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Essays on the Spatial Economy

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Essays on the Spatial Economy

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To my parents and my better half

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Abstract

Essays on the Spatial Economy

Economic activities vary across regions, and individuals and markets respond differently to macroeconomic shocks, national policies, or uniform local policies. Understanding the patterns of regional economies and predicting local trends are critical for policy-making and business decisions. This dissertation examines the outcomes of local economies in response to the most discussed policies and prevailing global trends. Specifically, it studies the impact of free college policies, monetary policy, and export slowdown.

Chapter 1 studies the effectiveness of Promise Programs in the short and long term, which aim to provide free or reduced-cost college tuition, fees, and other expenses to eligible students based on their residency, academic merit, or financial need. In chapter 1, I develop a dynamic spatial model that allows newborn agents to decide whether to attend college based on the skill premium and their education costs. Tuition cut provided by the local governments reduce newborn agents' education cost and increase college going rate, at the expense of local income tax. Some agents move and some agents stay. Chapter 1 finds that in places near innovative counties, many agents that received tuition cut move, unlikely to promote local development, whereas in distant places, enough stay makes the program worthwhile.

Chapter 2 investigates the heterogeneous effects of monetary policy on housing prices across growing cities and declining cities. Using the local projections method, we find that, overall, the nominal housing prices decrease by 3.4% within four years in response to a 1% interest rate increase. The housing prices drop by slightly more than 4% (trough) in growing areas, whereas the housing prices in declining areas drop by around 2.5% (trough). Urban growth contributes to the heterogeneous effects of monetary policy through the land scarcity channel.

Chapter 3 examines the impact of export slowdown on household saving rate with China Family Panel Studies survey data. I exploit variation in local exposure to export slowdown to study households' response to income shocks induced by global export slowdown following the Great Financial Crisis. Using a shift-share instrumental variable, I find that export slowdown is associated with a decrease in household saving rate, with the more pronounced effects concentrating on urban areas. To explain this consequence, we propose the inertia expectation adjustment mechanism, based on the Permanent Income Hypothesis: when adverse income shock hits, households keep consumption level if they keep high expectation of the future, thus lower the saving rates. I test this mechanism using data for households' confidence about the future and confirm that export slowdown decreases households' saving rates through this expectation adjustment mechanism.

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Chapter 1

Innovation Clusters and Spatial Inequality with a Local Brain Drain

1.1 Introduction

The increasing spatial inequality has become an important economic concern for policy makers in the federal governments and the local governments. Places are becoming more unequal, especially around innovative counties. Along with the rise of Silicon Valley, a widening gap of college attainment rate is observed between Santa Clara county and the nearby Stanislaus County. A local brain drain helps to explain this phenomenon. Talents born in the neighborhood of innovative counties are drawn away by attractive high-skilled wages, given that the migration costs are low within small distances.

Each innovative county, together with the other counties within 90km is defined as an innovation cluster. Motivated by the divergence of educational attainment inside innovation clusters, research questions naturally follow. Does this local divergence increase spatial inequality? Does the local brain drain interact with some externalities such as innovation externalities? If so, can policy interventions increase aggregate welfare and decrease spatial inequality? To answer these questions, I develop and calibrate a dynamic spatial model and assess the impacts of place-based policies on real GDP and spatial inequality.

Talents are the key factors in the long-lasting economic development in Silicon Valley. Numerous high-skilled workers bring innovation to the local economy, which also determines the local productivity growth. With the hope of either not being left behind by Silicon Valley or becoming the next Silicon Valley, city and county governments are trying to stimulate local economic development through place-based policies to foster or attract talents. However, human capital accumulation is a long-term investment, which cannot be quantified by the canonical static spatial model. On the same track as the new pioneer works (Desmet et al. (2018), Cruz Álvarez and Rossi-Hansberg (2021), Kleinman et al. (2021)), the dynamic spatial general equilibrium in this paper allows for the study of the trends in the U.S. and the long-run effects of place-based policies on real GDP and spatial inequality.

This paper starts with the empirical evidence that proximity to innovative counties makes low-educated counties experience a slower growth in educational attainment, which refers to the share of adults over 25 years old with bachelor's degrees in this paper. Innovative counties in 1980 are identified if its weighted sum of patents is greater than 97th percentile at the national level. Each innovative county, together with all the counties within 90km is defined as an innovation cluster. A low-educated county is identified if its educational attainment is lower than 25th percentile at the state level. Regression results show that low-educated counties inside innovation clusters in 1980 experienced a slower educational growth than low-educated counties outside the innovation clusters during 1980-2013. The results are robust to different thresholds for innovative counties and low-educated counties.

Moreover, I document the fact that the divergence of educational attainment contributes to the U-shape spatial inequality. Educational attainment affects regional income per capita. Variance decomposition shows that educational attainment explains 32% of the standard deviation of the log income per capita, the measure of spatial inequality in the literature, across all the counties in the US. For the subsample of counties inside innovation clusters, educational attainment explains 64% of the spatial inequality. The divergence of educational attainment increases the spatial inequality inside innovation clusters, and contributes to the U-shape spatial inequality during 1980-2010.

I extend Desmet et al. (2018) with two types of skill and endogenous education decisions.

At the end of each period, a fraction of people die and a slightly larger fraction of people are born. Population growth is allowed in the model. For the newborn agents, they can make decisions whether to pursue higher education at the beginning of their newborn period. If they choose not to attend universities, they work as a low-skilled worker in the newborn period. If they choose to pursue higher education, they spend time in schools and pay tuition fees. In their newborn period, they work as a high-skilled worker for the rest of time after their graduation. Agents can only make decisions of education in their newborn periods, and they cannot change their skill types in the later periods.

Newborn agents are heterogeneous in the time cost of higher education. They pay tuition fees to schools, which is proportional to the local high-skilled income. Schools hire high-skilled workers. One high-skilled worker can teach a fixed number of students. Zero profits in schools imply that tuition fees are determined by high-skilled income and student-to-faculty ratio.

Consistent with the literature Castro and Coen-Pirani (2016), when making decisions of education, newborn agents have myopic view that their expectation about the future is based on the current information. Newborn agents' information resources about wages by skill can be restricted to their birthplaces, or relaxed to a broad range such as the neighborhood of their hometowns, or all over the country. Considering the high-skilled and low-skilled wages, the cost of time spent in schools, and tuition fees, newborn agents decide whether to attend college. The fraction of newborn agents enrolled in college is affected by the ratio of high-skilled to low-skilled wages, which determines the return to higher education.

The provision of information affects newborn agents' demand for higher education and the local college enrollment rate. In Stanislaus County, for example, high-skilled wages are not lucrative relative to low-skilled wages. If newborn agents born in Stanislaus county only have the wage information in their hometown, they will have less incentive to attend schools. But if they get access to wage information in the neighborhood such as Santa Clara county, their demand for higher education will increase. As more newborn agents pursue higher education, the college enrollment rate increases.

Firms use land, high-skilled and low-skilled labor as the inputs of production. Firms hire high-skilled workers to create innovation, which improves the firm's high-skilled labor productivity in the current period and contributes to the local productivity growth for the next period. Following the technology evolution in Desmet et al. (2018), the local productivity in the current period is determined by the local innovation, the local productivity, and the aggregate productivity at the national level in the last period.

The local brain drain interacts with the innovation externalities. For example, high-skilled workers move from Stanislaus to Santa Clara, creating innovation and contributing to the local productivity growth in Santa Clara. However, the local brain drain leaves fewer researchers in Stanislaus and thus less innovation and slower productivity growth.

In each period, utilities by skill, population by skill, wages by skill, land rents, price index, local innovation and productivity, and college enrollment rate are determined for each place in equilibrium. This dynamic spatial model is tractable and I calibrate the model with the 2007 county-level data for the US. County is the unit of analysis for two reasons. First, featuring the increasing spatial inequality inside innovation clusters requires a fine geographic scale, which cannot be captured by state-level data. Second, counties have their local governments that can conduct place-based policies to deal with externalities and increase welfare. In contrast, MSA areas are delineated for the purpose of population census and statistical data.

Besides using some parameters from the literature, I calibrate the elasticity of demand for higher education, migration costs by skill, and local productivity. I collect county-level data from IPUMS for college enrollment rate among individuals aged 18-19 years old, and county-level high-skilled and low-skilled wages. I construct the regression specification based on the model, and estimate the elasticity of demand for higher education. I calculate the enrollment rate in each county with the estimated elasticity and obtain the predicted national enrollment rate, 38%. The observed enrollment rate in 2007 is 42.2%.

With the data for county-to-county migration flows by educational attainment from 2007 American Community Survey (ACS), I recover the county-to-county migration costs by skill. Using the nonparametric cubic spline method, I estimate the nonlinear effects of distance on migration costs. High-skilled and low-skilled migration costs increase sharply when distance increases from 0km to 90km. In line with the literature, high-skilled migration costs are lower than low-skilled migration costs. In addition, migration flow data shows that the total number of migrants by distance drops drastically when distance increases from 60km to 100km, which corroborates that brain drain tends to happen locally.

Following Desmet et al. (2018), local productivity can be calculated based on the wages adjusted by labor force. I recover the local productivity in each county for 2007 with the county-level population by skill, wages by skill, and college enrollment rates in 2007. Though the college enrollment rate of newborn agents can affect the population by skill, the scale of its short-term impact is small, as newborn agents are small parts of the total population. According to the IPUMS, the annual birth rate is 1.8%, which implies the tiny fraction of newborn agents. According to the map for the distribution of local productivity, East Coast and West Coast have high local productivity, which is harmonious with the real world.

For model validation, I estimate the evolution of technology with the local productivity for 2007, the local productivity and the local innovation for 2006. Local productivity for 2006 is calibrated with the same method mentioned above. In a novel manner different from Desmet et al. (2018), I create a proxy value for the local innovation with the patent data from United States Patent and Trademark Office (USPTO). The patent data is not used in neither their paper, nor the other calibration procedure in this paper. With the calibrated 2006, 2007 local productivity and the proxied 2006 innovation for almost 3000 counties, the estimated impacts of the past innovation and the past local productivity on the current local productivity are close to the values in Desmet et al. (2018).

To study the trend of spatial inequality during 1980-2010, I further calibrate the local productivity for 1980. With the county-level population by skill, wages, and the calibrated local productivity for 1980, I run the model starting from 1980 for 30 periods without any policy interventions. The simulation results reproduce the U-shape spatial inequality, with a turning point around 1996. This U-shape spatial inequality across the country is driven by the increasing spatial inequality inside innovation clusters. The latter is affected by the local brain drain, which leads to the divergence of educational attainment inside innovation clusters.

To illustrate the contribution of local brain drain to spatial inequality, I conduct counterfactual experiments through lowering migration costs within small distances for high-skilled people, which strengthens the local brain drain channel. Simulation results show that lower migration costs decrease spatial inequality in the short term, but accelerates the turning point of spatial inequality, and leads to higher spatial inequality in the long term. It confirms that the local brain drain determines the pace of divergence across places.

With the concern of increasing spatial inequality, numerous place-based policies have been implemented by local governments recently. Promise Program is one of the relevant programs widely conducted, in which 81 cities or counties across 36 states provide place-based scholarships with an expectation of local economic development. Inspired by the Promise Program, I investigate 50% tuition subsidies in low-educated counties, sponsored by the local income tax revenue. I assess the place-based policies with the percentage change of real GDP and spatial inequality induced by the policy intervention.

Tuition subsidies can stimulate local development through encouraging more newborn agents to become high-skilled, but taxes can decrease real GDP simultaneously. Moreover, this policy might decrease spatial inequality, through increasing the number of high-skilled workers in low-educated counties. But the additional high-skilled workers due to the tuition subsidies might leave. How this policy affects real GDP and spatial inequality is determined by many factors. Therefore a quantitative analysis based on the dynamic general equilibrium is needed.

First, I consider 50% tuition subsidies in 28 low-educated counties inside the innovation clusters. Real GDP at the national level gains from this policy in the short run and the long run. Specifically, it gains by 0.11% after ten years. The place-based tuition subsidies do not decrease spatial inequality. For the 28 low-educated counties, local real GDP even loses more than 0.2% immediately, though it gradually recovers during the following 10 years. On the one hand, people leave after getting higher education, and these counties do not benefit from more high-skilled workers. On the other hand, stayers in these counties bear the burden of income taxes, thus tuition subsidies lead to real GDP losses in the local economies. The results corroborate that the local brain drain plays an important role in the low-educated counties inside innovation clusters.

Second, I consider 50% tuition subsidies in 287 low-educated counties outside the innovation clusters. Real GDP at the national level loses by 0.35% in the first year and recovers after 5 years. It gains 0.2% after 10 years. Real GDP does not gain in the short run, because the additional high-skilled workers due to the tuition subsidies barely move to any innovative counties with high local productivity, thus their contribution to the economy cannot compensate for the tax burden immediately. As high-skilled workers stay, they contribute to the local economic development and real GDP gains in the long run. This policy decreases spatial inequality by 0.4% after 10 years as the local brain drain is less pronounced.

Furthermore, under the scenario that tuition fees are high, I re-consider 50% tuition subsidies in 28 low-educated counties inside the innovation clusters. Similar to the results in the first policy experiment, real GDP at the national level gains in the short run and the long run, and spatial inequality is not improved. Importantly, real GDP gains 0.43% after 10 years, which is more sizable than the first policy experiment. When tuition fees are high, a 50% tuition subsidy can be more effective in encouraging students to enroll in college. But it also brings greater loss in the local real GDP for the 28 low-educated counties, as taxes are higher when tuition fees are higher given the same subsidy rate.

Some other real-world policies are discussed, including Relocation Incentives, Information Provision, and Tuition Subsidies sponsored by the federal government. How to connect the real-world policies with the model, and how to adjust the model for policy experiments are also demonstrated. Relocation Incentives and Information Provision can be assessed directly based on this model. The former can attract inflows of talents, and the latter can stimulate investment on higher education by keeping young people informed that high-skilled wages are lucrative in other places.

Tuition Subsidies sponsored by the federal government are related to Free Community College in the Biden Plan. Cross-region collaboration under the federal policies can cope with the cross-region externalities induced by the local brain drain. Compared to place-based policies, federal policies can also increase real GDP and it might decrease spatial inequality in a more efficient way. Federal policy experiments are challenging in terms of numerical analysis, and further exploration in theory is needed.

This paper is related to three strands of the literature. First, it contributes to the strand of dynamic spatial models (Desmet and Rossi-Hansberg (2014), Desmet et al. (2018), Cruz Álvarez and Rossi-Hansberg (2021), and Conte et al. (2022)). I extend the model in Desmet et al. (2018) with two types of skill and endogenous education decisions. As researchers are mainly high-skilled workers, education is critical to innovation and the growth of aggregate productivity. The theoretical extension in this paper enriches the mechanism of economic development with endogenous education decisions. It also justifies subsidies to education, as real GDP gains from some place-based tuition subsidies.

Moreover, this paper contributes to the general strand of quantitative spatial models with evaluating long-term policy impacts. Complementing the global economy in Desmet et al. (2018), this paper analyzed the policies within a country. Through calibration based on county-level data for the US, this paper can evaluate the long-term impacts of place-based policies conducted by local governments, which cannot be assessed by the static spatial models in the literature.

Second, this paper is related to the strand of geographic proximity in urban economics. Proximity to large cities might enhance population growth through positive spillover effects and large market access, but it might also hurt such growth through competition (Krugman (1993), Tabuchi and Thisse (2011), Cuberes et al. (2021)). This paper contributes to the literature by introducing the local brain drain as a novel mechanism that proximity to innovative counties hurts high-skilled population growth for low-educated counties. In addition, as high-skilled workers are key to innovation, adjacency brings negative impacts to the local productivity in the long term, which is a missing piece of canonical central place theory.

Third, this paper speaks to the trend of "Great Convergence" and "Great Divergence", Diamond (2016), Giannone et al. (2017), Kleinman et al. (2021). Diamond (2016) suggests that endogenous amenities reinforce diverging location choices by skill. This paper emphasizes that geography also matters. Within small distances inside innovation clusters, the divergence of educational attainment is more evident.

Giannone et al. (2017) documents the transition from "Great Convergence" to "Great Divergence" that places are becoming more equal in terms of wages during 1940 to 1980, but more unequal after 1980. She develops a dynamic spatial model and matches the overall trend with skill-biased technical change as exogenous productivity shock. In this paper, the transition is captured by the U-shape (initially decreasing then increasing) income inequalities between places. I develop and calibrate a dynamic spatial model that reproduces the U-shape spatial inequality with innovation endogenously determined. Innovation can increase high-skilled labor productivity, thus firms choose spending on innovation based upon high-skilled wages and its demand for high-skilled labor.

A recent working paper Kleinman et al. (2021) shows that the interaction between capital and labor dynamics plays a central role in explaining the observed decline in the rate of income convergence across U.S. states. Skills of labor and innovation are not considered in their paper. Different from their focus on convergence, this paper sheds light on the faster pace of divergence with educational growth and technology evolution as the drivers, which are determined by endogenous education decisions and innovation decisions.

The rest of the paper is organized as follows. Section 1.2 presents data resources and the empirical evidence. Section 1.3 develops a dynamic spatial model. Section 1.4 provides calibration results. Section 1.5 presents the quantitative results and discusses other policies implemented in the US recently. Section 1.6 concludes.

1.2 Data and Empirical Evidence

In this section, I document the divergence of educational attainment inside innovation clusters in the US. I also show that this local divergence increases spatial inequality inside innovation clusters, and contributes to the U-shape spatial inequality across the country.

1.2.1 Data

I use county-level data for the major part of the paper. For empirical analysis, I use patent data from United States Patent and Trademark Offices (USPTO), distance data from NBER County Distance Database, education data from IPUMS, and income per capita data from Bureau of Economic Analysis (BEA).

For calibration and estimation, I collect college enrollment rate from IPUMS, county-to-county migration flows by educational attainment from American Community Survey (ACS), population and wages by skill from IPUMS, and natural amenities from U.S. Department of Agriculture (USDA).

1.2.2 Divergence of Educational Attainment

The divergence of educational attainment is observed inside innovation clusters in the United States. For example, Santa Clara county is a world-famous innovative county in the heart of Silicon Valley. Stanislaus is one of its neighboring counties. In 1980, the educational attainment was 26% in Santa Clara and 12% in Stanislaus. In 2013, it was 50% in Santa Clara and 17% in Stanislaus. The gap of educational attainment had been widened from 14% to 33% during three decades.

Figure 1.1 and Figure 1.2 are presented for data visualization. Educational attainment is colored in grey. A darker color implies a higher college attainment rate. Around Santa Clara county, places are becoming more unequal in terms of educational attainment. Besides Stanislaus, the divergence can also be observed between Santa Clara and another neighboring county, Merced.[1]

Figure 1.3 and 1.4 provide the maps of educational attainment and innovation level by county, which gives a comprehensive view for the entire country. On the maps, innovative counties are marked by the weighted sum of patents. A larger green dot represents a higher weighted sum of patents and a higher local innovation level. In 1980, educational attainment was relatively uniform in the US. In contrast, it was varied across counties in 2013, especially around innovative counties that are marked by larger green dots.

[1]According to NBER County Distances Database, the great circle distance between Santa Clara and Stanislaus is 71.65km, and the great circle distance between Santa Clara and Merced is 85.72km.

Figure 1.1: Educational Attainment in Santa Clara and Stanislaus, 1980

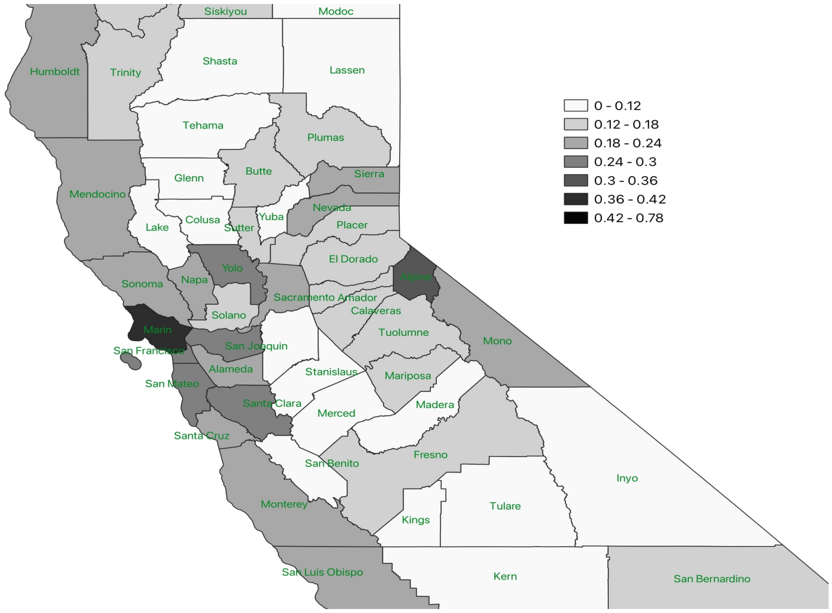
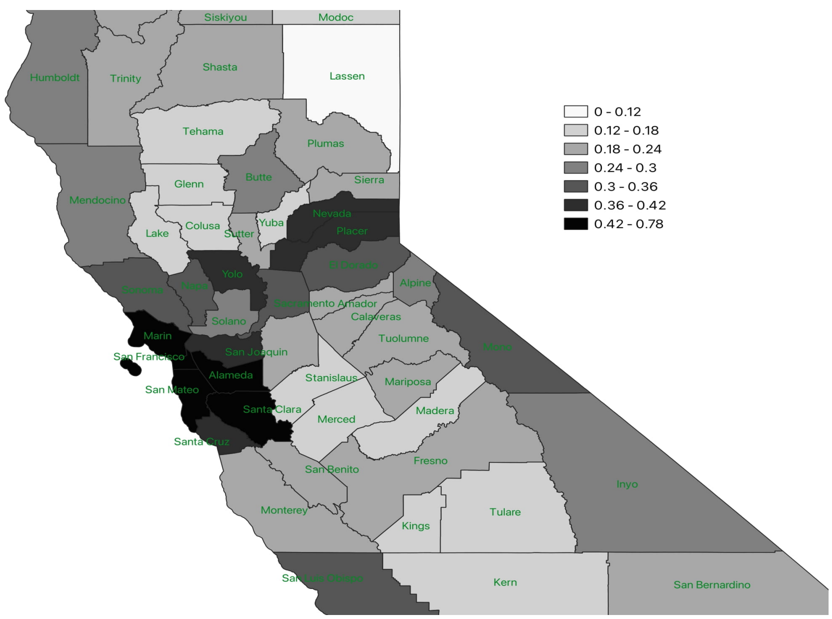
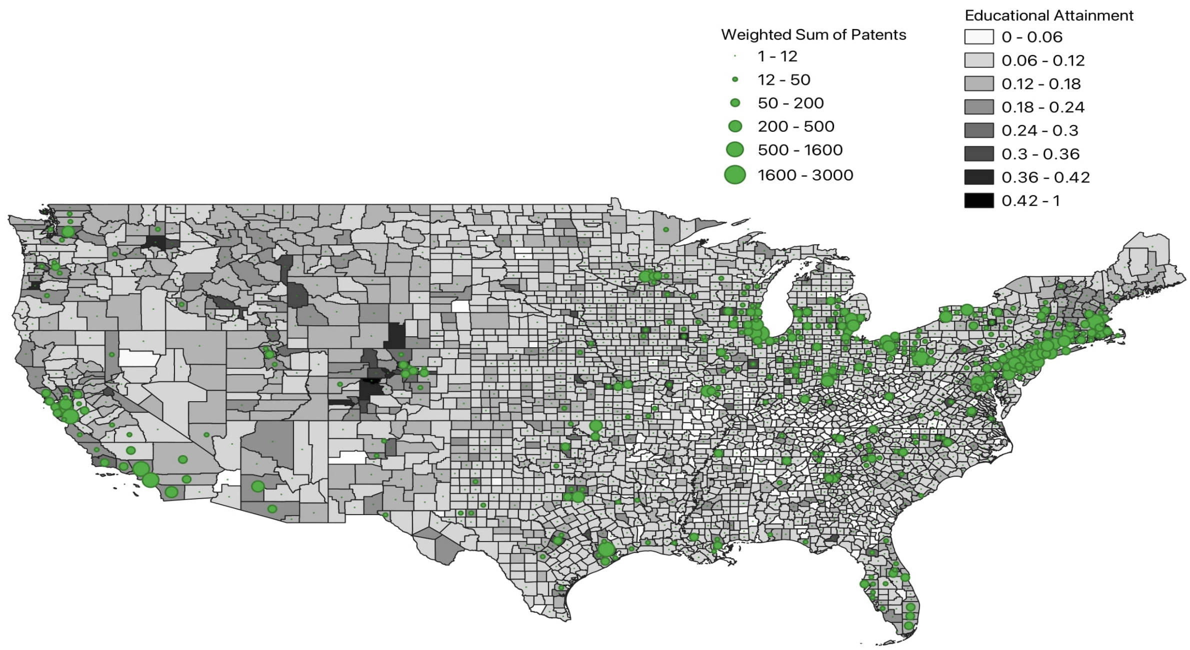


Figure 1.2: Educational Attainment in Santa Clara and Stanislaus, 2013



Meanwhile, it is also noticeable that some counties outside innovation clusters had evenly become more educated during 1980-2013. See the West North Central region in Figure 1.4. Does proximity to innovative counties hurt growth in educational attainment for some counties? Motivated by this question, an empirical specification is constructed to compared educational growth for low-educated counties inside and outside innovation clusters.

Figure 1.3: Innovative Counties and College Completion Rates in 1980



First, I identify innovative counties if its weighted sum of patents is greater than p(97) at the national level in 1980.[2] Then I define each innovative county and the neighboring counties within 90km[3] together as an innovation cluster[4]. Furthermore, I identify a low-educated county if its educational attainment is lower than p(25) at the state level. The empirical strategy is specified as

$$\Delta edu_c = \alpha_s + \beta_1 D_1 + \beta_2 D_2 + \epsilon_c$$

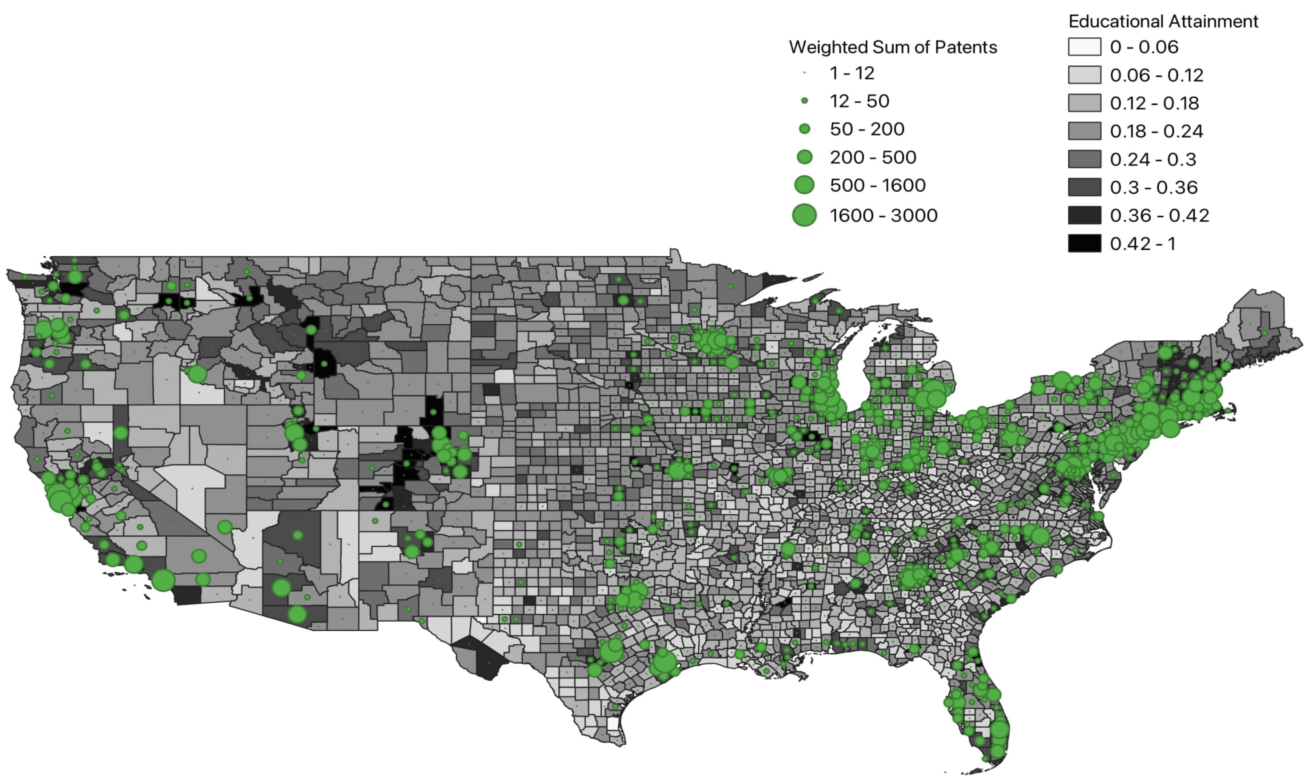
[2]In 1980, 1780 counties have at lease one inventor. With the 97th percentile as threshold, 53 innovative counties are identified.

[3]Data for distances are collected from NBER County Distance Database. County Distances are great-circle distances calculated based on internal points in the geographic area.

[4]When two innovative counties are close, such as Alameda County where UC Berkeley is located, and Santa Clara County where Stanford University is located, they are combined into one innovation cluster.

where δedu_c denotes the change of educational attainment in county c between 1980 and 2013. D_1 and D_2 are dummies for low-educated counties. D_1 denotes low-educated counties inside innovation clusters in 1980. D_2 denotes low-educated counties outside innovation clusters in 1980. α_s denotes the state fixed effects. Standard errors are clustered at the state level.

Figure 1.4: Innovative Counties and College Completion Rates in 2013



If β_1 is smaller than β_2, then low-educated counties inside innovation clusters experienced a slower educational growth than low-educated counties outside innovation clusters. As shown in Table 1.1, β_1 is more negative than β_2 and the results hold with different thresholds for low-educated counties. This pattern also holds with different distance thresholds for defining innovation clusters. See Appendix 1.6 Table A1.1 and A1.2.[5]

[5]In Table A1.1, I change the distance from 90km to 75km to re-define innovation clusters. In Table

Table 1.1: Educational Growth in Low-educated Counties

	Δedu_i	Δedu_i	Δedu_i
D_1, inside innovation clusters in 1980	-0.0341***	-0.0329***	-0.0337***
	(0.007)	(0.005)	(0.005)
D_2, outside innovation clusters in 1980	-0.0214***	-0.0208***	-0.0220***
	(0.004)	(0.004)	(0.004)
P-value for difference	0.069	0.043	0.060
Threshold for low-educated	p(25)	p(30)	p(35)

Results above indicate that proximity to innovative counties makes low-educated counties experience a slower growth in educational attainment. This divergence of educational attainment inside innovation clusters can be explained by a local brain drain: talents born in the neighborhood are drawn away by attractive high-skilled wages, given that migration costs are low. Estimation results in section 1.4.2 corroborates this channel that (1) migration costs are low within small distances, thus brain drain happens in a local area; (2) high-skilled migration costs are lower than low-skilled migration costs.

1.2.3 U-shape Spatial Inequality

The local divergence of educational attainment can increase spatial inequality inside innovation clusters. Educational attainment affects regional income per capita as

$$\frac{w^h(r)N^h(r) + w^\ell(r)N^\ell(r)}{N^h(r) + N^\ell(r)} = \frac{N^h(r)}{N^h(r) + N^\ell(r)} \times \left(w^h(r) + w^\ell(r)\frac{N^\ell(r)}{N^h(r)} \right) \tag{1.1}$$

where $w^h(r)$ and $w^h(r)$ are high-skilled and low-skilled wages county r. The left-hand side of this equation is income per capita by definition. The first term at the right-hand side is educational attainment. In a location, Income per capita increases as educational attainment becomes higher.

A1.2, I change the threshold for innovative counties from 159 to 175, as the 97th percentile of the weighted sum of patents at the national level is 159 in 1980.

