gaining HSR access in 2003. Additionally, we omitted cities with missing values in the required economic variables. Since our sample period extends from 2005 to 2017, we also excluded cities gaining HSR access in 2017. The final dataset comprises 188 cities, totaling 2256 observations, with 124 cities having HSR access before 2017. Figure 3 illustrates the proportion of prefecture cities within our sample gaining HSR access over the years. The graph depicts a rapid increase in the percentage of HSR cities starting from 2008, surpassing 60% after 2015.

Table 2.1 summarizes selected economic variables at prefecture city level. All variables listed in the table above are annual data observed at the end of each year. Data of employment and population are in thousand persons, while GDP and government expenditures are in million RMB.

As the variable description in the Table 2.1 suggests, to total employment is defined as the sum of employment in non-private organizations, self-employment, and employment in private firms. It worth noting that farmers, and people who are self-employed but not are not registered with industrial & commercial bureau are excluded from calculation of employment. In China, farmers are not registered with industrial & commercial bureau, and they do not pay income tax either. However, farmers represent large proportion of total population in China, about 41%[9]. Because farmers are

[9] See https://www.yicai.com/news/100915547.html

not counted as employment, the ratio of employment to population is small. Public Employment is the number of employed people in government, non-profitable organizations, state-owned companies and public listed corporations. Private Employment is number of people employed by private firms and people registered with industrial & commercial bureau as self-employed. Owner of small businesses and people hired by private firms fall into this category. Pop_2005, GDP_2005 and Expend_2005 are population, real GDP and government expenditure on infrastructure in 2005. They will be used as control variables in our model.

2.3 Identification Strategy

2.3.1 Baseline estimation with TWFE model

We use TWFE model as baseline to estimate the impact of HSR on employment.

$$\ln \text{Employment}_{i,t} = \alpha \text{HSR}_{\text{year}} \times \text{HSR}_{\text{city}} + u_t \times X^{'}_{i,2005}\beta + u_t + \sigma_j + \epsilon_{i,t} \tag{2.1}$$

In equation (2.1), $\text{Employment}_{i,t}$ represents the number of employed people (including self-employment and employment in private and private originations) in city i and year t. The dependent variable is natural logarithm-transformed for normalizing the distribution. Since we use logarithm transformation, average treatment effect estimated by the model measures estimated average percentage change in employment driven by HSR. HSR_{city} is a dummy variable, taking the value of 1 if the corresponding city has high-speed rail (HSR) and 0 otherwise. HSR_{year} is another dummy variable, equaling 1, if the HSR city has HSR in operation in that year, and 0 otherwise. The interacted term $\text{HSR}_{city} \times \text{HSR}_{year}$ serves as the variable of interest. The coefficient, α, indicates the impact of HSR on employment. A significantly positive α suggests that HSR contributes to employment growth.

Year dummy variable, u_t is 1 at specific year, otherwise 0. $X^{'}_{i,2005}$ denotes a set of outcome variables (logarithmically transformed) for city i in year 2005, which includes population, real GDP, and government spending on public infrastructure. According to Chinese Ministry of Railway (Qin, 2014), placement of HSR lines is based on a series of factors including economic development, population, resource distribution, national security and environmental concerns. We picked population, real GDP and government expenditure on infrastructure, because they could not only affect employment, but also are potential determinants of whether a city become a HSR city and the timing of gaining HSR. Instead of using these outcome variables at year t as controls, we use these variables interacted with the year dummy, u_t, as control variables. These outcome variables may be interconnected with our dependent variable, employment, as employment can influence GDP, population and government spending, and in return, those covariates can affect employment as well. The outcome variables in 2005 are predetermined. Therefore, using outcome variables interacted with year dummy as controls helps eliminate potential issues related to reverse causality.

u_t is also year fixed effect that control the impact of time trend on employment, while σ_t is prefecture city fixed effect, accounting for the specific characteristics of each city influencing employment. Standard errors are clustered at the prefecture city level. In our baseline estimation, we use equation 2.1 to identify the impact of HSR on total employment, individual & private employment, and employment in non-private organizations respectively.

2.3.2 CSDID with Doubly Robust Estimator

As previously discussed, TWFE model performs well when the treatment effect remains constant across treated entities and over the treatment period. However, if the treatment effect is fixed over time but heterogeneous across treated units, the TWFE estimates a variance-weighted average treatment effect. The weights are determined by sample size and the timing of being treated, and it may not reflect the average treatment effect as expected. According to Goodman-Bacon (2021), in the presence of a time-varying treatment effect, the TWFE model may assign negative weights to comparisons between early treated groups and late treated groups, potentially introducing bias to the estimated treatment effect. Due to this concern, we opt to use CSDID model for primary part of our analysis. We will discuss some assumptions related to CSDID, before we introduce the method to identify ATT.

Assumption 1 Staggered Treatment. Once the unit is treated, it stays treated thereafter, and the treatment cannot be reversed.

Assumption 2 Random Sampling. Potential outcome and treatment allocation are independent and identically distributed (iid). This assumption means that treatment and treatment timing are randomly assigned to treated units.

Assumption 3 Treated Group and "Not-Yet-Treated" Group Hold Conditional Parallel Trends. This assumption means that treated group and not-yet-treated group are comparable in the absent of treatment, conditional on available covariates.

In the context of High-Speed Railway, Assumption 1 is likely to hold true. Once an HSR station is established in a city, it is assumed to remain there indefinitely. However, Assumption 2 may not hold as HSR is unlikely to be randomly assigned to each city. Larger and wealthier cities are more likely to gain access to HSR earlier than their counterparts. Consequently, treatment effects are likely to vary across different treated cohorts. To address this, it is reasonable to use not-yet-treated units as a control group, provided there are enough units in this category. The never-treated group might possess unique characteristics that differentiate them from the treated group. In our case, cities without HSR stations in our sample period may differ significantly from HSR cities in certain aspects, rendering non-HSR cities incomparable to HSR cities. In contrast, cities gaining HSR access later (not-yet-treated group) should be more comparable to cities gaining HSR earlier. However, Assumption 3 may not hold if not all covariates are well-controlled, even when not-yet-treated units are used as the control group.

There are three methods in CSDID to recover group-time average treatment effect. They are outcome regression, inverse probability weighting, and doubly robust estimator respectively. When utilizing not-yet-treated units as the control group, outcome regression necessitates accurate control of all differences between the earlier treated group and the later treated group to ensure the conditional parallel trend assumption holds. Inverse probability weighting requires the correct estimation of the probability of unit i being in group g (treated at time g), conditional on covariates X, and on whether unit i is in group g or in an appropriate comparison group. The doubly robust approach combines the inverse probability weighting model and outcome regression.

While these three methods are identical in terms of identification, they differ in the aspect of estimation. The doubly robust approach holds an advantage over its counterparts. It works well as long as either the differences between the early treated and late treated groups are well-controlled or the probability that a unit belongs to group g is correctly calculated. According to Callaway and Sant'Anna (2021), these estimands yield identical results if Assumption 1-3 hold. However, as HSR is not randomly assigned to each city, and it is extremely challenging to control all differences between the earlier treated and later treated groups in practice. In such cases, as suggested by Callaway and Sant'Anna (2021), the doubly robust approach is preferable to alternative methods from an estimation perspective, as it leverages both outcome regression and inverse probability components.

In our paper, We use Doubly robust approach to recover the Average Treatment Effect of HSR on employment. Doubly robust estimator is shown as Equation 2.2. Here, represents units receiving treatment at time g, corresponding to cities gaining access to HSR in year g. The control group consists of cities that have not yet gained HSR access by year t but become HSR cities before the end of our sample period (2017). ATT(g,t) represents the average treatment effect of cohort g at time t, indicating the average impact of HSR on cities gaining HSR access in year g by year t.

$$\text{ATT(g,t)} = \mathbb{E}\left[\left(\frac{G_g}{\mathbb{E}[G_g]} - \frac{\frac{P_{g,t}(X)(1-D_t)(1-G_g)}{1-P_{g,t}(X)}}{\mathbb{E}\left[\frac{P_{g,t}(X)(1-D_t)(1-G_g)}{1-P_{g,t}(X)}\right]}\right)(Y_t - Y_{g-1} - m^{ny}_{g,t}(X))\right] \tag{2.2}$$

G is defined as time period when a unit is first become treated. $G_g = 1$ if a unit first become treated in period g, otherwise 0. $Y_t - T_{g-1}$ calculate the difference in outcome of cohorts g (unites treated at period g) between period t (post-treatment period) and period $g-1$ (one period before the treatment). $m^{ny}_{g,t}(X) = \mathbb{E}[Y_t - Y_{g-1}|X, D_t = 0, D_g = 0]$ is outcome regression for the not-yet-treated group by time t over the period between time t and time g-1. $Y_t - Y_{g-1} - m^{ny}_{g,t}(X)$ measures the difference-in-difference between unites treated in period g and not-yet-treated group by time t. if units treated in period g is comparable to not-yet treated units, $Y_t - Y_{g-1} - m^{ny}_{g,t}(X)$ can be considered as treatment effect. Since not all not-yet-treated units are comparable to units treated in period g, Doubly robust approach assigns different weights to each comparison based on how comparable the unit is to units treated in period g. The more comparable the unit i is to cohort g, the larger weight will be assigned to the comparison group $Y_t - Y_{g-1} - m^{ny}_{g,t}(X)$. $P_{g,t}(X)$ is propensity score that implies the probability of unit i being first treated in period g, conditional on covariates X before treatment and on either being a member of cohort g or a member of not-yet-treated group by period t. $P_{g,t}(X)$ is estimated by logit regression. As we previous discussed, outcome regression relies on X covariates to successfully control all the difference before treatment, while inverse probability weighting model relies on correctly calculate the probability of being first treated in period g conditional on X. The advantage of doubly robust approach is that this method will be valid, if either the outcome evolutions of the comparison group is correctly modelled or the probability of being first treated in period g is correctly calculated.

Recovering ATT(g,t) is just the first step to estimate overall treatment effect. Researchers are more interested in the overall average treatment effect up to a certain period, and how the average treatment effect evolves at each period after treatment, rather than ATT(g,t). Thus, we need to calculate the overall ATT and ATT dynamics by aggregating ATT(g,t). The CSDID package in STATA provides us with the aggregation schemes to calculate the overall average treatment effect and ATT dynamics in event study.

Equation 2.3 is the aggregation scheme to calculate overall average treatment effect. θ_W^O is the weighted average of all identified ATT(g,t) that assigning more weights to the ATT(g,t) with a larger group size. θ_W^O is comparable to treatment effects estimated by DID or TWFE model. Unlike the TWFE model, θ_W^O rules out the problem of negative weights raised by time-varying treatment effect.

$$\theta_{es}(e) = \sum_{g \in G} \mathbf{1}(g + e \leq T) \cdot \text{ATT(g,g+e)} \cdot P(G = g | G + 2 \leq T) \tag{2.3}$$

, where

$$K = \sum_{g \in G} \sum_{t=2}^{T} \mathbf{1}(t \geq g) \cdot P(G = g | G \leq T)$$

Equation 2.4 is the aggregation scheme to calculate ATT dynamics. $\theta_{\text{es}}(e)$ is the average treatment effect e period after treatment across all groups that are ever observed to have participated in the treatment for e time periods. It is comparable to the average treatment effect estimated in event study by DID or TWFE model. This aggregation scheme provides flexibility for researchers to estimate average treatment effects over a specified period.

$$\theta_{es}(e) = \sum_{g \in G} \mathbf{1}(g + e \leq T) \cdot \text{ATT(g,g+e)} \cdot P(G = g | G + e \leq T) \tag{2.4}$$

2.3.3 Impact of HSR on non-private employment vs private employment by CSDID

First, we estimate the average treatment effect of HSR on total employment, employment in non-private organizations, and individual & private employment using the CSDID method[10]. We calculate both unconditional ATT and conditional ATT (conditional on outcome variables in 2005). Similar to the baseline estimation, we include GDP, population, and government spending on public infrastructure in 2005 as

[10] Equation 2.2 is used to recover the average impact of HSR on employment of the cities gaining access to HSR in year g by time t, ATT(g,t). Then, ATT is calculated by aggregating ATT(g,t) using Equation 2.3.

covariates. However, in the CSDID setup, we do not need to interact these outcome variables with the year dummy. These covariates not only influence employment but could also affect whether a city has HSR and when it gains HSR access. Given that the primary purpose of constructing the HSR network is to enhance transportation, cities with larger populations might be prioritized. Additionally, cities with higher GDP and government spending are likely to gain HSR access earlier than their counterparts. Although most cities in China gained access to HSR after 2008, the plan for constructing the HSR network was formulated in 2008 or even earlier. Hence, it is sensible to use those outcome variables before 2008 as covariates. We assume either parallel trend holds conditional on those covariates, or the probability of a city belonging to a specific treated cohort is correctly calculated.

The HSR network revolutionizes mid- to long-distance travel, making it faster and more convenient. Lin (2017) notes a remarkable 9% increase in total transportation ridership due to HSR. This surge in HSR ridership can significantly benefit businesses situated near HSR stations, particularly those offering consumer goods, catering, and other face-to-face services. The influx of travelers to HSR cities is expected to fuel growth in retail and tourism-related industries. Consequently, we anticipate a substantial positive impact on employment in service industries associated with travel. Given that businesses providing retail and catering services, such as small grocery stores and restaurants near HSR stations, are likely to be private enterprises, we expect a strong impact of HSR on individual & private employment. On the contrary, the HSR network may not directly stimulate employment in non-profitable organizations and industries unrelated to travel. Thus, the anticipated impact of HSR on non-private employment is expected to be less significant.

Compared to overall average treatment effect, we are more interested in how the impact of HSR network on employment evolves after treatment. Hence, we use event study to identify the dynamic effect of HSR on different type of employment discussed above. The dynamic impact of HSR on employment is estimated by equation 2.4. To be consistent with event study of traditional DID or TWFE model, we use *long2* option in STATA to set the average treatment one period prior to the treatment as zero. Therefore, the estimated ATT at each period stands for the difference in ATT between ATT in that period and ATT one period before the treatment. We expect individual & private employment to response to HSR immediately, since it is relatively easy to start a small business, and hiring process in small business is simple and flexible.

2.3.4 Testing impact of HSR on retail & whole sale industry

If the impact of HSR on individual & private employment is significantly positive and greater than that on employment in non-private organizations, we will proceed to identify and estimate the treatment effect of HSR on employment in the retail & wholesale industry using the method discussed above. Individual & private employment are clustered in retail & whole sale industry and service industries related to travel. Our objective is to test whether the growth in individual & private employment in HSR cities is driven by expansion in industries directly associated with travel.

2.3.5 Estimating impact of HSR on government spending on public infrastructure

When estimating the impact of HSR on employment, we aim to isolate the influence of other factors on employment outcomes. Government spending on public infrastructures is one of such factors that can create job opportunities. For instance, the development of a plaza with numerous stores, restaurants, and parking lots can contribute to individual & private employment.

If cities with large government expenditure are more likely to gain access to HSR, or if local governments spend more on public infrastructure after their cities have HSR in operations, we need to control the impact of government spending on employment. Government spending on public infrastructure in 2005 is added to our model as covariates. However, it is essential to test whether government expenditure on public expenditures increase after a city gains access to HSR. To address this concern, we will apply the CSDID method to test the impact of HSR on government spending on infrastructures in the section of robustness check.

2.4 Empirical results analysis

2.4.1 Estimation results for employment by TWFE model

The unconditional estimated impact of HSR on employment by TWFE model are reported in Table 2A. In Column 1, we employ the logarithm transformation of total employment at the prefecture city level as the dependent variable. Column 2 uses the logarithm transformation of individual & private employment, while Column 3 uses the logarithm transformation of employment in non-private organizations as the dependent variable.

HSR_i represents HSR city dummy, taking the value of 1 if a city has HSR, and 0 otherwise. HSR_t is HSR year dummy. HSR_i interacted with HSR_t, $\mathrm{HSR}_i \times \mathrm{HSR}_t$, is our variable of interest, which indicates if a city i has HSR in operation in year t. All models in Table 2.2 only control for year and city fixed effects. Standard errors are clustered at city level. As shown in the Table 2A, HSR on average increases total employment by about 3.5% (at 10% significance level), boosts individual & private employment by 5.0% (at 10% significance level), while showing no significant impact on employment in non-private organizations. Although, results for total employment and individual & private employment are only significant at 10% level, they still provide some evidence that the impact of HSR on individual & private employment is stronger than its impact on non-private employment.

The HSR impact on different types of employment, conditioned on variables including population, real GDP, and government spending on infrastructure in 2005, is reported in Table 2.3. Upon incorporating these variables interacted with year dummy as controls, the impact of HSR appears to be insignificant for all types of employment. However, it is important to note that the impact of HSR estimated by the TWFE model might be subject to inaccuracies. If the treatment is time-varying, potential negative weights assigned to the comparison of the early treated group and the late treated group could lead to either an overestimation or underestimation of the average treatment effect. Specifically, if the treatment effect is positive and increasing over some periods, the TWFE model is likely to underestimate the average treatment effect. Therefore, our analysis will rely on the results yielded by the CSDID method rather than the TWFE model.

2.4.2 Estimation results for employment by CSDID

Average treatment effects of HSR on different types of employment are presented in Table 2.4. In Column 1, the average treatment effect of HSR on total employment is reported. Column 2 shows the average treatment effect of HSR on individual & private employment, while Column 3 reports the average treatment effect of HSR on employment in non-private organizations. The row of unconditional ATT reflects the average treatment effect estimated by CSDID without any covariates, and the row of conditional ATT represents the average treatment effect estimated conditional on population, real GDP, and government expenditure on infrastructure in 2005.

It is worth noting that the impacts of HSR on different types of employment estimated by CSDID are considerably larger and more significant than those estimated by the TWFE model. This observation indicates that the TWFE model underestimates the treatment effect of HSR on employment, primarily due to the negative weights assigned to certain comparisons of the early treated group and the late treated group.

The results from Table 2.4, without any covariates, suggest that HSR, on average, increases total employment by 7.1%, individual & private employment by 9.7%, and non-private employment by 4.7%. When considering our covariates, the conditional average treated effects show that HSR, on average, increases total employment by 6.8% and individual & private employment by 14%, with no significant impact on non-private employment. We place more emphasis on conditional average treated effects, as we believe cities with similar population, GDP, and government spending are more comparable.

Our results suggest heterogenous impact of HSR on different type of employment, with much more significant impact observed in individual & private employment. The robust effect on individual & private employment can be explained by the boost in service industries, including retail, catering, hotels, and other travel-related sectors, as HSR attracts more visitors to HSR cities. The majority of businesses in these industries are small private firms, contributing to the substantial growth in individual & private employment after a city gains access to HSR. In contrast, we do not observe a significant impact of HSR on employment in non-private organizations. Several factors contribute to this result. First, non-private organizations likely include non-profit organizations and large companies not directly linked to tourism. HSR does not immediately create job opportunities in these sectors. Second, jobs in non-private organizations tend to be stable. While HSR enhances overall utility, it may not prompt individuals with stable jobs to relocate from non-HSR cities to HSR cities.

2.4.3 Dynamics of HSR treatment effect on employment by CSDID event study

Compared to fixed average treatment effect, we are more interested in understanding how the treatment effects of HSR on employment evolve over the post treatment periods. Figure 2.3 presents the conditional dynamic average treatment effect (conditional on all selected outcome variables) of HSR on total employment, Figure 2.4 illustrates the conditional dynamic average treatment effect of HSR on individual & private employment, and Figure 2.5 shows the dynamic average treatment effect of HSR on employment in non-private organizations. All dynamic ATTs are estimated using CSDID event study approach. Data results of impact of HSR on different type of employment based on event study is shown in Table B.1 in Appendix.

The horizontal axis in Figure 2.3 represents periods since a city gained access to HSR. The zero point indicates the year a city acquired HSR, and subsequent values denote the years following the city's implementation of HSR. Similar to the event study of the traditional TWFE model, the estimated treatment effect at one period prior to treatment is set to zero. This signifies that the dark blue dots measure the difference in the average treatment effect between the corresponding period shown on the horizontal axis and one period before the treatment. The average treatment effect of every period before treatment is not statistically different from zero, providing evidence that the parallel trend is likely to hold before treatment.

Average treatment effects of HSR on total employment are significantly positive (at a 5% significance level) up to two years after a city gains access to HSR. To be more specific, HSR, on average, increases total employment by 4.1% one year after a city has HSR and boosts employment by 5.4% two years after HSR is in operation.

Figure 2.4 illustrates how the impact of HSR on individual & private employment evolves over time. The average treatment effect of each period prior to treatment is statistically zero, supporting the assumption of a pre-parallel trend. From the graph, it is evident that individual & private employment responds to HSR immediately. The average treatment effects of HSR become significantly positive one year after a city implements HSR. This rapid response in individual & private employment can be attributed to the flexibility of self-employment and the straightforward recruiting process in small businesses.

The average treatment effect shows an increasing trend up to three years after treatment, remaining significantly positive up to seven years post-treatment. To be more specific, HSR, on average, increases individual & private employment by 10.5% one year after a city has HSR, boosts individual & private employment by 12.6% two years after HSR in operation, and increases individual & private employment by 15.1% three years after a city gaining access to HSR.

Figure 2.5 shows that average treatment effect of every post-treatment period is not significant different from zero, indicating that HSR has no impact on employment in non-private organizations.

2.4.4 Impact of HSR on employment in retail & whole industry

To prove our hypothesis that the positive impact of HSR on travel-related industries, such as retail & wholesale, contributes to the growth in individual & private employment after a city has HSR, we conduct further testing on the impact of HSR on employment in the retail & wholesale industry. The average treatment effect of HSR, estimated using the CSDID method, is reported in Table 2.5. The second column presents the unconditional average treatment effect of HSR, while the third column presents the average treatment effect conditional on population, real GDP, and government spending on infrastructure.

The results from Table 2.5 highlight that, on average, HSR leads to a substantial increase of about 14% in employment within the retail & wholesale industry, and this positive effect remains significant regardless of whether other outcome variables are included as covariates. These findings strongly suggest that HSR significantly stimulates travel-related industries. Given that individual & private employment is concentrated in the retail & wholesale industry, our results provide compelling evidence that the growth in individual & private employment following a city's adoption of HSR can be attributed to the impact of HSR on travel-related sectors such as retail and wholesale.

Figure 2.6 illustrates the event study of the conditional average treatment effect of HSR on the retail & wholesale industry using the CSDID method. The graph shows that the average treatment effect during all pre-treatment periods is not significantly different from zero, supporting the assumption of a pre-parallel trend. The impact of HSR on employment in the retail & wholesale industry becomes significantly positive two years after a city adopts HSR, and this positive effect persists for at least two years.

2.5 Robustness Check

The event study results provide support for the assumption of a pre-treatment parallel trend, but it is important to note that this assumption cannot be directly tested. As discussed earlier, an increase in government spending on infrastructure could potentially create job opportunities. In the scenario where cities boost government expenditure on infrastructure after they have HSR, the impact of this increased spending on employment might be mistakenly attributed to HSR, leading to an overestimation of HSR's impact on employment. To address this concern, it becomes essential to examine whether government spending on infrastructure experiences a significant increase after a city adopts HSR.

Figure 2.7 presents the event study of the average treatment effect of HSR on government spending on infrastructure. The graph shows that the average treatment effect of HSR on government spending on infrastructure is not statistically different from zero both before and after a city has HSR in operation. This implies that the substantial growth observed in individual & private employment after a city adopts HSR is not driven by an increase in government spending. These findings contribute to the robustness of our empirical results.

2.6 Conclusions

In this paper, we employ the CSDID method with the Doubly Robust estimator to estimate the impact of HSR on various types of employment. Our results reveal a significant positive impact of HSR on employment, contrasting with the underestimation observed in the TWFE model. This underestimation is attributed to the negative weights assigned to comparisons between early and late treated cohorts, when the treatment effect is time-varying.

Moreover, our analysis uncovers a heterogeneous impact of HSR on different types of employment. On average, HSR increases individual & private employment by 14%, while showing no significant impact on employment in non-private organizations. The direct promotion of travel-related industries, where individual & private employment is clustered, accounts for the substantial growth observed in individual & private employment following a city having HSR in operation. In contrast, employment in non-private organizations, less likely to be associated with travel, remains unaffected.

To further understand the drivers of individual & private employment growth, we investigate the impact of HSR on employment in the retail & wholesale industry. The significant positive impact on this sector provides empirical evidence that the notable expansion in individual & private employment after a city has HSR is indeed fueled by the growth in travel-related industries. In addition, our analysis reveals that this growth in individual & private employment is not driven by government spending on infrastructure, reinforcing the robustness of our results.

Our findings hold practical implications for city planners. When deliberating on HSR network construction, it is crucial for planners to recognize that, beyond its role in facilitating transportation, HSR can stimulate employment in small businesses.

Figure 2.1: HRS network and House Price

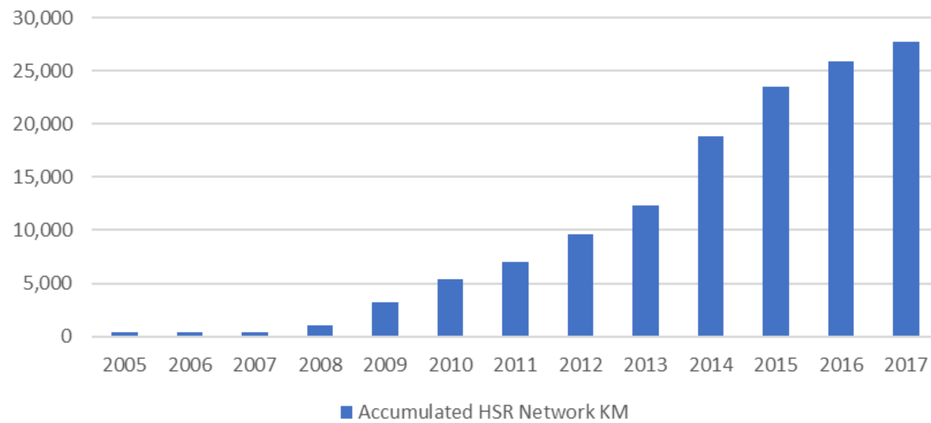


Figure 2.2: High Speed Railway Map of China in 2017

Notes. The Map is sourced from https://en.wikipedia.org/wiki/High-speed_rail_in_China.

Table 2.1: Data description

variable name	No. obs	mean	min	max
Employment	2639	653.9	86.5	17290.8
Non_private_employment	2639	508.7	54.2	8780.5
Private_employment	2639	481.9	14.5	9517.3
Pop_2005	203	4118.1	431.1	13602.6
Industry	2639	247.3	4.3	2975.9
Retail_whole	2639	25.6	0.6	1230.4

Notes. Employment denotes the number of total employed people; Non_private_employment denotes the number of people employed by non-private firms; Private_employment denotes individual and private employment; Pop_2005 denotes population (usual residence) at the end of 2005; Industry denotes the number of employed people in second industry; Retail_whole denotes number of employed people in retail and whole sale industry.

Table 2.2: Unconditional impact of HSR on employment by TWFE model

variable name	1	2	3
Dep. var	ln employment	ln private	ln non-private
$\text{HSR}_i \times \text{HSR}_t$	0.035* (0.018)	0.050* (0.031)	0.024 (0.018)
year FE	Y	Y	Y
city FE	Y	Y	Y
No. obs	2256	2256	2256

Notes. Standard error is in parentheses. $*** = p < 0.01$, $** = p < 0.05$, and $* = p < 0.1$.