This equation can be rewritten by taking logs at both sides as

$$log\left(\frac{w^h(r)N^h(r)+w^\ell(r)N^\ell(r)}{N^h(r)+N^\ell(r)}\right)=log\left(\frac{N^h(r)}{N^h(r)+N^\ell(r)}\right)+log\left(w^h(r)+w^\ell(r)\frac{N^\ell(r)}{N^h(r)}\right)$$

Variance decomposition shows that educational attainment explains 32% of the standard deviation of log income per capita across the country, which is the measure of spatial inequality in the literature Gaubert et al. (2021).[6]

Focusing on the innovation clusters with a subsample of 277 counties, educational attainment explains 64% of spatial inequality.[7]. Moreover, I calculate the spatial inequality for each innovation cluster.[8] There were 53 clusters in 1980 and I obtain the average value over the 53 clusters. The average spatial inequality is displayed in Figure 1.5, corroborating that the local divergence pushes up the spatial inequality inside innovation clusters.

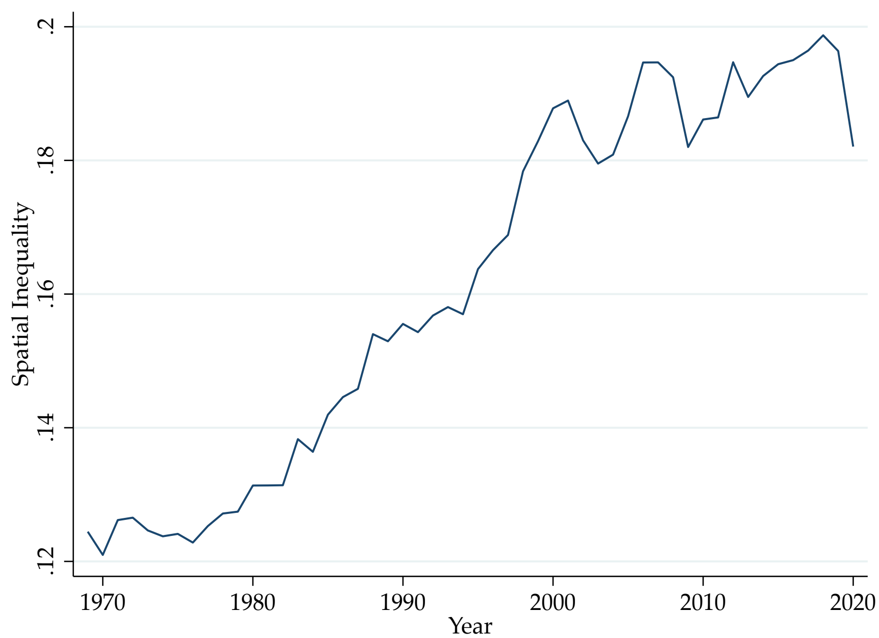
The local divergence drives up the spatial inequality not only inside innovation clusters, but also across innovation clusters. Moving from the local scope to a national scope, the local divergence contributes to the U-shape spatial inequality across the country. I calculate the spatial inequality across all the innovation clusters (277 counties) and across the country (3147 counties), which are presented in Figure 1.6a and 1.6b. The figures show that spatial inequality across the country decreased during 1970-1995, but increased afterwards, whereas spatial inequality across innovation clusters kept increasing since 1975. Moreover, compared to the national spatial inequality, the spatial inequality across the innovation clusters started from a lower value (0.25 vs 0.18), but ended at a higher value (0.23 vs 0.26).

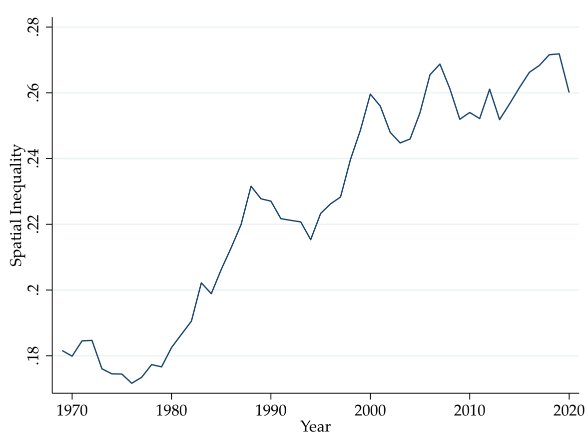
[6]In Gaubert et al. (2021), spatial inequality is measured by the standard deviation of log income per capita weighted by the local population. Spatial inequality across states based on pretax income ranges from 0.12 to 0.2 during 1960 and 2015. Spatial inequality across counties ranges from 0.25 to 0.35 during 1970 and 2015.

[7]In 1980, around 53 innovative counties, there were 277 counties inside innovation clusters in total. In 2018, around 155 innovative counties, there were 677 counties inside innovation clusters in total. Same threshold is applied to identify innovative counties across the time.

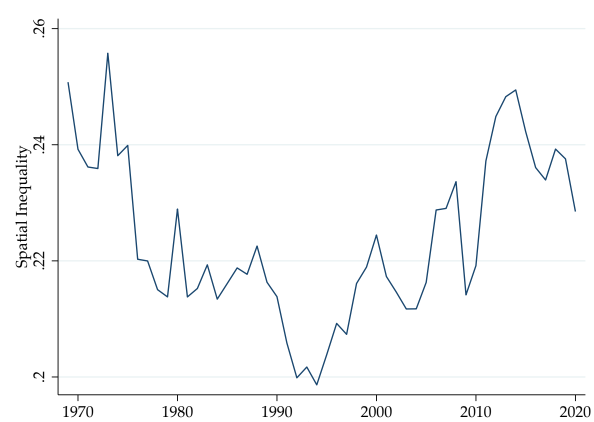
[8]For example, there was an innovation cluster led by Santa Clara county including 9 counties in 1980. I calculate the variance of log income per capita across these 9 counties, which is the spatial inequality for this "Silicon Valley" cluster.

Figure 1.5: Average Spatial Inequality inside Innovation Clusters





(a) Spatial Inequality across all the Innovation Clusters



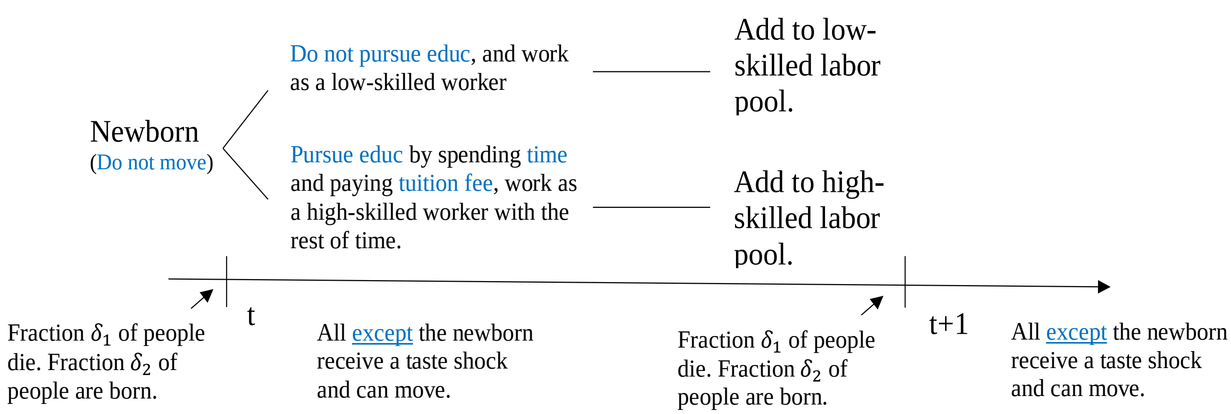
(b) Spatial Inequality across the Country

The divergence of educational attainment is characterized by the model in the next section, with two types of skill and endogenous educational attainment introduced. In section 1.4 and 1.5, the calibration results corroborate the local brain drain channel, and the simulation results confirm that the local divergence contributes to the U-shape spatial inequality.

1.3 Model

This model extends Desmet et al. (2018) with two types of skill and endogenous education choice. As Figure 1.7 demonstrates, at the end of each period, a fraction δ_1 of people die and a fraction δ_2 of people are born. All except the newborn agents receive a taste shock and can move. Newborn agents decide whether to pursue higher education and become high-skilled. They do not move in their newborn periods. If a newborn agent decides to pursue education, they spends time in schools and pays tuition fee, they works as a high-skilled worker in their birthplace with the rest of time in period t. They adds to the high-skilled labor pool at the end of period t. If a newborn agent decides not to pursue education, they works as a low-skilled worker in the entire period t. Agents can only pursue education in their newborn periods.

Figure 1.7: Timeline



Consider an economy that occupies a closed and bounded set Ω of a two-dimensional surface. Location $r \in \Omega$ has land density $H(r) > 0$, where $H(\cdot)$ is normalized as $\int_{\Omega} H(r)dr = 1$. In location r, the population density of high-skilled workers is $N_t^h(r)$ and the population density of low-skilled workers is $N_t^\ell(r)$. Firms produce a good $\omega \in [0,1]$ using land, high-skilled labor h and low-skilled labor ℓ. Firms innovate using high-skilled labor.

1.3.1 Preferences

Agents derive utility from local amenities and from consuming a set of differentiated products. Their preferences are constant elasticity of substitution (CES). Except for the newborn, agents can move to the destination r_t from the place of origin, or in other words, the place of residence in the last period r_{t-1}. The period utility of agent i is given by

$$u_t^{i,s}(r_{t-1}, r) = a_t(r)\Big[\int_0^1 c_t^\omega(r)^\rho d\omega\Big]^{\frac{1}{\rho}} \varepsilon_t^i(r)/m^s(r_{t-1}, r_t) \tag{1.2}$$

where s denotes the skill type of agent i, with $s = h$ if they is high-skilled and $s = \ell$ if they is low-skilled. $1/[1-\rho]$ is the elasticity of substitution with $0 < \rho < 1$. $a_t(r)$ denotes amenities in place r at period t. $c_t^\omega(r)$ denotes consumption of good ω. $m^s(r_{t-1}, r_t) \geqslant 1$ is the bilateral migration cost between locations r_{t-1} and r_t for skill s agents. $\varepsilon_t^i(r)$ is a taste shock following a Fréchet distribution.

$$Pr[\varepsilon_t^i(r) \leqslant z] = e^{-z^{-1/\eta}} \tag{1.3}$$

The log of $\varepsilon_t^i(r)$ has variance $\pi^2\eta^2/6$ with $\eta < 1$. Taste heterogeneity is greater as η is higher. $\varepsilon_t^i(r)$ is independent and identically distributed across individuals, time, and locations.

Agents' utilities from local amenities are homogeneous. Amenities $a_t(r)$ in location r is given by

$$a_t(r) = \bar{a}(r)N_t(r)^{-\lambda}$$

where $\bar{a}(r) > 0$ is exogenously given. $N_t(r) = N_t^h(r) + N_t^\ell(r)$ is the total population per unit of land at location r in period t. An increase in population density $N_t(r)$ results in congestion externalities and a decrease in amenities $a_t(r)$. λ is the elasticity of amenities to population.

High-skilled agents can work either as workers or researchers in manufacturing firms, or as teachers in schools. Low-skilled agents can only work in firms. Agents of skill type s in the manufacturing sector earn from work $w_t^s(r)$ and land income $R_t^s(r)$. Firms pay land rent, thus land income is allocated among workers in firms based on their contribution, as (1.4) demonstrates.

$$R_t^s(r) = \frac{w_t^s(r)}{w_t^h(r)\bar{L}_t^{h,M}(r) + w_t^\ell(r)\bar{L}_t^{\ell,M}(r)} R_t(r) \quad s = h, \ell \tag{1.4}$$

where $R_t(r)$ denotes rent per unit of land. $\bar{L}_t^{h,M}(r)$ and $\bar{L}_t^{\ell,M}(r)$ are the total high-skilled and low-skilled labor in the manufacturing sector. In each location, high-skilled workers can move freely between manufacturing firms and schools, and teachers receive payment from schools which is equal to outside options, i.e. $w_t^h(r) + R_t^h(r)$.

Total income of an agent is $w_t^s(r) + R_t^s(r)$. The ratio of high-skilled workers' land income to low-skilled workers' land income $\frac{R_t^h(r)}{R_t^\ell(r)}$ equals to the ratio of wages $\frac{w_t^h(r)}{w_t^\ell(r)}$, thus the ratio of total income $\frac{w_t^h(r)+R_t^h(r)}{w_t^\ell(r)+R_t^\ell(r)}$ equals to the ratio of wage $\frac{w_t^h(r)}{w_t^\ell(r)}$ as well. Agents cannot write debt contracts with each other, and they simply consume their income in each period. $u_t^s(r)$ denotes how individuals of skill type s value the characteristics of location r, which is a good measure of the desirability of a location. $u_t^s(r)$ is based on exogenous amenities, congestion force and real consumption.

$$u_t^s(r) = \bar{a}(r) N_t(r)^{-\lambda} \frac{\left[w_t^s(r) + R_t^s(r)\right]}{P_t(r)} \tag{1.5}$$

where $P_t(r)$ denotes the price index at location r in period t,

$$P_t(r) = \left[\int_0^1 p_t^\omega(r)^{-\rho/(1-\rho)} d\omega\right]^{-(1-\rho)/\rho}$$

At location r, the ratio of high-skilled workers' desirability to low-skilled workers' desirability equals to the ratio of real consumption, the ratio of income, and thus the ratio of wages.

$$\frac{u_t^h(r)}{u_t^\ell(r)} = \frac{w_t^h(r) + R_t^h(r)}{w_t^\ell(r) + R_t^\ell(r)} = \frac{w_t^h(r)}{w_t^\ell(r)} \tag{1.6}$$

1.3.2 Education

At the beginning of each period, newborn agents decide whether to pursue higher education. An agent born in period t pursues higher education by spending time in schools and paying tuition fees in their birthplace b at this period. Schools hire high-skilled workers as teachers with high-skilled income $w_t^h(b) + R_t^h(b)$. The production function of education is $\kappa L_t^{h,S}(b)$, where $L_t^{h,S}(b)$ is the high-skilled labor in schools. One newborn agent needs one unit of education to become high-skilled, and one teacher within a school can transfer κ students to high-skilled workers. Thus, κ can be understood as student-to-faculty ratio.

Schools decide the number of teachers demanded to maximize their profits, given the price of education $S_t(b)$, or tuition fees in schools. To hire teachers, schools need to pay equal to the outside options, $w_t^h(b) + R_t^h(b)$.

$$\max_{L_t^h} \kappa S_t(b) L_t^{h,S} - \Big(w_t^h(b) + R_t^h(b)\Big) L_t^{h,S}$$

Zero profit condition implies that the tuition fees are proportional to the high-skilled wages,

$$S_t(b) = \frac{1}{\kappa}\Big(w_t^h(b) + R_t^h(b)\Big) \tag{1.7}$$

Newborn agent i receives an idiosyncratic time cost shock e^i, which represents the time they needs to spend in school. $(e^i)^a$ follows a uniform distribution, i.e. $(e^i)^a \sim \mathcal{U}(0,1)$. Newborn agents do not move. After agent i finishes school, they works as a high-skilled worker in their birthplace b with the rest of time at period t and earn wages $(1-e^i)w_t^h(b)$ accordingly. Land is allocated based on agents' contribution to the production of goods, thus agent i's total income is $(1-e^i)\Big(w_t^h(b) + R_t^h(b)\Big)$. If agent i pursues higher education, their period t utility is given by

$$\begin{aligned} u_t^{h,i}(b) &= a_t(b)\frac{\Big(1 - e^i - \frac{1}{\kappa}\Big)\Big[w_t^h(b) + R_t^h(b)\Big]}{P_t(b)} \\ &= \Big(1 - e^i - \frac{1}{\kappa}\Big) u_t^h(b) \end{aligned}$$

If agent i does not pursues higher education, they works as a low-skilled worker at the entire period t,

$$u_t^{\ell,i}(b) = a_t(b)\frac{\Big[w_t^\ell(b) + R_t^\ell(b)\Big]}{P_t(b)} = u_t^\ell(b)$$

Agents can live for multiple periods, and they can only get higher education when they are newborn agents. Newborn agents maximize their lifetime utility when making decisions of education. They do not have perfect foresight about the evolution of income, thus they develop expectations about the future based on the past information. This attribute is described as myopic view in the literature Castro and Coen-Pirani (2016). In this model, newborn agents make decisions of education in period t before they enter the labor market, thus their expectations are based on the period $t-1$.

Newborn agents are assumed to have no information about the world outside their hometowns, and they make decisions of education based on the information in their birthplaces b. This information friction assumption can be relaxed, and newborn agents can get access to a broader range of information such as the neighborhood of their birthplaces b. In the extreme case, students have the complete information about wages across the entire space Ω. The provision of information is discussed in section 1.5.3.

If agent i born at the period t pursues higher education, their expected lifetime utility is

$$\Big(1 - e^i - \frac{1}{\kappa}\Big)u_{t-1}^h(b) + \sum_{n=1}^{\infty}\Big[\beta(1-\delta_1)\Big]^n u_{t-1}^h(b) = \Big[\Big(1 - e^i - \frac{1}{\kappa}\Big) + \frac{\beta(1-\delta_1)}{1-\beta(1-\delta_1)}\Big]u_{t-1}^h(b)$$

where $(1 - e^i - \frac{1}{\kappa})u_{t-1}^h(b)$ is agent i's expected utility for period t, and $[\beta(1-\delta_1)]^s u_{t-1}^h(b)$ is his expected utility for period $t+s$. β is the discounting factor of newborn agents and δ_1 is the mortality rate.

If agent i chooses not to pursue higher education, his expected lifetime utility is

$$u_{t-1}^\ell(b) + \sum_{n=1}^{\infty}\Big[\beta(1-\delta_1)\Big]^n u_{t-1}^\ell(b) = \frac{1}{1-\beta(1-\delta_1)}u_{t-1}^\ell(b)$$

Agents are indifferent between attending and not attending schools when

$$\Big[(1 - e^i - \frac{1}{\kappa}) + \frac{\beta(1-\delta_1)}{1-\beta(1-\delta_1)}\Big]u_{t-1}^h(b) = \frac{1}{1-\beta(1-\delta_1)}u_{t-1}^\ell(b)$$

The cutoff time cost e^* satisfies

$$e_t^*(b) = \frac{1 - \frac{u_{t-1}^\ell(b)}{u_{t-1}^h(b)}}{1-\beta(1-\delta_1)} - \frac{1}{\kappa} = \frac{1 - \frac{w_{t-1}^\ell(b)}{w_{t-1}^h(b)}}{1-\beta(1-\delta_1)} - \frac{1}{\kappa}$$

where the second equal sign holds, as utilities by skill are proportional to wages by skill in equation (1.6). If the time cost for agent i is small, i.e. $e^i \leqslant e_t^*(b)$, they choose to attend school and to become a high-skilled worker. Newborn agents decide whether to pursue higher education based on the observable wages in the last period. This feature is in line with reality.

As $(e^i)^a$ follows a uniform distribution, the fraction of agents born in location b at period t pursuing education is given by

$$e_t^*(b)^a = \Big(\frac{1 - \frac{w_{t-1}^\ell(b)}{w_{t-1}^h(b)}}{1 - \beta(1-\delta_1)} - \frac{1}{\kappa}\Big)^a \tag{1.8}$$

It is intuitive that higher skill premium $\frac{w_{t-1}^h(b)}{w_{t-1}^\ell(b)}$ and lower tuition fees $\frac{1}{\kappa}$ will increase the fraction of newborn agents attending schools.

The school enrollment rate is endogenously decided by local variables in the last period, thus it is predetermined for the current period. This feature keeps the simplicity and tractability of spatial dynamic model with endogenous education introduced. It is derived from newborn agents' static expectations based on the past skill premium in the place of birth, $\frac{w_{t-1}^h(b)}{w_{t-1}^\ell(b)}$. The assumption that newborn agents are ignorant about places other than their hometowns can be relaxed.

For extensions, newborn agents have complete information for the last period all over the country and can choose a place to get educated and reside. Being aware that high-skilled jobs are well-paying nearby, people inside innovation clusters have motivation to pursue higher education. In this case, a local brain drain can be beneficial through stimulating human capital formation.

The school enrollment rate determines the labor demand from schools accordingly

$$L_t^{h,S}(b) = \frac{1}{\kappa} e_t^*(b)^a \times \Big(\delta_2 N_{t-1}(b)\Big) \tag{1.9}$$

where $N_{t-1}(b)$ is the total population density in the last period, and δ_2 is the birth rate. Therefore, $\delta_2 N_{t-1}(b)$ is the population density of newborn agents.

The school enrollment rate also decides the high-skilled labor supplied by newborn agents. For each newborn agent i who attend schools, they supplies $1 - e^i$ unit of labor.

$$\delta_2 N_{t-1}(b) \times \int_0^{e_t^*(b)^a} (1-e)de = \delta_2 N_{t-1}(b) \times \left(e_t^*(b)^a - \frac{e_t^*(b)^{2a}}{2}\right) \tag{1.10}$$

The low-skilled labor supplied by newborn agents is

$$\delta L_{t-1}(b) \times \int_{e_t^*(b)^a}^1 1de = \delta \bar{L}_{t-1}(b) \times \Big(1 - e_t^*(b)^a\Big) \tag{1.11}$$

While newborn agents stay in hometowns when they are young, the other agents can move and reside in other places. The local labor supply is composed of labor from newborn agents and labor from non-newborn agents who choose to live there, which is determined after migration and is discussed in the next subsection.

1.3.3 Migration

In each period, agents receive their idiosyncratic taste shock and choose where to live with migration costs taken into consideration. Migration costs are symmetric $m^s(b,r) = m^s(r,b) \quad \forall b,r \in \Omega$. There is no cost to stay, i.e. $m^s(b,b) = 1$. As equation (1.2) shows, agents' period t utility depends on the migration cost $m^s(r_{t-1}, r)$ between the place of origin r_{t-1} and the destination r, not on the series of locations $\bar{r}_- = (r_0, ..., r_{t-2})$ in the history.

The location choice of agents for the current period might affect their utility in the next period $u^{i,s}_{t+1}(r_t, r)$, and they might take the future into consideration when making present decision. However, agents do not know their future tastes over places and the desirability of locations later on, i.e. $\epsilon_{t+n}(\cdot)$ and $u_{t+n}(\cdot)$, $n \geqslant 1$. Consistent with the feature of myopic view that newborn agents, other agents also develop their expectations for the future based on current information, i.e. $\mathbb{E}_t[u^s_{t+1}(\cdot)] = \mathbb{E}_t[u^s_{t+2}(\cdot)] = ... = \mathbb{E}_t[u^s_t(\cdot)] = u^s_t(\cdot)$ and $\mathbb{E}_t[\epsilon^i_{t+1}(\cdot)] = \mathbb{E}_t[\epsilon^i_{t+2}(\cdot)] = ... = \epsilon^i_t(\cdot)$.

With this characteristic, non-newborn agents always live in places where they achieve utility maximization for period t,

$$r_t = \arg\max_{r \in \Omega} u^{i,s}_t(r_{t-1}, r) = \arg\max_{r \in \Omega} u^s_t(r)\epsilon^i_t(r_{t-1}, r)/m^s(r_{t-1}, r)$$

Agents' location choice depends only on current variables and not on the future factors. People live in the present when the future is unknown. Desmet et al. (2018) also have this static location decision within a dynamic spatial framework, though they derive this property under a different assumption.

According to the equation above and the Fréchet distribution of taste preferences in equation (1.3), the shares of people moving between locations can be derived. The probability that skill s agents from location b prefer location r is given by

$$Pr(u_t^s(b,r) \geqslant u_t^s(b,v), \forall v \in \Omega) = \frac{u_t^s(r)^{1/\eta} m^s(b,r)^{-1/\eta}}{\int_\Omega u_t^s(v)^{1/\eta} m^s(b,v)^{-1/\eta} dv}$$

This corresponds to the fraction of skill s population at location b that moves to location r,

$$\frac{n_t^s(b,r)}{(1-\delta_1)N_{t-1}^s(b)H(b)} = \frac{u_t^s(r)^{1/\eta} m^s(b,r)^{-1/\eta}}{\int_\Omega u_t^s(v)^{1/\eta} m^s(b,v)^{-1/\eta} dv} \tag{1.12}$$

where $n_t^s(b,r)$ denotes the number of agents of skill type s moving from place b to place r. $(1-\delta_1)N_{t-1}^s(b)H(b)$ denotes the population of non-newborn agents of skill type s residing at location b in the last period.

The high-skilled population is equal to the number of newborn agents who pursue higher education, plus the number of people who move there or stay there.

$$N_t^h(r)H(r) = e_t^*(r)^a \Big(\delta_2 N_{t-1}(r)\Big) H(r) + \int_\Omega n_t^h(b,r)db \tag{1.13}$$

According to equation (1.10), the total high-skilled labor supply is given by

$$L_t^h(r)H(r) = \left(e_t^*(r)^a - \frac{e_t^*(r)^{2a}}{2}\right) \times \Big(\delta_2 N_{t-1}(r)\Big) H(r) + \int_\Omega n_t^h(b,r)db \tag{1.14}$$

The second term in the equation above is slightly different from equation (1.13), as newborn agents supply only a part of their time if they attend schools.

As newborn-agents without pursuing higher education work for the entire period, the low-skilled population is equal to the total low-skilled labor supply. According to (1.11), it can be obtained that

$$N_t^\ell(r)H(r) = L_t^\ell(r)H(r) = \Big(1 - e_t^*(r)^a\Big) \times \Big(\delta_2 N_{t-1}(r)\Big) H(r) + \int_\Omega n_t^\ell(b,r)db \tag{1.15}$$

1.3.4 Technology and Firms

Firms use land and labor to produce a good $\omega \in [0,1]$. A firm using $L_t^{h,\omega}(r)$ and $L_t^{\ell,\omega}(r)$ production workers per unit of land at location r at time t produces $q_t^\omega(r)$ units of good ω per unit of land,

$$q_t^\omega(r) = z_t^\omega(r)\Big[(\phi_t^\omega(r)^{\gamma_1} L_t^{h,\omega}(r)^\mu)^\sigma + (\bar{A}^\ell(r) L_t^{\ell,\omega}(r)^\mu)^\sigma\Big]^{1/\sigma}$$

where γ_1, μ, $\sigma \in (0,1]$. The elasticity of labor substitution is $\frac{1}{1-\sigma}$. A firm's productivity is determined by its high-skilled productivity shifter $\phi_t^\omega(r)^{\gamma_1}$, which is decided by skill-biased innovation $\phi_t^\omega(r)$, low-skilled productivity shifter $\bar{A}^\ell(r)$, and a good-specific productivity shifter $z_t^\omega(r)$. The labor cost of skill-biased innovation is $\nu\phi_t^\omega(r)^\xi$ additional units of high-skilled labor per unit of land, where $\xi > \gamma_1/[1-\mu]$.

The productivity shifter $z_t^\omega(r)$ is the realization of a random variable that is i.i.d. across goods and time. All the productivity shifters in location $r \in S$ are drawn from the same Fréchet distribution

$$F(z,r) = e^{-T_t(r)z^{-\theta}}$$

where $T_t(r) = \tau_t(r)N_t(r)^\alpha$, and $\alpha \geqslant 0$ and $\theta > 0$. The value of $\tau_t(r)$ depends on past innovation decisions $\phi_{t-1}(r)$ in this location and $\tau_{t-1}(\cdot)$ in other places,

$$\tau_t(r) = \phi_{t-1}(r)^{\theta\gamma_1}\Big[\int_\Omega \tau_{t-1}(v)dv\Big]^{1-\gamma_2}\tau_{t-1}(r)^{\gamma_2} \tag{1.16}$$

where γ_1 determines the dynamic impact of innovation on local productivity. γ_2 controls technology spillover effects. $\gamma_1, \gamma_2 \in [0,1]$.

As discussed in Desmet and Rossi-Hansberg (2014), firm's optimization problem is a static problem. After firm owners obtain their draws from productivity shifter $z_t^\omega(r)$, a potential firm at r maximizes its current profits per unit of land by choosing

$$\max_{L_t^{h,\omega}(r), L_t^{\ell,\omega}(r), \phi_t^\omega(r)} p_t^\omega(r,r)z_t^\omega(r)[(\phi_t^\omega(r)^{\gamma_1}L_t^{h,\omega}(r)^\mu)^\sigma + \bar{A}^\ell(r)L_t^{\ell,\omega}(r)^{\mu\sigma}]^{1/\sigma}$$
$$- w_t^h(r)L_t^{h,\omega}(r) - w_t^\ell(r)L_t^{\ell,\omega}(r) - w_t^h(r)\nu\phi_t^\omega(r)^\xi - R_t(r)$$

where $p_t^\omega(r,r)$ is the price of a good ω produced and sold at location r.

A firm's bid rent per unit of land guarantees that all firms make zero profits. Combining F.O.Cs, an expression for land rent can be obtained,

$$\begin{aligned} R_t(r) &= p_t^\omega(r,r)z_t^\omega(r)[(\phi_t^\omega(r)^{\gamma_1}L_t^{h,\omega}(r)^\mu)^\sigma + (\bar{A}^\ell(r)L_t^{\ell,\omega}(r)^\mu)^\sigma]^{1/\sigma} \\ &\quad - w_t^h(r)L_t^{h,\omega}(r) - w_t^\ell(r)L_t^{\ell,\omega}(r) - w_t^h(r)\nu\phi_t^\omega(r)^\xi \\ &= \frac{1}{\mu}\Big(w_t^h(r)L_t^{h,\omega}(r) + w_t^\ell(r)L_t^{\ell,\omega}(r)\Big) - w_t^h(r)L_t^{h,\omega}(r) - w_t^\ell(r)L_t^{\ell,\omega}(r) - w_t^h(r)\nu\phi_t^\omega(r)^\xi \end{aligned} \tag{1.17}$$

which can be rewritten as

$$R_t(r) = \left[\frac{(1-\mu)\xi}{\gamma_1}\left(1+\bar{A}^{\ell}(r)^{\frac{1}{1-\mu\sigma}}\left(\frac{w_t^h(r)}{w_t^{\ell}(r)}\right)^{\frac{\mu\sigma}{1-\mu\sigma}}\phi_t^{\omega}(r)^{-\frac{\gamma_1\sigma}{1-\mu\sigma}}\right)-1\right]w_t^h(r)\nu\phi_t^{\omega}(r)^{\xi} = g\Big(\phi_t^{\omega}(r)\Big)$$

Land rent is taken by all the firms. Appendix 1.6 shows that $\phi_t^{\omega}(r) = g^{-1}\Big(R_t(r)\Big)$ is uniquely determined if land rent is strictly increasing in a firm's investment in technology. Then a firm's innovation decision is independent of its idiosyncratic productivity draws, $z_t^{\omega}(r)$. And the decisions of innovation $\phi_t^{\omega}(r)$ and labor demand $L_t^{h,\omega}(r)$, $L_t^{\ell,\omega}(r)$ are identical across goods ω, so the superscript ω can be omitted.

As firms' decisions are identical within a location, F.O.Cs for a firm's profit maximization problem have implications for local innovation and local labor demand:

$$L_t^{\ell}(r) = L_t^{\ell,M}(r) = \left(\frac{\xi\nu\mu}{\gamma_1}\right)\left[\bar{A}^{\ell}\left(\frac{w_t^h(r)}{w_t^l(r)}\right)\right]^{\frac{1}{1-\mu\sigma}}\phi_t(r)^{\xi-\frac{\gamma_1\sigma}{1-\mu\sigma}} \tag{1.18}$$

$$\phi_t(r)^{\xi} = \frac{\gamma_1}{\xi\nu\mu}L_t^{h,M}(r) \tag{1.19}$$

The total low-skilled labor is equal to the labor of low-skilled production workers $L_t^{\ell}(r) = L_t^{\ell,M}(r)$. The total high-skilled labor is the total high-skilled labor in manufacturing firms including production workers and researchers, plus teachers in schools.

$$\begin{aligned} L_t^h(r) &= L_t^{h,M}(r) + \nu\phi_t(r)^{\xi} + L_t^{h,S}(r) \\ &= \bar{L}_t^{h,M}(r) + \frac{e_t^*(r)^a}{\kappa} \times \Big(\delta_2 N_{t-1}(r)\Big) \end{aligned} \tag{1.20}$$

The identical decisions of innovation and labor across firms provide a simple relation between $p_t^{\omega}(r,r)$ and $z_t^{\omega}(r)$, which is similar to Eaton and Kortum (2002).

$$p_t^{\omega}(r,r) = \left(\frac{1}{\mu}\right)^{\mu}\left(\frac{\xi\nu}{\gamma_1}\right)^{1-\mu}\left[1+\bar{A}_{\ell}(r)^{\frac{1}{1-\mu\sigma}}\phi_t(r)^{-\frac{\gamma_1\sigma}{1-\mu\sigma}}\left(\frac{w_t^h(r)}{w_t^{\ell}(r)}\right)^{\frac{\mu\sigma}{1-\mu\sigma}}\right]^{1-\frac{1}{\sigma}}\phi_t(r)^{-\gamma_1+\xi(1-\mu)}\frac{w_t^h(r)}{z_t^{\omega}(r)}$$

$p_t^{\omega}(r,r)$ can be rewritten as

$$p_t^{\omega}(r,r) = \frac{mc_t(r)}{z_t^{\omega}(r)}$$

where $mc_t(r)$ denotes the input cost as

$$mc_t(r) \equiv \left(\frac{1}{\mu}\right)^{\frac{1}{\mu}}\left(\frac{\xi\nu}{\gamma_1}\right)^{1-\mu}\left[1+\bar{A}_L(r)^{\frac{1}{1-\mu\sigma}}\phi_t(r)^{-\frac{\gamma_1\sigma}{1-\mu\sigma}}\left(\frac{w_t^h(r)}{w_t^{\ell}(r)}\right)^{\frac{\mu\sigma}{1-\mu\sigma}}\right]^{1-\frac{1}{\sigma}}\phi_t(r)^{-\gamma_1+\xi(1-\mu)}w_t^h(r) \tag{1.21}$$

$mc_t(r)$ is determined by land rents, high-skilled and low-skilled wages. It is given and common for all the firms in place r at period t.

1.3.5 Prices, Export Shares, and Trade Balance

Let $\varsigma(v, r) \geqslant 1$ denote the symmetric iceberg cost of transporting a good from r to v. Then the price of a good ω, produced in r and sold in v, will be

$$p_t^{\omega}(v, r) = p_t^{\omega}(r, r)\varsigma(v, r) = \frac{mc_t(r)\varsigma(v, r)}{z_t^{\omega}(r)} \tag{1.22}$$

It is the standard trade structures based on Eaton and Kortum (2002). The export probability $\pi_t(v, r)$ that a given good produced in location r is sold in v is given by

$$\pi_t(v, r) = \frac{T_t(r)[mc_t(r)\varsigma(v, r)]^{-\theta}}{\int_{\Omega} T_t(u)[mc_t(u)\varsigma(v, u)]^{-\theta} du} \quad \text{all} \quad r, v \in \Omega \tag{1.23}$$

The price index in location s is given by

$$P_t(v) = \Gamma\Big(\frac{-\rho}{(1-\rho)\theta} + 1\Big)^{-\frac{1-\rho}{\rho}} \left\{ \int_{\Omega} T_t(u)[mc_t(u)\varsigma(v, u)]^{-\theta} du \right\}^{-1/\theta} \tag{1.24}$$

Borrowing and lending is not allowed across places, and trade balance is imposed within each location. Education is local service and non-tradable, thus trade balance implies that the total income on goods produced in location r is equal to the total expenditure on goods from r. According to equation (1.17), total income from goods produced in r is given by

$$R_t(r) + w_t^h(r)L_t^{h,M}(r) + w_t^{\ell}(r)L_t^{\ell,M}(r) + w_t^h(r)\nu\phi_t(r)^{\xi} = \frac{1}{\mu}\Big(w_t^h(r)L_t^{h,M}(r) + w_t^{\ell}(r)L_t^{\ell,M}(r)\Big)$$

For any location v, the total expenditure on goods is the sum of workers' income deducted by payment for education and teachers' income. Thus, the total expenditure on goods in a location can be expressed as

$$\begin{aligned}&\Big[\frac{1}{\mu}\Big(w_t^h(v)L_t^{h,M}(v) + w_t^{\ell}(v)L_t^{\ell,M}(v)\Big) - S_t(v)e^*(v)^a\Big(\delta_2 N_{t-1}(v)\Big)\Big] + L_t^{h,S}(r)\Big(R_t^h(v) + w_t^h(v)\Big)\\ &= \frac{1}{\mu}\Big(w_t^h(v)L_t^{h,M}(v) + w_t^{\ell}(v)L_t^{\ell,M}(v)\Big)\end{aligned}$$

where the second inequality holds as students' payments for tuition equal to teachers' income. Hence the trade balance can be written as

$$H(r)\Big(w_t^h(r)L_t^{h,M}(r) + w_t^{\ell}(r)L_t^{\ell,M}(r)\Big) = \int_{\Omega} \pi_t(v, r)H(v)\Big(w_t^h(v)L_t^{h,M}(v) + w_t^{\ell}(v)L_t^{\ell,M}(v)\Big)dv \tag{1.25}$$

1.3.6 Equilibrium

I define a dynamic competitive equilibrium as follows. Given a set of locations Ω and their initial technology, exogenous amenity, high-skilled and low-skilled population density, enrollment rate, and land function (τ_0, $\bar{a}$, N_0^h, N_0^ℓ, e_0, H), as well as bilateral trade and migration cost functions (ς, m), a competitive equilibrium is a set of functions (u_t^h, u_t^ℓ, e_t^*, ϕ_t, $L_t^{h,M}$, $L_t^{\ell,M}$, N_t^h, N_t^ℓ, w_t^h, w_t^ℓ, R_t, P_t, τ_t, T_t) such that

- People choose whether to pursue higher education (1.8).
- People choose where to live (1.12),(1.13) and (1.15).
- Utilities are determined by real income and amenities (1.5) and (1.24).
- Firms optimize and markets clear, (1.18) and (1.19) hold.
- Land markets are in equilibrium (1.17).
- Trade balance implies that (1.21), (1.23) and (1.25) hold.
- Labor markets clear (1.14), (1.15), and (1.20).
- Technology evolves according to (1.16).

1.4 Calibration

Most of the parameters are from the literature, displayed in Table 1.2. County-level data for the US in 2007 is used for calibration of elasticity of demand for higher education, migration costs by skill, local productivity, and exogenous amenity. The calibration results allow me to run simulations with and without policy interventions.

1.4.1 Elasticity of Demand for Higher Education

Taking logs of (1.8), the relationship between the college enrollment rate and the ratio of low-skilled to high-skilled wages is given by

$$log(Enrollment\ Rate_{b,t}) = const + a \times log\Big[\frac{1 - \frac{w^\ell_{b,t-1}}{w^h_{b,t-1}}}{1-\beta(1-\delta)} - \frac{1}{\kappa}\Big] + \epsilon_{b,t}$$

Table 1.2: Parameter Values

Parameter	Target/Source
$\lambda = 0.32$	Relation between amenities and population (Desmet et al. (2018))
$\eta = 0.5$	Elasticity of migration flows with respect to income (Monte et al. (2018))
$\alpha = 0.06$	Static elasticity of productivity to density (Carlino et al. (2007))
$\theta = 6.5$	Trade elasticity (Eaton and Kortum (2002))
$\mu = 0.8$	Labor or nonland share in production (Desmet and Rappaport (2017))
$\gamma_1 = 0.319$	Relation between population distribution and growth (Desmet et al. (2018))
$\gamma_2 = 0.993$	
$\nu = 0.15$	(Desmet and Rossi-Hansberg (2015))
$\varsigma(\cdot,\cdot)^{-\theta} = dist(\cdot,\cdot)^{-1.29}$	(Monte et al. (2018))
$\frac{1}{1-\sigma} = 1.5$	Elasticity of substitution between more and less educated workers (Ciccone and Peri (2005))
$\bar{a}(\cdot)$	Exogenous amenities from USDA

where *Enrollment* $Rate_{b,t}$ is the college enrollment rate in county b, year t. *const* is a constant term. The bracket term represents $e_t^*(b)$. Inside the bracket, $\frac{w_{b,t-1}^{\ell}}{w_{b,t-1}^{h}}$ is the ratio of low-skilled to high-skilled wages at county b in the last year. κ is the student-faculty ratio. β is newborn agents' discounting factor, δ is birth/mortality rate, which is also the fraction of newborn agents over the total population. Based on National Center for Education Statistics (NCES), the student-to-faculty ratio κ is approximately 14. According to IPUMS, the national mortality rate is 0.8%, thus $\delta_1 = 0.008$. Population growth rate is 1% in 2007, thus $\delta_2 = 0.018$

To estimate the elasticity of demand for higher education a and newborn agents' discounting factor β, I use a nested regression method. In the outer loop, I choose the value of $\beta \in [0, 1]$ and calculate the bracket term. For the inner side, I regress the log of college enrollment rate on the log of bracket value to obtain the coefficient a. The regression is weighted by local population. I use the estimated $\hat{a}$ to calculate the college enrollment rate for each county, then I predict the national level of college enrollment rate based on the model. By comparing the predicted national enrollment rate with the observed rate, the sum of squared error is obtained. I pick up the optimal pair (β, a) that returns the minimum sum of squared error.

IPUMS provides the county-level undergrad or graduate school enrollment data for people aged between 18-19. It also provides the college enrollment rate at the national level. I use IPUMS enrollment data to obtain estimates $\beta = 0.39$ and $a = 0.47$ with 95% confidence interval [0.40,0.54].[9] The predicted national enrollment rate is 38%. The national undergrad or graduate schools enrollment rate based on IPUMS data is 42.2%.[10]

1.4.2 Migration Costs

Before estimating migration costs, the graph for the total number of migrants by distance is displayed, to confirm that a large part of migrants move locally. Then I estimate migration costs with county-to-county migration flows, and present nonlinear effects of distance on

[9]The value of β is consistent with the literature that young people tend to be more impatient than elder people and this impatience plays a role in human capital formation, Cadena and Keys (2015).

[10]According to NCES, the national immediate enrollment rate for 4-year college or university is 43.1% in 2007, which is calculated by enrollment rate of high school completers aged between 16-24.

migration costs.

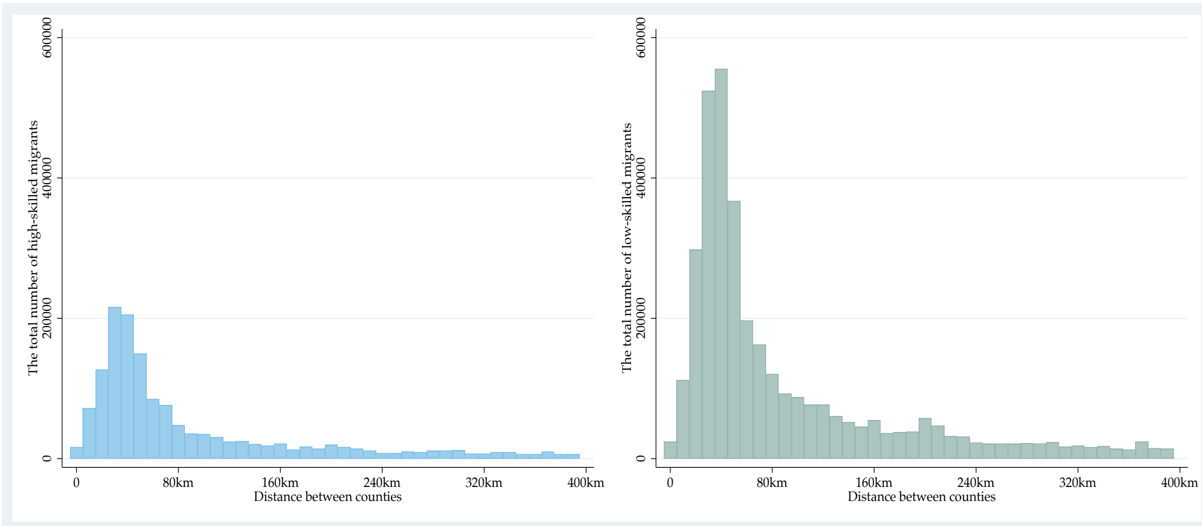
I combine the number of migrants by skill between counties from 2007-2011 ACS, with great-circle distances between counties from NBER.[11] I calculate the total number of migrants for each bin of distances ranging from 0 to 400km with 10km bandwidth, which is presented in Figure 1.8. We can find large high-skilled and low-skilled migration flows when distances are smaller than 90km. The total number of migrants drops sharply as distance increases from 60km to 100km, and it stays at a low value when distance is greater than 160km.

The figure confirms that local migration flow takes up a large proportion. In the literature, migration flows are determined by migration costs and utility. The equation below can illustrate the migration pattern by skill, where $s = h, \ell$ denotes high-skilled and low-skilled people respectively.

$$\frac{n^s(b,r)}{N^s(b)} = \frac{u^s(r)^{1/\eta} m^s(b,r)^{-1/\eta}}{\int_\Omega u^s(v)^{1/\eta} m^s(b,v)^{-1/\eta} dv} \tag{1.26}$$

[11] ACS data only provides information about migrants who are 25 years old and elder.

Figure 1.8: The total number of migrants by distance



The panels plot the total number of low-skilled migrants (left) and high-skilled migrants (right) by distance in 2007. The bandwidth of bins for distance is 10km. The panel focuses on distances ranging from 0 to 400km.

$n^s(b,r)$ denotes the number of migrants between the origin b and the destination r. $N^s(b)$ denotes population in the origin before migration. $u^s(r)$ denotes utility in the destination. $m^s(b,r)$ denotes migration costs. η is the inverse of the elasticity of migration flows with respect to real income. I set $\eta = 0.5$ according to the literature Desmet et al. (2018). Ω represents all the domestic locations, as people consider destinations all over the country when they move.

Based on this equation, migration costs can be recovered with the number of migrants, the population before migration, and utility. Besides the number of migrants $n^s(b,r)$, 2007-2011 ACS also provides the population by skill in the county of residence 1 year ago, which corresponds to the population before migration $N^s(b)$. According to Moretti (2013), utility $u^s(b)$ can be proxied by county-level real wage, which is nominal wage deflated by price index at the county level.

County-specific price index can be calculated with national consumer price index (CPI) and local housing prices. In 2007 CPI, rent of primary residence takes up to 5.93% and owners' equivalent rent of primary residence takes up to 23.83%. I obtain rent for renters-occupied housing units and housing values for owner-occupied housing units by city from IPUMS. County-specific rent index is calculated as county-level rent deflated by national rent \$871. County-specific owners' equivalent rent index is calculated as county-level housing values deflated by national housing values \$186,200. Therefore, county-specific CPI is equal to 70.24% × national CPI + 5.93% × county-specific rent index + 23.83% × county-specific owners' equivalent rent index.

I start with calculating the denominator in equation (1.26) with the share of stayers $\frac{n^s(b,b)}{N^s(b)}$. Staying takes no costs, thus $m^s(b,b) = 1$. The denominator is given by

$$\int_{\Omega} u^s(v)^{1/\eta} m^s(b,v)^{-1/\eta} dv = \frac{N^s(b)}{n^s(b,b)} \times u^s(b)^{1/\eta}$$

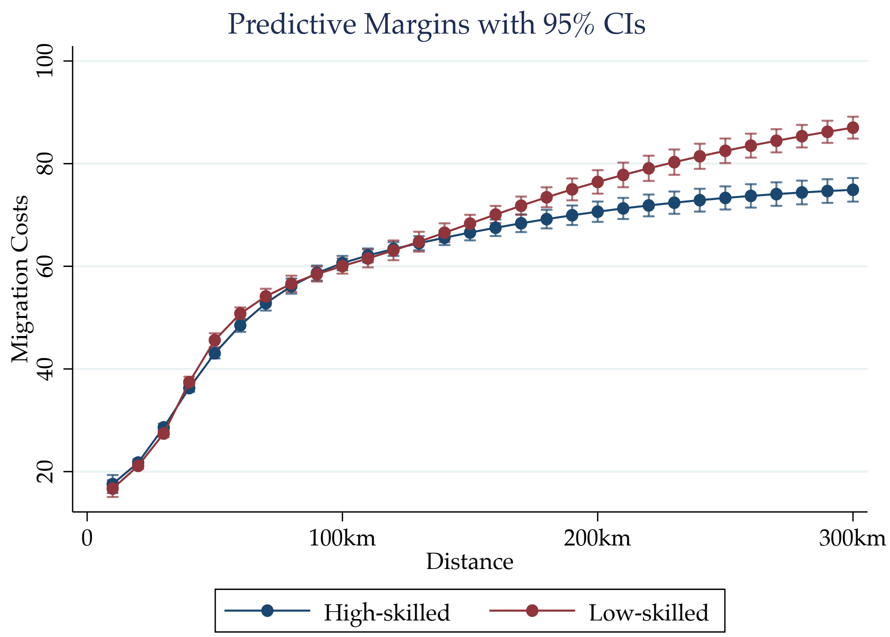
Therefore, migration costs can be obtained as

$$m^s(b,r)^{-1/\eta} = \frac{1}{u^s(r)^{1/\eta}} \times \int_{\Omega} u^s(v)^{1/\eta} m^s(b,v)^{-1/\eta} dv \times \frac{n^s(b,r)}{N^s(b)}$$

Migration costs are determined by distance and network effects. I use the cubic spline regression to estimate the nonlinear effects of distance on migration costs, controlling spatial correlation of ancestry for network effects.[12] The estimated migration costs for high-skilled and low-skilled people are displayed in Figure 1.9 below.

[12]The cubic spline regression table is presented in appendix Table A1.3.

Figure 1.9: Estimated Migration Costs by Distance



The figure plots the estimated migration costs by distance through cubic spline regression. The bandwidth for distance is 10km. 95% confidence intervals are included. The panel focuses on distances ranging from 0 to 300km.

We can find that migration costs are low within short distances. But migration cost increases sharply, as distance goes up from 30km to 100km. Then the impacts of distance on migration costs become smaller. High-skilled migration costs are smaller than low-skilled migration costs. The results support the local brain drain channel and are consistent with the literature.

The nonlinear effects of distance on migration costs can be explained from a psychological perspective. For example, if a young person leaves their parents and resides in a place not far away, they can drive back to visit his family frequently. But if this young person resides in a distant place, they can rarely reunite with his family, probably during public holidays only. Other mechanisms can be explored by researchers in the future.

The geographic feature of migration costs corroborates the local brain channel that talents inside innovation clusters are drawn to innovative counties, at a low migration cost.

It implies that places inside innovation clusters, especially those with fewer high-skilled job opportunities and lower human capital, might not be able to keep talents. Local brain drain can fuel divergence of educational attainment and contribute to increasing spatial inequality, which is illustrated in the next subsection.

1.4.3 Productivity

In this subsection, I start with calibrating the parameter ξ, which determines the number of researchers needed to produce one unit of innovation $\nu\phi_t(r)^\xi$. Based on 1.19, the ratio of demand for researchers to demand for high-skilled workers is $\frac{\gamma_1}{\xi\mu}$. According to World Bank, US has 3777 researchers per million people in 2007. Given that the educational attainment is %27.5, there are 1.37 researchers per hundred people and $\xi = 29$. With ξ calibrated, innovation $\phi_t(r)$ is obtainable as the local high-skilled labor supply is known. The high-skilled productivity shifter $\phi_t(r)^{\gamma_1}$ is also at hand.

Given with the high-skilled productivity shifter, I can measure the time-invariant low-skilled productivity shifter $\bar{A}^\ell(\cdot)$. According to the first order conditions to firms' problem, $\bar{A}^\ell(\cdot)$ can be calibrated as the relative labor productivity $\frac{\phi_t(r)^{\gamma_1\sigma}}{\bar{A}^\ell(r)}$ is equal to the relative wage adjusted by relative labor supply.[13]

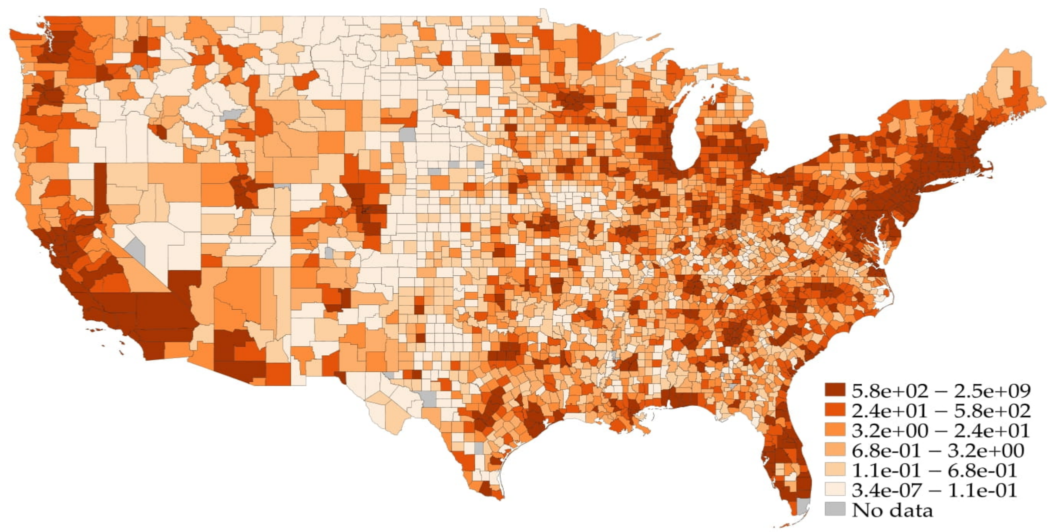
Generally, productivity is measured by wages adjusted by labor supply. According to Desmet et al. (2018), local productivity $\tau_t(r)$ and $\frac{\bar{a}}{u_t(r)}$ can be recovered with high-skilled and low-skilled labor and wages by location. In this model extended with endogenous education decisions, high-skilled and low-skilled labor supply are determined by the high-skilled and low-skilled population, and college enrollment rates of newborn agents. Therefore, the county-level wages by skill, population by skill, and college enrollment rate allow me to recovered productivity $\tau_t(r)$. The details of calibration procedure is shown in appendix 1.6. The map of productivity $\tau_{2007}(r)$ is presented in Fig 1.10.[14] Productivity in East Coast

[13]See equation (1.32) in Appendix 1.6.

[14]Alaska and Hawaii are not included for calibration, which are not part of contiguous United States. In addition, I drop the counties with high-skilled population less than 300 and low-skilled population less than 1200. Some counties without data for wages are also excluded, as population and wages are needed in calibration for productivity. In the end, 2965 counties are kept for calibration. There are 3143 counties in the 50 states and District of Columbia in total.

and West Coast are high, which is consistent with the real world.

Figure 1.10: The Map for Local Productivity $\tau_{2007}(r)$



For model validation, I further the evolution of technology. According to equation (1.16), productivity $\tau_t(r)$ is affected by innovation in the last period $\phi_{t-1}(r)$. After taking logs, the relationship between $\tau_t(r)$ and $\phi_{t-1}(r)$ can be expressed as,

$$ln\Big(\tau_t(r)\Big) = \theta\gamma_1 ln\Big(\phi_{t-1}(r)\Big) + (1-\gamma_2)ln\Bigg[\int \eta\tau_{t-1}(v)dv\Bigg] + \gamma_2 ln\Big(\tau_{t-1}(r)\Big)$$

I use the weighted sum of patents per squared mile in 2006 as a proxy value for $\phi_{t-1}(\cdot)$. Patent data is collected from USPTO, a separate database, which is not used in other calibration procedure. To re-scale the patent data, I regress the log of $\phi_{2007}(t)$ based on the model on the log of weighted sum of patents per squared mile for 2007, and obtain the coefficient 0.196.[15] Then I predict $\hat{\phi}_{2006}(t)$ with patent data for 2006, which is used as the proxy value for innovation in 2006.

With the data for population and wages in 2006, $\tau_{2006}(\cdot)$ can also be calibrated. I regress the log of calibrated $\tau_{2007}(r)$ on the log of proxied innovation $\hat{\phi}_{2006}(r)$ and the log of $\tau_{2006}(r)$. In column (2), the coefficient of $\hat{\phi}_{2006}(r)$ is statistically significant and equal to 2.78, which is close to what the model suggests $\theta\gamma_1 = 2.07$. The coefficient of

[15] See details in Appendix 1.6 Table A1.4.

$\tau_{2006}(\cdot)$ is 0.979, close to $\gamma_2 = 0.993$ in the literature. $R^2 = 0.9674$ indicates a good model fitness. For robustness check, I use the total patent count per squared mile to proxy the innovation value. The results displayed in column (2)-(3) are similar. The results are robust to different methods of measuring innovation with patent data.

Table 1.3: Evolution of Technology

	(1)	(2)	(3)
	$log(\tau_{2007})$	$log(\tau_{2007})$	$log(\tau_{2007})$
$log(\tau_{2006})$	0.986***	0.979***	0.977***
	(295.94)	(250.50)	(239.26)
$log(\hat{\phi}_{2006})$		2.781**	3.045***
		(3.18)	(3.65)
Patent		Weighted Sum	Count
R^2	0.9673	0.9674	0.9674
Observations	2963	2963	2963

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Besides $\tau_{2007}(r)$ and $\tau_{2006}(r)$, I also calibrate $\tau_{1980}(r)$ to run the simulation starting from 1980 for 30 periods. $\tau_{1980}(r)$ is recovered based on county-level population by skill, college enrollment rate, and income per capita. The data for county-level wages by skill is unavailable, thus I obtain the proxy values for high-skilled wages with population by skill, income per capita, the ratio of high-skilled to low-skilled wages as

$$w^h_{1980}(r) = \frac{w^h_{1980}(r)N^h_{1980}(r) + w^\ell_{1980}(r)N^\ell_{1980}(r)}{N^h_{1980}(r) + N^\ell_{1980}(r)} \times \frac{N^h_{1980}(r) + N^\ell_{1980}(r)}{N^h_{1980}(r)} \div \left(1 + \frac{w^\ell_{1980}(r)}{w^h_{1980}(r)} \times \frac{N^\ell_{1980}(r)}{N^h_{1980}(r)}\right)$$

which is derived from equation (1.1). The relative high-skilled wage $\frac{w^h_{1980}(r)}{w^\ell_{1980}(r)}$ is calculated with the relative high-skilled productivity and the relative high-skilled labor input.[16] After $w^h_{1980}(r)$ is obtained, $w^\ell_{1980}(r)$ can also be calculated.

[16]See equation (1.32) in Appendix 1.6.

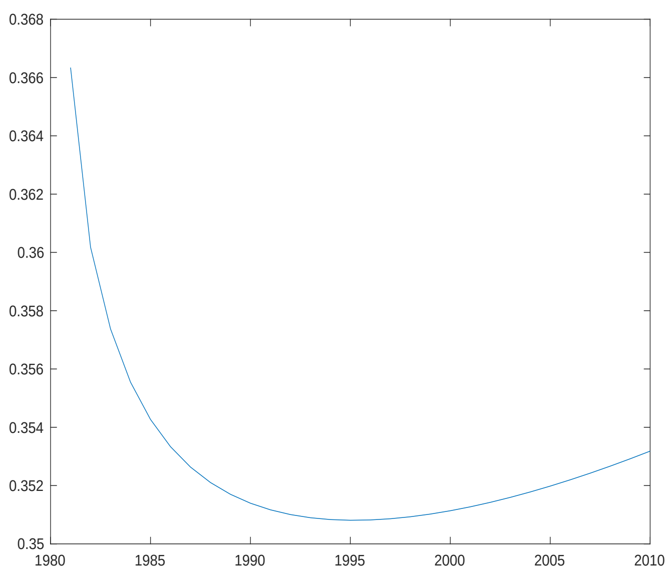
1.5 Quantitative Experiments

1.5.1 U-shape Spatial Inequality

To study the trend of spatial inequality during 1980-2010, I start the simulation from 1980 and run for the sequential 30 periods, with the calibrated productivity $\tau_{1980}(\cdot)$, distribution of population by skill $N^h_{1980}(\cdot)$, $N^\ell_{1980}(\cdot)$, and enrollment rate $e_{1980}(\cdot)$. As section 1.3.6 illustrates, wages by skill w^h, w^ℓ and population density by skill N^h, N^ℓ in each place in equilibrium are determined period by period. The simulated values allow us to calculate income per capita. Spatial inequality is measured in the same way as section 1.2.3 and the literature, that is the standard deviation of log income per capita.

The simulated spatial inequality is presented in Figure 1.11 below. We can see that the model simulation matches the trend of U-shape inequality in section 1.2.3 Figure 1.6b, with a turning point around 1996. This U-shape spatial inequality across the country is driven by the increasing spatial inequality inside innovation clusters. The latter is affected by the local brain drain, which leads to the divergence of educational attainment inside innovation clusters.

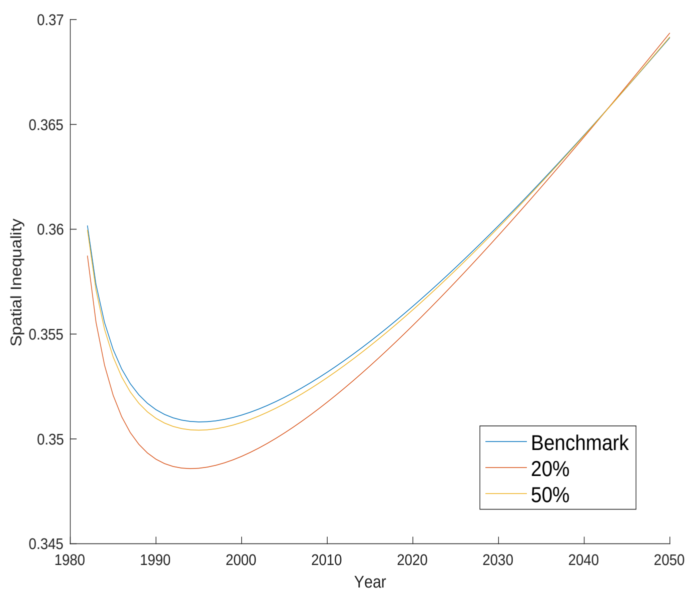
Figure 1.11: Simulated U-shape Spatial Inequality



To illustrate the contribution of local brain drain to spatial inequality, counterfactual experiments through lowering migration costs are conducted. Specifically, migration costs within 50km for high-skilled workers are set to be 20% and 50% of the benchmark values. I re-run the simulations for 1980-2010 and compare the trends of spatial inequality under different migration costs. In a world of frictionless migration, utilities are equal across places. Lowering migration costs might decrease spatial inequality, but it can also strengthen the local brain drain channel, which increases spatial inequality.

As Figure 1.12 displays, lower migration costs decrease spatial inequality in the short term, but leads to an earlier turning point of spatial inequality. When migration costs within 50km for high-skilled workers are 20% of the benchmark values, turning point moves from 1996 to 1993. Higher mobility decreases spatial inequality immediately, but accelerates the divergence inside innovation clusters through the local brain drain and leads to higher spatial inequality in the long term. After 2040, spatial inequality under lower migration costs even outpaces the spatial inequality in the benchmark. This counterfactual experiment corroborates that the local brain drain plays a role in the trend of spatial inequality.

Figure 1.12: Spatial Inequality under Lower Migration Costs within 50km for High-skilled Workers



1.5.2 Place-based Tuition Subsidies

In the last subsection, simulation starting from 1980 sheds light on the U-shape spatial inequality during 1980-2013, and shows that the local brain drain contributes to the trend of spatial inequality. In this subsection, I start simulation from 2007 and implement policy interventions in 2008. Simulations are based on the 2007 IPUMS data for the distribution of population by skill and wages by skill, college enrollment rate, and calibrated productivity τ_{2007}.

To assess the policies, I investigate the change of real GDP. As section 1.3 demonstrates, some externalities occur and local brain drain interacts with these externalities: congestion externalities, innovation externalities, and externalities of technology diffusion. Policies might deal with these externalities and increase real GDP at the national level. I also take a look at spatial inequality, aiming to find policies that increase national real GDP and decrease spatial inequality simultaneously.