Table 2.3: Conditional impact of HSR on employment by TWFE model

variable name	1	2	3
Dep. var	ln employment	ln private	ln non-private
$HSR_i \times HSR_t$	0.014 (0.019)	0.043 (0.034)	−0.005 (0.019)
$\ln pop_{2005} \times$ year dummy	Y	Y	Y
$\ln GDP_{2005} \times$ year dummy	Y	Y	Y
$\ln expend_{2005} \times$ year dummy	Y	Y	Y
year FE	Y	Y	Y
city FE	Y	Y	Y
No. obs	2256	2256	2256

Notes. Standard error is in parentheses. $*** = p < 0.01$, $** = p < 0.05$, and $* = p < 0.1$.

Table 2.4: Impact of HSR on employment with CSDID

variable name	1	2	3
Dep. var	ln employment	ln private	ln non-private
unconditional ATT	0.071*** (0.021)	0.097** (0.039)	0.047** (0.023)
conditional ATT	0.068*** (0.029)	0.140*** (0.041)	0.002* (0.032)
No. obs	2256	2256	2256

Notes. Standard error is in parentheses. $*** = p < 0.01$, $** = p < 0.05$, and $* = p < 0.1$.

Table 2.5: Impact of HSR on employment in retail & whole industry

variable name	1	2
Dep. var	ln(retail + whole sale)	ln(retail + whole sale)
ATT	0.144*** (0.045)	0.140*** (0.047)
No. obs	2256	2256

Notes. Standard error is in parentheses. $*** = p < 0.01$, $** = p < 0.05$, and $* = p < 0.1$.

Figure 2.3: Impact of HSR on total employment by event study

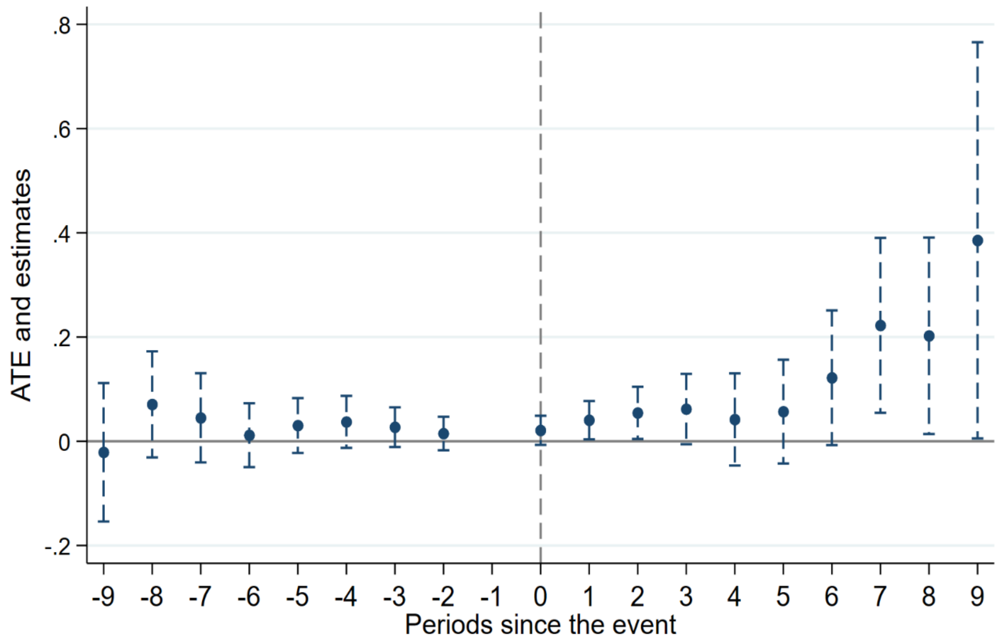


Figure 2.4: Impact of HSR on Private employment by event study

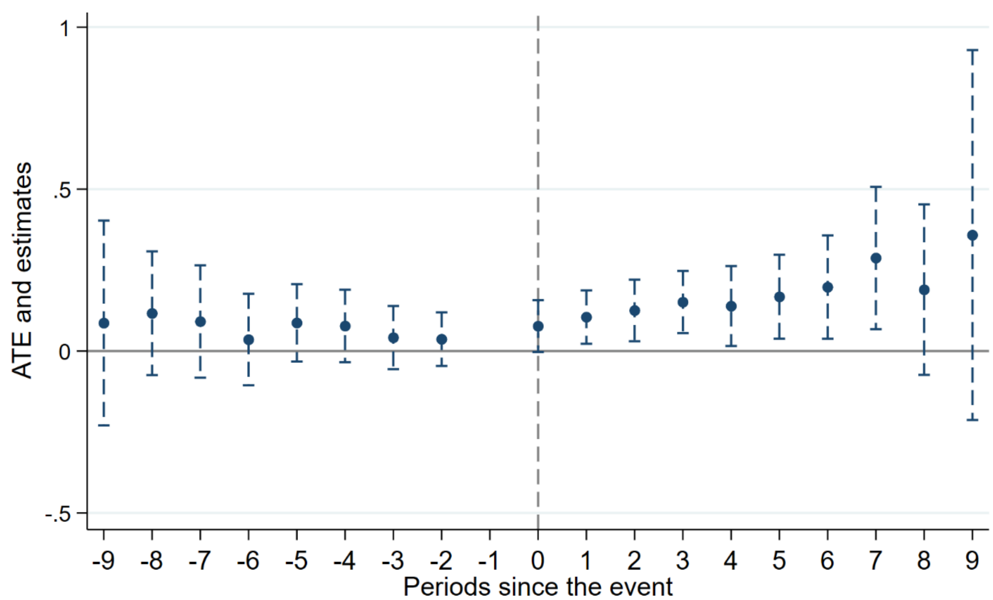


Figure 2.5: Impact of HSR on non-Private employment by event study

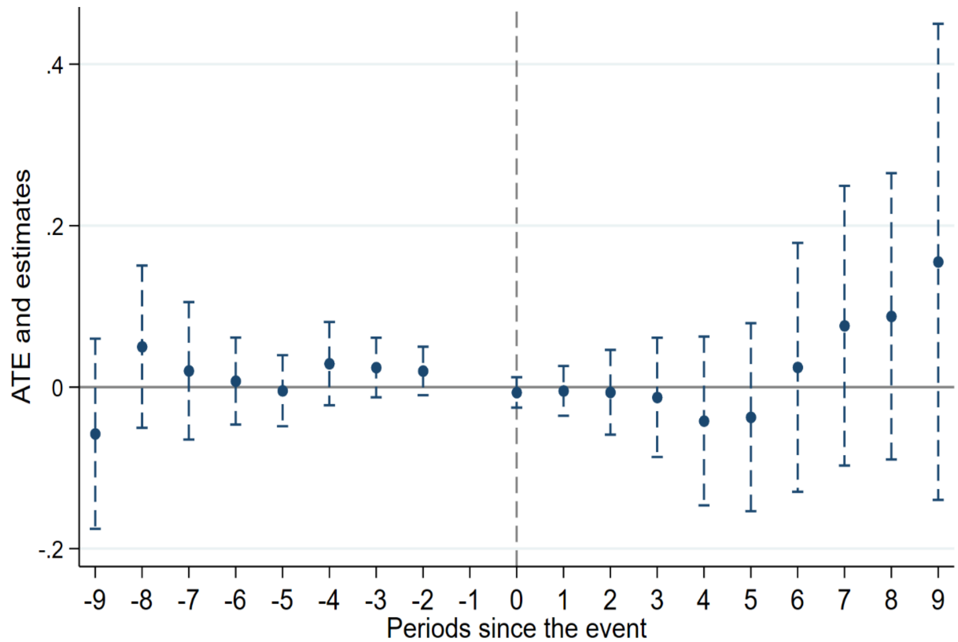


Figure 2.6: Impact of HSR on Retail employment by event study

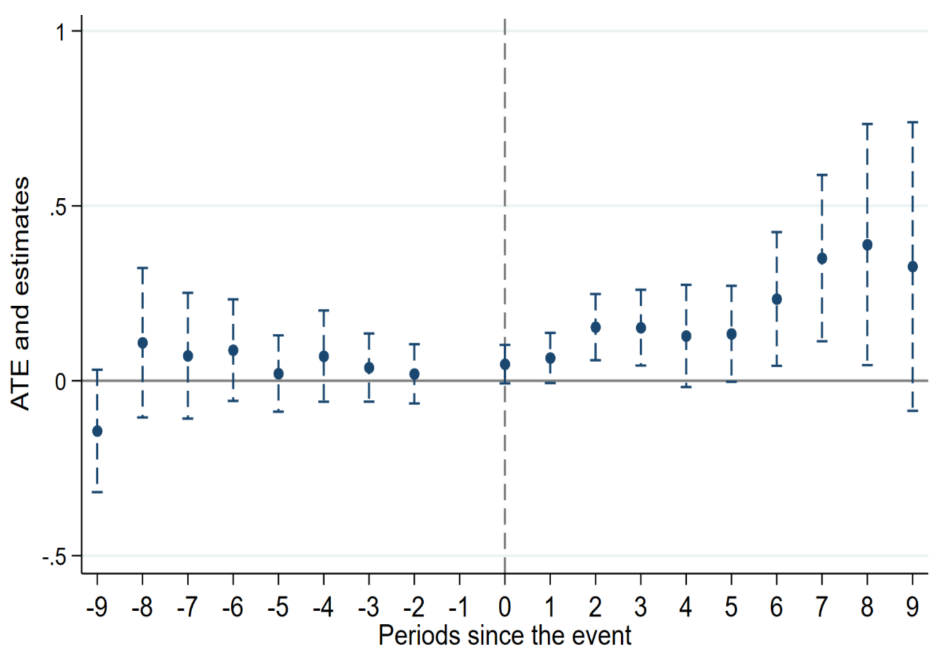
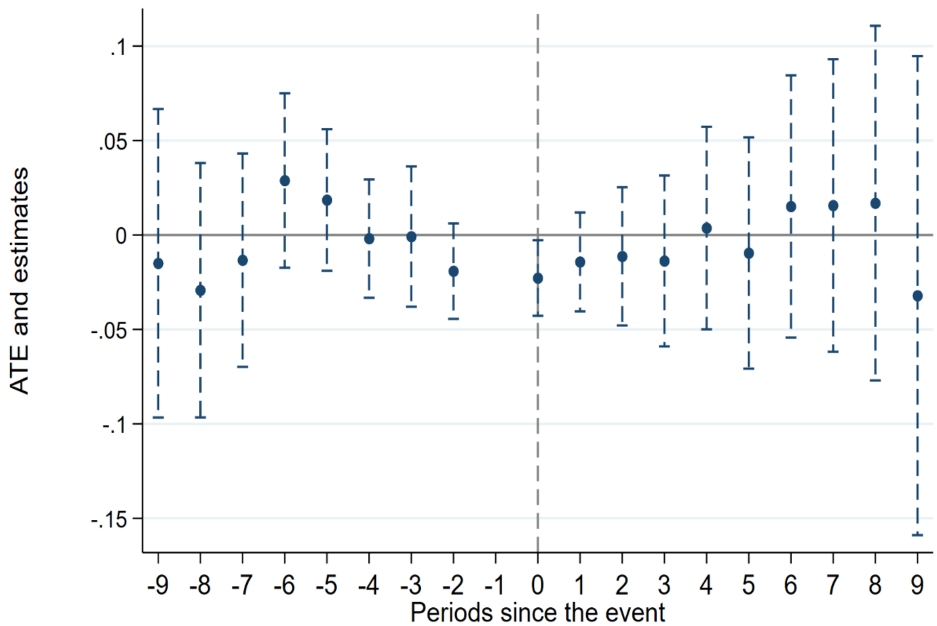


Figure 2.7: Impact of HSR on government spending



Chapter 3

MONETARY POLICY AND HOUSE PRICE IN CHINA

3.1 Introduction

Over the last decade, the persistent and rapid escalation in housing prices has become a source of economic and political concern, given its being a source of social challenges. In 2020, the ratio of housing prices to wages[1] in China ascended to 28.40, positioning it as the eighth highest globally. Comparative analysis, as depicted in Figure 3.1, illustrates that this ratio stands at 18.63 in the United States, 21.67 in Singapore, and 19.41 in Korea, highlighting the pronounced disparity relative to other developed nations. This issue is particularly worse within China itself, where Shenzhen[2] exhibits the most elevated ratio at 41.6. This implies that a median-income family would need to allocate every yuan of their post-tax earnings for over 41 years to afford a residence in Shenzhen. In other first-tier cities[3], this ratio surpasses 30. Figure 3.2 shows the internal disparity in the housing price-to-wage ratio within China, revealing that in the top one hundred cities, over 70% exhibit a ratio exceeding 10. The geographical distribution of these ratios, as illustrated by the heat map, indicates a pronounced concentration of high housing price-to-income ratios along the southeast coast, with a gradual decrease when moves inland. Notably, all first-tier cities

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[1] It is defined as the disposable income

[2] Shenzhen is one of the four tier-one cities, and it is in the Guangdong Province.

[3] Depending on five indicators: the concentration of commercial resources, the city's hub, the activity of urban, people, the diversity of lifestyles, and future plasticity, 347 cities in China are put into one of the tiers. We have six categories: tier-one, new tier-one, tier-two, tier-three, tier-four, and tier-five. There are only four cities classified as tier-one: Beijing, Shanghai, Shenzhen, and Guangzhou. There are 15 new tier-one, 30 tier-two, 70 tier-three, 90 tier-four, and 128 tier-five cities.

are located in the Eastern region, demonstrating significant regional variances across China.

In recent years, China has observed a consistent decline in birth rates, with the rate of newborns dropping to a mere 0.72% in 2021. Concurrently, the country is experiencing a decrease in marriage rates along with an uptick in divorces. Between 2013 and 2020, marriage registrations fell from 13.47 million to 8.13 million, whereas divorces escalated from 580,000 in 1987 to 3.73 million in 2020, as illustrated in Figure 3.3.