I begin with exploring place-based policies implemented by local government with income tax revenue. Recently, a place-based program is widely conducted in the US: Promise Program. In the Promise Program, 81 cities or counties across 36 states provide place-based scholarships, with an expectation of local economic development. Inspired by Promise Program, I focus on the impacts of place-based tuition subsidies on real GDP and spatial inequality. Other place-based policies including Relocation Incentives and Information Provision, and federal policies such as Free Community College in the Biden Plan are discussed in the next subsection.

Tuition subsidies can encourage more students to enroll in college through lowering the cost of education. Consider a 50% tuition subsidy in place b, and denote $tax(b)$ as the corresponding income tax to sponsor the subsidy. According to equation (1.8), the new enrollment rate $e_t^{**}(b)^a$ is obtained as

$$e_t^{**}(b)^a = \Big(\frac{1 - \frac{[1-tax(b)][w_{t-1}^{\ell}(b)+R_{t-1}^{\ell}(b)]}{[1-tax(b)][w_{t-1}^{h}(b)+R_{t-1}^{h}(b)]}}{1-\beta(1-\delta_1)} - 0.5 \times \frac{1}{\kappa}\Big)^a = \Big(\frac{1 - \frac{w_{t-1}^{\ell}(b)}{w_{t-1}^{h}(b)}}{1-\beta(1-\delta_1)} - 0.5 \times \frac{1}{\kappa}\Big)^a \quad (1.27)$$

As mentioned in equation (1.6), total income ratios are equal to wage ratios. Income taxes are the same for high-skilled and low-skilled workers. Therefore, post-tax income ratio equals to the pre-tax wage ratio, which derives the second equation above. With a 50% tuition subsidy, students pay half of the original tuition fees, and $\frac{1}{\kappa}$ is multiplied by 0.5 inside the parentheses.

The county-specific income tax is determined by tuition subsidies and enrollment rates as

$$\begin{aligned}
&0.5 \times \frac{1}{\kappa}\Big(w_t^h(b) + R_t^h(b)\Big) \times e_t^{**}(b)^a\Big(\delta_2 N_{t-1}(b)\Big) \\
&= tax_t(b) \times \Big[\Big(w_t^h(b) + R_t^h(b)\Big)L_t^h(b) + \Big(w_t^h(b) + R_t^h(b)\Big)L_t^\ell(b)\Big]
\end{aligned}$$

The left-hand side of this equation is the local government spending for tuition subsidies offered to all the students $e_t^{**}(b)^a\Big(\delta_2 N_{t-1}(b)\Big)$. The right-hand side of this equation is the local government revenue through taxing income, from all the high-skilled labor $L_t^h(b)$ and all the low-skilled labor $L_t^\ell(b)$. Under the place-based policies, real GDP in place b is adjusted by tax and equal to $(1 - tax_t(b)) \times \Big[(w_t^h(b) + R_t^h(b))L_t^h(b) + (w_t^h(b) + R_t^h(b))L_t^\ell(b)\Big]/P(b)$, where $P(b)$ is the local price index. In the other places without tuition subsidies, no taxes are levied. I aggregate post-tax real GDP across places and obtain the real GDP at the national level.

This model setting allows me to assess various place-based tuition subsidies. First, I consider 50% tuition subsidies in 28 low-educated counties inside the innovation clusters.[17] To catch up in educational attainment, local government in these counties might implement tuition subsidies, with the hope of reducing the gap between places.

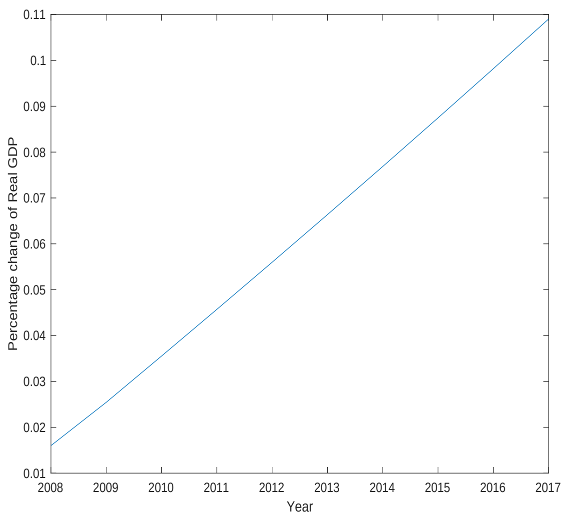
Tuition subsidies can stimulate local development through encouraging more newborn agents to become high-skilled, but taxes can decrease real GDP simultaneously. Moreover, this policy might decrease spatial inequality, through increasing the number of high-skilled workers in low-educated counties. However, these low-educated counties inside the innovation clusters are affected by the local brain drain, and the additional high-skilled workers due to the tuition subsidies might still leave. How this policy affects real GDP and

[17] In section 1.2.2, I identify innovative counties, and define each innovative county together with all the counties within 90km as an innovation cluster. Here I track these innovation clusters in the simulations. Similar to section 1.2.2, I identify a low-educated county if its educational attainment is lower than 10th percentile at the state level.

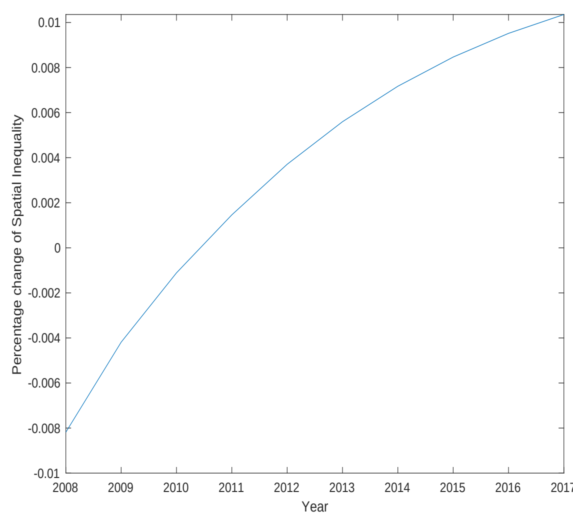
spatial inequality is ambiguous, and a quantitative analysis based on the policy experiments is needed.

Figure 1.13 panel (a) illustrates the policy experiment results. The left panel presents the percentage change of real GDP at the national level. The percentage change is calculated by comparing the simulated real GDP under the place-based tuition subsidies, with the real GDP in the benchmark without any policy intervention. Real GDP gains in the short run and the long run. Specifically, it gains by 0.11% after ten years.

Figure 1.13: 50% tuition subsidies in 28 low-educated counties inside the innovation clusters



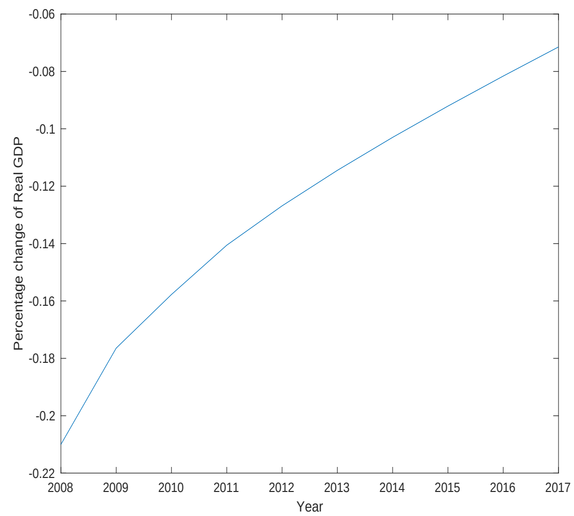
(a) Percentage Change in Real GDP



(b) Percentage Change in Spatial Inequality

The right panel presents the percentage change of spatial inequality across the country, compared to the benchmark. The place-based tuition subsidies do not decrease spatial inequality. Specifically, it increases spatial inequality by 0.01% after 10 years, as panel (b) shows. I further check the percentage change of real GDP in the 28 low-educated counties. Figure 1.14 shows that these places experience Real GDP loss. Real GDP loses more than 0.2% immediately, and gradually recovers during the following 10 years. This figure confirms that the local brain drain plays an important role in the low-educated counties inside innovation clusters. On the one hand, people leave after getting higher education, and these counties do not benefit from more high-skilled workers. On the other hand, stayers in these counties bear the burden of income taxes, thus tuition subsidies lead to real GDP losses in the local economies.

Figure 1.14: Percentage Change of Real GDP in the 28 low-educated counties

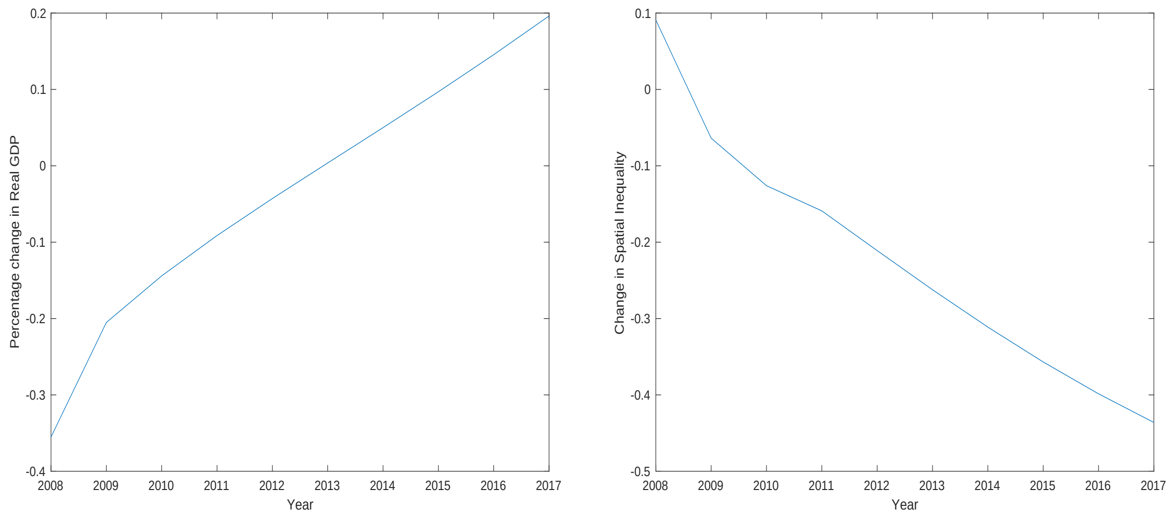


Though real GDP loses in these low-educated counties, real GDP gains at the national level. The additional high-skilled workers encouraged by tuition subsidies move to innovative counties, where they have high labor productivity. Furthermore, they can contribute to innovation and the aggregate productivity growth, due to the externalities of technology diffusion.

The local brain drain plays a major part in the low-educated counties inside innovation clusters. But for low-educated counties outside innovation clusters, local brain drain is less pronounced as wage differentials across places are not huge. The impact of tuition subsidies might be different in these places. Therefore, I consider a second policy: 50% tuition subsidies in 287 low-educated counties outside the innovation clusters. The simulation results are presented in Figure 1.15.

Panel (a) displays the percentage change of real GDP under the second policy. Real GDP loses by 0.35% in the first year and recovers after 5 years. Real GDP gains 0.2% after 10 years. As these low-educated counties are far away from any innovation clusters, the additional high-skilled workers encouraged by tuition subsidies barely move to any innovative county. They stay in places with low productivity, where their contribution to the economy cannot compensate for the tax burden immediately. This explains why real GDP does not gain in the short run, unlike the first policy.

Figure 1.15: 50% tuition subsidies in 287 low-educated counties outside the innovation clusters



(a) Percentage Change in Real GDP (b) Percentage Change in Spatial Inequality

As high-skilled workers stay, they contribute to the local economic development and real GDP gains in the long run. This result is consistent with the intuition that education is a long term investment. Simply comparing the scale of real GDP gains under the first and the second policy,[18] the first policy is more effective in increasing real GDP. However, in terms of decreasing spatial inequality, the second policy works better. Panel (b) shows that the second policy decreases spatial inequality by 0.4% after 10 years. It is in line with panel (a) that high-skilled workers stay in the low-educated counties outside innovation clusters.

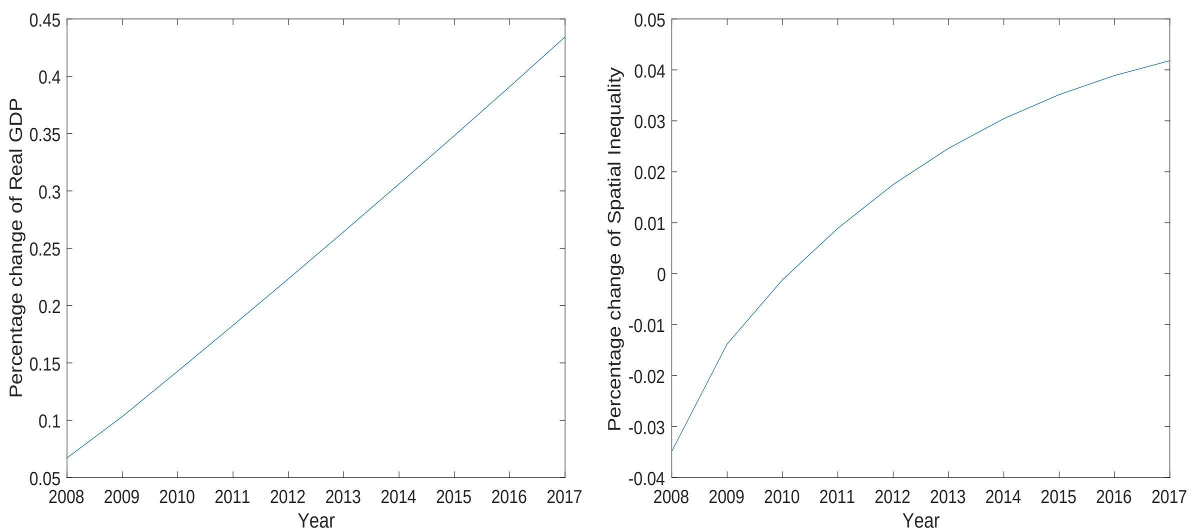
Tuition subsidies can increase real GDP, and I further check the effectiveness of the first policy when tuition fees are high. Tuition fees are determined by the student to faculty ratio. In public universities, the student to faculty ratio is 14, but it can be high in

[18] The U.S. has 3243 counties in total. In the first policy, 28 low-educated counties implement tuition subsidies and real GDP gains 0.11% after 10 years. Here 287 counties ($287 \approx 10 \times 28$) implement tuition subsidies, but real GDP gains just double the size ($0.2\% \approx 2 \times 0.11\%$).

some private universities. For example, in California Institute of Technology, the student to faculty ratio is 3. In Princeton University, the student to faculty ratio is 5. I further assess the first policy with resetting the student-to-faculty ratio $\kappa = 4$.

Figure 1.16 presents the percentage change of real GDP and spatial inequality. Similar to Figure 1.13, real GDP gains in the short run and the long run. Specifically, real GDP gains 0.43% after 10 years, which is more sizable than the benchmark case with $\kappa = 14$. The reason for greater real GDP gains is that when tuition fees are high, a 50% tuition subsidy can be more effective in encouraging students to enroll in college. In this case, the place-based policy leads to more high-skilled workers, who move to innovative counties and contribute to aggregate productivity growth.

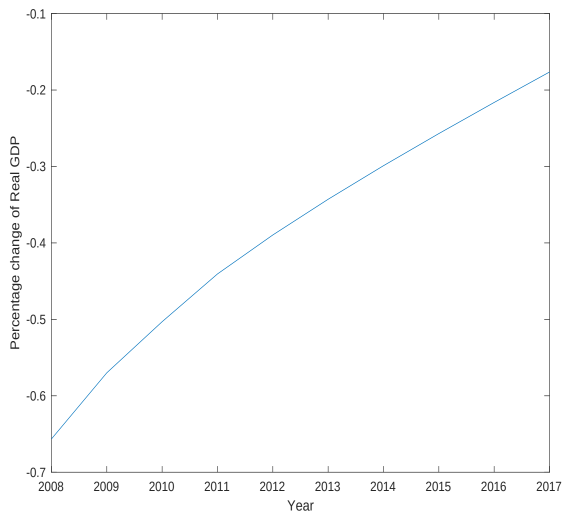
Figure 1.16: When tuition fees are high, 50% tuition subsidies in 28 low-educated counties inside the innovation clusters.



(a) Percentage Change in Real GDP (b) Percentage Change in Spatial Inequality

Real GDP gains, but spatial inequality is not improved as panel (b) displays. Moreover, in the low-educated counties inside innovation clusters, local real GDP still loses. Figure 1.17 shows that real GDP in the 28 low-educated counties loses by 0.65% immediately and gradually recovers. After 10 years, these counties still suffer from 0.2% real GDP losses. The size of real GDP loss is large compared the benchmark case that tuition fees are not high in Figure 1.14. The reason is that given the same subsidy rate, taxes are higher when tuition fees are higher. Heavier tax burden makes stayers lose more because of this policy. The place-based tuition subsidies foster prosperity of national economy, at the expense of some local economies. And federal policy interventions might be needed to deal with the cross-region externalities.

Figure 1.17: Percentage Change of Real GDP in the 28 low-educated counties, when tuition fees are high.



1.5.3 Extensions of Policy Interventions

In this subsection, I discuss some other real-world policies, including Relocation Incentives, Information Provision, and Tuition Subsidies sponsored by the federal government. Relocation Incentives and Information Provision can be assessed directly based on this model. Experiments in federal policies, however, are more challenging than the first two policies. How to connect the real-world policies with the model, and how to adjust the model for policy experiments are also demonstrated.

Relocation Incentives are place-based policies that local government attract talents with a lump sum cash ranging from $1000 to $10,000. For example, Chattanooga, Tennessee offers computer developers $1,250 in relocation expenses to bolster its tech population.[19]

[19]This city also provides some other relocation packages including $10,000 forgivable mortgage, but here I focus on the lump sum cash.

This city are not big innovative county, but can provide career opportunities and have potentials of economic growth. It is worthy to conduct policy experiments in counties with high productivity and medium level of educational attainment, and to see if Relocation Incentives can make this type of places become innovation hubs in the future.

In the model, suppose that place r offers a lump sum cash for relocation, which is proportional to local high-skilled income, $c \times (w_t^h(r) + R_t^h(r))$. According to equation (1.5), for high-skilled workers in any other place b, the utility of residing in r becomes

$$u_t^h(r) = \bar{a}(r) N_t(r)^{-\lambda} \frac{(1+c)(w_t^h(r) + R_t^h(r))}{P_t(r)}$$

According to equation (1.12), improving $u_t^h(r)$ will increase the number of people moving into place r as

$$\frac{n_t^h(b,r)}{(1-\delta_1)N_{t-1}^h(b)H(b)} = \frac{((1+c)u_t^h(r))^{1/\eta} m^h(b,r)^{-1/\eta}}{\int_{\Omega/r} u_t^s(v)^{1/\eta} m^h(b,v)^{-1/\eta} dv + ((1+c)u_t^h(r))^{1/\eta} m^h(b,r)^{-1/\eta}}$$
$$\approx (1+c)^{1/\eta} \times \frac{u_t^h(r)^{1/\eta} m^s(b,r)^{-1/\eta}}{\int_{\Omega} u_t^s(v)^{1/\eta} m^s(b,v)^{-1/\eta} dv}$$

where Ω/r represents all the places except for r. Migration flow from place b to place r is approximately multiplied by $(1+c)^{1/\eta}$.

At the same time, local government collects income taxes $tax_t(r)$ from high-skilled and low-skilled stayers, whose utility becomes

$$u_t^s(r) = \bar{a}(r) N_t(r)^{-\lambda} \frac{(1 - tax(r))(w_t^s(r) + R_t^s(r))}{P_t(r)}$$

where $s = h, \ell$.

For agents who reside in place r in the last period, utilities of staying become lower. Therefore, the number of stayers is decreased

$$\frac{n_t^s(r,r)}{(1-\delta_1)N_{t-1}^s(r)H(r)} = \frac{((1-tax_t(r))u_t^s(r))^{1/\eta} m^s(r,r)^{-1/\eta}}{\int_{\Omega/r} u_t^s(v)^{1/\eta} m^s(r,v)^{-1/\eta} dv + ((1-tax(r))u_t^s(r))^{1/\eta} m^s(r,r)^{-1/\eta}}$$
$$\approx (1 - tax_t(r))^{1/\eta} \times \frac{u_t^s(r)^{1/\eta}}{\int_{\Omega} u_t^s(v)^{1/\eta} m^s(r,v)^{-1/\eta} dv}$$

where $n_t^s(r,r)$ denotes the number of stayers of skill type s. The second approximation is derived as there are no costs of staying, $m^s(r,r) = 1$. The fraction of stayers in place r is approximately multiplied by $(1 - tax_t(r))^{1/\eta}$.

Local government budget constraint holds. Income tax revenue from stayers should equal to spending on relocation incentives. Income tax rate is determined as

$$tax_t(r) \times \Big((w_t^h(r) + R_t^h(r)) \times n_t^h(r,r) + (w_t^\ell(r) + R_t^\ell(r)) \times n_t^\ell(r,r) \Big) = c \times \int_{\Omega/r} (w_t^h(r) + R_t^h(r)) \times n_t^h(b,r) db$$

If the inflows due to the relocation incentives increase more than the outflows due to the income taxes, population in place r gains from this policy. Meanwhile, as people who move in due to this policy are high-skilled, the number of high-skilled people increases if population gains.

In addition to Relocation Incentives, Information Provision can also increase the number of high-skilled people. Through providing newborn agents information that high-skilled wages are attractive in some other places than their hometown, Information Provision can encourage more newborn agents to enroll in college. In the literature, researchers study how schools and districts keep students informed about school policies, assessments, and financial aid opportunities, and how the use of this information helps students improve their educational outcomes. This paper can complement the literature, exploring information about return to education and newborn agents' decisions of investment on education.

The corresponding policy experiment can be conducted by relaxing the information friction assumption in subsection 1.3.2. Newborn agents can have the past information about utilities residing in a broad range of places, $u_{t-1}^h(\cdot)$ and $u_{t-1}^\ell(\cdot)$, instead of their birthplace b only. In the extreme case, newborn agents are informed about the distribution of $u_{t-1}^h(r)$ and $u_{t-1}^\ell(r)$ across the whole country $\forall r \in \Omega$. Under this scenario, newborn agents in place b can search for the place r_1 that maximizes high-skilled utilities with high-skilled migration cost considered,

$$r_1 = \arg\max_{r \in \Omega} u_{t-1}^h(r)/m^h(b,r)$$

Similarly, place r_2 maximizes low-skilled utilities with low-skilled migration cost considered.

According to equation (1.8), college enrollment rate becomes

$$e_t^*(b)^a = \Big(\frac{1 - \frac{u_{t-1}^\ell(r_2)/m^\ell(b,r_2)}{u_{t-1}^h(r_1)/m^h(b,r_1)}}{1 - \beta(1-\delta_1)} - \frac{1}{\kappa} \Big)^a$$

Information Provision can increase college enrollment rates effectively, especially in low-educated counties inside the innovation clusters, where high-skilled wages can be lucrative in the neighborhood. To further assess this policy, I will collect the estimated costs of the provision of information from the literature.

Besides the Place-based Tuition Subsidies, Relocation Incentives, and Information Provision executed by local governments, federal policies can also increase real GDP and it might decrease spatial inequality in a more efficient way. Cross-region collaboration under the federal policies can cope with the cross-region externalities induced by the local brain drain. Furthermore, in the real world, federal government indeed provides tuition assistance to college students. Free Community College in the Biden Plan is a relevant proposal. An agent who finishes a two-year community college can transfer as a senior student to a 4-year university, and obtain a bachelor degree with two more years. Free Community College can deduct half of the tuition fees for attending universities.

Compared to the place-based tuition subsidies, federal government can collect income tax revenue from the whole country Ω, and subsidize 50% tuition in a subset of places Ω_1. In this case, the new enrollment rate $e_t^{**}(b), b \in \Omega_1$ is the same as equation (1.27). The federal government budget constraint is given by

$$\begin{aligned}
&\int_{\Omega_1} 0.5 \times \frac{1}{\kappa}\Big(w_t^h(b) + R_t^h(b)\Big) \times e_t^{**}(b)^a \Big(\delta_2 N_{t-1}(b)\Big) db \\
&= tax_t \times \int_{\Omega} \left(\Big(w_t^h(r) + R_t^h(r)\Big) L_t^h(r) + \Big(w_t^h(r) + R_t^h(r)\Big) L_t^\ell(r) \right) dr
\end{aligned}$$

where tax_t is the federal income tax in period t, which is uniform across places.

Under the federal policy, the national trade balance holds, but regional trade balance (1.25) does not hold. Counties with tuition subsidies receive net cash inflows from the federal government. The challenging part of the policy experiment is that the equation system cannot be reduced to 6 equations according to the appendix 1.6. Following Desmet et al. (2018), regional trade balance is a critical in steps for reducing equations. I will explore some other spatial models in the literature for federal policy experiments.

1.6 Conclusion

The transition from "Great Convergence" to "Great Divergence", captured by the U-shape (initially decreasing then increasing) income inequalities between places, has raised public concerns. This paper explains this national transition with a local scope. It provides empirical evidence that proximity to innovative counties makes low-educated counties experience a slower growth in educational attainment in the US. A local brain drain channel is proposed to explain this pattern. This paper further documents the fact that the local divergence of educational attainment increases the spatial inequality inside the innovation clusters, and contributes to a U-shape spatial inequality across the country during 1980-2010.

Motivated by the stylized facts, this paper develops and calibrates a dynamic spatial model, which reproduces the U-shape spatial inequality. Counterfactual experiments illustrate that the local brain drain channel can accelerate the pace of "Great Divergence". In addition, policy experiments show that 50% tuition subsidies in 28 low-educated counties inside innovation clusters increase 0.1% real GDP after 10 years. The subsidies do not decrease spatial inequality, as people leave after getting higher education. Policy experiments unveils that educational growth is a novel mechanism of economic development in quantitative spatial models. It also emphasizes that geography plays a key role in the effectiveness of place-based policies.

Besides tuition subsidies, some other policies including Relocation Incentives, Information Provision, and federal tuition subsidies are discussed. Compared to the place-based policies, federal policies might increase real GDP and decrease spatial inequality in a more efficient way, as cross-region collaboration can cope with the cross-region externalities induced by the local brain drain. Policy experiments on federal policies will be explored in the future.

Appendix

Proof

First order conditions

The first order conditions for a firm's profit maximization problem are

$$\mu p_t^\omega(r) z_t^\omega(r) \Big[(\phi_t^\omega(r)^{\gamma_1} L_t^{h,\omega}(r)^\mu)^\sigma + \bar{A}^\ell(r) L_t^{l,\omega}(r)^{\mu\sigma} \Big]^{\frac{1}{\sigma}-1} \times \phi_t^\omega(r)^{\gamma_1 \sigma} L^{h,\omega}(r)^{\mu\sigma-1} = w_t^h(r) \tag{1.28}$$

$$\mu p_t^\omega(r) z_t^\omega(r) \Big[(\phi_t^\omega(r)^{\gamma_1} L_t^{h,\omega}(r)^\mu)^\sigma + \bar{A}^\ell(r) L_t^{l,\omega}(r)^{\mu\sigma} \Big]^{\frac{1}{\sigma}-1} \times \bar{A}^\ell(r) L^{\ell,\omega}(r)^{\mu\sigma-1} = w_t^\ell(r) \tag{1.29}$$

$$\gamma_1 p_t^\omega(r) z_t^\omega(r) \Big[(\phi_t^\omega(r)^{\gamma_1} L_t^{h,\omega}(r)^\mu)^\sigma + \bar{A}^\ell(r) L_t^{l,\omega}(r)^{\mu\sigma} \Big]^{\frac{1}{\sigma}-1} \times L^{h,\omega}(r)^{\mu\sigma} \phi_t^\omega(r)^{\gamma_1\sigma-1} = \xi \nu w_t^h(r) \phi_t^\omega(r)^{\xi-1} \tag{1.30}$$

(1.19) can be derived if we divide (1.28) multiplied by $L_t^{h,\omega}(r)$ with (1.30) multiplied by $\phi_t^\omega(r)$,

$$\nu w_t^h(r) \phi_t^\omega(r)^\xi = \frac{\gamma_1}{\xi\mu} w_t^h(r) L_t^{h,\omega}(r) \tag{1.31}$$

If we divide (1.28) by (1.29) directly,

$$\frac{\phi_t(r)^{\gamma_1\sigma}}{\bar{A}^\ell(r)} \left(\frac{L_t^{h,\omega}(r)}{L_t^{\ell,\omega}(r)} \right)^{\mu\sigma-1} = \frac{w_t^h(r)}{w_t^\ell(r)} \tag{1.32}$$

from which (1.18) can be derived as

$$\begin{aligned}
\frac{L_t^{\ell,\omega}(r)}{L_t^{h,\omega}(r)} &= \left(\bar{A}^\ell(r) \frac{w_t^h(r)}{w_t^\ell(r)} \phi(r)^{-\gamma_1\sigma} \right)^{\frac{1}{1-\mu\sigma}} \\
L_t^{\ell,\omega}(r) &= \left(\bar{A}^\ell(r) \frac{w_t^h(r)}{w_t^\ell(r)} \right)^{\frac{1}{1-\mu\sigma}} \phi(r)^{\frac{-\gamma_1\sigma}{1-\mu\sigma}} L_t^{h,\omega}(r) \\
&= \left(\bar{A}^\ell(r) \frac{w_t^h(r)}{w_t^\ell(r)} \right)^{\frac{1}{1-\mu\sigma}} \left(\frac{\gamma_1}{\xi\nu\mu} L_t^{h,\omega}(r) \right)^{\frac{-\gamma_1\sigma}{\xi(1-\mu\sigma)}} L_t^{h,\omega}(r) \\
&= \left(\frac{\xi\nu\mu}{\gamma_1} \right)^{\frac{\gamma_1\sigma}{\xi(1-\mu\sigma)}} \left[\bar{A}^\ell(r) \left(\frac{w_t^h(r)}{w_t^l(r)} \right) \right]^{\frac{1}{1-\mu\sigma}} L_t^{h,\omega}(r)^{1-\frac{\gamma_1\sigma}{\xi(1-\mu\sigma)}}
\end{aligned}$$

Land rent

The second equation in (1.17) can be derived if we combine (1.28) multiplied by $L_t^{h,\omega}(r)$ and (1.29) multiplied by $L_t^{\ell,\omega}(r)$

$$\mu p_t^\omega(r) z_t^\omega(r) \Big[(\phi_t^\omega(r)^{\gamma_1} L_t^{h,\omega}(r)^\mu)^\sigma + \bar{A}^\ell(r) L_t^{l,\omega}(r)^{\mu\sigma} \Big]^{\frac{1}{\sigma}} = w_t^h(r) L_t^{h,\omega}(r) + w_t^\ell(r) L_t^{\ell,\omega}(r) \tag{1.33}$$

In the next step, I want to express $R_t(r)$ as an equation of $\phi_t^\omega(r)$. I start from expressing $w_t^h(r)L_t^{h,\omega}(r)$ by $\nu w_t^h(r)\phi_t^\omega(r)^\xi$. According to (1.31), the relationship between high-skilled labor cost and innovation costs is

$$\nu w_t^h(r)\phi_t^\omega(r)^\xi = \frac{\gamma_1}{\mu\xi} w_t^h(r)L_t^{h,\omega}(r)$$

Then I need to express $w_t^h(r)L_t^{h,\omega}(r)$ by $\phi_t^\omega(r)$. Dividing (1.28) multiplied by $L_t^{h,\omega}(r)$ with (1.29) multiplied by $L_t^{\ell,\omega}(r)$, together with (1.32) we can obtain

$$\frac{(\phi_t^\omega(r)^{\gamma_1} L^{h,\omega}(r)^\mu)^\sigma}{\bar{A}^\ell(r)L_t^{l,\omega}(r)^{\mu\sigma}} = \left(\frac{\phi_t^\omega(r)^{\gamma_1\sigma}}{\bar{A}^\ell(r)}\right)^{\frac{1}{1-\mu\sigma}} \left(\frac{w_t^\ell(r)}{w_t^h(r)}\right)^{\frac{\mu\sigma}{1-\mu\sigma}} \tag{1.34}$$

According to (1.17) and the equations above, $R_t(r)$ can be written as

$$\begin{aligned} R_t(r) &= \frac{1-\mu}{\mu}\Big[w_t^h(r)L_t^{h,\omega}(r) + w_t^\ell(r)L_t^{\ell,\omega}(r)\Big] - \nu w_t^h(r)\phi_t^\omega(r)^\xi \\ &= \frac{1-\mu}{\mu} w_t^h(r)L_t^{h,\omega}(r)\left[1 + \left(\frac{\bar{A}^\ell(r)}{\phi_t^\omega(r)^{\gamma_1\sigma}}\right)^{\frac{1}{1-\mu\sigma}} \left(\frac{w_t^h(r)}{w_t^\ell(r)}\right)^{\frac{\mu\sigma}{1-\mu\sigma}}\right] - \nu w_t^h(r)\phi_t^\omega(r)^\xi \\ &= \left[\frac{(1-\mu)\xi}{\gamma_1}\left(1 + \left(\frac{\bar{A}^\ell(r)}{\phi_t^\omega(r)^{\gamma_1\sigma}}\right)^{\frac{1}{1-\mu\sigma}} \left(\frac{w_t^h(r)}{w_t^\ell(r)}\right)^{\frac{\mu\sigma}{1-\mu\sigma}}\right) - 1\right]\nu w_t^h(r)\phi_t^\omega(r)^\xi = g(\phi_t^\omega(r)) \end{aligned}$$

The uniqueness and existence of $\phi_t^\omega(r)^* = g^{-1}(R_t(r))$ can be guaranteed by fixed-point theorem with $g(0) = 0$ and $g'(\phi_t^\omega(r)) > 0$. $g'(\phi_t^\omega(r))$ is given by

$$\begin{aligned} g'(\phi_t^\omega(r)) = v w_t^h(r)\Bigg(&\frac{\xi((1-\mu)\xi - \gamma_1)}{\gamma_1}\phi_t^\omega(r)^{\xi-1} \\ &+ \frac{(1-\mu)\xi}{\gamma_1}\Big(\frac{\gamma_1\sigma}{1-\mu\sigma} + \xi\Big)\bar{A}^\ell(r)^{\frac{\sigma}{1-\mu\sigma}}\Big(\frac{w_t^h(r)}{w_t^\ell(r)}\Big)^{\frac{\mu\sigma}{1-\mu\sigma}}\phi_t^\omega(r)^{\frac{\gamma_1\sigma}{1-\mu\sigma}+\xi-1}\Bigg) \end{aligned}$$

The latter term inside the parenthesis is positive, thus $(1-\mu)\xi - \gamma_1 > 0$ is a sufficient condition for $g'(\phi_t^\omega(r)) > 0$. This condition for parameters is also required for the increasing property of $g(\phi_t^\omega(r))$ in Desmet et al. (2018).

Input costs

Dividing the bracket in (1.18) by $\Big(\phi_t(r)^{\gamma_1}L_t^h(r)^\mu\Big)^\sigma$ and multiply $\Big(\phi_t(r)^{\gamma_1}L_t^h(r)^\mu\Big)^{1-\sigma}$ outside the bracket, together with (1.34), (1.18) becomes

$$\mu p_t^\omega(r)z_t^\omega(r)\left[1 + \left(\frac{\bar{A}^\ell(r)}{\phi_t^\omega(r)^{\gamma_1\sigma}}\right)^{\frac{1}{1-\mu\sigma}}\left(\frac{w_t^h(r)}{w_t^\ell(r)}\right)^{\frac{\mu\sigma}{1-\mu\sigma}}\right]^{\frac{1}{\sigma}-1} \times \phi_t(r)^{\gamma_1}L_t^h(r)^{\mu-1} = w_t^h(r)$$

Combining the equation above with (1.19), we can find that

$$p_t^\omega(r) = \frac{1}{\mu}\Big(\frac{\xi\nu\mu}{\gamma_1}\Big)^{1-\mu}\left[1 + \left(\frac{\bar{A}^\ell(r)}{\phi_t^\omega(r)^{\gamma_1\sigma}}\right)^{\frac{1}{1-\mu\sigma}}\left(\frac{w_t^h(r)}{w_t^\ell(r)}\right)^{\frac{\mu\sigma}{1-\mu\sigma}}\right]^{1-\frac{1}{\sigma}} \phi_t(r)^{\xi(1-\mu)-\gamma_1}\frac{w_t^h(r)}{z_t^\omega(r)}$$

which corresponds to the expression for $p_t^\omega(r)$ in the main text.

Reduce Equation systems

The equation system can be reduced to 6 equations for $(u_t^h(\cdot),\ u_t^\ell(\cdot),\ \bar{L}_t^{h,M}(\cdot),\ \bar{L}_t^{\ell,M}(\cdot),\ w_t^h(\cdot),\ w_t^\ell(\cdot))$. $\bar{L}_t^{h,M}(r)$ is the total high-skilled labor in the manufacturing sector, with $\bar{L}_t^{h,M}(r) = \Big(1 + \frac{\gamma_1}{\xi\mu}\Big)L_t^{h,M}(r)$. $\bar{L}_t^{\ell,M}(r)$ is the total low-skilled labor in the manufacturing sector, with $\bar{L}_t^{\ell,M}(r) = L_t^{\ell,M}(r)$.

We start from re-writing $u_t^h(r)$. Based on (1.4), the numerator in (1.5) can be expressed as

$$\begin{aligned} w_t^h(r) + R_t^h(r) &= w_t^h(r)\Big(1 + \frac{R_t(r)}{w_t^h(r)\bar{L}_t^{h,M}(r) + w_t^\ell(r)\bar{L}_t^{\ell,M}(r)}\Big) \\ &= w_t^h(r)\frac{1}{\mu}\frac{w_t^h(r)L_t^{h,M}(r) + w_t^\ell(r)L_t^{\ell,M}(r)}{w_t^h(r)\bar{L}_t^{h,M}(r) + w_t^\ell(r)\bar{L}_t^{\ell,M}(r)} \\ &= w_t^h(r)\frac{1}{\mu}\frac{\frac{\mu\xi}{\mu\xi+\gamma_1} + \frac{w_t^\ell(r)\bar{L}_t^{\ell,M}(r)}{w_t^h(r)\bar{L}_t^{h,M}(r)}}{1 + \frac{w_t^\ell(r)\bar{L}_t^{\ell,M}(r)}{w_t^h(r)\bar{L}_t^{h,M}(r)}} \end{aligned} \tag{1.35}$$

where the second equation is derived according to (1.17), and the third equation is derived according to (1.31). And $u_t^h(r)$ can be written as

$$u_t^h(r) = \bar{a}(r)\bar{L}_t^{h,M}(r)^{-\lambda}\Big(1+\frac{(\frac{(e^*)^{2a}}{2} + \frac{(e^*)^a}{\kappa})\delta_2 N_{t-1}}{\bar{L}_t^{h,M}}+\frac{\bar{L}_t^{\ell,M}(r)}{\bar{L}_t^{h,M}(r)}\Big)^{-\lambda}\frac{w_t^h(r)}{P_t(r)}\Big(\frac{1}{\mu}\frac{\frac{\mu\xi}{\mu\xi+\gamma_1} + \frac{w_t^\ell(r)\bar{L}_t^{\ell,M}(r)}{w_t^h(r)\bar{L}_t^{h,M}(r)}}{1 + \frac{w_t^\ell(r)\bar{L}_t^{\ell,M}(r)}{w_t^h(r)\bar{L}_t^{h,M}(r)}}\Big) \tag{1.36}$$

where $(\frac{(e^*)^{2a}}{2} + \frac{(e^*)^a}{\kappa})\delta\bar{L}_{t-1}$ is the time that students spend in schools and also the number of teachers, as (1.9) and (1.10) illustrates. It is a value predetermined by variables in the last period. We make notations to simply the equation above as

$$\mathcal{S}(r) = 1 + \frac{(\frac{(e^*)^{2a}}{2} + \frac{(e^*)^a}{\kappa})\delta_2 N_{t-1}}{\bar{L}_t^{h,M}} + \frac{\bar{L}_t^{\ell,M}(r)}{\bar{L}_t^{h,M}(r)} \quad \text{with} \quad \bar{L}_t^{h,M}(r)\mathcal{S}(r) = N_t(r)$$
$$\mathcal{A}(r) = \frac{\mu\xi}{\mu\xi+\gamma_1} + \frac{w_t^\ell(r)\bar{L}_t^{\ell,M}(r)}{w_t^h(r)\bar{L}_t^{h,M}(r)} \quad \text{with} \quad w_t^h(r)\bar{L}_t^{h,M}(r)\mathcal{A}(r) = w_t^h(r)L_t^{h,M}(r) + w_t^\ell(r)L_t^{\ell,M}(r)$$
$$\mathcal{B}(r) = 1 + \frac{w_t^\ell(r)\bar{L}_t^{\ell,M}(r)}{w_t^h(r)\bar{L}_t^{h,M}(r)} \tag{1.37}$$

where $\mathcal{S}, \mathcal{A}, \mathcal{B}$ only depends on $\bar{L}_t^{h,M}(r)$, $\frac{\bar{L}_t^{\ell,M}(r)}{\bar{L}_t^{h,M}(r)}$, $\frac{w_t^\ell(r)}{w_t^h(r)}$, parameters and some predetermined values.

Substituting (1.24) into (1.36), $u_t^h(r)$ is given by

$$u_t^h(r) = \bar{a}(r)\bar{L}_t^{h,M}(r)^{-\lambda}\mathcal{S}^{-\lambda}\frac{w_t^h(r)}{\Big[\int_\Omega T_t(v)[mc_t(v)\varsigma(r,v)]^{-\theta}dv\Big]^{-\frac{1}{\theta}}\bar{p}}\Big(\frac{1}{\mu}\frac{\mathcal{A}(r)}{\mathcal{B}(r)}\Big) \tag{1.38}$$

where

$$\bar{p} = \Big[\Gamma\Big(\frac{-\rho}{(1-\rho)\theta}+1\Big)\Big]^{-\frac{1-\rho}{\rho}}$$

According to (1.28), it can be derived that

$$mc_t(r) = \frac{1}{\mu}\Big(\frac{\gamma_1}{\xi\nu\mu}\Big)^{-\frac{\gamma_1}{\xi}}\Big(\frac{\xi\mu}{\xi\mu+\gamma_1}\Big)^{\frac{1}{\sigma}-\mu-\frac{\gamma_1}{\xi}}\Bigg[\frac{\xi\mu}{\xi\mu+\gamma_1}+\frac{w_t^\ell(r)\bar{L}_t^{\ell,M}(r)}{w_t^h(r)\bar{L}_t^{h,M}(r)}\Bigg]^{1-\frac{1}{\sigma}}\bar{L}_t^{h,M}(r)^{1-\mu-\frac{\gamma_1}{\xi}}w_t^h(r)$$

$mc_t(r)$ can be expressed as

$$mc_t(r) = \mu^{\frac{1}{\sigma}-\mu-1}\Big(\frac{\gamma_1}{\xi\nu}\Big)^{-\frac{\gamma_1}{\xi}}\Big(\frac{\xi}{\xi\mu+\gamma_1}\Big)^{\frac{1}{\sigma}-\mu-\frac{\gamma_1}{\xi}}\mathcal{A}(r)^{1-\frac{1}{\sigma}}w_t^h(r)\bar{L}_t^{h,M}(r)^{1-\mu-\frac{\gamma_1}{\xi}} \tag{1.39}$$

where the fifth equation is derived based on (1.34).

Then (1.38) can be expressed as

$$\bar{p}\Big[\int_\Omega T_t(v)[\mu mc_t(v)\varsigma(r,v)]^{-\theta}dv\Big]^{-\frac{1}{\theta}} = \frac{\bar{a}(r)}{u_t^H(r)}w_t^h(r)\bar{L}_t^{h,M}(r)^{-\lambda}\mathcal{S}(r)^{-\lambda}\frac{\mathcal{A}(r)}{\mathcal{B}(r)}$$
$$\Big(\frac{\bar{a}(r)}{u_t^h(r)}\Big)^{-\theta}w_t^h(r)^{-\theta}\bar{L}_t^{h,M}(r)^{\lambda\theta}\mathcal{S}(r)^{\lambda\theta}\Big(\frac{\mathcal{A}(r)}{\mathcal{B}(r)}\Big)^{-\theta}$$
$$= \bar{p}^{-\theta}\int_\Omega T_t(v)[\mu mc_t(v)\varsigma(r,v)]^{-\theta}dv$$
$$= \kappa_1\int_\Omega T_t(v)\mathcal{A}(v)^{-(1-\frac{1}{\sigma})\theta}w_t^h(v)^{-\theta}\bar{L}_t^{h,M}(v)^{-(1-\mu-\frac{\gamma_1}{\xi})\theta}\varsigma(r,v)^{-\theta}dv$$

This yields the first set of equations that u_t^h, w_t^h, $\frac{w_t^\ell}{w_t^h}$, $\bar{L}_t^{h,M}$ and $\frac{\bar{L}_t^{\ell,M}}{\bar{L}_t^{h,M}}$ have to solve.

$$\begin{aligned}&\Big(\frac{\bar{a}(r)}{u_t^h(r)}\Big)^{-\theta} w_t^h(r)^{-\theta}\bar{L}_t^{h,M}(r)^{\lambda\theta}\Big(\frac{\mathcal{A}(r)}{\mathcal{B}(r)}\Big)^{-\theta}\mathcal{S}(r)^{\lambda\theta}\\ &=\kappa_1\int_\Omega \tau_t(v)\varsigma(r,v)^{-\theta}w_t^h(v)^{-\theta}\bar{L}_t^{h,M}(v)^{\alpha-(1-\mu-\frac{\gamma_1}{\xi})\theta}\mathcal{A}(v)^{-(1-\frac{1}{\sigma})\theta}\mathcal{S}(v)^{\alpha}dv\end{aligned}\tag{1.40}$$

where

$$\kappa_1=\Big[\frac{\mu\xi+\gamma_1}{\xi}\Big]^{(\frac{1}{\sigma}-\mu-\frac{\gamma_1}{\xi})\theta}\mu^{(\mu-\frac{1}{\sigma})\theta}\Big[\frac{\xi\nu}{\gamma_1}\Big]^{-\frac{\gamma_1\theta}{\xi}}\bar{p}^{-\theta}$$

According to (1.37), trade balance (1.25) can be written as

$$H(r)w_t^h(r)\bar{L}_t^{h,M}(r)\mathcal{A}(r)=\int_\Omega \pi_t(v,r)H(v)w_t^h(v)\bar{L}_t^{h,M}(v)\mathcal{A}(v)dv$$

With the expression (1.24) for $P_t(v)$, $\pi_t(v,r)$ in (1.23) can be written as

$$\pi_t(v,r)=\bar{p}^{-\theta}T_t(r)[mc_t(r)\varsigma(v,r)]^{-\theta}P_t(v)^{\theta}$$

Meanwhile, $P_t(v)$ can be further expressed by $u_t^h(v)$ based on (1.5) and (1.37),

$$\begin{aligned}P_t(v)&=\frac{\bar{a}(v)}{u_t^h(v)}\bar{L}_t(v)^{-\lambda}[w_t^h(v)+R_t^h(v)]\\ &=\frac{\bar{a}(v)}{u_t^h(v)}\Big(\bar{L}_t^{h,M}(v)\mathcal{S}(v)\Big)^{-\lambda}w_t^h(v)\frac{1}{\mu}\frac{\mathcal{A}(v)}{\mathcal{B}(v)}\end{aligned}$$

Therefore, trade balance condition is obtained as

$$\begin{aligned}&H(r)w_t^H(r)\bar{L}_t^{h,M}(r)\mathcal{A}(r)\\ &=\bar{p}^{-\theta}\int_\Omega T_t(r)[\mu mc_t(r)\varsigma(v,r)]^{-\theta}\Big(\frac{\bar{a}(v)}{u_t^h(v)}\Big)^{\theta}H(v)\bar{L}_t^{h,M}(v)^{1-\lambda\theta}w_t^h(v)^{1+\theta}\mathcal{S}^{-\lambda\theta}\Big(\frac{\mathcal{A}(v)^{1+\theta}}{\mathcal{B}(v)^{\theta}}\Big)dv\end{aligned}$$

Moving $T_t(r)[\mu mc_t(r)]^{-\theta}$ to the left-hand side and substituting $T_t(r)=\tau_t(r)\bar{L}_t(r)^{\alpha}$ yields that

$$\begin{aligned}&\tau_t(r)^{-1}H(r)w_t^h(r)^{1+\theta}\bar{L}_t^{h,M}(r)^{1-\alpha+(1-\mu-\frac{\gamma_1}{\xi})\theta}\mathcal{A}(r)^{1+(1-\frac{1}{\sigma})\theta}\mathcal{S}(r)^{-\alpha}\\ &=\kappa_1\int_\Omega \varsigma(v,r)^{-\theta}\Big(\frac{\bar{a}(v)}{u_t^h(v)}\Big)^{\theta}H(v)\bar{L}_t^{h,M}(v)^{1-\lambda\theta}w_t^h(v)^{1+\theta}\mathcal{S}(v)^{-\lambda\theta}\frac{\mathcal{A}(v)^{1+\theta}}{\mathcal{B}(v)^{\theta}}dv\end{aligned}\tag{1.41}$$

This gives the second set of equations that u_t^h, $\bar{L}_t^{h,M}$, w_t^h, $\frac{\bar{L}_t^{\ell,M}}{\bar{L}_t^{h,M}}$ and $\frac{w_t^\ell}{w_t^h}$ have to solve.

Taking the ratio of the left-hand sides of (1.40) and (1.41):

$$f_1(r)=\frac{\tau_t(r)^{-1}H(r)w_t^h(r)^{1+\theta}\bar{L}_t^{h,M}(r)^{1-\alpha+(1-\mu-\frac{\gamma_1}{\xi})\theta}\mathcal{A}(r)^{1+(1-\frac{1}{\sigma})\theta}\mathcal{S}(r)^{-\alpha}}{\Big(\frac{\bar{a}(r)}{u_t^h(r)}\Big)^{-\theta}w_t^h(r)^{-\theta}\bar{L}_t^{h,M}(r)^{\lambda\theta}\mathcal{S}(r)^{\lambda\theta}\Big(\frac{\mathcal{A}(r)}{\mathcal{B}(r)}\Big)^{-\theta}}$$

$f_1(r)$ also equals the ratio of the right-hand sides. Using $\varsigma(r,v) = \varsigma(v,r)$, $f_1(r)$ can be rewritten as

$$f_1(r) = \frac{\int_\Omega f_1(v)^{-\lambda} f_2(v,r)dv}{\int_\Omega f_1(v)^{-(1+\lambda)} f_2(v,r)dv} \tag{1.42}$$

where

$$f_2(v,r) = \frac{\tau_t(v)^{-\lambda}}{\varsigma(v,r)^\theta}\left[\frac{\bar{a}(v)}{u_t^h(v)}\right]^{(1+\lambda)\theta} H(v)^{1+\lambda} w_t^h(v)^{1+\theta+(1+2\theta)\lambda} \bar{L}_t^{h,M}(v)^{1-\lambda\theta-\lambda[\alpha-1+[\lambda+\frac{\gamma_1}{\xi}-(1-\mu)]\theta]}$$
$$\times \mathcal{A}(v)^{1+\theta+\lambda[1+2(1-\frac{1}{\sigma})\theta]} \mathcal{B}^{-(1+\lambda)\theta} \mathcal{S}(v)^{-\lambda(\alpha+\theta+\lambda\theta)}$$

Write (1.42) as

$$f_3(r) = \frac{f_1(r)^{-\lambda}}{\int_\Omega f_1(v)^{-\lambda} f_2(v,r)dv} = \frac{f_1(r)^{-(1+\lambda)}}{\int_\Omega f_1(v)^{-(1+\lambda)} f_2(v,r)dv}$$

Similar to Desmet et al. (2018), I use the notation

$$g_1(r) = f_1(r)^{-\lambda}$$

and

$$g_2(r) = f_1(r)^{-(1+\lambda)}$$

The last equation can be written as

$$g_1(r) = \int_\Omega f_3(r) f_2(v,r) g_1(v) dv \tag{1.43}$$

and

$$g_2(r) = \int_\Omega f_3(r) f_2(v,r) g_2(v) dv \tag{1.44}$$

g_1 and g_2 are both solutions to the integral solution

$$x(r) = \int_\Omega K(v,r)x(v)dv \tag{1.45}$$

Give the nonnegativity, continuity and square-integrability of $K(v,r)$, the solution to (1.45) exists and is unique up to a scalar multiple.

$$g_1(r) = \varpi^h g_2(r)$$

where ϖ^H is a constant. Therefore, $f_1(r)$ satisfies

$$f_1(r)^{-\lambda} = \varpi^h f_1(r)^{-(1+\lambda)}$$

from which

$$f_1(r) = \varpi^h$$

That is

$$\varpi^h = \frac{\tau_t(r)^{-1} H(r) w_t^h(r)^{1+\theta} \bar{L}_t^{h,M}(r)^{1-\alpha+(1-\mu-\frac{\gamma_1}{\xi})\theta} \mathcal{A}(r)^{1+(1-\frac{1}{\sigma})\theta} \mathcal{S}(r)^{-\alpha}}{\left(\frac{\bar{a}(r)}{u_t^h(r)}\right)^{-\theta} w_t^h(r)^{-\theta} \bar{L}_t^{h,M}(r)^{\lambda\theta} \mathcal{S}(r)^{\lambda\theta} \left(\frac{\mathcal{A}(r)}{\mathcal{B}(r)}\right)^{-\theta}}$$

It means that

$$\begin{aligned} w_t^h(r) = \bar{w} \Big[\frac{\bar{a}(r)}{u_t^h(r)}\Big]^{-\frac{\theta}{1+2\theta}} \tau_t(r)^{\frac{1}{1+2\theta}} H(r)^{-\frac{1}{1+2\theta}} \bar{L}_t^{h,M}(r)^{\frac{\alpha-1+[\lambda+\frac{\gamma_1}{\xi}-(1-\mu)]\theta}{1+2\theta}} \\ \times \mathcal{A}(r)^{-1+\frac{\theta}{(1+2\theta)\sigma}} \mathcal{B}(r)^{\frac{\theta}{1+2\theta}} \mathcal{S}(r)^{\frac{\lambda\theta+\alpha}{1+2\theta}} \end{aligned} \tag{1.46}$$

where $\bar{w} = (\varpi)^{\frac{1}{1+2\theta}}$.

Equilibrium Conditions

Trade balance conditions implies that (1.46) holds in equilibrium. Utility is determined by real income and amenity, thus (1.40) and the equation below need to be satisfied,

$$\frac{u_t^h(r)}{u_t^\ell(r)} = \frac{w_t^h(r)}{w_t^\ell(r)} \tag{1.47}$$

On the labor supply side, $u_t^h(r)$, $u_t^\ell(r)$, $\bar{L}_t^{\ell,M}(r)$, and $\bar{L}_t^{h,M}(r)$ need to agents' optimal location choice conditions (1.12), (1.13), and (1.15). According to (1.14) and (1.20), these equations can be written as

$$\begin{aligned} \bar{L}_t^{h,M}(r)H(r) = \left(e_t^*(r)^a - \frac{e_t^*(r)^{2a}}{2} - \frac{e_t^*(r)^a}{\kappa}\right)\Big(\delta_2 N_{t-1}(r)\Big)H(r) \\ + (1-\delta_1)\int_\Omega \frac{u_t^h(r)^{1/\eta} m^h(b,r)^{-1/\eta}}{\int_\Omega u_t^h(v)^{1/\eta} m^h(b,v)^{-1/\eta} dv} N_{t-1}^h(b)H(b)db \end{aligned} \tag{1.48}$$

$$\begin{aligned} \bar{L}_t^{\ell,M}(r)H(r) = \Big(1 - e_t^*(r)^a\Big)\Big(\delta_2 N_{t-1}(r)\Big)H(r) \\ + (1-\delta_1)\int_\Omega \frac{u_t^\ell(r)^{1/\eta} m^\ell(b,r)^{-1/\eta}}{\int_\Omega u_t^\ell(v)^{1/\eta} m^\ell(b,v)^{-1/\eta} dv} N_{t-1}^\ell(b)H(b)db \end{aligned} \tag{1.49}$$

On the labor demand side, $\bar{L}_t^{\ell,M}(r)$, $\bar{L}_t^{h,M}(r)$, $w_t^{\ell}(r)$, and $w_t^h(r)$ need to satisfy (1.32), the first order conditions for firms' profit maximization. With $L_t^{h,M}(r) = \frac{\xi\mu}{\xi\mu+\gamma_1}\bar{L}_t^{h,M}(r)$ and $\nu\phi_t(r)^{\xi} = \frac{\gamma_1}{\xi\mu+\gamma_1}\bar{L}_t^{h,M}(r)$, (1.32) can be expressed as

$$\left(\frac{\gamma_1}{\nu(\xi\mu+\gamma_1)}\right)^{\frac{\gamma_1\sigma}{\xi}}\left(\frac{w_t^{\ell}(r)}{w_t^h(r)}\right)\bar{L}_t^{h,M}(r)^{\frac{\gamma_1\sigma}{\xi}} = \left(\frac{\xi\mu}{\xi\mu+\gamma_1}\right)^{\mu\sigma-1}\bar{A}^{\ell}(r)\left(\frac{\bar{L}_t^{\ell,M}(r)}{\bar{L}_t^{h,M}(r)}\right)^{\mu\sigma-1} \tag{1.50}$$

In a sum, given parameters, exogenous amenity $\bar{a}(\cdot)$, land density $H(\cdot)$, migration costs $m^h(\cdot,\cdot)$ and $m^{\ell}(\cdot,\cdot)$, population density in the last period $\bar{L}_{t-1}(\cdot)$, $\bar{L}_{t-1}^h(\cdot)$ and $\bar{L}_{t-1}^{\ell}(\cdot)$, predetermined school enrollment rate $e_t^*(\cdot)$ and predetermined productivity $\tau_t(\cdot)$, in equilibrium (u_t^h, u_t^{ℓ}, $\bar{L}_t^{h,M}$, $\bar{L}_t^{\ell,M}$, w_t^h, w_t^{ℓ}) at each period need to satisfy these equations (1.40), (1.46), (1.47), (1.48), (1.49), (1.50).

At the end of each period, the total low-skilled population is equal to the total low-skilled labor in the manufacturing sector, $N_t^{\ell}(r) = \bar{L}_t^{\ell,M}(r)$. The total high-skilled population can be obtained as

$$N_t^h(r) = \bar{L}_t^{h,M}(r) + \frac{e_t^*(r)^{2a}}{2}\Big(\delta_2 N_{t-1}(r)\Big) + \frac{e_t^*(r)^a}{\kappa}\Big(\delta_2 N_{t-1}(r)\Big)$$

where the first two terms at the right-hand side represents the total number of high-skilled workers in the manufacturing sector. The last term denotes the number of teachers.

The dynamic equilibrium in this economy is a series of market outcomes that are determined period by period and the equations above are satisfied. Connection between the current period and the next period is established by human capital formation and technology evolution, for which (1.8) and (1.16) holds.

Recover Productivity

Substituting (1.46) to (1.40), it is given that

$$\begin{aligned}&\left[\frac{\bar{a}(r)}{u_t^h(r)}\right]^{-\frac{\theta(1+\theta)}{1+2\theta}}\tau_t(r)^{-\frac{\theta}{1+2\theta}}H(r)^{\frac{\theta}{1+2\theta}}\bar{L}_t^{h,M}(r)^{\lambda\theta-\frac{\theta}{1+2\theta}[\alpha-1+(\lambda+\frac{\gamma_1}{\xi}-(1-\mu))\theta]}\mathcal{A}(r)^{-\frac{\theta^2}{(1+2\theta)\sigma}}\mathcal{B}(r)^{\frac{\theta(1+\theta)}{1+2\theta}}\mathcal{S}(r)^{\lambda\theta}\\&=\kappa_1\int_{\Omega}\left[\frac{\bar{a}(v)}{u_t^h(v)}\right]^{\frac{\theta^2}{1+2\theta}}\tau_t(v)^{\frac{1+\theta}{1+2\theta}}\varsigma(v,r)^{-\theta}H(v)^{\frac{\theta}{1+2\theta}}\bar{L}_t^{h,M}(r)^{1-\lambda\theta+\frac{1+\theta}{1+2\theta}[\alpha-1+(\lambda+\frac{\gamma_1}{\xi}-(1-\mu))\theta]}\\&\times\mathcal{A}(v)^{\frac{\theta(1+\theta)}{(1+2\theta)\sigma}}\mathcal{B}(v)^{-\frac{\theta^2}{1+2\theta}}\mathcal{S}(v)^{\alpha-\frac{\theta}{1+2\theta}(\lambda\theta+\alpha)}dv\end{aligned} \tag{1.51}$$

According to equation (1.46), $\tau_t(r)$ can be expressed as

$$\tau_t(r) = (\bar{w}^h)^{-(1+2\theta)} \left[\frac{\bar{a}(r)}{u_t^h(r)}\right]^{\theta} H(r) w_t^h(r)^{1+2\theta} \bar{L}_t^{h,M}(r)^{1-\alpha-[\frac{\gamma_1}{\xi}+\lambda-(1-\mu)]\theta} \times \mathcal{A}(r)^{(1+2\theta)-\frac{\theta}{\sigma}} \mathcal{B}^{-\theta} \mathcal{S}(r)^{-(\alpha+\lambda\theta)} \tag{1.52}$$

Plugging this equation into the equation (1.40), $\frac{\bar{a}(r)}{u_t^h(r)}$ satisfies

$$\left[\frac{\bar{a}(r)}{u_t^h(r)}\right]^{-\theta} w_t^h(r)^{-\theta} \bar{L}_t^{h,M}(r)^{\lambda\theta} \left(\frac{\mathcal{A}(r)}{\mathcal{B}(r)}\right)^{-\theta} \mathcal{S}(r)^{\lambda\theta} = \kappa_1 (\bar{w}^h)^{-(1+2\theta)} \int_S \left[\frac{\bar{a}(r)}{u_t^h(s)}\right]^{\theta} H(r) \varsigma(r,s)^{-\theta} w_t^h(s)^{1+\theta} \bar{L}_t^{h,M}(s)^{1-\lambda\theta} \frac{\mathcal{A}(v)^{1+\theta}}{\mathcal{B}(v)^{\theta}} \mathcal{S}(v)^{-\lambda\theta} ds \tag{1.53}$$

After deriving the equations above, I connect data from IPUMS to match $\bar{L}_{2007}^{h,M}(\cdot)$ and $\bar{L}_{2007}^{\ell,M}(\cdot)$. The total population $N_{2007}(r) \times H(r)$ is the number of people who are out of age for attending schools, plus the number of newborn agents. Data from IPUMS includes the population of high-skilled and low-skilled people 25 years old and elder in 2007, denoted by $pop_{2007}^{h,E}$ and $pop_{2007}^{\ell,E}$ respectively. IPUMS also has data for population at the age of 20 years old denoted by pop_{2007}^{Y}, corresponding to the population of newborn agents.