This trend is accompanied by diminishing marriage, fertility[4], and population growth rates[5], in stark contrast to the rising divorce rate. Additionally, the average age at which individuals marry is increasing, with the demographic cohort of 25-29 years now becoming the predominant age group for marriage, supplanting the 20–24-year age group. In response, China introduced a "divorce cooling-off period"[6] in 2021 as an amendment to the Marriage Law, aiming to mitigate these trends, which has subsequently ignited vigorous debate.

This shift towards lower marriage rates and higher divorce rates has promoted the growth of the single economy, characterized by singles' tendency towards lower savings and higher consumption rates, which positively contributes to economic expansion. On the other hand, due to the deepening of the aging population, the low marriage rate and the high divorce rate have slowed down the growth rate of my country's labor force. As demonstrated in Figure 3.4, the labor force participation rate for males and

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[4] Defined as the ratio of newly born population and average population number in a given year.

[5] Marriage and divorce rate are defined as the number of populations that are getting married or divorced divided by the average population in a given year.

[6] Under the principle of freedom of divorce, if both parties to marriage apply for a voluntary divorce, within a certain period of time from the date when the marriage registration authority receives the application, either party can withdraw the application for divorce and terminate the registration and divorce procedures.

females declined from 71.7% in 2009 to 67.4% in 2020. This change reflecting a significant challenge for China since labor forcebeing the main driver for economic growth. In the face of these demographic and socio-economic transformations, addressing the dual issues of declining marriage and fertility rates, coupled with an increase in divorce rates, is important for enhancing GDP growth.

In the traditional Chinese societal norms, homeownership is means establishing a stable foundation for life. Marriage come with various financial obligations, including dowries, the prerequisite of acquiring real estate prior to marriage, mortgage payments, and the costs associated with raising children. In China, the term 'dowry' refers to the financial and material contributions (such as cars, houses, jewelry, etc.) traditionally provided by the groom and his family to the bride and her relatives. however, the current high costs of housing and high educational expenses have become the discouragement to marriage for young people, particularly within top tier cities. Between 1998 and 2018, the average national price for new commercial housing surged from 1,854 yuan per square meter to 8,544 yuan. Concurrently, from 2004 to 2018, the total personal home purchase loan balance escalated from 1.6 trillion yuan to 25.8 trillion yuan, marking a 16.1 times, accounting for more than 50% of the balance of household loans, compared with 54% in 2018. This rise has led to the mortgage-to-income ratio (the ratio of personal home loan balances to dis- posable income) soaring from 16.2% to 47.6%, thereby elevating the household sector's debt-to-income ratio[7] from 28.6% to 88.4%.

Addressing the escalating housing prices is crucial for economic growth and dealing with associated social issues. Over the past two decades, the government has enacted several rounds of real estate price control policies[8]. However, these interventions

[7] defined as the resident debt balance to the disposable income.

[8] For example, 'National Eight Rules' in March 2005, 'National Four Rules' in December 2009, 'New National Eight Rules' in January 2011, 'New National Five Rules' in 2013 February.

have primarily achieved only temporary suppression of housing prices but fueling long-term increases. In the era of credit currency, currency issuance is not long endorsed by precious metals. It is easily causing money over-issuance, triggering different degrees of inflation. Despite rapid economic development and an increasing rate of urbanization in recent decades, China faces persistent rises in housing prices, frequent and unusual stock market volatility, and an expanding M2- to-GDP ratio. These phenomena pose challenges to China's future economic development. More and more economists have focused on China's massive M2 issuance in recent years, but no single hyperinflation has happened as the economic theories predicted. According to the National Bureau of Statistics, at the end of 2020, China's M2 witnessed a 9.2% year-over-year increase, while the Consumer Price Index (CPI) only rose by 2.5% in the same period.

The equation of money supply, $PY = MV$, how is such a large amount of money generated and what absorbs the massive amount of currency is worth thinking about. The circulation of base currency can proceed via two ways: a closed cycle and an expansion cycle. In the context of countries with mature capital markets, the former pathway is typically observed. Following the issuance of base currency by the central bank, the aggregate volume of financial instruments generated remains constant, with the central bank retaining absolute authority over the total money supply. Contrastingly, China is to the latter model. The reason is that because of China's compulsory foreign exchange settlement system, the foreign exchange obtained by enterprises through foreign trade must be sold to commercial banks, which in turn must be sold to the central bank. Consequently, the central bank is obliged to reissue base currency equivalent to the foreign exchange to maintain the system's integrity. By the end of 2019, the balance of foreign exchange accounts reached to 21.23 trillion yuan, representing 10% of the total M2. Additionally, China's elevated savings rate and loose credit environment facilitate the transformation of various savings deposits into another source of M2 via the currency creation activities of commercial banks.

Typically, the money is flows into one of three sectors: the real economy, the asset market (the real estate market), and the capital market. Given that M2 exhibits lower liquidity compared to M0 and M1[9], it is plausible that excess money supply gravitates towards the real estate market. This hypothesis arises from the exclusion of housing prices (and capital market investments) from China's Consumer Price Index (CPI) calculations, potentially explaining why an oversupply of M2 has not precipitated hyperinflation, as illustrated in Figure 3.5. Take one step further, investment in the capital and asset markets is considered interchangeable. With investors allocating their wealth to one of these markets. Consequently, the question arises: Is there a connection between the flourishing capital market and elevated housing prices, and if so, how is this relationship manifested? The capital market's expansion engenders a wealth effect, amplifying demand for non-durable goods (including consumption) and possibly for housing, thereby exerting upward pressure on housing prices. By deploying a Structural Vector Autoregression (SVAR) model incorporating proxies for the real estate market, monetary policy indicators, and other macroeconomic variables, along with impulse response analysis and variance decomposition, we can empirically examine these propositions.

The subsequent structure of this paper is delineated as follows: Section 3.2 provides a comprehensive review of literature pertinent to the topic at hand. Section 3.3 delves into the mechanisms through which varying monetary policies within China impact the housing market. Section 3.4 and Section 3.5 details the empirical findings regarding the effects of monetary policy on Chinese housing prices, along with additional related outcomes. Finally, Section 3.6 offers a conclusion of the study's findings and implications.

3.2 Literature Review

This research is related with two principal strands of literature. The first strand is the money supply and commodity price. In many countries, literature shows the

[9] In China, M0 is defined as the cash in circulation, M1 is defined as M0 plus demand deposits (check deposits and credit card deposits), M2 is defined as M1 plus savings and time deposits.

relation between money supply and the commodity market, which is the start of this proposal. For example, Grauwe and Polan (2005), Friedman and Kuttner (1992), and Bachmeier and Swanson (2005). They provided evidence of the positive relationship between the money supply (M2) and the price level. The application uses M2 to improve the prediction of inflation. One interesting application, Binner et al. (2010), used a deep learning model, a recurrent neural network, to provide the same evidence of the relation between the money supply and the overall price level. This worked is a robust test. In China, we have the same situation. Sun and Ma (2004) and Chen et al. (2017) showed a positive relation between M1 and price level.

The second strand explores the implications of monetary policy on the housing market. This inquiry mainly utilizes the structural vector autoregression (SVAR) model to discern the effects on housing prices. For example, Iacoviello (2005), the SVAR model in the UK context by Elbourne (2008), a panel SVAR for emerging markets by Singh and Nadkarni (2020), and a Bayesian SVAR model for Scandinavian countries by Rosenberg (2019) used a Bayesian SVAR model to investigate the case in Scandinavian countries. These studies collectively indicate that the impact of monetary policy on housing prices varies by country and is typically asymmetric, with a general consensus that expansionary monetary policy tends to elevate housing prices. In the U.S., monetary policy exhibits different impacts in different periods. Prior to the financial crisis, monetary policy works more effectively than in the post-financial crisis period. Much literature also focuses on the monetary policy's impact on the other aspect of the housing market in different countries, the price volatility. Tsai (2013), Cooper et al. (2016), and Kelly et al. (2018) study the monetary policy's impact on the volatility of the housing price. Although the focus on second-order moments is outside the scope of this paper.

Regarding the Chinese real estate market and monetary policy, the literature is less developed. Li et al. (2021) investigated the immediate effects and transmission velocity of monetary policy on real estate prices, finding a direct correlation between M2 increases and real estate price rises within the same period. Komijani and Haeri

(2013) offered a theoretical examination of housing prices in the transmission mechanism of monetary policy, including the transmission to the real estate regulation and the transmission to the real economy. They utilized monthly data from January 1999 to December 2006, and the indicator includes the 30-day average interest rate of the national interbank market. The stationarity test, co-integration test, and impulse response analysis based on VECM demonstrate the delayed yet significant long-term effects of monetary policy variables on housing prices. Chen et al. (2018) posited that bank loans could be a long-term Granger cause of fluctuations in housing prices, with impulse function analysis underscoring a positive correlation between housing prices and bank credit, the results of impulse function analysis show that the impact of house prices on bank credit is correspondingly positive. Conversely, Yan et al. (2019) employed five VAR models identified a paradoxical effect wherein higher interest rates were associated with rising housing prices, challenging conventional theoretical expectations. Mishkin (2001) applied a structural VAR model to analyze the transmission of monetary policy through real estate prices, concluding that monetary policy can effectively influence housing price dynamics, although the impact on the broader economy remains limited.

Researchers' attention within the realm of Chinese housing market research has mainly been directed towards diverse aspects beyond conventional analyses. Yang et al. (2018) investigated the spillover effects within China's housing market, employing a high-dimensional generalized VAR model to demonstrate the intricate interactivity among city- level monthly housing prices. They identified that variables such as a city's administrative status, population size, GDP, and level of secondary education play significant roles in influencing the positive spillover patterns observed. Zhang and Pan (2021) explored the asymmetric impacts of monetary policy and output shocks on the housing market, while Ding et al. (2020) examined the tail causalities between the money supply and real estate prices in China, finding that smaller and inland cities exhibit heightened sensitivity to fluctuations in the broad money supply (M2), particularly within tail quantile intervals of housing market returns. Additionally, Koivu

(2012) analyzed the wealth effect of real estate in China, noting that expansionary monetary policy tends to elevate asset prices and that positive shifts in residential prices bolster household consumption, albeit with minimal influence from stock prices from the perspective of households.

In summary, the majority of research employed the VAR model, with less frequent use of the SVAR model incorporating macroeconomic identification strategies. When the SVAR model is utilized, the Cholesky decomposition method is often applied, imposing robust assumptions on the economic framework regarding the transmission of information across various variables, needing a strong economic theoretical underpinning. Moreover, much of the existing research is characterized by limited data range, which may not fully capture the dynamics between variables of interest due to potential structural changes over time. Furthermore, while some studies have ventured into city-level analyses, there is a notable absence of research focusing on region-level effects. Addressing these gaps, this paper employs a SVAR model with exclusion restrictions to identify the impacts of monetary policy on housing prices across China, offering an exhaustive examination of monetary policy effects. Additionally, this study analyzes the differential influences of monetary policy across various Chinese regions to reveal the primary drivers of housing market dynamics within distinct geographical contexts.

3.3 Theoretical Supports

Prior to delving into the impacts of monetary policy, it is important to establish the foundational premise that requires an explicit assumption is the effectiveness of the monetary policy. If monetary policy is neutral, it would imply it without of any influence on the real economy and thereby then its transmission mechanism itself is meaningless. Since Keynes established the macroeconomic analysis framework, various economic schools have introduced theories on the transmission mechanisms of monetary policy, grounded in their respective theoretical underpinnings and interpretations. Among these, the concept of monetary channels stands out as particularly significant.

Both traditional Keynesianism and monetarism believe that monetary policy's influence is transmitted exclusively through monetary variables. While Keynesian thought posits that this occurs primarily via the price of money, whereas monetarism focuses the significance of the quantity of money. The monetary channel assumes the existence of perfect financial market and complete information, where loans are fully interchangeable with bonds and stocks, to the extent of categorizing loans as a variant of bonds. The money channel emphasizes the liability side of the balance sheet and ignores the asset side, which believes the source of the money sup- ply to be unimportant; that is, whether the money supply is caused by bank loans or the purchase of securities, its impact on economic activity is the same. The monetary channel can be divided into the interest rate, exchange rate, asset price, and wealth effect channels according to the different transmission processes.

3.3.1 Interest rate channel

The utilization of interest rate as one of the critical instruments for monetary policy. The traditional Keynesian school emphasizes the impact of the real interest rate level on corporate investment and believes that loose monetary policy will cause the interest rate level to drop, thereby reducing the financing cost of enterprises and stimulating investment. This principle is equally applicable to the real estate sector in China, where purchasing property is considered an investment. Thus, monetary policy, by modulating interest rates, indirectly impacts the cost burden on real estate purchasers, influences demand within the real estate market, and ultimately bears upon housing prices through the mechanisms of supply and demand. The interest rate channel emphasizes that the real interest rate has a more significant impact on investment than the nominal interest rate because the real interest rate level represents the cost of using funds. An escalation in interest rates heightens the financing expenses for real estate developers and increases the acquisition costs for property buyers through mortgage loans, thereby disturbing the equilibrium of supply and demand within the housing market and influencing property values.

In China, where mortgages being the primary method of property acquisition with the purchased asset serving as collateral, fluctuations in interest rates directly impact the affordability of home purchases, thereby influencing demand. An increase in interest rates elevates the capital cost associated with property acquisition, prompting potential buyers to exit the market, which in turn diminishes demand in the real estate sector and exerts a downward pressure on housing prices, and vice versa. On the other hand, the real estate sector is capital-intensive industry. It relies heavily on financing through loans for its development and investment. Consequently, an uptick in interest rates raises the capital cost of investments, inhabiting the investment activities of real estate firms, reducing the supply of new properties, and potentially leading to an increase in housing prices, and vice versa.

Comprehensively, the effect of an expansionary monetary policy employing interest rate mechanisms depends on the relative strength between demand and supply forces within the market. In addition, interest rates serve as a crucial metric and regulatory tool in monetary management, influencing market expectations to a significant extent. Market participants, in response to reductions in interest rates, anticipate an expansionary monetary policy, which in turn stimulates market demand and promotes an upward trajectory in housing prices.

3.3.2 Money supply channel

The concept of money supply refers to the aggregate amount of money that a nation sustains within the regular framework of its socio-economic activities at a given moment, serving as a pivotal intermediary objective of monetary policy. According to the assumption of non-neutrality of money, variations in the money supply exert influence on the aggregate economic output and price levels, positioning the money supply as a fundamental instrument through which the central bank controls the macroeconomic.

An increase in the money supply indicates of an expansionary monetary policy, characterized by persistently low interest rates relative to the prevailing liquidity preference. With characteristics of the real estate sector, a significant portion of the capital requisite for its development and investment is procured via bank loans. Consequently, a decrease in interest rates mitigates the financial burden of borrowing for real estate firms, thereby fostering investment within the industry. An escalation in real estate investment leads an increase in housing transactions. In scenarios where the real estate market is booming, both the supply and demand for real estate will increase, thereby facilitating transactions and consequentially elevating housing prices.

Economic progression is inseparably linked to capital investment. The increase of the money supply alleviates the financial constraints on economic expansion, ensuring an uptick in investment levels, which is advantageous for the overall economic development, considering capital constitutes a critical input for enterprise production. Collectively, within the context of an economic upsurge, residents' income levels rise, and via the wealth effect transmission, the enhancement of residents' wealth augments their capacity to purchase homes. This, in turn, increase demand within the real estate market and leading in an increase in housing prices.

This paper differentiates among the various monetary policy instruments, as each tool exhibits distinct temporal responsiveness. Moreover, this analysis utilizes monthly data, suggesting that different instruments may have varied impacts on housing prices in China. Furthermore, the interest rate in China has not been fully liberalized, with the government maintaining a degree of control over bank lending rates, presenting an additional variable in this dynamic.

3.4 Methodology

3.4.1 Data

To use the fullest extent of available observational data, this study employs monthly datasets spanning from January 2001 to December 2019. The data, sourced from the CEIC database[10], are categorized into four segments: monetary policy indicators (inclusive of the broad money supply, M2, and the interest rate, int), housing prices (hp), variables pertaining to the real economy (such as consumption, con; investment, inv; and GDP, gdp), and finally, price inflation (inf).

M2 represents a comprehensive measure of money supply, and M0 (currency in circulation) and M1 (M0 plus demand deposits), further extended by quasi-currencies such as time deposits and savings, reflecting both the current and potential purchasing power within the economy. M1 serves as an indicator of the existing purchasing power within the economic framework, whereas M2 not only mirrors this actual purchasing power but also encapsulates the potential purchasing power. This distinction allows M2 to articulate the dynamism present within the investment and intermediary markets, offering a broader perspective on economic liquidity and its capacity for future growth (Berkelmans et al., 2016). Although the primary intermediary variable in China is the money supply, the interest rate is also detected simultaneously. This paper considers that China's interest rate has not been fully marketized, and the government has not entirely relaxed the control of bank lending interest rates. When the monetary authorities use monetary policy to regulate the macroeconomy, they will also achieve this by adjusting the bank's deposit and loan interest rates. Changes in lending rates will change the level of liquidity in the market and the borrowing costs of residents and businesses. Therefore, the paper selects the 30-day average interest rate of inter-bank lending to represent the market interest rate as other monetary policy proxies.

Given the quarterly nature of GDP data versus the monthly frequency of other variables, the study confronts the challenge of data frequency inconsistency. One way to address this issue is to use industry growth (monthly frequency) to be the proxy for GDP. But it seems this series is not reliable in CEIC. Consequently, this paper uses another way to address the issue, constructing monthly GDP data using third-order polynomial interpolation. For the house price, this paper uses the average house price

[10] https://www.ceicdata.com/en

for the housing price, which is calculated by dividing the sales of all newly constructed houses by the overall areas within one year. These series are available in CEIC. A wildly used housing market index is the national house climate index. In this paper, we are not using this index because it has more than two unit roots, and we don't want to twice-difference the series. The log difference of the CPI calculates inflation. It is worth mentioning that the original CPI data we got from the CEIC data is Y-o-Y. Here we manually transform it into month-to-month and then calculate the inflation.

All nominal variables are adjusted for inflation using the CPI and subjected to the X-12 filter to eliminate seasonal fluctuations, ensuring the integrity and comparability of the data analysis.

3.4.2 Identification Strategy

The methodology adopted in this research is predicated on the use of a Structural Vector Autoregression (SVAR) model, incorporating short-run identification strategies. The specified SVAR model is represented as follows:

$$AY_t = \phi(L)Y_t + \epsilon_t$$

where Y_t denotes the vector of endogenous variables encompassing money supply, policy rate, consumption, investment, output, inflation, and housing prices. The term $\phi(L)$ signifies a polynomial of the lag operator, articulated as $\phi(L) = \phi_1 L + ... + \phi_p L^p$. Here, ϵ_t represents structural innovations, characterized by their orthogonality across both time and equations. Assuming, for simplicity $\Sigma_\epsilon \equiv \text{var}(\epsilon_t) = I$, the identity matrix, inverting A, facilitates the derivation of the reduced-form VAR model:

$$Y_t = \psi(L)Y_t + B\epsilon_t$$

where $B = A^{-1}$ and $\psi(L) = B\phi(L)$. rendering the reduced-form innovations orthogonal across time, albeit not necessarily so across equations. Denoting $u_t = B\epsilon_t$, it follows $\Sigma_u \equiv \text{var}(u_t)$ may not be a diagonal matrix. Recovery of the SVAR model from its reduced-form counterpart is contingent upon the acquisition of B, achievable through the application of Cholesky decomposition to Σ_u

$$\Sigma_u = \Gamma\Gamma'$$

where Γ is a lower-triangle matrix. Consequently, $\text{var}(\Gamma u_t) = \Gamma\text{var}(u_t)\Gamma' = \Gamma\Gamma' = \Sigma_w$, suggesting Γ could serve as B. Given that only the reduced-form model can be empirically estimated, reconstructing the SVAR from the reduced form necessitates certain restrictions. The requisite number of restrictions equates to the difference between the freely estimated parameters of the SVAR and those of the reduced form, $(n^2-n)/2$, indicative of the zero elements within Γ which symbolize imposed structural constraints, thereby negating contemporaneous effects. This recursive identification allows variables to respond contemporaneously solely to shocks preceding them in order, albeit predicated on potentially stringent assumptions. In instances where a suitable variable ordering is elusive, an alternative exclusion identification strategy may be employed, necessitating that at least $(n^2-n)/2$ elements in matrix B be constrained to zero, effectively excluding contemporaneous effects of certain variables. The rationale for adopting short-run identification lies in the monthly data frequency, considering that policy impacts are temporally lagged, with real economy variables particularly unresponsive to immediate monetary policy shocks.

3.5 Results

3.5.1 Baseline regression

In this segment of the study, the objective is to reveal the impact of various monetary policies on housing prices within the Chinese context. To this end, I employ a Structural Vector Autoregression (SVAR) model, incorporating a constellation of seven variables: pol- icy rate, M2 (broad money supply), house price, consumption, investment, inflation, and GDP. The model is specified with the following identification restrictions:

$$\begin{bmatrix} u_t^{\text{hp}} \\ u_t^{\text{int}} \\ u_t^{\text{M2}} \\ u_t^{\text{con}} \\ u_t^{\text{inv}} \\ u_t^{\text{inf}} \\ u_t^{\text{gdp}} \end{bmatrix} = \begin{bmatrix} 1 & \cdot & \cdot & 0 & 0 & \cdot & \cdot \\ 0 & 1 & \cdot & \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & 1 & \cdot & \cdot & \cdot & \cdot \\ \cdot & 0 & 0 & 1 & 0 & \cdot & \cdot \\ \cdot & 0 & 0 & 0 & 1 & \cdot & \cdot \\ 0 & 0 & 0 & \cdot & \cdot & 1 & 0 \\ 0 & 0 & 0 & \cdot & \cdot & 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t^{\text{hp}} \\ \varepsilon_t^{\text{int}} \\ \varepsilon_t^{\text{M2}} \\ \varepsilon_t^{\text{con}} \\ \varepsilon_t^{\text{inv}} \\ \varepsilon_t^{\text{inf}} \\ \varepsilon_t^{\text{gdp}} \end{bmatrix}$$

To utilizing the specified identification strategy, the assumption is that monetary policy exerts no immediate influence on real economy variables. This is reasonable assumption due to the delayed effectiveness of monetary policies, particularly when analyzed through monthly data. Similarly, output and price levels are considered to not impact each other contemporaneously, and neither do consumption and investment directly influence housing prices within the same period. Furthermore, it is assumed that shocks to housing prices do not instantaneously affect monetary policy.

According to the Akaike Information Criterion (AIC), the optimal lag order for the reduced-form Vector Autoregression (VAR) model is identified as two. The 95% confidence intervals are calculated using bootstrap methods. The empirical findings, as illustrated in Figure 3.6, reveal that a 1% increase in money supply significantly elevates inflation by 0.3%, aligning with theoretical economic expectations.

There was a significant increase of 1.4% over the same period for house prices. The response of house prices slowly dies to 0, which lasts for about half a year. After that, the response of house prices to the money supply becomes insignificant. For consumption, consumption fell 1% contemporaneously. In addition, the impact of consumption on the money supply is more persistent than that of housing prices, and the effect lasted for 20 months. We know that the CPI, the good price, deflates the house price, and the CPI increases contemporaneously by about 1.4%, which means the nominal house price increase by over 2%. That means the money supply has a significant effect on house price control. A positive impact on the year-on-year growth rate of money supply has a significant positive effect on the completion of real estate investment in the short term. Investment completions increased by 0.6% over the same period, and then their positive impact increased over time but reached 1.5% by the 40th month. This shows that the development of the real estate industry is highly dependent on financial support, and the increase in money supply will bring a relatively loose financial environment to real estate development companies, thereby driving the continuous growth in real estate investment.

Unlike from that of money supply shocks, the policy rate shocks imposing a distinct impact on housing prices, as shown in Figure 3.7. Highlighted by a significant 0.1% decline in housing prices, peaking after three quarters before dissipating after five quarters. But this shock has a more transitory effect on consumption. Compared to the money supply shock, the policy rate shock has a longer but milder effect on the house price. In the short run, housing prices are more sensitive to money supply shocks, which account for a larger variance in housing prices. Over the long run, the variance in housing prices attributable to money supply shocks remains consistent, while the variance explained by policy rate shocks gradually increases. However, collectively, money supply and policy rate shocks explain less than 15% of the variance in housing prices.

An important observation is the contemporaneous decline in consumption following a money supply shock, attributed to the concomitant rise in inflation and the resultant increase in the cost of non-housing commodities. Figure 3.8 illustrates the macroeconomic responses to housing price shocks, illustrating two primary effects: the substitution effect and the wealth effect. The substitution effect, where increased housing prices lead households to favor non-housing commodities, contrasts with the wealth effect, where rising housing prices, as a form of investment, enhance household wealth, thereby increasing consumption of non-housing goods. Again, the house price is deflated by the CPI, so we know that there are more significant house price changes compared to the commodity price. The rise in house prices did not lead to a significant increase in consumption at first, but consumption rose significantly after a lag of 10 months to a year.

This indicates that while immediate shifts in housing prices do not substantially alter consumption patterns. In the medium term, the crowding-in effect of rising house prices peaked. With the impact of the house price shock waned to insignificant a year later.

3.5.2 Time-varying effects

This study covers a timeline that includes the 2008 financial crisis and subsequent iterations of housing price control policies. The Structural Vector Autoregression (SVAR) model conventionally presupposes parameter stability, yet the dynamic interplay among variables might exhibit variability. To address potential instability in the relationship between monetary policy and housing prices, this research employs a rolling window Granger causality test, which offers dual benefits. Firstly, if the causal relation is not stable but time-varying, the rolling window test is reasonable. Secondly, this methodology allows for the detection of instability across various sub-samples, as noted by Xu (2016). To implement this, a 36-month window is established to estimate a VAR model, which is then incrementally moved forward by one month. In each estimation phase, GDP, inflation, consumption, and investment are controlled to facilitate a Granger causality analysis, determining whether monetary policy can predict future housing prices, as evidenced by the collection of p-values.

Figure 3.9 reveals that the money supply exerts a more consistent influence on housing prices compared to policy rates. This is indicating periods where the money supply Granger causes changes in housing prices more frequently than policy rate adjustments. However, there exist intervals wherein neither monetary policy instrument Granger causes housing price fluctuations, particularly from 2009 to 2013, suggesting an aftermath of the financial crisis. Following the crisis, the Chinese government's deployment of a four trillion yuan stimulus plan for infrastructure investment ostensibly absorbed significant monetary injections, with the funds predominantly channeled towards infrastructure rather than residential housing, thus not eliciting a proportional increase in housing prices. It is noteworthy that at the beginning of the examined period, monetary supply and policy rate alternately Granger cause housing prices, with the money supply leading and policy rate adjustments following. Moreover, the study tests various specifications of the rolling window Granger causality approach, including adjustments for consumer confidence and mortgage rates. The results demonstrating robustness across different control variables.