The number of newborn agents pursuing higher education is $e_{2007}^*(r)^a \times pop_{2007}^Y(r)$, with $e_{2007}^*(r)^a$ as the observed school enrollment rate. The number of teachers is $\frac{1}{\kappa} \times e_{2007}^*(r)^a \times pop_{2007}^Y(r)$. The total high-skilled labor in the manufacturing sector is the high-skilled labor supply from newborn agents attending schools, plus the high-skilled population elder than 25 years old, deduct the number of teachers

$$\bar{L}_{2007}^{h,M}(r) = \left[\left(e_{2007}^*(r)^a - \frac{e_{2007}^*(r)^{2a}}{2} - \frac{1}{\kappa} \times e_{2007}^*(r)^a\right) \times pop_{2007}^Y(r) + pop_{2007}^{h,E}(r)\right] / H(r) \tag{1.54}$$

Similarly, the total low-skilled labor supply in the manufacturing sector is the low-skilled labor supply from newborn agents not attending schools, plus the low-skilled population elder than 25 years old

$$\bar{L}_{2007}^{\ell,M}(r) = \left[\left(1 - e_{2007}^*(r)^a\right) pop_{2007}^Y(r) + pop_{2007}^{\ell,E}(r)\right] / H(r) \tag{1.55}$$

With $\bar{L}_{2007}^{h,M}$, $\bar{L}_{2007}^{\ell,M}$ according to the model, and w_{2007}^h, w_{2007}^{ℓ} directly from data, I am able to calibrate τ_{2007} and $\frac{\bar{a}(r)}{u_{2007}^h(r)}$. I first estimate $\frac{\bar{a}(r)}{u_{2007}^h(r)}$ according to (1.53) and then substitute the estimated $\frac{\bar{a}(r)}{u^h_{2007}(r)}$ back to (1.52) to obtain $\tau_{2007}(r)$. The convergence method here follows Desmet et al. (2018).

Figures and Tables

Table A1.1: Educational Growth in Low-educated Counties with 75km as the threshold for innovation clusters

	Δedu_i	Δedu_i	Δedu_i
D_1, inside innovation clusters in 1980	-0.0355***	-0.0367***	-0.0372***
	(0.007)	(0.006)	(0.006)
D_2, outside innovation clusters in 1980	-0.0217***	-0.0209***	-0.0221***
	(0.004)	(0.004)	(0.004)
P-value for difference	0.109	0.050	0.058
Threshold for low-educated	p(25)	p(30)	p(35)

Table A1.2: Educational Growth in Low-educated Counties with 175 as the threshold for innovation clusters

	Δedu_i	Δedu_i	Δedu_i
D_1, inside innovation clusters in 1980	-0.0355***	-0.0367***	-0.0373***
	(0.007)	(0.007)	(0.006)
D_2, outside innovation clusters in 1980	-0.0217***	-0.0210***	-0.0222***
	(0.004)	(0.004)	(0.004)
P-value for difference	0.1229	0.0559	0.063
Threshold for low-educated	p(25)	p(30)	p(35)

Table A1.3: Cubic Spline Regression: The Average Effects of Distance on Migration Costs

	(1)	(2)
	High-skilled	Low-skilled
Distance	0.282***	0.322***
	(0.00592)	(0.00563)
Spatial Correlation of Ancestry	-47.31***	-76.80***
	(3.040)	(3.631)
Observations	24681	37086

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

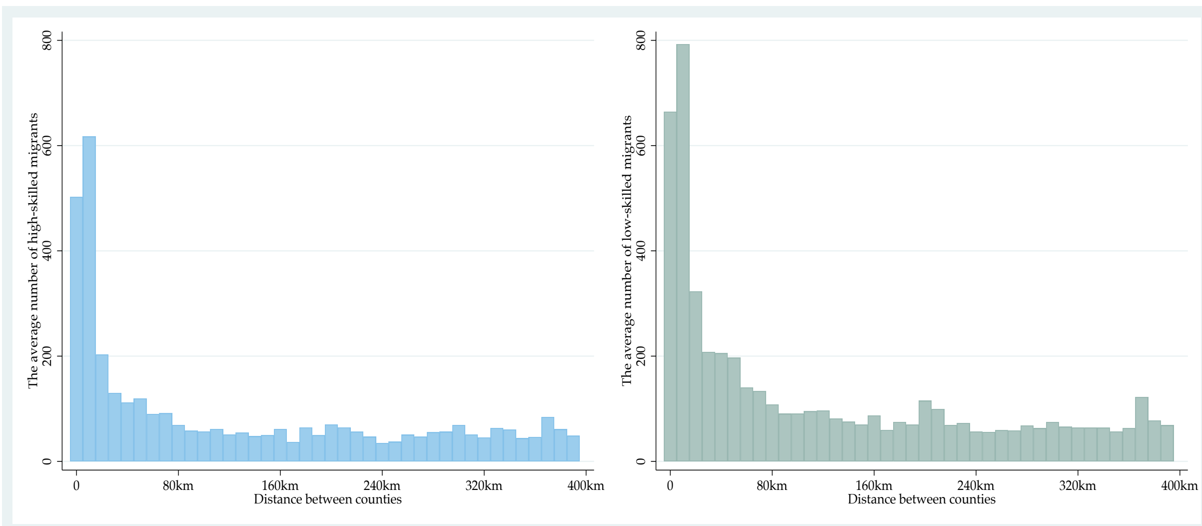
Table A1.4: Scale Patent Data

	(1)	(2)
	$\log(\phi_{2007})$	$\log(\phi_{2007})$
log of Patent per squared mile	0.196***	0.131***
	(36.40)	(41.80)
Processing Method	The weighted Sum	Count
Observations	2963	2963

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A1.1: The average number of migrants by distance



The panels plot the average number of low-skilled migrants (left) and high-skilled migrants (right) by distance in 2007. The bandwidth of bins for distance is 10km. The panel focuses on distances ranging from 0 to 400km.

Chapter 2

Urban Growth, Land Scarcity and Heterogeneous Monetary Policy Effects

2.1 Introduction

How monetary policy affects the real economy is a critical question in macroeconomics. Given the importance of housing market fluctuations in driving the business cycle (Leamer (2007) and Leamer (2015)), a natural step to understand the transmission of monetary policy is to investigate its effects on housing markets. However, not all housing markets are alike. Some cities have inelastic housing supply generated by regulations and/or topographic interruptions (Saiz (2010)), while others have relatively large supply elasticity. Some cities grow, while others decline (Glaeser and Gyourko (2005)). These regional factors may have important implications on monetary policy transmission. Aastveit and Anundsen (2018) has shown that the Saiz elasticity, interacting interestingly with the asymmetric monetary policy, leads to the heterogeneous monetary policy impacts. Yet, how urban growth influences the monetary policy's effect on housing prices remains less studied.

To answer this question, this paper uses the local projections method (Jordà (2005)) to explore this question, which is adjusted to allow for state dependence[1]. We follow Glaeser and Gyourko (2005) by identifying cities with urban growth or urban decline based on

[1]It is similar as Tenreyro and Thwaites (2016) for monetary policy, Auerbach and Gorodnichenko (2012) and Ramey and Zubairy (2018) for fiscal policy.

their MSA level population growth rate. We show that housing prices in growing cities are more sensitive to monetary policy. And housing supply elasticity measured in Saiz (2010) is not the main driver of this result. Instead, we propose a novel channel through which population growth contributes to the house price sensitivity to monetary policy–the land scarcity channel.

Land scarcity is a different mechanism compared to the housing supply elasticity channel. The housing supply elasticity channel is captured by either geographical interruptions or policy regulations as in Saiz (2010), while the land scarcity channel corresponds to the relative abundance of land available. For a city with relative fixed amount of land, a large population inflow depletes the available land quickly, and pushes the city to a state of land scarcity where the land supply curve is much steeper. When a monetary policy shock shifts the housing demand, the response of equilibrium price depends on the elasticity of the housing supply curve. Thus urban growth leads to land scarcity and generates more sensitive responses of housing prices to monetary policy.

We provide a simple model based on Nathanson and Zwick (2018) to show that urban growth contributes to heterogeneous monetary policy effects through the land scarcity channel. If there is excess land available for construction, the housing demand shifts created by monetary policy shocks work through the adjustment in housing supply. However, if population inflow creates housing demand that cannot be fully satisfied by the available land, then the equilibrium condition dictates that only a fraction of inflow residents with high reservation price end up buying, creating upward pressure on the housing price. Therefore, once the available land is exhausted, our model shows that the housing market clears via adjustment of housing prices alone (no quantity adjustment as the land is exhausted), generating a more sensitive price response following a monetary policy shock. The simple model provides a theoretical guide to test the land scarcity channel. When construction cost of houses is stable as Davis and Palumbo (2008) suggests, land scarcity is associated with high land value share. Using the land value share data from Davis et al. (2021), our empirical evidence that supports the land scarcity channel.

Our finding that the effects of monetary policy depend on the regional population trends has implications in the space dimension and the time dimenstion. The common monetary policy shock can generate various housing price responses across regions. This can help to explain regional heterogeneity of many other related variables. For example, the consumption responses to monetary policy can display regional heterogeneity due to the wealth effect or the collateral effect caused by housing price adjustments. Moreover, as monetary policy affects housing prices differently across cities, its aggregate effects depend on the distribution of city growth rates and may change over time. Urban growth and urban decline are determined by many time-varying local factors including immigration, internal migration and urbanization. Thus the dynamics of urban growth across space can be a candidate to explain the time-varying monetary policy effects.

This paper relates to several strands of literature. There is a growing literature investigating the housing market as an aggregate and its impact on the economy (Iacoviello (2005), Jordà et al. (2015), Jarocinski and Smets (2008)). There is also a strand of literature estimating the effects of house prices on households borrowing and consumption (Mian and Sufi (2011), Mian et al. (2013), Cloyne et al. (2019) ,Guren et al. (2018) among others.). However, unlike ours, these papers do not focus on the regional heterogeneity in monetary policy effects on housing prices and give the reason. An emerging strand of literature investigates the heterogeneity across US housing markets (Del Negro and Otrok (2007), Fischer et al. (2019) and Aastveit and Anundsen (2018)). Our paper contributes to this strand by providing a new factor that leads to regional heterogeneity of monetary policy effects: the local population trends. Specifically, we find that the responsiveness of housing prices to monetary policy is more sensitive upon urban growth.

This paper also relates to the state-dependent monetary policy literature. Tenreyro and Thwaites (2016) studies the different monetary policy effects during expansion and recession. Angrist et al. (2018) shows that contractionary monetary policy is more effective. Aastveit and Anundsen (2018) instead finds contractionary monetary policy is less effective for house prices. Furthermore, they also find the housing supply elasticity plays significant different roles for contractionary and expansionary monetary policy shocks. Different from these papers focusing on the asymmetric effects between expansionary and contractionary monetary policy shocks, we focus on the different effects of monetary policy for growing cities and declining cities.

Population is one of the key determinants of local housing prices. Glaeser and Gyourko (2005) emphasizes the potential difference between urban growth and decline and its implication on housing prices. The urban economics literature pays less attention to the role of monetary policy in housing markets, while we focus on the effects of monetary policy on housing prices across growing cities and declining cities. Using a state-space model, Füss and Zietz (2016) show that both higher population growth and lower housing supply elasticity leads to larger house price responses to interest rate changes. Different from their paper, we use the state-dependent local projections method to show that housing prices are more sensitive to monetary policy in growing cities. We also propose a land scarcity channel via a theoretical model and additional empirical evidence.

Furthermore, we present the nonlinear monetary policy effects in population growth empirically and theoretically. There is a kink point in how population growth affects the effectiveness of monetary policy. Aastveit and Anundsen (2018) mention a kink point as well, but our paper is the first one that can rationalize a kink point via a theoretical model for housing markets. The kink point condition in their paper that house prices equal to the construction costs is naturally satisfied at the kink point in our model, though our kink point is determined by local population growth instead. Aastveit and Anundsen (2018) also show that Saiz elasticity plays a role in the heterogeneous responses of housing prices to monetary policy. Apart from Saiz elasticity which is mainly determined by the unchanging geographic elements, urban growth that caused regional heterogeneity in this paper is a time-varying economic factor worthy of policy makers' attention.

The rest of the paper goes as follows. The following section presents the data, the baseline empirical results that housing prices in growing cities are more sensitive to monetary policy. Section 2.3 shows a simple model that connects urban growth with the sensitivity of housing price to monetary policy. Next we show evidence for the land scarcity channel in section 2.4. Section 2.5 shows MSA-by-MSA level evidence. Section 2.6 concludes.

2.2 Urban Growth and Monetary Policy Effects

Some urban areas grow, others decline. The Pittsburgh area had a population of 2.70 million in 1975 and ends up with a population of 2.32 million in 2018, a total decline of around 14%. In contrast, the San Jose area had a population of 1.21 million in 1975 and ends up with a population of 1.99 million in 2018, a total growth of more than 64%. The question asked in this paper is: do the same interest rate reductions from monetary policy shocks have the same effects on house prices in San Jose as compared to Pittsburgh, and through what channel?

As emphasized in Glaeser and Gyourko (2005) and Glaeser et al. (2006), the population of a city is almost perfectly correlated with the size of its housing stock across space and over time[2]. The strong and significant relationship between housing units and population suggests current population growth will be translated into housing demand either at the current period or in future periods. Thus the local population trend will have important implications on land availability, residential investment, and house prices.

In this paper we investigate the responses of local housing prices to monetary policy shocks, especially how these responses differ conditional on local population trends. We apply the local projections method as of Jordà (2005) and allow for state-dependent effects as in Tenreyro and Thwaites (2016). The state of interest here is urban growth, and we define urban growth using MSA level population data. We use the monthly series of Romer-Romer shock updated by Wieland and Yang (2020) as the monetary policy shocks. We find house prices in growing areas are much more sensitive to monetary policy. The result is not purely driven by the supply elasticity, and the land scarcity plays a role.

2.2.1 Housing price and population growth data

We calculate the cumulative population growth from 1975 to 2007 for each MSA. The average of cumulative population growth is 40.3%, the minimum is -30.3% and the maximum is 203.4%. The distribution is skewed toward the positive domain. This is consistent with Glaeser and Gyourko (2005). Population declines much less slowly than it grows. Local population trends differ from each other significantly. In order to empirically

[2] We confirm this using our data as in the Appendix

test whether the effects of monetary policy depend on the local population trends, we need to classify areas as urban growth or urban decline. We classify growing areas as those with the cumulative population growth from 1975 to 2007 larger than the 25th of all MSAs (15.2%[3]), and later we also use different cutoffs as sensitivity checks. Alternatively, we calculate the average cumulative population growth of the past three years and compare it with the current year's population growth. If the current population growth is above the average, we classify these areas as growing, and otherwise declining.

The MSA level house price is the dependent variable of interest. House prices data are seasonally adjusted, monthly, metropolitan statistical area (MSA) data, from 1975 to 2020. The data are from Freddie Mac. Population data are annual, MSA level data from 1975 to 2020. The data are from the US Census Bureau.

2.2.2 Monetary Policy Shocks

Although the central bankers may not respond to the house prices explicitly when they make policy decisions, interest rate movements can still be endogenous to house price movements. This is due to the price movements affecting residential investment, which contributes significantly to the business cycle (Leamer (2007) and Leamer (2015)). Moreover, housing price movements will also generate consumption responses from households through wealth effects or collateral channels (Iacoviello (2005), Cloyne et al. (2019)). To investigate the effects of monetary policy on house prices, we need exogenous monetary policy shocks. We take the Romer-Romer shock series as in Romer and Romer (2004), which is widely used for identifying the effects of monetary policy in the literature. They measure the change in the Fed's target interest rate at each Federal Open Market Committee (FOMC) meeting. They then regress this change in the policy rate target on a set of variables that are believed to be the full set of factors the Fed considers when making policy decisions. These variables included in the set are real-time data and forecasts of past, current, and future inflation, output growth, and unemployment. The residuals from this regression constitute their measure of monetary policy shocks. This monthly series later was updated by Wieland and Yang (2020) to the end of 2007, which marks the endpoint of our sample

[3]US population was 216 million in 1975, the number was 301 million in 2007. That's a 39.4% increase.

period.

2.2.3 Baseline Specification

The local population trend has important implications on local housing prices. Monetary policy will also generate movements in local house prices. We are interested in how the effects of the same monetary policy differ conditional on various local population trends. We first estimate a simple linear model of house prices to monetary policy shocks using panel data. Then we shift to the state-dependent monetary policy to test whether there are significantly different responses of local house prices to monetary policy conditional on whether the area is growing or declining[4].

The linear model is as follows:

$$y_{i,t+h} = \alpha_i + \beta^h \epsilon_t + \phi' x_{i,t} + u_{i,t+h}. \tag{2.1}$$

$y_{i,t+h}$ is the cumulative house price growth rate from t to $t+h$. ϵ_t is the monetary policy shock (the Romer-Romer shock). The parameter α_i is the MSA fixed effect, while β^h captures the cumulative house price response to a monetary policy shock h months after the shock happens. We use Driscoll-Kraay standard errors to allow for possible spatial correlations and serial correlations. The data used in the local projections is panel data instead of time series data. We do not include the month-MSA level fixed effect because the key idea is to explore the effects of monetary policy, and the monetary policy shock is common to all MSAs in a certain month[5]. The control x includes lags of the variables in y and lags of monetary policy shocks. We include 12 lags for monthly data as suggested in Coibion (2012).

We then use state-dependent local projections to explore the heterogeneous responses that are dependent on urban growth or decline. Specifically, we estimate:

$$y_{i,t+h} = \alpha_i + \beta_g^h I_{i,g} \times \epsilon_t + \beta_d^h (1 - I_{i,g}) \times \epsilon_t + \phi' x_{i,t} + u_{i,t+h}, \tag{2.2}$$

[4]"State-dependent" here refers mainly to the estimation method. We are interested in the heterogeneous effects depending on urban growth. But the empirical strategy is essentially the same as to state-dependent monetary policy method.

[5]Goodhart and Hofmann (2008) discuss a similar issue in a different setting.

where $I_{i,g}$ is a dummy variable, and $I_{i,g} = 1$ indicates MSA i is in urban growth, 0 for urban decline[6]. The parameters of interest are β_g^h and β_d^h, where β_g^h captures the cumulative house price response to a monetary policy shock h months after the shock happens in growing areas, and β_d^h is the counterpart in declining areas. We are interested in whether β_g^h and β_d^h are statistically different and the reason for the possible difference.

2.2.4 Results

The general results are presented in Figure 1. The black line in the left graph corresponds to β^h in equation (2.1). Generally, the nominal house prices decrease by less than 3.6% within four years in response to 1% interest rate increase[7]. The overall effects are a combination of effects for growing areas and declining areas. The house prices drop by slightly more than 4% (trough) in growing areas. And the house prices in declining areas drop by around 2.5% (trough), much less than the response in growing areas. The red line corresponds to β_g^h in the right graph, and the blue line corresponds to β_d^h in equation equation (2.2). The shaded areas are the 95% error bands for the blue line.

Table 1 shows the responses at selected horizons and the p-value of the difference between the responses to monetary policy for areas in urban growth and urban decline. 36 months after one percentage shock in the policy rate, house prices decrease by 3.8% for growing areas and 2.2% for declining areas. The difference in responses is 1.6%, which is statistically significant as indicated by the small p-value (0.05).

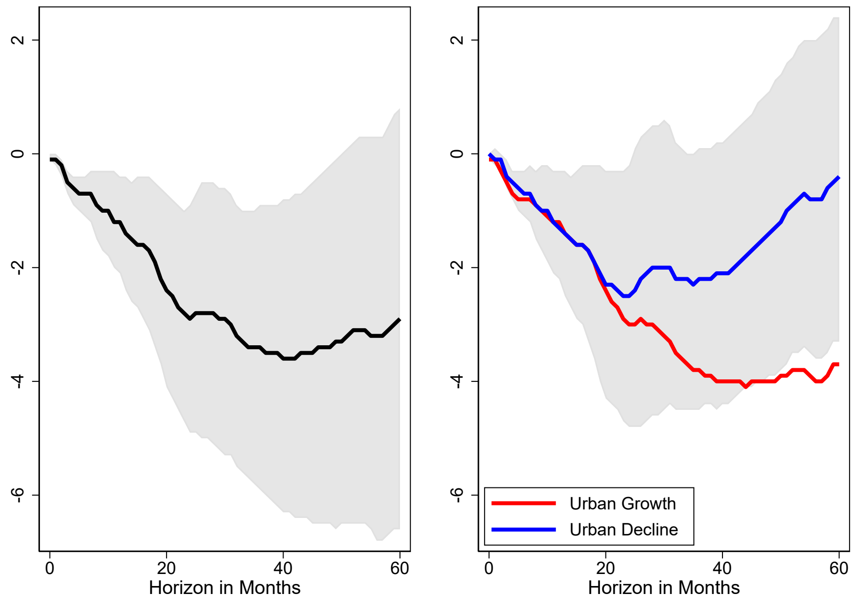
2.2.5 Robustness and Sensitivity Checks

We perform different types of robustness and sensitivity checks. We first vary the cutoffs to define urban growth. We try cutoffs at zero percentage, 50th percentile of the cumulative

[6]The urban growth here is not a time-varying state as common in the literature studying the state-dependent monetary policy effects, but a time-invariant characteristic for MSA i. When we switch to a different approach of identifying urban growth by comparing the current population growth with the average of past three years population growth, the urban growth dummy is then time-varying for a particular MSA. Then we should have $I_{i,g,t}$ as the indicator variable with time index t.

[7]Williams et al. (2015) has a summary of house price response to monetary policy shock after two years for various research using US data. The responses range from -1.7 to -10.4 percent. Our result is -2.9 percent after two years, which lies in the range of previous results.

Figure 1: Cumulative House Price Responses to Monetary Policy Shocks



Note: *Urban growth here is defined as cumulative population growth larger than 25th percentile. The black line in the left graph is the average cumulative house price response to monetary policy shocks. The red line in the right graph is for the house price response to monetary policy shocks in growing urbans, and the blue line is in declining urbans. The shaded area is the 95% error band for the blue line.*

population growth rate (34.6%). We also try a different approach to define urban growth. We classify a year for a specific MSA area urban growth if the current year cumulative population growth is above the average of cumulative population growth rate for the past three years. Our results are robust to these alternative settings, and the results are presented in the appendix.

2.2.6 The Housing Supply Elasticity in Urban Growth and Urban Decline

The housing supply elasticity plays a role in generating regional variation in house prices (Mian and Sufi (2011), Guren et al. (2018)). It also plays a role in explaining heterogeneous regional responses to expansionary monetary policy as in Aastveit and Anundsen (2018).

Table 1: Cumulative House Price Responses to Monetary Policy Shocks: Urban Growth

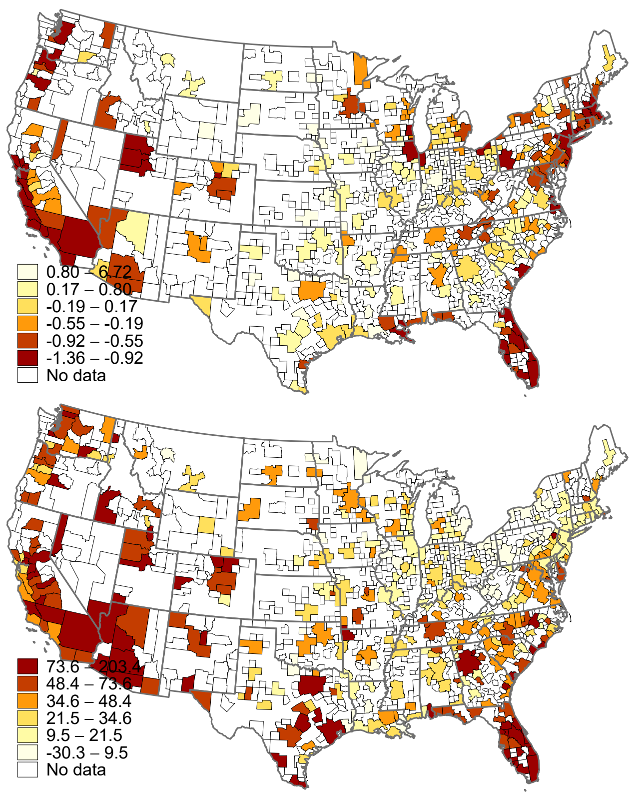
Horizon	Linear	Urban growth	Urban decline	P-value
6	-0.7	-0.8	-0.7	.64
12	-1.2	-1.2	-1.3	.97
18	-1.9	-1.9	-1.9	.96
24	-2.9	-3.0	-2.5	.45
30	-2.9	-3.2	-2.0	.09
36	-3.4	-3.8	-2.2	.05
42	-3.6	-4.0	-2.0	.04
48	-3.4	-4.0	-1.4	.02
54	-3.1	-3.8	-0.7	.01
60	-2.9	-3.7	-0.4	.02

Note: *Urban growth here is defined as cumulative population growth larger than 25th percentile. Column 1 is the selected horizon; Column 2 is the impulse responses for the average effect; Column 3 is the impulse responses for areas in urban growth; Column 4 is the impulse responses for areas in urban decline; Column 5 is the p-value for the difference between urban growth and urban decline.*

An expansionary monetary policy shock will lead to a higher demand for houses, thus drives up house prices. Areas with high supply elasticity will see less house prices increase in equilibrium as more supply (and/or expectation about more supply) presents in these areas. Aastveit and Anundsen (2018) also shows different asymmetric house price responses to contractionary and expansionary monetary policy shocks in elastic and inelastic areas. So, in general, low housing supply elasticity areas should be more sensitive to monetary policy. Are our results mainly driven by the different housing supply elasticity?

Maps of normalized Saiz elasticity (the top map of Figure 2) and cumulative population growth over 1975-2007 (the bottom map of Figure 2) show that the high cumulative population growth positively relates to low housing supply elasticity. The population seems to flow into more inelastic areas. The darker areas in the top map of Figure 2 are areas with inelastic housing supply (the west, northeastern, and Florida). The darker areas in the bottom map of Figure 2 are areas with higher population growth (the west, Florida, Texas). The northwestern has a low population growth rate, as well as some areas in California. This may be because these areas in 1975 have a large population to begin with. As we can see, high population growth areas coincide with low housing supply areas. So the sensitivity of house prices to monetary policy in these areas may be attributed to not only urban growth but also the inelastic housing supply.

Figure 2: Normalized Saiz Elasticity and Cumulative Population Growth Rate



Note: *The top map is for the normalized Saiz elasticity, and the bottom map is for the cumulative population growth rate in percentage from 1975 to 2007.*

In order to show that the different housing supply elasticity does not fully explain the larger sensitivity to monetary policy for growing cities, we perform the following regression:

$$\begin{aligned} y_{i,t+h} &= \alpha_i + \beta_g^h I_{i,g}\epsilon_t + \beta_d^h (1 - I_{i,g})\epsilon_t \\ &\quad + \beta_{g,E}^h I_{i,g}\gamma_i\epsilon_t + \beta_{d,E}^h (1 - I_{i,g})\gamma_i\epsilon_t + u_i. \end{aligned}$$

g indicates urban growth, and d indicates urban decline. $I_{i,g} = 1$ indicates MSA i is a growing city, and $I_{i,g} = 0$ is for a declining city. γ_i is the normalized Saiz housing supply elasticity for MSA i, which is time-invariant. β_g^h capture the cumulative response of house prices to monetary policy with the average housing supply elasticity for the growing area. And $\beta_{g,E}^h$ captures the marginal response of house prices to monetary policy shocks for urban growth if the housing supply elasticity were to increase by one standard deviation. Similar economic meaning applies when we change the g to d. $\beta_{g,E}$ and $\beta_{d,E}$ capture the additional responses to monetary policy if the MSA has a housing supply elasticity one standard deviation higher than the average. β_g and β_d capture the cumulative house price responses to monetary policy shocks if the MSA were to be of an average Saiz elasticity. The results are presented in Table 2.

Table 2: Cumulative House Price Responses to Monetary Policy Shocks: Controlling for the Saiz Elasticity

Horizon	Urban growth	Urban decline	P-value1	Elasticity in Growth	Elasticity in Decline	P-value2
6	-0.7	-0.7	.7	0.1	0.1	.93
12	-1.2	-1.2	.94	0.3	0.1	.29
18	-1.9	-1.9	.93	0.5	0.3	.23
24	-2.9	-2.6	.64	1.0	0.4	.07
30	-3.0	-2.1	.15	1.5	0.4	.03
36	-3.5	-2.3	.14	1.9	0.5	.04
42	-3.7	-2.2	.13	2.2	0.6	.05
48	-3.7	-1.7	.09	2.5	0.6	.05
54	-3.5	-1.1	.07	2.5	0.6	.06
60	-3.3	-0.8	.1	2.5	0.7	.08

Note: *Urban growth here is defined as cumulative population growth larger than 25th percentile of all MSAs from 1975 to 2007. Column 1 is the selected horizon; Column 2 is the cumulative house price responses for areas in urban growth controlling for Saiz elasticity; Column 3 is the cumulative house price responses for areas in urban decline controlling for Saiz elasticity; Column 4 is the p-value for the different house price responses between urban growth and decline; Column 5,6 are the marginal contribution of Saiz elasticity plays in urban growth and urban decline, respectively. Column 7 is the p-value for the different roles the Saiz elasticity plays in urban growth and urban decline.*

Columns two and three in Table 2 are the impulse responses for urban growth and decline at selected horizons with Saiz elasticity controlled. There are less responses for urban decline comparing to urban growth. We also find that the housing supply elasticity plays a more important role in responses to monetary policy for growing areas than for declining areas. Columns five and six in Table 2 shows the marginal monetary policy responses if the area had a one standard deviation housing supply elasticity higher than the mean. For example, 54 months after the shock, one standard deviation increase in housing supply elasticity will decrease the house price response by 2.5% as to 3.5% (a 71.4% reduction in the total response) for growing urbans. In contrast, one standard deviation increase in housing supply elasticity will decrease the house price response by 0.6% as to 1.1% (a 54.5% reduction in the total response) for declining urbans. The p-value is 0.06 for the different roles the housing supply elasticity plays in urban growth versus urban decline at $h = 54$.

More importantly, the difference in housing price responses remains for urban growth and urban decline even if all areas were to have the same average housing supply elasticity. We test the difference between the two responses at different horizons. The p-value for the difference suggests that the response for urban growth is significantly larger for areas with the average housing supply elasticity. For example, after 54 months of monetary policy shock, the house price decreases by 3.5% for urban growth and 1.1% for urban decline. And the p-value is 0.07. We can compare this result with previous result in Table 1 in which the role of housing supply elasticity is not controlled. For average growing areas compared with declining areas, after 54 months of monetary policy shock, the house price decreases by 3.8% for urban growth and 0.7% for urban decline. And the p-value is 0.01. After we switch our focus to the house prices responses only for areas with average elasticity, the difference between urban growth and decline shrinks from 3.1% to 2.40%[8], the p-value for the difference increases from 0.01 to 0.07. This suggests both urban growth and the housing supply elasticity contribute to the overall different responses to monetary policy shocks between growing areas and declining areas.

[8] 3.1=3.8-0.7, 2.4=3.5-1.1 at $h = 54$

2.3 Model

To motivate why trends in population growth can cause heterogeneous responses in the housing market following a monetary policy shock, we consider a simple two-period housing market framework of Nathanson and Zwick (2018) augmented with monetary policy to illustrate the key intuition.[9] Our model consists of unit measure of developers that supply houses via construction on a fixed amount of land endowment, and potential residents arriving in the two periods who receive utility from housing in the period in which they arrive. The model is able to demonstrate that future population inflow creates heterogeneity in the response of housing prices to monetary policy shocks through land scarcity.

2.3.1 Developers

In the housing market, all developers are initially endowed with a fixed amount of available land that sums up to N. In each period, developers can choose to build houses, buy and sell land, and sell constructed houses if available. A unit of housing can be built by combining a unit of land with a construction cost k_t. The construction process is reversible, therefore the existence of an equilibrium with overbuilding is ruled out. The developers have access to a bond market with a gross interest rate of r. Monetary policy in this model is considered as an unexpected adjustment in r in the initial period $t = 0$.