3.5.3 Region-varying effects

Regional differences play a pivotal role in the complex development of the real estate market across China. Due to the differences in geography, humanities, opening hours and degrees, and other conditions in the vast territory of China, there are differences in scale, structure, and trend at all levels of economic development. Consequently, the real estate market exhibits pronounced regional differences. Furthermore, the People's Bank of China has a Monetary Policy Department in China. The Monetary Policy Division is responsible for formulating monetary policy and participating in the adjustment and adjustment of monetary policy and macro-prudential policy, along with promoting market-oriented reforms of interest and exchange rates. Moreover, the central bank's organizational structure includes a regional headquarters, with the Shanghai headquarters operating under the main office's direction, primarily handling a portion of the central bank's operations. Additionally, nine regional sub-branches[11] execute the head office's policies and regulations, implement central monetary and credit policies within their jurisdictions, and oversee local financial markets. A standardized monetary policy is applied across these diverse regions, yielding disparate responses to the uniform monetary strategy. For analytical purposes, China's provinces are categorized into three regions[12]: eastern, central, and western. This study examines the

[11] In the East region: Tianjin sub-branch, Shenyang sub-branch, Shanghai sub-branch, Nanjing sub-branch, Jinan sub-branch, Guangzhou sub-branch; In the Mid region: Wuhan sub-branch; In the West region: Xian sub-branch, Chengdu sub-branch.

[12] Normally there are 11 provinces and cities in the east region: Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Liaoning, Guangdong, and

impacts of two monetary policy instruments across these distinct regions, as depicted in Figure 3.10 through impulse response functions.

Through the impulse response, we can see that the east region is consistent with the whole country's pattern, increasing in money supply increases house prices, and increasing policy rate decreases house prices. In the mid regions, the effects are opposite, increasing in money supply decreases house prices, and an increasing policy rate increases house prices. In the west region, the impact of monetary policy is not significant. For the east regions, the monetary policy affects the demand side of the housing market, and for the mid-region, the monetary policy affects the supply side of the regions. This distinction is rational, considering the eastern region's advanced economic development and higher household wealth, coupled with greater financial literacy, rendering real estate purchases primarily investment driven. Conversely, in the western regions, monetary policies' effects are minimal, possibly due to the relative economic disadvantage and the unique status of several provinces as autonomous regions, which often adopt distinct policies.

3.5.4 Robustness Check

To enhance the robustness of the analysis, we extended the baseline regression model from initially comprising seven variables to incorporate nine variables by introducing the two new variables: mortgage rate and the financial institution's credit balance in China. The inclusion of the mortgage rate is particularly pertinent to analyzing housing demand in China, where mortgages are a common method for acquiring homes. This is another monetary policy channel, the credit channel. The credit channel mainly affects the investment and consumption of the real estate market through

Hainan; 8 provinces in the mid-region: Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; 12 provinces in the west region: Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shannxi, Gansu, Qinghai, Ningxia, Xinjiang, Tibet the bank credit volume and the corporate balance sheet. In China's financial ecosystem, banks are the dominant players in the credit market, and the primary source of funds for the real estate industry comes from borrowing.

Consequently, bank credit levels will affect the changes in investment levels and prices in the real estate market. The central bank's employ open market operations, re-discounting, and adjustments to the deposit reserve ratio to adjust the money supply, inevitably affecting each lending bank's liquidity and lending capacity of individual banks. For instance, an expansionary monetary policy, such as reducing the deposit reserve ratio for commercial banks, enhances credit availability. This increased availability of bank loans facilitates easier access to financing for both suppliers and consumers in the real estate market, potentially boosting investment, consumption, and housing prices. Monetary policy exerts influence on housing prices via the balance sheet channel. When the central bank manipulates monetary policy instruments, such as adjusting benchmark lending rates, the external financing costs for enterprises escalate, leading to a deterioration in corporate financial health and a reduction in net assets. Banks, in evaluating credit risk, consider changes in an enterprise's net wealth to determine lending volumes. Moreover, given the real estate industry's reliance on bank loans, with properties often used as collateral, expansionary monetary policies elevate housing prices due to the increased expected profitability of real estate firms and increase collateral value. This scenario reduces the default risk perceived by banks, thereby increase banks' willingness to lend.

In this expanded analysis, I estimate a SVAR model with nine variables: house price, policy rate, M2, mortgage rate, credit balance, consumption, investment, inflation, and GDP. The mortgage rate is represented by the one-year bank mortgage rate, while the credit balance is denoted by the total loan balance across all financial institutions in China. The identification restrictions for this model are as follows:

$$
\begin{bmatrix} u_t^{\text{hp}} \\ u_t^{\text{int}} \\ u_t^{\text{r}} \\ u_t^{\text{cr}} \\ u_t^{\text{m2}} \\ u_t^{\text{con}} \\ u_t^{\text{inv}} \\ u_t^{\text{inf}} \\ u_t^{\text{gdp}} \end{bmatrix} = \begin{bmatrix} 1 & * & * & * & * & 0 & 0 & * & * \\ 0 & 1 & 0 & 0 & 0 & * & * & * & * \\ 0 & * & 1 & 0 & * & * & * & * & * \\ 0 & * & 0 & 1 & * & * & * & * & * \\ 0 & 0 & 0 & 0 & 1 & * & * & * & * \\ * & 0 & 0 & 0 & 0 & 1 & 0 & * & * \\ * & 0 & 0 & 0 & 0 & 0 & 1 & * & * \\ 0 & 0 & 0 & 0 & 0 & * & * & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & * & * & 0 & 1 \end{bmatrix} \begin{bmatrix} \epsilon_t^{\text{hp}} \\ \epsilon_t^{\text{int}} \\ \epsilon_t^{\text{r}} \\ \epsilon_t^{\text{cr}} \\ \epsilon_t^{\text{m2}} \\ \epsilon_t^{\text{con}} \\ \epsilon_t^{\text{inv}} \\ \epsilon_t^{\text{inf}} \\ \epsilon_t^{\text{gdp}} \end{bmatrix}
$$

In this analysis, I proceed under the assumption that monetary policy does not have a contemporaneous impact on the real economy variables, and house price shock does not have a contemporaneous impact on monetary policy.

Figure 3.13 presents the impulse responses to a one-standard deviation shock in monetary policy, using the methodology outlined in this section. The robustness of the results is evident from these responses. When the money supply increases, it can be seen that a significant increase in the house price, and the house price drops in response to an increase in the policy rate. Furthermore, housing prices exhibit a negative reaction to adjustments in both the mortgage rate and the credit balance policies.

The variance decomposition, as illustrated in Figure 3.14. It demonstrates that, among the four monetary policies analyzed, the money supply accounts for the most significant proportion of variation in housing prices.

3.6 Conclusions

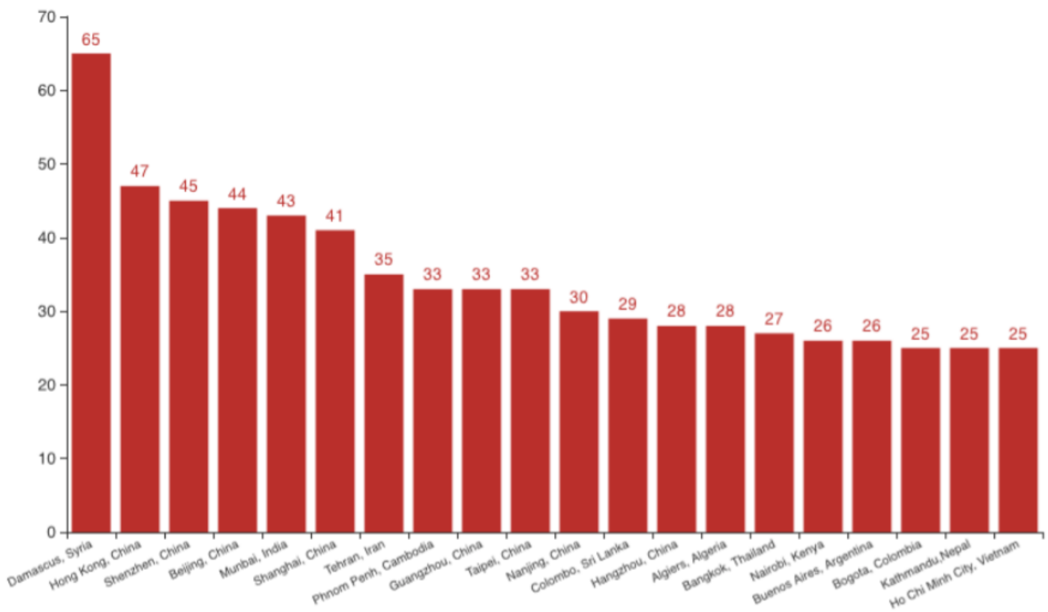
In China, the rapid escalation of housing prices has become a factor contributing to social instability. Investment in the real estate sector constitutes a significant portion of the nation's fixed-asset investments, with the real estate market expansion playing a crucial role in driving economic growth. Nonetheless, the influence of real estate market development on the economy is complicated. The rational, stable, and healthy development of the real estate market contribute significantly to economic growth. However, an overreliance on escalating investments in this sector as a mechanism for stimulating economic activity and addressing employment issues can lead to continuous increases in housing prices. Such increases in housing price will lead to later inflation, elevate living costs, diminish market demand, and exert additional pressure on the populace to afford housing, thereby becoming a source of social instability.

This study employs a Structural Vector Autoregression (SVAR) model with exclusion restrictions to analyze the effects of diverse monetary policies on housing prices. It assesses the implications of variations in money supply, policy rates, and mortgage rates on housing prices, acknowledging that interest rates in China have not yet achieved full marketization. The findings reveal that a 1% increment in the money supply significantly boosts inflation by 0.3%, aligning with economic theories, and that housing prices significantly decrease by 0.1% in response to a shock in the policy rate. Furthermore, the analysis demonstrates that in responding to the housing price shock, the wealth effect dominates the substitute effect, therefor, increases consumption.

The study also evaluates the temporal stability of these policies through a rolling window Granger causality test and explores the regional diversity of monetary policy impacts using data at the regional level. The rolling window Granger causality test shows that parameter stability is rejected. From 2009 to 2013, none of these monetary policies Granger caused house prices, likely a repercussion of the post-financial crisis era. In response to the global financial crisis, the Chinese government initiated a substantial investment plan in infrastructure to bolster the economy. Regional data analysis suggests that in the eastern region, responses align with the national pattern, where increases in money supply elevate housing prices, whereas hikes in policy rates decrease them. Conversely, in central regions, the effects are inverted, indicating that monetary policy influences the supply side of the market in these areas.

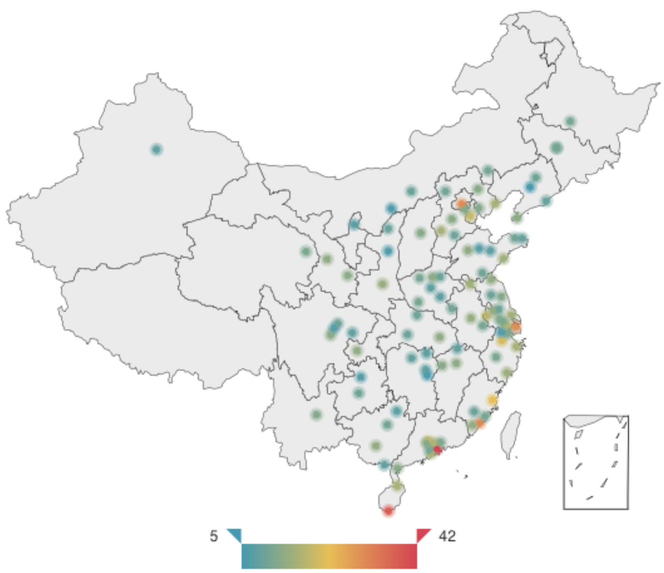
The paper acknowledges the introduction of measurement error into the model due to the use of third-order polynomial interpolation for deriving monthly GDP data, which potentially introduces an additional shock that could skew the SVAR analysis. Future research could employ a panel structural VAR model to estimate impulse responses, utilizing quarterly GDP data to solve this problem. Further expansion of this research could involve analyzing the differential impacts on housing prices across various regions, particularly examining whether the demand-side effects in eastern regions are driven by speculative housing transactions. Analyzing transaction-level data could yield better insights into this question.

Figure 3.1: City level house price to wage ratio



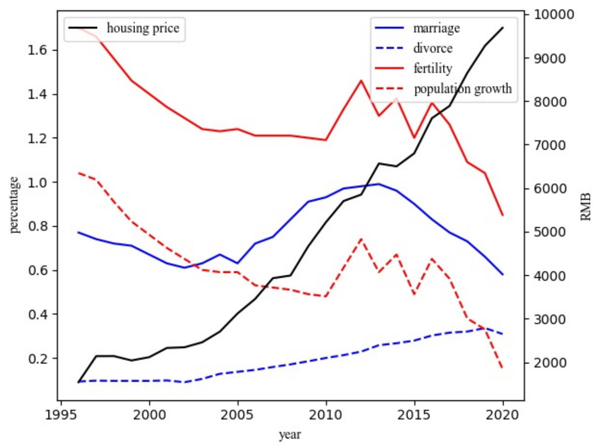
Notes. The graph shows the house price to wage ratio for the top twenty global cities in 2020. Among the top 20 cities, there are eight cities in China. Also the house price to wage ratio is defined as the median house price to the median disposable income with that city. Source: the author manually collected the data from the Internet.

Figure 3.2: Within China house price to wage ratio distribution



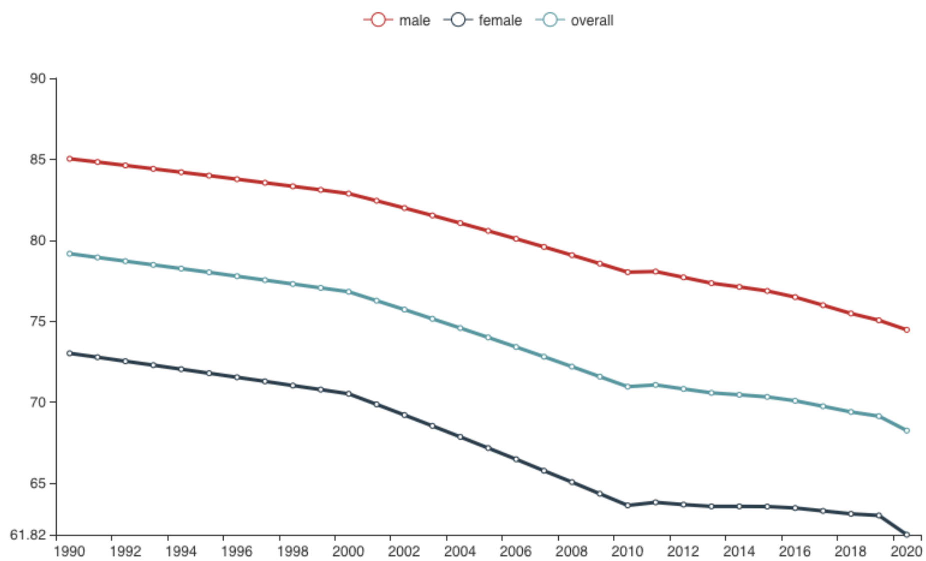
Notes. Above heat map shows the house price to wage ratio within China in 2021. Cities located in the east part of China, the ratio is higher comparing to the cities in the mid part and the west part. Source: the author maunally collected the data from the Internet.

Figure 3.3: House price, marriage rate, divorce rate, fertility rate, and population growth trend



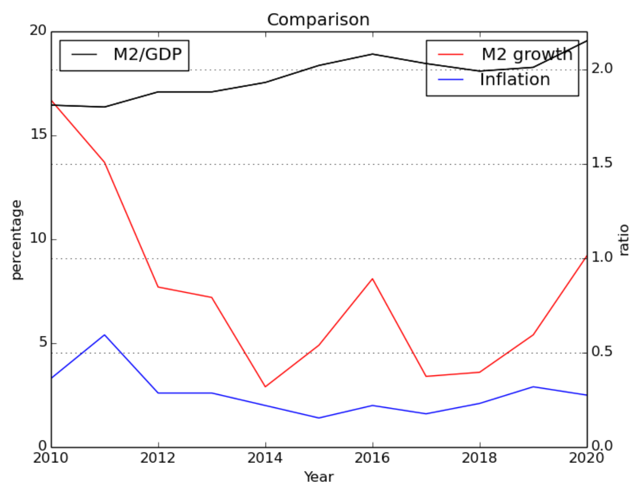
Notes. Data range: 1995-2020. Data frequency: yearly data. The black solid line represents the house price growth; The blue solid line shows the marriage rate, The blue dashed line represents the divorce rate; The red solid line represents fertility rate; The red dashed line shows the population growth. Fertility rate is defined as the ratio of newly born population and average population number in a given year. Marriage and divorce rate are defined as the number of population that are getting married or divorced divided by the average population in a given year. Data source: National Bureau of Statistics, http://www.stats.gov.cn/ztjc/xxgkndbg/gjtjj/.

Figure 3.4: Labor force participation rate



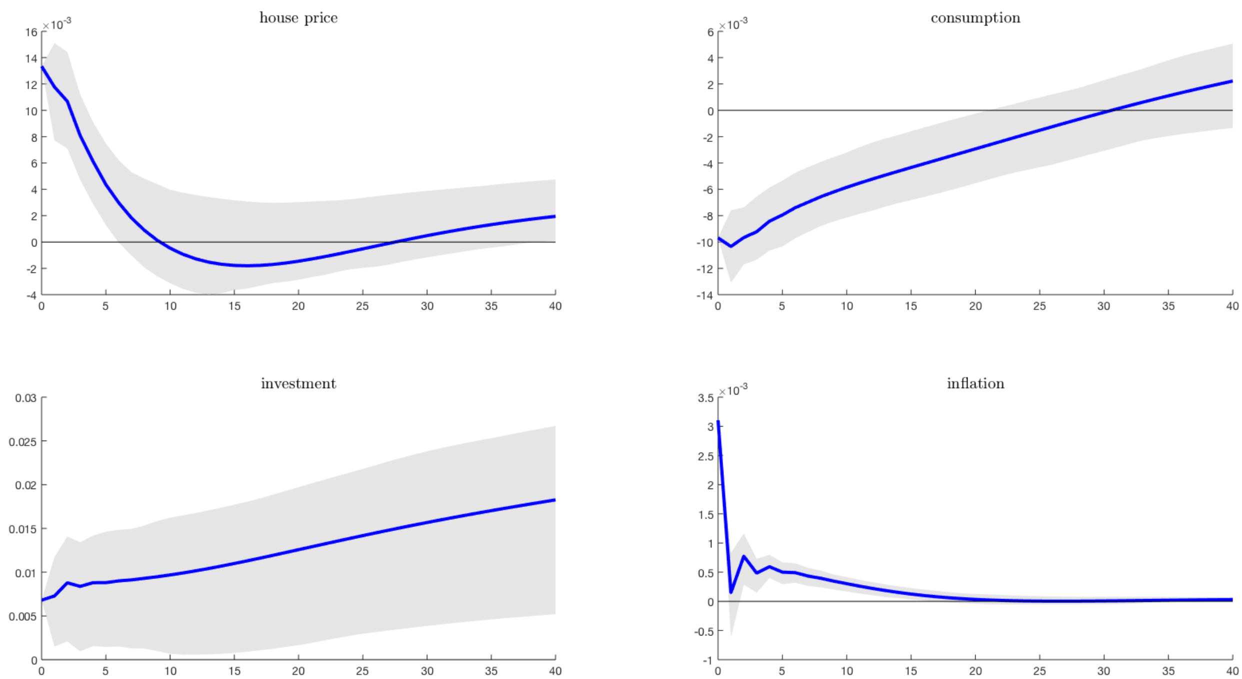
Notes. Data range: 1990-2020. Data frequency: yearly data. The figure shows the trend of labor participation rate in China from 1990 to 2020. Labor participation rate is defined as the number of working population over the number of population aged from 16 to 60 years old. Data source: CEIC database, https://www.ceicdata.com/en.

Figure 3.5: Money supply and inflation



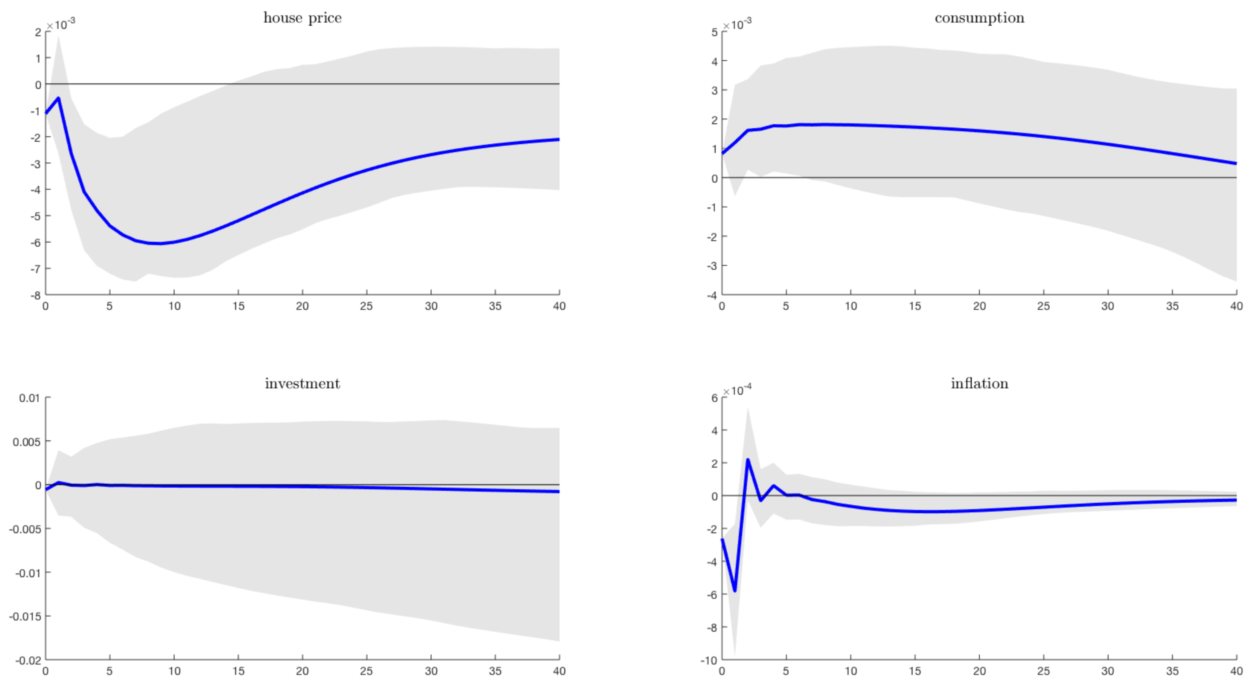
Notes. Data range: 2010-2020. Data frequency: yearly data. The figure shows the inflation, money supply growth. Data source: National Bureau of Statistics, http://www.stats.gov.cn/ztjc/xxgkndbg/gjtjj/.

Figure 3.6: Impulse responses to the money supply shock



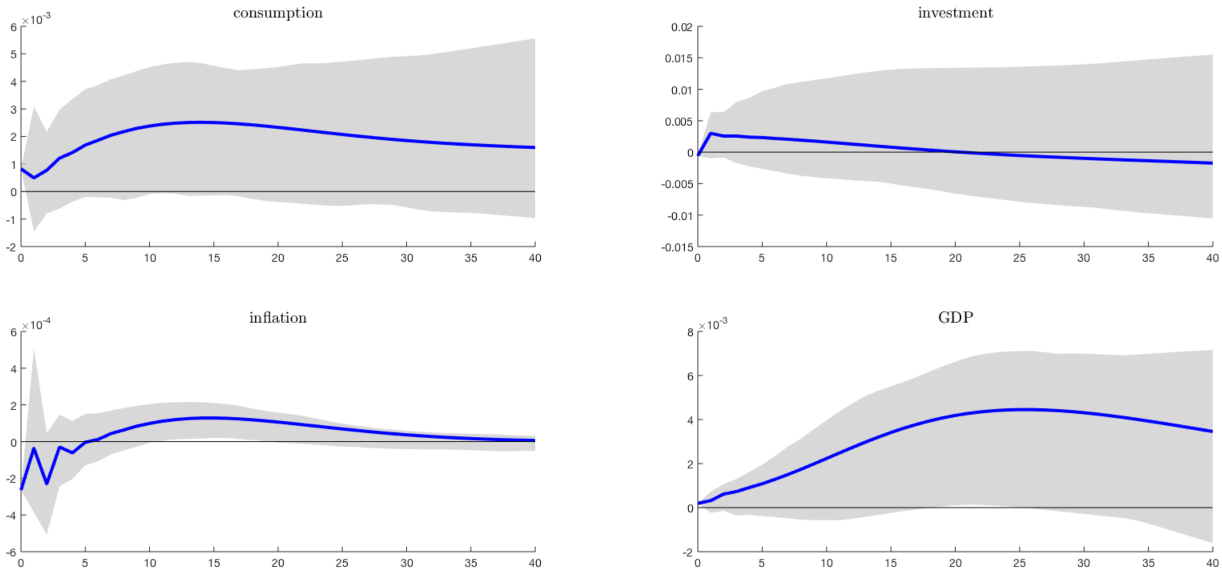
Notes. Data range: 2001:m1-2019:m12. The figure shows the impulse response of house price, consumption, investment, and inflation to one standard deviation money supply shock. The identification strategy is described in 3.4 and reduced-form VAR controls for 2 lags suggested by AIC. Here also presents the confidence interval, which is calculated using the bootstrap.

Figure 3.7: Impulse responses to the policy rate shock



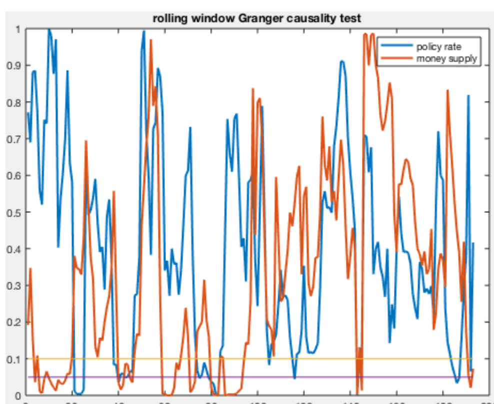
Notes. Data range: 2001:m1-2019:m12. The figure shows the impulse response of house price, consumption, investment, and inflation to one standard deviation policy rate shock. The identification strategy is described in 3.4 and reduced-form VAR controls for 2 lags suggested by AIC. Here also presents the confidence interval, which is calculated using the bootstrap.

Figure 3.8: Impulse responses to the house price shock



Notes. Data range: 2001:m1-2019:m12. The figure shows the impulse response of consumption, investment, inflation, and inflation to one standard deviation house price shock. The identification strategy is described in 3.4 and reduced-form VAR controls for 2 lags suggested by AIC. Here also presents the confidence interval, which is calculated using the bootstrap.

Figure 3.9: Rolling window Granger causality test



Notes. Data range: 2001:m1-2019:m12. We fixed a 36-month window to estimate a VAR model and move this window one month forward. In each estimation, we controlling for GDP, inflation, consumption, and investment to conduct Granger causality test to if the monetary policy Granger cause house price. We collect the p-value. The horizontal axis represents the date of the start of 36-month window, and the vertical axis is the p-value.