Each developer aims to maximize its expectation of liquidation value in the final period. The holdings of housing, land, and bonds at the beginning of the two periods $t = \{0, 1\}$ are denoted as H_t, L_t, and B_t. Housing and land are traded in a perfectly competitive market with prices p_t^h and p_t^l. Short selling of both housing and land is forbidden. In period 1, after making decisions on land and house transactions, and housing constructions, each developer receives the following liquidation value π:

[9]While examining the expectation disagreement mechanism in Nathanson and Zwick (2018) with monetary policy shocks is an interesting extension to study, for the purpose of brevity we only consider the simple case with expectation agreement.

$$\pi(p_1^h, p_1^l, H_1, L_1, B_1, r) = \max_{H_1^{sell}, L_1^{buy}, H_1^{build}} p_1^h H_1^{sell} - p_1^l L_1^{buy} - k_1 H_1^{build} + rB_1 \tag{2.3}$$

$$s.t. \quad H_1^{sell} \leqslant H_1^{build} + H_1 \tag{2.4}$$

$$H_1^{build} \leqslant L_1 + L_1^{buy}, \tag{2.5}$$

where H_1^{sell}, H_1^{build}, and L_1^{buy} are respectively housing sales, housing construction, and land purchases of the developer in period 1. H_1, and L_1 are the inventory of housing units and land carried to period 1 from period 0. In the initial period $t = 0$, the expectation of the liquidation value π is written as:

$$(H_0^{sell})^* \quad (L_0^{buy})^* \quad (H_0^{build})^* \quad \in \max_{H_0^{sell}, L_0^{buy}, H_0^{build}} \mathbf{E}\pi(p_1^h, p_1^l, H_1, L_1, B_1, r) \tag{2.6}$$

$$s.t. \quad H_0^{sell} \leqslant H_0^{build} \tag{2.7}$$

$$H_0^{build} \leqslant L_0 + L_0^{buy} \tag{2.8}$$

$$H_1 = H_0^{build} - H_0^{sell} \tag{2.9}$$

$$L_1 = L_0 + L_0^{buy} - H_0^{build} \tag{2.10}$$

$$B_1 = p_0^h H_0^{sell} - p_0^l L_0^{buy} - k_0 H_0^{build}, \tag{2.11}$$

where H_0^{sell}, H_0^{build}, and L_0^{buy} are respectively housing sales, housing construction, and land purchases of the developer in period 0. Following Nathanson and Zwick (2018), the building costs k_t are assumed to be $k_0 = 2k$ and $k_1 = k$.

2.3.2 Potential residents

In each period, the number of arriving potential residents is denoted as N_t. Residents are able to receive utility from owning houses only in the period in which they arrive. Each resident can only buy one house. We assume $N_0 < N$, so that there will be unused land $N - N_0$ in the initial period equilibrium. In period 1, $N_1 = N\mu$, where μ is the parameter controlling the relationship between population inflow and land endowment. μ can be rewritten as

$$\mu = \frac{N_1}{N} = \frac{N_0}{N} \times \frac{N_1}{N_0}$$

where $\frac{N_0}{N}$ reflects the land occupied in period 0. Land scarcity is severe as $\frac{N_0}{N}$ is closer to 1. $\frac{N_1}{N_0}$ is the population growth rate in period 1. Existing land scarcity and high future population growth rate simultaneously push up μ. If $\mu > 1$ the amount of land endowed to the developers is insufficient to satisfy the demand of all arriving residents, generating an upward pressure on the p_1^h from housing scarcity. We assume that μ is public knowledge in the initial period, which is consistent with our empirical focus of population inflow trends.

Resident utility comes from consumption c at $t = 1$, and housing services v received upon arrival. The utility is the sum $c + v$, where v is acquired conditional on the purchase of housing in the arrival period. v is drawn from an i.i.d. distribution across the arriving residents, following a complementary cumulative distribution $D(v)$ in the following form:

$$D(v) = \begin{cases} 1 & if \quad v < k \\ (k/v)^{\epsilon} & if \quad v \geqslant k \end{cases}. \tag{2.12}$$

Combining equation (2.12) with the assumptions on building costs indicates that the residents with least willingness in buying housing in period $t = 0$ is marginally indifferent in his decision of housing purchase in the steady state. At period $t = 1$, an arriving potential resident in this period makes a binary decision $H_1^{buy} \in \{0, 1\}$ to maximize the following objective:

$$(H_1^{buy})^* \in \arg\max_{H_1^{buy}} H_1^{buy}(v - p_1^h).$$

The existing residents who arrived in the previous period $t = 0$ decides whether to sell their houses represented by the binary variable $H_1^{sell} \in \{0, 1\}$ to maximize the following objective:

$$(H_1^{sell})^* \in \arg\max_{H_1^{sell}} H_1^{sell} p_1^h + rB_1 + v.$$

Once the decision is made, the maximized utility of the existing residents can be written as $u(p_1^h, B_1, r, v)$

At period 0, the arriving residents in this period makes a binary decision $H_0^{buy} \in \{0,1\}$ to maximize the following objective:

$$(H_0^{buy})^* \in \arg\max_{H_0^{buy}} H_0^{buy} \mathbf{E} u(p_1^h, -p_0^h H_0^{buy}, r, v).$$

2.3.3 Equilibrium

In the initial period $t = 0$, developers and the arriving residents observe μ and r and make decisions accordingly. Equilibrium is achieved when housing prices p_t^h and land prices p_t^l clear their corresponding markets. To study the effect of monetary policy, we consider $r = 1$ as a benchmark, and study how period $t = 0$ housing price p_0^h reacts when r deviates from its benchmark. Given a specified value of μ, we characterize the equilibrium response of p_0^h following a monetary policy shock as follows:[10]

Proposition 1 *In equilibrium, around $r = 1$, the effect of a monetary policy shock on the equilibrium housing price in period $t = 0$ is given by*

$$\frac{\partial p_0^h}{\partial r} = \begin{cases} 0 & if \quad \mu \leqslant 1 \\ -k(\mu^{\frac{1}{\epsilon}} - 1) & if \quad \mu > 1 \end{cases}. \tag{2.13}$$

As seen, the parameters μ that governs population inflow in period $t = 1$ give rise to heterogeneous responses of p_0^h to a monetary policy shock. Furthermore, When $\mu < 1$, the period $t = 1$ equilibrium shows that the city space is not fully converted to housing. Therefore, p_1^l and p_0^l are both 0 and there is no interest rate pass-through to land prices. Given the competitive housing market assumption, the housing prices p_t^h differ with the land prices p_t^l exactly by the amount of the construction cost k_t. Insensitivity of land prices when $\mu < 1$ also leads to insensitivity of housing prices to deviations in r.

When $\mu \geqslant 1$, the population inflow in period 1 and the land vacancy in period 0 determines the sensitivity of the response of p_0^h to a monetary policy shock. $\mu \geqslant 1$ implies that the number of arriving residents in period $t = 1$ exceeds the houses that can be supplied by the amount of land available. Therefore, to ensure the markets clear, both

[10] We detail the analytical derivation of the proposition in Appendix

p_1^h and p_1^l increase so that only a fraction of residents with more willingness in receiving housing utility end up buying. The increase in p_1^l spillovers to p_0^l, which causes the opportunity cost of holding lands in period $t = 0$ to be positive. Consequently, adjustment in the interest rate can now influence p_0^l, thus affecting p_0^h.

In theory, $\mu = \frac{N_0}{N} \times \frac{N_1}{N_0}$ determines $\frac{\partial p_0^h}{\partial r}$, which is consistent with our baseline results in section 2 that population growth rate matters when house markets are hit by a monetary policy shock. Urban growth contributes to the heterogeneity in the responses of housing prices, mediated by land scarcity. We provide empirical evidence to demonstrate that land scarcity is the one channel in section 4.

$\mu \geqslant 1$ is a necessary condition for monetary policy shocks to have effects on housing prices in our model. There is a kink point for the house price sensitivity to monetary policy. It supports our empirical estimation distinguishing urban growth from urban decline rather than investigating marginal effect population growth rate on sensitivity for house price to monetary policy shocks. In section 5, we provide the MSA-by-MSA level analysis to show that housing prices in declining or stagnating cities responds to monetary policy shocks significantly different to those cities in growth.

2.4 The Land Scarcity Channel

The model in the previous section suggests that high population growth rate can lead to land scarcity, thus heterogeneous monetary policy effects. Due to the lack of city-level land scarcity measurement, we use land value shares to proxy land scarcity. Land value share is defined as a fraction of the land value to the total house value. All else equal, the more scarce the land is, the higher the price for land, and thus the land value share. The use of such proxy is consistent with our model's implication. Since we assume in the model that construction costs do not respond to population inflows, the increase in housing price caused by land scarcity is purely attributed to land price increase, which results in an increase in the land value share. We show the housing price responds more sensitively to monetary policy in areas with higher land value share. We also show that population growth is positively correlated with land value share. These empirical results corroborate our conjecture that land scarcity channel contributes to the regional heterogeneity of monetary policy effects on the housing price.

Figure 3 presents the main idea[11]. The house price consists of the land price and the residential structure price[12]. For any city, it starts with abundant land. As population flows in, the city grows and the land is getting scarce. The city moves gradually from point A to point D as it grows. According to Davis et al. (2021), the structure cost is roughly constant within a city, thus the land share of a house value increases when the land price increases[13]. Any demand shock will cause a smaller movement in house prices at point A than at point D. The same size positive demand shock can move the equilibrium point from A to B, and from D to E. Unlike the housing supply elasticity, which is time invariant for each MSA, the land scarcity is time variant, depending on the population inflow. A city can start with abundant land, and ends up with limited available land.

We donot know which cities are around point A or which are around point D. A city starts at A initially, and could move to B after a small size population (relative to all available land) resides in this city. The house price sensitivity to demand shocks are of similar low levels at point A and point B. However, a larger population growth has a larger probability to push cities from point A to point D. Those cities with barely no growth or decline in population will stay at the flat zone in Figure 3. So we have our first conjecture:

Conjecture 1: Monetary policy shocks have a greater impact on house prices for areas in urban growth.

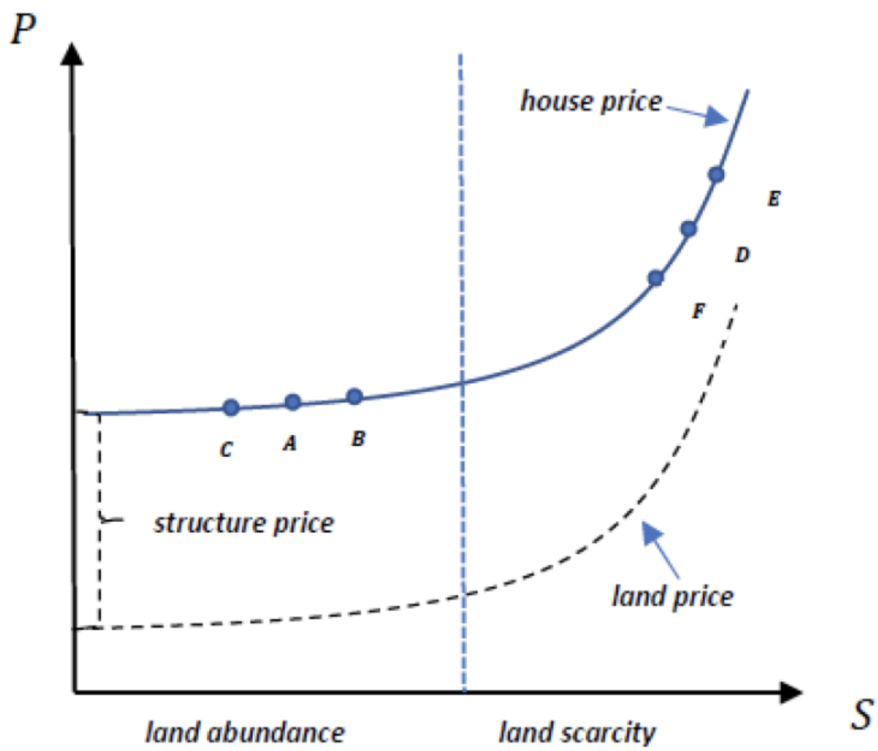
We have discussed in detail the results for above conjecture in previous sections. As

[11]This figure is similar to Davis and Palumbo (2008) and Aastveit and Anundsen (2018)

[12]The house price may be a marked-up price over a sum of the land price and the residential structure price. And inelastic supply areas may be associated with larger markups. We discard these details for simplification.

[13]Glaeser and Gyourko (2018) shows several stylized facts: the profit margin for homebuilders range from 9-11 percentage per annum across cycle, and the real construction costs have not risen much over time. The second fact is also supported by Davis and Heathcote (2007), Davis and Palumbo (2008) and Gyourko and Molloy (2015)

Figure 3: Housing Supply Curve



Note: *This figure shows the housing supply curve for an area with abundant land (to the left of the vertical dash line), and an area with scarce land (to the right of the vertical dash line). The house price consists of a varying land price with stable structure price, and the land value share (defined as the land price over the house price) is much higher when the land is scarce in a certain area.*

showed in Figure 3, the land value consists a larger share of the total house value in areas with scarce land. We have the following conjecture:

Conjecture 2: Monetary policy shocks have a greater impact on house prices for areas with the land price consisting a larger share of the house value.

We test conjecture 2 directly using annual land value share data from Davis et al. (2021).

$$y_{i,t+h} = \alpha_i + \beta^h \epsilon_t + \beta^{h,l} l_i \epsilon_t + \phi' x_{i,t} + u_{i,t+h},$$

of which l_i is the normalized land value share in 2012. Ideally, we would use time series data for land value share for each MSA if we have the data. Davis et al. (2021) provide only annual land value share data from 2012 to 2019 for a large number of MSAs. We use 2012 land value share as a characteristic for MSAs. $\beta^{h,l}$ captures the marginal sensitivity of housing price to monetary policy if the land value share increase by one standard deviation. The land value share goes from 0.10 to 0.68, and the normalized land value share goes from -1.68 to 3.87. The regression results suggesting the land value share has important implication on house price response to monetary policy shocks. For example, 36 months after an exogenous 1 percentage increase in interest rate, the house price will decrease by 3.4 percentage for areas with the average land value share. There will be an additional 3 more percentage decrease if that area is with two standard deviation higher land value share.

The sensitivity of housing price to monetary policy depends on whether the area is at point A or point D. Our conjecture is that past population growth pushes up the land value share. If the past population inflow is N_0 and the total available land is N. Then $\frac{N_0}{N}$ measures the land scarcity. As more population reside in an area, the land is more scarce. The larger $\frac{N_0}{N}$ is, the more scarce the land is. Figure 4 shows the annual population growth and the annual land value share change for the San Jose area and the Pittsburgh area. We can see the co-movement of these two variables. The largest divergence for the two

Table 3: Cumulative House Price Responses to Monetary Policy Shocks: Land Value Share

Horizon	Linear	Interaction	P-value
6	-0.7	-0.1	.05
12	-1.2	-0.3	.03
18	-1.9	-0.5	.03
24	-2.9	-0.9	.01
30	-2.9	-1.3	.01
36	-3.4	-1.5	.01
42	-3.6	-1.7	.01
48	-3.4	-1.8	.01
54	-3.2	-1.7	.02
60	-3.0	-1.6	.04

Note: *Land value share in 2012 is from Davis et al. (2021). Column 1 is the selected horizons in month. Column 2 is the cumulative house price response to monetary policy shocks if the MSA is at the average land value share in 2012. Column 3 is the marginal house price sensitivity to monetary policy shocks if the land value share were to increase by one standard deviation. Column 5 is the p-value indicating how different Column 4 from zero.*

series in the San Jose area happens around the Financial Crisis Period[14].

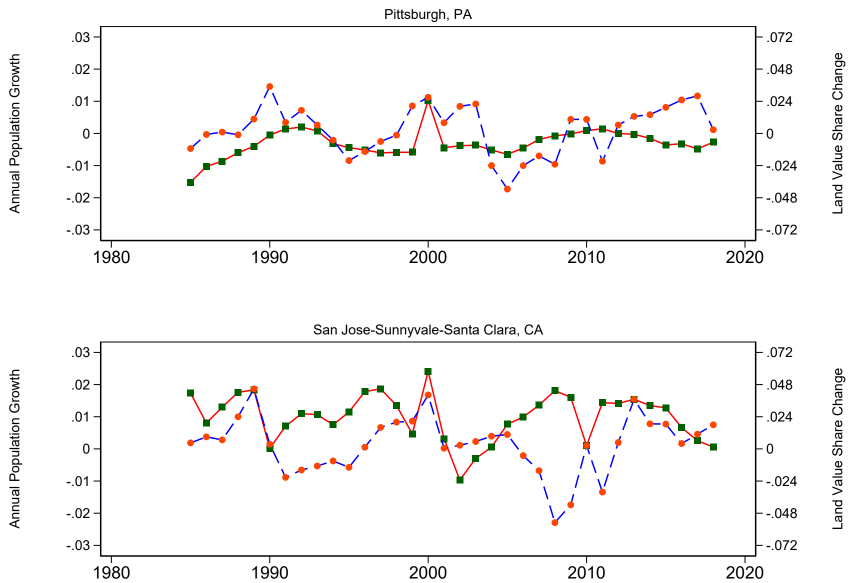
We formally test the relationship between land value share and past population growth directly using:

$$l_{i,12-19} = \alpha + \beta POP_{i,12-19} + u_i,$$
$$l_{i,12-19} = \alpha + \beta_1 POP_{i,12-19} + \beta_2 POP_{i,12-19} l_{i,12} + u_i,$$

of which $l_{i,12-19}$ is the change in land value share in from 2012 to 2019 for MSA i, $POP_{i,12-19}$ is the population growth from 2012 to 2019 for MSA i. The data again is from Davis et al.

[14]This data set is from Davis and Palumbo (2008) online data source which covers more than 40 MSAs, but it has data from 1984 till recent period. The website is https://www.aei.org/historical-land-price-indicators/. Later we use Davis et al. (2021) for it contains, although shorter sample period, a larger number of MSAs.

Figure 4: The San Jose Area and The Pittsburgh Area



Note: *The red real line is for the annual population growth rate, on the left scale. And the blue dash line is for the land value share change in percentage, on the right scale. The land value share data is from Davis and Palumbo (2008) with updated data posted online.*

(2021). Table 4 shows the results. One percentage population growth has contributed to a 0.25 percentage increase in land value share from 2012 to 2019. And from estimation (2) we know that if the existing land value share is higher in 2012, and marginally the following population growth will have a larger effect on the land value share. Back to Figure 3, if the preexisting population is large, the starting point is near D, then it is more likely the same population growth will push up the land value share.

2.5 MSA-by-MSA Analysis

In this section, we present evidence that urban growth has implications on responses of housing prices to monetary policy in a different way. Instead of a panel regression, we perform local projections MSA-by-MSA. We get the deepest (largest in absolute value, the house price response to monetary policy is negative.) house price responses within

Table 4: Land Value Share Change and Population Growth

	(1)	(2)
Cumulative Population Growth 2012-2019	0.25***	-0.02
	(6.29)	(-0.14)
Cumulative Population Growth 2012-2019 × Land Value Share 2012		0.94*
		(1.94)
Constant	-0.03***	-0.03***
	(-9.82)	(-10.00)
Adjusted R^2	0.113	0.125
Observations	354	354

t statistics in parentheses

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

Note: *The dependent variable is the land value share change between 2012 and 2019.*

60 months after estimation as the cumulative response for a certain MSA. And then we regress the deepest cumulative response on MSA characteristics. Now we perform the linear local projection for each MSA m:

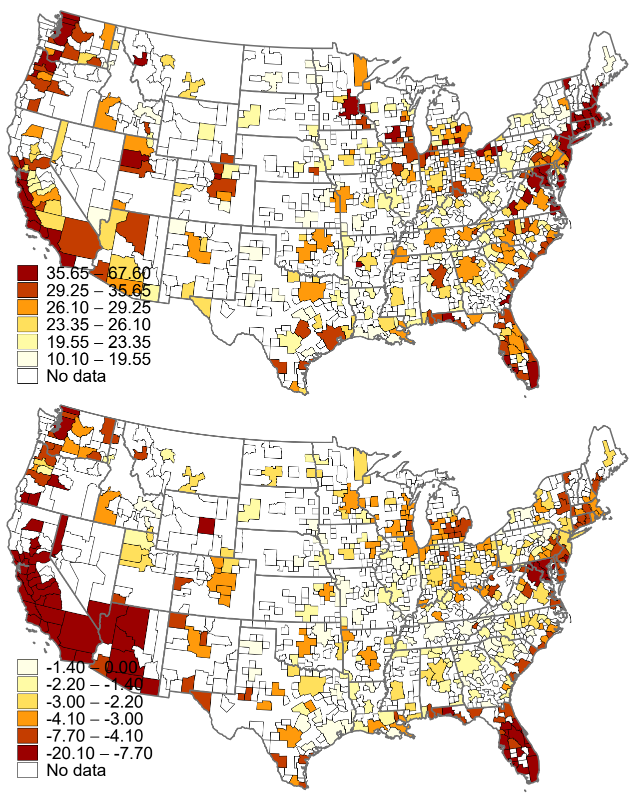
$$y_{m,t+h} = \alpha_m + \beta_m^h \epsilon_t + \phi' x_{m,t} + u_{m,t+h},$$

and we collect all the β_m^h across h for each MSA m. Then we get $\beta_m = min\{\beta_m^h\}$. For a one-unit exogeneous increase in Federal Funds rate, β_m captures the deepest cumulative house price drop within 60 months[15]. We visualize the deepest response in the bottom map of Figure 5.

We then explore how β_m can be affected by MSA level characteristics: population growth, urban growth, land value share, and Saiz elasticity. We perform the following regressions:

[15]There are 15 out of 354 MSAs where the deepest response is at $h = 60$.

Figure 5: Land Value Share in 2012 and House Price Response to Monetary Policy Shocks



Note: *The top map is for land value share in 2012. Land value share is defined as the land value as a fraction of the house value. We use data in 2012 for MSAs from Davis et al. (2021). The bottom one is the deepest response of housing price to monetary policy in percentage from MSA-by-MSA estimation results.*

$$y_i = \alpha + \beta^e \gamma_i + u_i,$$

$$y_i = \alpha + \beta^e \gamma_i + \beta^p POP_i + u_i,$$

$$y_i = \alpha + \beta^e \gamma_i + \beta^p POP_i + \beta^{e,p} POP_i \gamma_i + u_i,$$

$$y_i = \alpha + \beta^p POP_i + u_i,$$

$$y_i = \alpha + \beta^p POP_i + \beta^{p,g} POP_i I_{ug} + u_i,$$

of which y_i is the deepest response of house price to monetary policy shocks within 60 months for MSA i. γ_i is the Saiz elasticity for MSA i. POP_i is the cumulative population growth rate from 1975 to 2007. I_{ug} is an indicator for urban growth. Column (1)-(5) correspond to the above estimations respectively.

Table 5: House Price Responses, Population Growth, Urban Growth, and Saiz Elasticity

	(1)	(2)	(3)	(4)	(5)
Saiz Elasticity	1.17***	0.85***	0.22*		
	(5.28)	(4.27)	(1.88)		
Cumulative Population Growth 1975-2007		-4.73***	-10.09***	-5.35***	4.02*
		(-7.43)	(-9.51)	(-9.73)	(1.89)
Saiz Elasticity × Cumulative Population Growth 1975-2007			2.67***		
			(5.95)		
Urban Growth defined by 0=1 × Cumulative Population Growth 1975-2007					-9.77***
					(-3.85)
Constant	-7.40***	-4.81***	-3.39***	-2.19***	-1.94***
	(-11.50)	(-8.22)	(-8.09)	(-11.52)	(-8.11)
Adjusted R^2	0.168	0.321	0.389	0.247	0.252
Observations	270	270	270	382	382

t statistics in parentheses

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

Note: *The dependent variable is the deepest cumulative house price response to monetary policy shocks in percentage, it is generally negative.*

The dependent variable in all these regressions are the deepest negative cumulative response of housing price to monetary policy. The larger the response, the bigger the absolute value of y_i. The first estimation suggests that if the area has one unit larger housing supply elasticity than another area, the house price response can be smaller by 1.17 percentage than the other area. Column (2) of Table 5 shows the role of local population trends. If the cumulative population growth rate increase by a 100 percentage, the house price response can increase by a 4.73 percentage, controlling for the Saiz elasticity. As we move to the third column, we see that population growth can increase the house price sensitivity to monetary policy, however, if at the same time, the area also has a large housing supply elasticity, the response can be buffered. Column (4) and (5) shows clearly the non-linearity of population growth on house price sensitivity to monetary policy. The interaction term of urban grow with population is significantly negative and large in magnitude, which indicates a sharp difference of population growth to housing price sensitivity to monetary policy. This is one aspect we want to emphasize in addition to population growth's contribution to housing price sensitivity to monetary policy shock as in Füss and Zietz (2016).

We also check the role of land value share and urban growth using MSA-by-MSA estimation result. Specifically, we perform the following regressions:

$$y_i = \alpha + \beta^l l_i + u_i,$$
$$y_i = \alpha + \beta^l l_i + \beta^p POP_i + u_i,$$
$$y_i = \alpha + \beta^l l_i + \beta^{l,g} l_i I_{ug} + u_i,$$

of which y_i is the deepest response of house price to monetary policy shocks within 60 months for MSA i. l_i is the land value share in 2012 for the same MSA. POP_i and I_{ug} are the same as previously defined. The results are in Table 6. The first column shows the house price will decrease by an additional 1.57 if the MSA were to have a 10 percentage higher land value share[16]. We also see clearly the key difference between urban growth and urban decline in the last column.

2.6 Conclusion

This paper finds that house prices in growing areas are more sensitive to monetary policy, which can not be fully explained by the different housing supply elasticities across areas.

[16]The land value share goes from 0.10 to 0.68, which is 10% to 68%.

Table 6: House Price Responses, Land Value Share, and Urban Growth

	(1)	(2)	(3)
Land Value Share as of a House 2012	-15.70***	-13.46***	-9.92***
	(-8.01)	(-7.26)	(-5.56)
Cumulative Population Growth 1975-2007		-5.11***	
		(-8.36)	
Urban Growth defined by 25 percentile=1 × Land Value Share as of a House 2012			-7.34***
			(-7.49)
Constant	-0.06	1.46***	-0.07
	(-0.11)	(3.05)	(-0.14)
Adjusted R^2	0.137	0.344	0.186
Observations	354	354	354

t statistics in parentheses

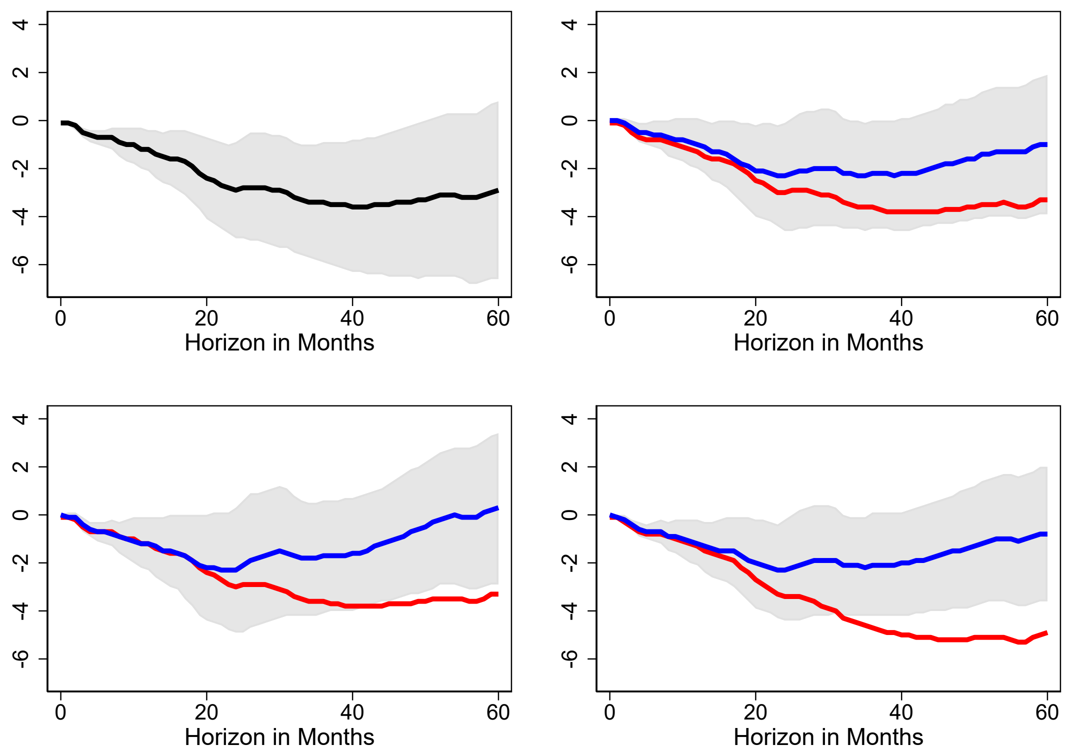
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: *The dependent variable is the deepest cumulative house price response to monetary policy shocks in percentage, it is generally negative.*

Instead, we propose the heterogeneous regional responses of house prices to monetary policy can arise from land scarcity caused different local population trends. Population inflow creates housing demand that can not be satisfied by existing land, generating a shortage of housing supply where only residents with more willingness in receiving housing utility end up buying. The depletion of land create an inelastic supply curve, which increase the sensitivity of housing price to monetary policy shocks. Our detailed analysis using data on land value shares and additional MSA-by-MSA analysis show that it is indeed the land scarcity channel the generate the heterogeneous monetary policy responses in housing prices.

Appendix

Figure A2.1: House Price Response to Monetary Policy



Note: *The black line is the linear response. The red line for urban growth, the blue line for urban decline, and the shaded area is the 95 percent error band for urban decline. The top left is the linear case, the top right is for urban growth defined as current year's population growth above the average of past three years. The bottom left is for urban growth defined as zero percentage cumulative growth from 1975 to 2007. The bottom right is for urban growth defined as 50th percentile of cumulative population growth.*

Table A2.1: Non-linearity of Population Growth on House Price Sensitivity to Monetary Policy

Horizon	Linear	Population	P-value1	Urban-growth	P-value2
6	-.7	.31	.74	-.39	.68
12	-1.15	1.58	.34	-1.75	.3
18	-1.68	3.56	.21	-4.11	.15
24	-2.19	3.06	.45	-4.69	.24
30	-1.56	3.13	.44	-6.34	.13
36	-1.58	3.87	.33	-8.17	.07
42	-1.3	4.12	.35	-9.46	.06
48	-.7	3.33	.54	-9.72	.11
54	-.18	1.91	.77	-8.92	.21
60	-.01	1.31	.86	-8.3	.31

Note: *The local projections here are* $y_{i,t+h} = \alpha_i + \beta^h \epsilon_t \epsilon_t + \beta_p^h POP_i \epsilon_t + \beta_{g,p}^h I_{i,g} POP_i \epsilon_t + u_i$. *Column 2,3,5 correspond to* β^h,β_p^h, *and* $\beta_{g,p}^h$ *respectively. The most important result here is that the larger sensitivity of house prices to monetary policy shocks is mainly driven by areas in growth.*

Table A2.2: House Price Responses by two States:
Urban Growth and Elastic Supply

Horizon	Grow;Elastic	Grow;Inelastic	Decline;Elastic	Decline;Inelastic
6	-.72	-.8	-.66	-.71
12	-1.06	-1.48	-1.13	-1.41
18	-1.55	-2.5	-1.65	-2.28
24	-2.31	-3.98	-2.07	-3.09
30	-2.25	-4.58	-1.49	-2.57
36	-2.58	-5.49	-1.55	-2.97
42	-2.69	-5.96	-1.3	-2.84
48	-2.54	-6.07	-.7	-2.28
54	-2.4	-5.9	-.09	-1.54
60	-2.3	-5.66	.19	-1.25

Note: *We group MSAs into four groups according to whether it is in growth and whether it has elastic housing supply. Urban growth is defined as those with cumulative population growth rate from 1975 to 2007 above the 25 percentile of all MSAs. A MSA has elastic supply if the Saiz elasticity is above the average. Generally, growing areas with inelastic supply have the largest house price response to monetary policy shocks.*

Table A2.3: House Price Responses by two States:
Urban Growth and Land Value Share High

Horizon	Grow;LandH	Grow;LandL	Decline;LandH	Decline;LandL
6	-.82	-.66	-.76	-.61
12	-1.36	-1.06	-1.43	-1.06
18	-2.22	-1.56	-2.17	-1.67
24	-3.44	-2.37	-2.89	-2.13
30	-3.83	-2.32	-2.47	-1.45
36	-4.55	-2.66	-2.82	-1.51
42	-4.9	-2.78	-2.58	-1.36
48	-4.95	-2.6	-2.01	-.79
54	-4.81	-2.41	-1.26	-.23
60	-4.6	-2.31	-.89	-.03

Note: *We group MSAs into four groups according to whether it is in growth and whether it has elastic housing supply. Urban growth is defined as those with cumulative population growth rate from 1975 to 2007 above the 25 percentile of all MSAs. A MSA has a high land value share if it is above the average. Generally, growing areas with high land value share have the largest house price response to monetary policy shocks.*

Proposition 1 proof

Since the housing market and the land market are perfectly competitive, in equilibrium $p_t^h = p_t^l + k_t$. Failure of this condition would cause the developer to buy or sell infinite amount of land, which is contradictory to market clearing. Furthermore, to avoid infinite demand on land, p_t^l has to be non-negative. Therefore, p_1^h is strictly positive, which implies the housing owned by agents arrived in period $t = 0$ will all be sold in period $t = 1$. The number of housing owned by the period $t = 0$ residents is assumed to be Q_r.