Figure 3.10: Estimated impulse responses for different regions

Figure 3.12: Money supply shocks

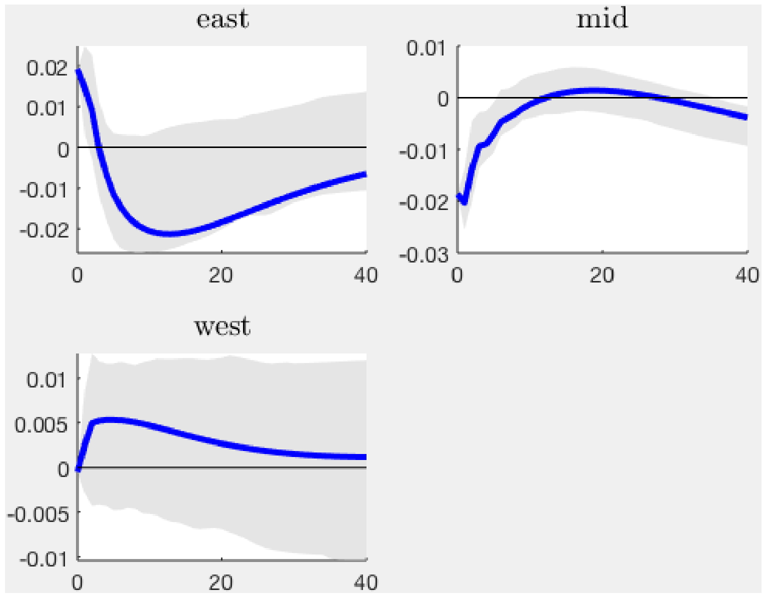
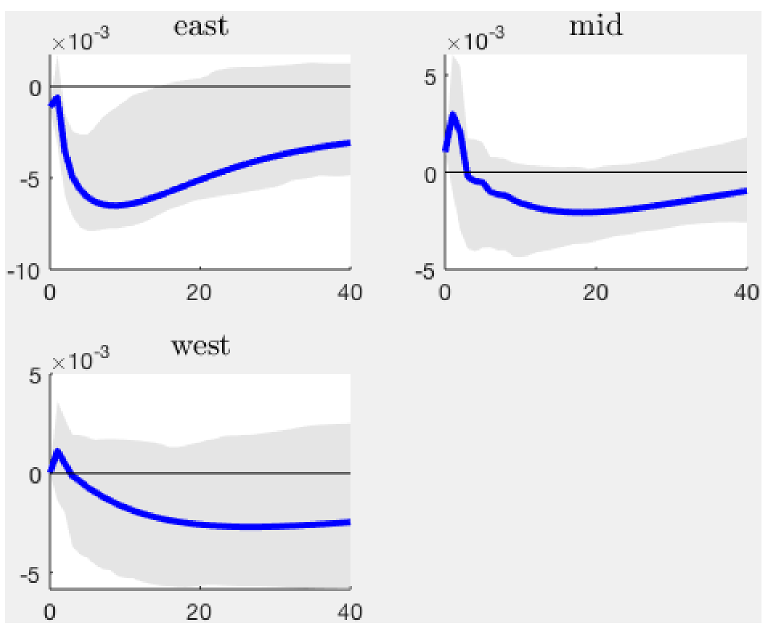
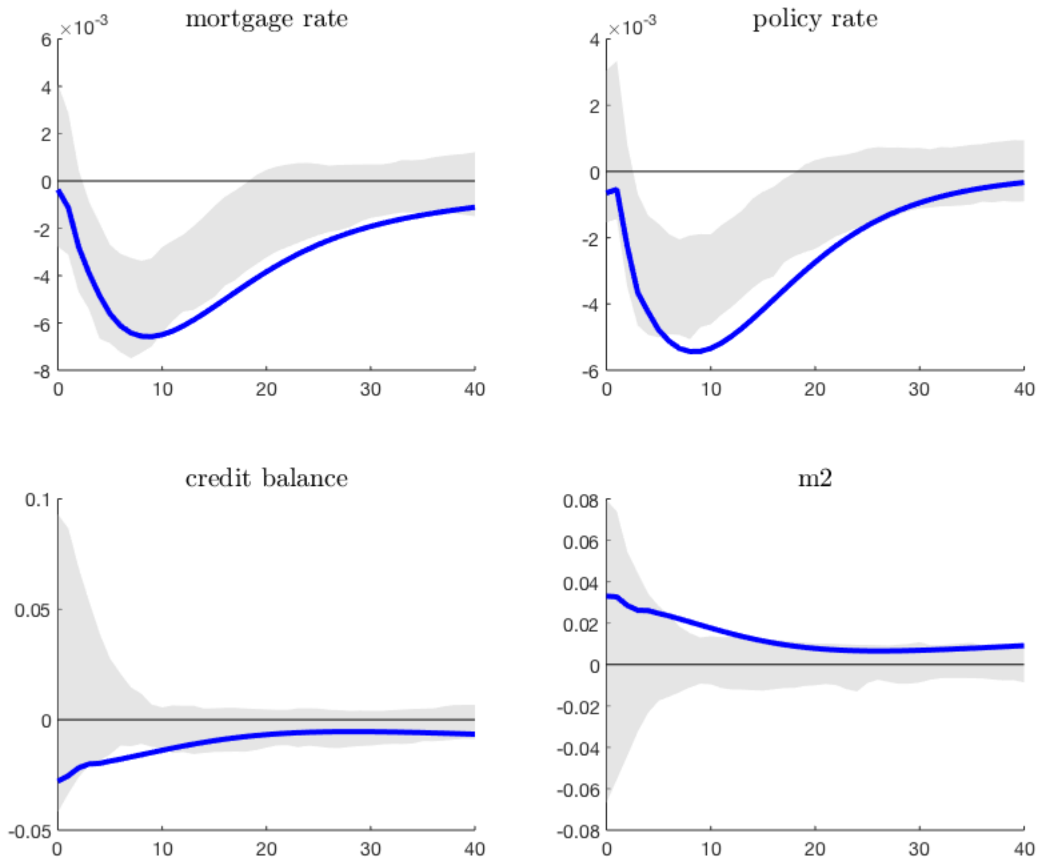


Figure 3.13: Policy rate shocks



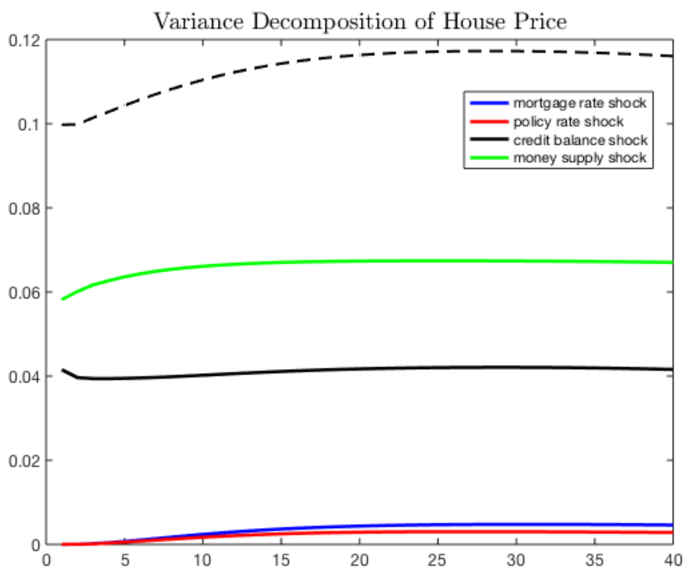
Notes. Data range: 1960:q2-2020:q1. Due to the convention, all provinces in China are divided into three regions: the east, the mid, and the west region. Reduced form VAR has two lag (AIC) for all the regions. Using bootstrap to calculate the impulse responses.

Figure 3.13: Robustness test: impulse response of house price to different monetary policy shocks



Notes. Data range: 2001:m1-2019:m12. The figure shows the impulse response of the house price to one standard deviation money supply shock, policy rate shock, mortgage rate shock, and the credit balance shock. The reduced-form VAR controls for 2 lags suggested by AIC. Here also presents the confidence interval, which is calculated using the bootstrap.

Figure 3.14: Robustness test: variance decomposition of house price



Notes. Data range: 2001:m1-2019:m12. The figure shows the variance decomposition of the house price. The reduced-form VAR controls for 2 lags suggested by AIC.

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Appendix A

CHAPTER 1 APPENDIX

Table A.1: Institutional level impact of international enrollment on native enrollment

	(1)	(2)	(3)
	year FE	yearFE stateFE	yearFE× stateFE
		2SLS	
international	4.036**	3.692***	3.945***
	(1.513)	(1.349)	(1.46)
		First stage	
international	0.662***	0.720**	0.692***
	(0.271)	(0.283)	(0.266)
		OLS	
international	0.352*	0.410**	0.412**
	(0.198)	(0.194)	(0.187)
year FE	Yes	Yes	Yes
state FE	No	yes	Yes
state controls	Yes	No	No
N	892	892	864

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note. The dependent variable is first year, first time, full time, degree seeking native students enrolled in college c, year t. The independent variable is first year, first time, full time, degree seeking international students enrolled in college c year t. Column 1 is identification strategy with state level control along with year fixed effect, state unemployment rate and logged college age population (18-24), matched with institution's location by state. Column 2 is identification strategy with year fixed effect and state fixed effect. Column 3 is identification strategy with state year fixed effect. Coefficients reflect the impact on native enrollment of 1 additional international student enrolled in school level. Standard errors in parentheses.

Table A.2: Impact of international enrollment on native enrollment by major

	(1) Education	(2) Engineer	(3) Math	(4) Physical	(5) Business
international (state control)	-0.102	1.896***	-0.202*	0.859***	1.552***
	(0.209)	(0.938)	(0.109)	(0.248)	(0.419)
N	868	868	868	868	868
international (year/state FE)	-0.0677	1.661**	-0.183*	0.841***	1.386***
	(0.203)	(0.833)	(0.102)	(0.225)	(0.36)
N	868	868	868	868	868
international (year×state FE)	-0.00855	1.815**	-0.188*	0.781***	1.536***
	(0.269)	(0.9)	(0.0972)	(0.2)	(0.429)
N	844	844	844	844	844

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Note.*The dependent variable is first year, first time, full time, degree seeking native students enrolled in college c, year t, major m. The independent variable is first year, first time, full time, degree seeking international students enrolled in college c year t. Section 1 is identification strategy with state level control along with year fixed effect, state unemployment rate and logged college age population (18-24), matched with institution's location by state. Section 2 is identification strategy with year fixed effect and state fixed effect. Section 3 is identification strategy with state year fixed effect. Coefficients reflect the impact on native enrollment in certain major of 1 additional international student enrolled at school level. Standard errors in parentheses.

Table A.3: The impact of international enrollment on native enrollment by race and gender

	(1) male	(2) female	(3) white	(4) black	(5) asian	(6) hispanic
international (state control)	2.671***	1.365***	1.873***	0.174*	-0.017	0.605
	(0.917)	(0.642)	(0.58)	(0.0966)	(0.0157)	(0.368)
N	892	892	892	892	892	892
international (year/state FE)	2.420***	1.272***	1.676***	0.178*	-0.0171	0.582*
	(0.826)	(0.57)	(0.483)	(0.0959)	(0.0143)	(0.303)
N	892	892	892	892	892	892
international (year×state FE)	2.603***	1.342***	1.718***	0.169*	-0.0188	0.610*
	(0.837)	(0.674)	(0.513)	(0.087)	(0.0157)	(0.315)
N	864	864	864	864	864	864

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

*Note.*The dependent variable is first year, first time, full time, degree seeking native students enrolled in college c, year t, by race and gender. The independent variable is first year, first time, full time, degree seeking international students enrolled in college c year t. Section 1 is identification strategy with state level control along with year fixed effect, state unemployment rate and logged college age population (18-24), matched with institution's location by state. Section 2 is identification strategy with year fixed effect and state fixed effect. Section 3 is identification strategy with state year fixed effect. Coefficients reflect the impact on native enrollment in certain race and gender of 1 additional international student enrolled at school level. Standard errors in parentheses.

Appendix B

CHAPTER 2 APPENDIX

Table B.1: Conditional Impact of HSR on Employment (Event Study)

	1	2	3
Dep	ln employment	ln private	ln non-private
-9	-0.021	0.087	-0.058
	(0.068)	(0.161)	(0.060)
-8	0.071	0.117	0.050
	(0.052)	(0.097)	(0.051)
-7	0.045	0.091	0.020
	(0.044)	(0.0489)	(0.043)
-6	-0.012	0.036	0.008
	(0.031)	(0.072)	(0.027)
-5	0.030	0.087	0.004
	(0.027)	(0.061)	(0.022)
-4	0.037	0.078	0.029
	(0.025)	(0.057)	(0.026)
-3	0.027	0.042	0.024
	(0.019)	(0.050)	(0.019)
-2	0.015	0.037	0.020
	(0.016)	(0.042)	(0.016)
0	0.021	0.07^{*}	-0.007
	(0.014)	(0.041)	(0.010)
1	0.041^{**}	0.105^{**}	-0.005
	(0.019)	(0.042)	(0.016)
2	0.054^{**}	0.126^{***}	-0.006
	(0.026)	(0.049)	(0.027)
3	0.062^{*}	0.151^{***}	-0.013^{**}
	(0.034)	(0.049)	(0.038)
4	0.042	0.139^{**}	-0.042
	(0.045)	(0.063)	(0.038)
5	0.057	0.168^{**}	-0.015
	(0.051)	(0.066)	(0.0397)
6	0.122^{*}	0.198^{**}	-0.037
	(0.066)	(0.081)	(0.059)
7	0.222^{***}	0.288^{***}	0.025^{**}
	(0.086)	(0.112)	(0.079)
8	0.202^{**}	0.190	0.088
	(0.096)	(0.134)	(0.090)
9	0.386^{**}	0.358	0.155
	(0.194)	(0.291)	(0.150)

Notes. Standard error is in parentheses. $*** = p < 0.01$, $** = p < 0.05$, and $* = p < 0.1$.

Table B.2: Impact of HSR on employment ratio with CSDID

variable name	1	2	3
Dep. var	$\frac{\text{employment}}{\text{population}}$	$\frac{\text{private}}{\text{population}}$	$\frac{\text{non-private}}{\text{population}}$
unconditional ATT	0.025^{***} (0.007)	0.024^{**} (0.007)	0.012^{**} (0.004)
conditional ATT	0.031^{***} (0.007)	0.030^{***} (0.006)	0.014^{*} (0.005)
No. obs	2256	2256	2256

Notes. Standard error is in parentheses. $*** = p < 0.01$, $** = p < 0.05$, and $* = p < 0.1$.