Because p_1^h is positive, equation (2.4) binds and the objective equation (2.3) can be rewritten as $p_1^h H_1 + p_1^l (H_1^{build} - L_1^{buy}) + rB_1$. Consider the case of $p_1^l = 0$ and $p_1^h = k_1 = k$. Housing market can not be cleared with this price combination if $\mu > 1$. If $\mu \leqslant 1$, then for the unit measure of developers, the equilibrium can be achieved as follows:

1. For developers with $N\mu \leqslant L_1 + H_1 + Q_r$, the equilibrium decision in period $t = 1$ will be $L_1^{buy} = 0$, $H_1^{build} = N\mu - Q_r - H_1$, $H_1^{sell} = N\mu - Q_r$.

2. For developers with $N\mu > L_1 + H_1 + Q_r$, the equilibrium decision in period $t = 1$ will be $L_1^{buy} = 0$,$H_1^{build} = -H_1$,$H_1^{sell} = 0$.

If $p_1^l > 0$, then both equations (2.4) and (2.5) bind. Summing across the developers constraints yields $\sum H_1^{sell} = \sum H_1 + \sum L_1$. This implies that in $t = 1$ all available space are converted to housing. Given $p_1^h > k$, only a fraction of arriving residents in $t = 1$ is willing to buy housing. Therefore, equilibrium with $p_1^l > 0$ can be achieved only with the condition $\mu > 1$. Using the market clearing condition where home sales equal to N, the unique equilibrium for prices are $p_1^h = k\mu^{\frac{1}{\epsilon}}$ and $p_1^l = k\mu^{\frac{1}{\epsilon}} - k$. Equilibrium decisions for the developers in this case are: $H_1^{build} = L_1$, $L_1^{buy} = 0$,$H_1^{sell} = H_1^{build} + H_1$.

In period $t = 0$, the expected liquidation value of the developer can be derived as follows:

$$\pi = p_1^h H_1 + p_1^l (H_1^{build} - L_1^{buy}) + rB_1$$

$$= p_1^h H_1 + p_1^l L_1 + rB_1 \tag{2.14}$$

$$= p_1^h H_1 + p_1^l L_1 + r(p_0^h H_0^{sell} - p_0^l L_0^{buy} - k_0 H_0^{build}) \tag{2.15}$$

$$= (p_1^h - rp_0^h)H_1 + (p_1^l - rp_0^l)L_1 + rp_0^l L_0 \tag{2.16}$$

$$= (p_1^h - rp_0^h)H_1 + (p_1^h - rp_0^h + (2r-1)k)L_1 + rp_0^l L_0. \tag{2.17}$$

Since we assume $N_0 < N$, in period $t = 0$ we know the equilibrium L_1 is positive and finite. Therefore, to satisfy the market clearing condition in the land market, the condition $(p_1^h - rp_0^h + (2r-1)k) = 0$ has to be satisfied. Utilizing the previously derived equilibrium p_1^h The equilibrium period $t = 0$ housing price at can now be derived as:

$$p_0^h = \begin{cases} 2k & if \mu \leqslant 1 \\ 2k + \frac{k(\mu^{\frac{1}{\epsilon}} - 1)}{r} & if \mu > 1 \end{cases}. \tag{2.18}$$

Proposition 1 follows immediately by differentiating on $r = 1$.

Elasticity in Urban Growth and Decline

We check the relation between house prices and population growth by regressing the cumulative house price growth over the cumulative population growth from 1975 to 2007.

$$y_i = \alpha + \beta x_i + u_i.$$

y_i is the cumulative house price growth for MSA i. x_i is the cumulative population growth. The coefficient is 0.41 and statistically significant (as column 1 in Table A2.4). A 0.41 percent increase in house prices is associated with one percent population growth.

We check the role of housing supply elasticity in understanding house prices during urban growth and urban decline.

$$y_i = \alpha + \beta x_i + \beta_E x_i \gamma_i + u_i,$$

of which y_i is the cumulative house price growth for MSA i. x_i is the cumulative population growth. γ_i is the normalized Saiz elasticity. β_E is the parameter of interest here. The estimated β is 0.18, statistically significant. And the estimated β_E is -0.45, also statistically significant (as column 2 in Table A2.4). This is to say, for an area with the mean Saiz elasticity, a one percent increase in the cumulative population growth is associated with a 0.18 percent increase in house price. Moreover, if the area has a one-standard-deviation elasticity higher than the mean Saiz elasticity. The house price growth rate for one percent population growth is 0.45 percent lower. The higher the housing supply elasticity, the lower the house price growth.

Glaeser and Gyourko (2005) points out the asymmetry between urban growth and urban decline. We test this asymmetry using our data:

$$y_i = \alpha + \beta_g I_{g,i} x_i + \beta_d (1 - I_{g,i}) x_i + u_i$$

of which $I_{g,i}$ indicates a positive cumulative population growth. β_g captures the effects of the cumulative population growth on cumulative house prices growth for urban growth. β_d captures the same thing for urban decline. The estimations for β_g and β_d are 0.38 and 1.30 respectively, statistically significant (as column 3 in Table A2.4). For unit percentage

Table A2.4: House Price, Urban Growth, and Saiz Elasticity

	(1)	(2)	(3)
Cumulative Population Growth 1975-2007	0.41***	0.18**	1.30***
	(8.50)	(2.50)	(3.36)
Normalized Saiz Elasticity × Cumulative Population Growth 1975-2007		-0.45***	
		(-7.00)	
Urban Growth defined by 0=1 × Cumulative Population Growth 1975-2007			-0.92**
			(-2.26)
Constant	1.39***	1.46***	1.42***
	(54.46)	(44.95)	(48.79)
Adjusted R^2	0.145	0.304	0.149
Observations	382	270	382

t statistics in parentheses

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

Note: *House price, population growth rate are both cumulative growth rate from 1975 to 2007.*

increase in population, house price increases by 0.38 percent. For unit percentage decline in population, house price declines 1.30 percent, higher than the population decline. We confirm Glaeser and Gyourko (2005) results using our data that house prices increase less than population growth for urban growth and house prices decrease more than population decline for urban decline.

Chapter 3

Export Slowdown and Household Savings in China

3.1 Introduction

During the export expansion period from 2001 to 2007 in China, household saving rate was high and remained increasing, which is a puzzle widely discussed in the literature. At the same time, import competition on labor markets stimulated growth of household debt in the United States, according to Barrot et al. (2022). Following the onset of the Great Financial Crisis in 2009, the annual growth rate of world exports of goods and services declined sharply from 11.8% in 2010 to 1.1% in 2019. As a result, China entered a period of export slowdown since 2010, during which the household saving rate decreased from 2010 to 2015 and then rebounded after 2016.

We hypothesize that export shocks can influence household savings. More specifically, export slowdown is associated with a reduction in Chinese household saving rates during 2010-2016. Export slowdown is an adverse income shock for the export-driven countries, and it can affect households' saving behavior in China. We examine our hypothesis using a nationally representative biannual household survey data, Chinese Family Panel Studies (CFPS). We exploit cross-city variation in exposure to export shocks to study the impact of export slowdown on household saving rate. To handle the potential bias concerns in panel regressions, we construct a Bartik instrumental variable to estimate the causal impact of export slowdown on household saving rate. The instrument relies on world trade flows excluding China and uses the city's weight computed with its initial product export share.

We find empirical evidence that export slowdown led to decreasing household saving rate in China. Our results hold after controlling other local economy factors including housing prices, local government's fiscal investment, and development of financial institutes. The results are not the by-product of family size, average household age, and other demographic characters across areas. A 100 USD per capita reduction in export growth causes a 1.19 percentage point decrease in the household saving rate. On average, export slowdown contributes to a 3.59 percentage point decrease in household saving rate during 2010-2016.

We show that the decrease in saving rate is due to an increase in consumption and a decrease in family income as the results of export slowdown. We propose the expectation adjustment mechanism based on Permanent Income Hypothesis (PIH) to explain this phenomenon. During a period of export slowdown, households may maintain their confidence in the future even if their family income declines. They may not adjust their expectations downward, and maintain or increase their consumption level. This optimistic expectation adjustment can lead to a decrease in the household saving rate in response to export slowdown.

We examine the relationship between export slowdown and households' expectation adjustment, using the data for households' confidence about the future from CFPS. Based on the PIH theory, the expectation adjustment term is constructed as households' future confidence relative to their current family income. We find that export slowdown is associated with a significant increase in expectation adjustment, indicating that households lower their expectation about the future at a slower pace than the decline of current family income. It means that households are optimistic comparing the future to the present despite the adverse income shock.

We next test the expectation adjustment mechanism. We add the expectation adjustment in the baseline regression. The estimated coefficient for the impact of export shocks on saving rate becomes smaller in magnitude and insignificant. We further add the interaction term of export shock and expectation adjustment, and find that the sign of the coefficient flip. It indicates that export slowdown decreases household saving rate mainly through the expectation adjustment mechanism.

We investigate the timing of households' adjustment of their expectations in response to export shocks. We utilize a quarterly national-level index of confidence over the income growth in the future from the Urban Depositor Survey (UDS), examining whether individuals adjust their expectations in a sluggish manner or disregard negative income shocks entirely. Our findings demonstrate that individuals maintain their confidence in the future following the occurrence of trade shocks, and only significantly adjust their expectations in 2014, five years after the advent of export slowdown. This phenomenon is observed not only during the export slowdown period of 2010-2016 but also during the export expansion period of 2001-2007.

Additionally, we examine the timing of expectation adjustment at the household level using year-over-year regression analysis. Using the same data as the main results, we obtain year-specific estimates for the impact of export slowdown on expectation adjustment. Our findings indicate that in 2010 and 2012, an export slowdown is associated with optimistic expectation adjustment, whereas in 2016, it leads to lower future confidence relative to current family income. This abrupt change occurred in 2014, which is consistent with the trend captured by UDS data. Households do adjust their expectation and saving behavior, but there is a lag in their adjustment. Our evidence for the inertia of expectation adjustment further supports the hypothesis that export slowdown decreases household saving rates during 2010-2016.

The pattern of export slowdown reducing household saving rates is primarily driven by the urban households. We observe that export slowdown decreases family income for urban households. In contrast, export slowdown does not reduce rural households' family income due to government subsidies provided by the Rural Development Policy, though export slowdown leads to a reduction in wage for both urban and rural households. Moreover, in response to export slowdown, rural households decrease their consumption, while urban households increase their consumption. As a result, an export slowdown is associated with an increase in rural household saving rates and a decrease in urban household saving rates.

We also conduct an IV regression analysis at the city level using aggregate household data, which confirmed these findings.

This paper contributes to three strands of literature. The first strand explore the relationship between large-scale shocks and household saving rate using individual data (Barrot et al. (2022), He et al. (2018)). Barrot et al. (2022) argue that the adverse impact of import competition on income stimulated household debt expansion in the United States in the 2000s. Based on Permanent Income Hypothesis, they propose that the increase in leverage is associated with import competition perceived as transitory shocks to income, rather than shocks long-lasting in the future. However, the panel data they use for the main results does not include agents' future expectation. To supplement their study, we provide more direct and rich empirical evidence on how export slowdown decreases saving rates through households' expectation adjustment, using information on households' income, consumption, their expectations about the future, and their demographic characteristics from CFPS.

The second strand is export slowdown and local economy (Campante et al. (2023), Ma et al. (2022)). Campante et al. (2023) find that prefectures that experienced a more severe export slowdown witnessed a significant increase in incidents of labor strikes. Ma et al. (2022) find higher crime rates in cities that experience a more severe export slowdown. We find lower household saving rates in cities exposed to a more severe export slowdown shock. Export slowdown is a global trend that may continue in the future. The findings in this strand of literature have critical economic meanings and political implications for export-driven countries.

The third strand is the literature studying the puzzle of high Chinese households saving rates (Wei and Zhang (2011), Zhou (2014), Baker et al. (2022), Choukhmane et al. (2023)). Wei and Zhang (2011) explain the puzzle with an innovative mechanism: the sex ratio and competition in local marriage market, which inspires research on household saving rates and demographic factors. Zhou (2014) analyzes the impact of the number of brothers and shows that having an additional brother reduces an individual's household savings rate by at least 5 percentage points. Choukhmane et al. (2023) constructs a life-cycle model and shows that the one-child policy significantly increased the human capital of the only child generation and can account for a third to 60% of the rise in aggregate savings.

Unlike most studies in this literature, this paper is one of the few that investigates Chinese household saving rates after 2010, making it a pioneering work in this field. Another such pioneering work is Baker et al. (2022), which uses individual data from 2010-2017 to suggest that income growth, financial instability, and credit access – rather than demographic factors or the one-child policy – are the primary causes of high savings rates among Chinese households. Our study complements theirs by arguing that trade shocks can influence income growth and determine household saving rates. Additionally, our paper documents the fact that Chinese household saving rates increased during the export expansion period and decreased during the export slowdown period. To the best of our knowledge, this is the first paper to propose a potential explanation for China's high household savings rate and bridge the periods of 2001-2007 and 2010-2016.

In the remainder of this paper, we discuss data sources in Section 2. We present the empirical strategy and empirical results in Section 3. We propose and test the mechanism in Section 4 and 5. We discuss the extensions for future research in Section 6. Section 7 concludes.

3.2 Data Sources

3.2.1 Export Slowdown Shocks

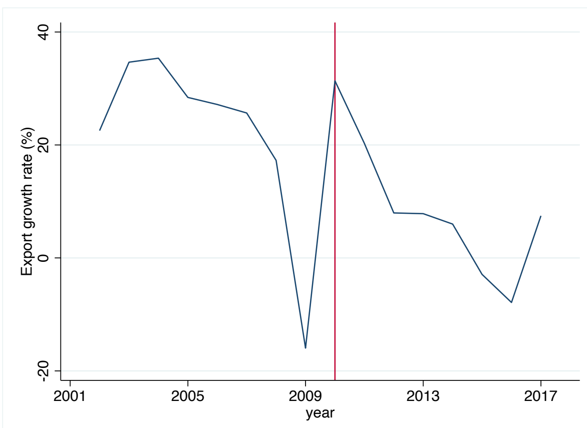
We exploit the China Custom Database (1997-2017), which provides annual data for the dollar value of imports and exports by city and product at 8-digit Harmonized System level. We compute the total export values by aggregating exports of all cities, and the trend of Chinese export growth is presented in Figure 1 panel (a)[1]. Since 2010, Chinese export expansion has slowed down, in contrast to the consistently high growth levels observed during the period from 2002 to 2008, or after China joined the World Trade Organization

[1] For the period 1992-1996, the China Custom Database provides the dollar value of imports and exports by province and product at 6-digit Harmonized System level. We use it to compute the aggregate exports of all provinces. Different from Campante et al. (2023) and Ma et al. (2022), we don't limit exports to the manufacturing sector only. We will redo it for robustness check later.

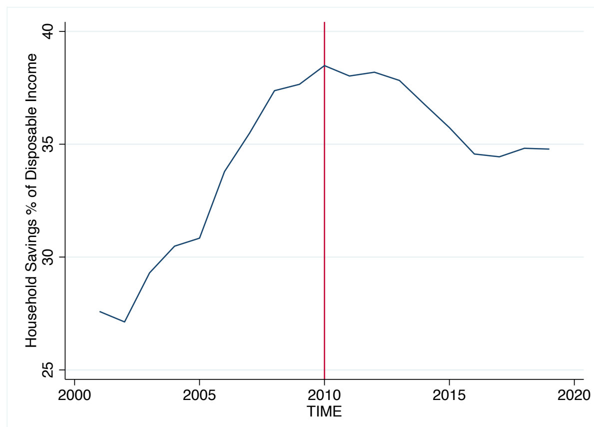
(WTO) in 2001 and before the Global Financial Crisis in 2009.

Similar to exports, the household saving rate in China experienced notable changes over the years, as illustrated in 1 panel (b)[2]. After China joined the WTO, the saving rate began to rise sharply and continued to increase during the period of export expansion from 2001 to 2008. However, it started to decline following the onset of Global Financial Crisis and continued to decrease during the initial phase of export slowdown from 2010 to 2014. Subsequently, the saving rate showed a slight rebound from 2016 to 2020. There is a clear co-movement between the exports and the household saving rate, indicating a correlation between these two variables.

Figure 1: Export Slowdown and Aggregate Household Savings in China



(a) Export Growth of China



(b) Aggregate Household Saving Rate of 120 cities

Following Campante et al. (2023), we choose 2010 as the base year, which is the beginning of China's exports slowdown. To measure a city's exposure to the global trade slowdown, we construct $ExpShock_{ct}$ with the biannual change[3] of exports per capita within that city:

$$ExpShock_{ct} = Export_{ct} - Export_{ct-2}, \quad Export_{ct} = \frac{\sum_k X_{ckt}}{L_{c,2010}}$$

[2]We are using the national level data for household savings from OECD data source. Here the household savings are measured as % of household disposable income.

[3]As CFPS provides the biannual survey data for 2010, 2012, 2014 and 2016, we calculate the biannual change of exports accordingly.

where X_{ckt} is the exports (100 USD) of product k in city c and year t; $L_{c,2010}$ denotes the total population of city c in 2010.[4] We utilize the variation in exposure across cities and time to identify the impact of export slowdown on household savings in China.

3.2.2 Household Savings

We utilize China Family Panel Studies (CFPS) to study household savings. It is a nationally representative, biannual longitudinal survey of Chinese communities, families, and individuals launched in 2010 by the Institute of Social Science Survey (ISSS) of Peking University, China. The CFPS respondents are tracked through annual follow-up surveys. It covers 25 provinces and provides information on city location, urban or rural areas of each household.

The CFPS database includes data on household income, consumption, assets, housing, and other indicators for household financial behavior. Following Choukhmane et al. (2023), we measure the household saving rate as one minus the ratio of consumption to income. In some cases, household income may be zero or very low, while household consumption remains stable, resulting in an extremely negative saving rate. To address this issue, we exclude observations if their family income falls in the lower tail (10th percentile) of their city's income distribution for a year during 2010-2016[5].

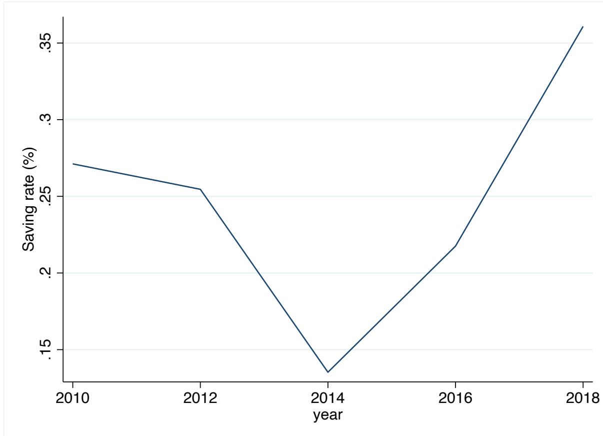
Figure 2 presents the aggregate household saving rate based on this dataset, which is measured as one minus the ratio of aggregate consumption to aggregate family income. The aggregate saving rate declined during 2010-2014 and rebounded since 2016, which is similar to the aggregate saving rates based on another survey data, China Household Finance Survey (CHFS). It is comparable to Figure 1 panel (b), though the latter displays a higher saving rate as it considers disposable income instead of gross income.

Besides economic well-being variables, CFPS also provides family members' demographic characteristics, employment status, social network and participation, health, public opinions and subjective beliefs. Table 1 presents the summary statistics for a set of house-

[4]We obtain the total population of each prefecture-level city from the China City Statistical Yearbook.

[5]The empirical results are robust to the 2.5th percentile and 5th percentile thresholds for excluding observations.

Figure 2: Aggregate Household Saving Rate based on CFPS



hold characteristics, which are controlled in the empirical specification.

Table 1: Summary Statistics Table for the Year 2010

	Observations	Mean	Standard Deviation	25% Percentile	50% Percentile	75% Percentile	90% Percentile
Savings rate	3959	5.29	98.7	-11.1	27.6	53.3	69.5
Family Income	4205	39073.6	49100.4	17477.5	27949.5	47000	74560
Family Size	4485	4.24	1.66	3	4	5	6

3.3 Empirical Results

3.3.1 Empirical Strategy

We perform the panel regression at the household level. Regressions are weighted by the sampling weights assigned to each household by CFPS.

$$y_{hct} = \alpha + \beta_1 ExpShock_{ct} + \beta_2 log(\text{Family Income}_{hct}) + \beta_3^{'} Z_{hct} + \beta_4^{'} \Gamma_{ct} + \gamma_t + \gamma_c + \epsilon_{hct} \quad (3.1)$$

where y_{ht} is the saving rate of household h at year t. The location of household h is city c. $ExpShock_{ct}$ is city c's exposure to the shock of export slowdown. γ_t is the year fixed effect and γ_c is the city fixed effect. Standard errors are clustered at the province level.

Following He et al. (2018), we include the log-level of family income in Z_{ht} as an explanatory variable to control for the potential effects of non-homothetic preferences. We also control for other household characteristics, including family size and the dummy variable for urban or rural household. Besides the local exposure to export slowdown shocks, saving rate might be influenced by other local economic factors. We incorporate local public debt (1 billion RMB) in Γ_{ct}, which is related to local government investment in urban infrastructure. We include local housing prices (1000 RMB), which can influence household saving behavior. Furthermore, we include the number of newly constructed bank branches, measured in units of 100 branches, to account for changes in the local development of financial institutions.

3.3.2 Instrumental Variable

The estimation results obtained through ordinary least squares (OLS) regression may be biased due to omitted variables and endogeneity issues. Firstly, there may be a reverse causality issue where household saving rate influences export growth rate. For example, lower household saving rates may be associated with higher consumption levels, which could lead firms to shift their focus towards the domestic market and reduce their level of exports.

Secondly, uncontrolled factors can lead to omitted variable bias. In our analysis, we have included local public debt to account for some of these factors related to export slowdown. However, it is possible that the local government has implemented other policies to mitigate the adverse impacts of export slowdown, which could result in underestimation of the actual effects of export growth rate on saving rate.

To avoid the endogeneity issue and omitted variable bias, we follow Campante et al. (2023) and construct a Bartik instrument. It relies on the trade flows at the product level rather than the local level, and focuses on world trade flows excluding China, i.e. the Rest of the World (ROW). We use data from UN Comtrade Database, and obtain change in exports from the ROW to the ROW at HS 6-digit level.

To measure a city's exposure to the global trade shocks by product, we compute the city's weight with its initial product export share. The Bartik instrument is calculated by summing the weighted exposure over all the products.

$$ExpShockROW_{ct} = \sum_k \frac{X_{ck,2008}}{\sum_c X_{ck,2008}} \frac{\Delta X_{kt}^{ROW}}{L_{c,2010}} \tag{3.2}$$

where $L_{c,2010}$ is total population in city c and the base year 2010; $\Delta X_{kt}^{ROW} = X_{kt}^{ROW} - X_{kt-1}^{ROW}$ is the change in exports of product k from the ROW to the ROW between t and $t-1$. $X_{ck,2008}$ is city c's export of product k in 2008. $\sum_c X_{ck,2008}$ is the total exports of product k in 2008. $\frac{X_{ck,2008}}{\sum_c X_{ck,2008}}$ is the initial export share of product k in city c.

3.3.3 Baseline Results

Table presents the baseline results for equation (3.1). Columns (1)-(3) are OLS estimates, column (4) present 2SLS estimates using the Bartik IV in equation (3.2). The results show that an export slowdown (a more negative $ExpShock_{ct}$ value) is associated with a lower saving rate. With the Bartik instrument, the estimated coefficient remains significantly positive and becomes larger. The Bartik IV addresses the endogeneity issue and omitted variable bias discussed above.

According to column (4), the impact of export slowdown on household saving rate is sizable. A 100 USD per capita reduction in export growth causes a 1.19 percentage point decrease in the household saving rate. From 2008 to 2010, the total export value grew from 1.43 trillion to 1.58 trillion. Export per capita increased by 113 USD. From 2014 to 2016, the total export value shrunk from 2.34 trillion to 2.09 trillion. Export per capita increased by 188 USD. On average, export slowdown contributes to a 3.59 percentage point decrease in household saving rate during 2010-2016.

3.3.4 Export Slowdown and Family Income

As discussed in Campante et al. (2023) and Ma et al. (2022), export slowdown during 2010-2018 led to higher unemployment risk, lower disposable urban income, thus more labor strikes, and higher criminal rates in China. This adverse economic shock to family income may have influenced Chinese households' financial behavior. We examine the relationship between export slowdown and family income. We use a similar specification to the baseline 3.1, where y_{hct} is the log of family income instead of household saving rate.

Table 2: Baseline Results

	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	IV
$ExpShock_{ct}$	-0.134	-0.241	0.460***	1.194**
	(0.303)	(0.182)	(0.158)	(0.501)
$FamilySize_{hct}$	-10.20***	-9.525***	-10.99***	-10.99***
	(0.930)	(1.132)	(0.862)	(0.863)
$ln(FamilyIncome_{hct})$	81.05***	82.17***	91.42***	91.43***
	(4.711)	(4.670)	(5.092)	(5.091)
$Urban_{hct}$	-4.994*	-7.850***	-4.964**	-4.990**
	(2.681)	(2.700)	(2.272)	(2.273)
$PublicDebt_{ct}$	-0.592**	-0.0984	0.0811	0.104
	(0.273)	(0.149)	(0.0839)	(0.0864)
Num of New Bank Branches$_{ct}$	-2.391	-3.204	-1.107	-0.917
	(5.245)	(3.529)	(2.789)	(2.773)
Housing Prices$_{ct}$	-2.505***	-1.879***	-0.360	0.00596
	(0.707)	(0.460)	(0.314)	(0.487)
City FE	N	Y	Y	Y
Year FE	Y	N	Y	Y
First-stage F-stat	-	-	-	27.51
N	15743	15743	15743	15743

Standard errors in parentheses

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

Table 3: Export Slowdown and Family Income

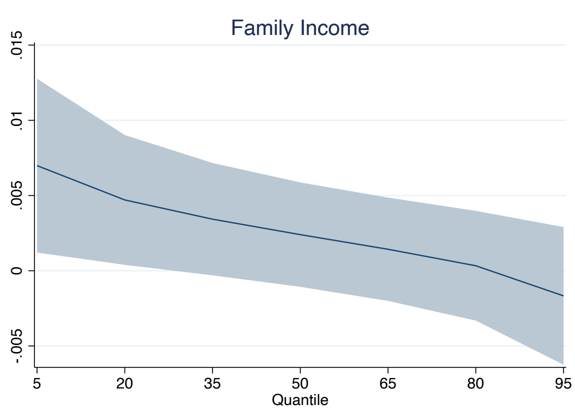
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	Urban-OLS	Urban-IV	Rural-OLS	Rural-IV
$ExpShock_{ct}$	-0.000236	0.00170	0.0000521	0.00244	-0.00108	-0.00158
	(0.00110)	(0.00270)	(0.00112)	(0.00289)	(0.00302)	(0.00841)
N	16658	16658	8040	8040	8559	8559

Standard errors in parentheses

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

In Table 3 column (2), it can be observed that export slowdown results in a slight overall decrease in family income, although the estimate is imprecise. To further explore the impacts of export shock across the distribution of family income, we utilize Instrumental Variable Quantile Regression. The coefficients, along with their corresponding 95% confidence intervals, are presented in Figure 3. The findings reveal that export slowdown is associated with a decrease in family income for most households, with significant impact observed among households whose family income falls below the 30th percentile.

Figure 3: The Impacts of Export Shock on Family Income



To further examine the relationship, we divided the full sample into urban and rural subsamples and analyzed the regression results in columns (3)-(6). In urban households, the effect of export slowdown is similar to that in all households. However, in rural households, there is an observed increase in family income, although the estimated coefficient is insignificant.

One possible explanation for the negative correlation between export shock and family income in rural households could be the Rural Development Policy. Governments may implement policies aimed at supporting rural farmers, such as increasing subsidies, providing financial assistance, or promoting domestic consumption of agricultural products, as a means to offset the negative impacts of export slowdown. In the CFPS dataset, family income is composed of five main categories: wage income, business income, property income, transfer income, and other income[6]. Transfer income may reflect subsidies provided to rural households.

We exclude government subsidies from the total family income by deducting the transfer income. We re-investigate the effects of export slowdown on the adjusted family income. The results presented in Table 4 indicate a decline in adjusted family income for both urban and rural households as a result of the export slowdown.

Table 4: Export Shocks and Adjusted Family Income

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	Urban-OLS	Urban-IV	Rural-OLS	Rural-IV
$ExpShock_{ct}$	-0.000739	0.00277	-0.000421	0.00355	-0.00131	0.00336
	(0.00144)	(0.00274)	(0.00155)	(0.00287)	(0.00413)	(0.00793)
N	16989	16989	7754	7754	9166	9166

Standard errors in parentheses

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

The impact of export slowdown on family income varies among urban and rural

[6]Wage income includes employment income from agriculture or non-agricultural sectors; business income includes income from self-owned agricultural production and the self-owned portion of income from individual and private enterprises; property income includes income from family-owned rental properties, land, and other family assets or equipment; transfer income mainly refers to government subsidies and donations of monetary or material value received by the household; other income includes gifts, cash gifts, and income reported under the category of "other income".

households, leading to potential differences in saving behavior. Column (2) show that export slowdown significantly decreases saving rates in urban households. Columns (3)-(4) display insignificantly negative estimates for rural households. The magnitude of the estimates is small and close to zero. These findings suggest that the decline in household saving rates induced by export slowdown is primarily driven by urban households' behaviors.

Table 5: Export Slowdown and Saving Rates across Urban and Rural Households

	(1)	(2)	(3)	(4)
	Urban-OLS	Urban-IV	Rural-OLS	Rural-IV
$ExpShock_{ct}$	0.464*	1.163**	-0.338	-0.164
	(0.237)	(0.572)	(0.605)	(1.458)
N	7565	7565	8120	8120

Standard errors in parentheses

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

3.3.5 Household Savings at the City Level

At the household level, the household saving rate tends to decrease along with export slowdown. We then examine the relationship between export growth per capita and the household saving rate at the city level. We aggregate family income and consumption by year and city, with survey sample weights assigned to each household. The city-level household saving rate is measured as one minus the aggregate consumption divided by the aggregate family income.

We re-estimate the effect of export shock on the household saving rate at the city level. The regression model controls for the family income per capita at the city level and other local economic factors, which are similar in specification to the baseline regression (3.1). The results are presented in Table 6.

$$y_{ct} = \alpha + \beta_1 ExpShock_{ct} + \beta_2 log(\text{Per Capita Family Income}_{ct}) + \beta_3' \Gamma_{ct} + \gamma_t + \gamma_c + \epsilon_{ct} \quad (3.3)$$

As shown in columns (1) and (2), a decrease in household saving rate at the city level is associated with export slowdown. To further investigate this relationship, we divide

Table 6: Baseline Results at the City Level

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	Urban-OLS	Urban-IV	Rural-OLS	Rural-IV
$ExpShock_{ct}$	-0.269	0.389***	0.186	0.678***	-0.874	-1.824**
	(0.204)	(0.150)	(0.152)	(0.202)	(0.651)	(0.906)
log(PC FamilyIncome$_{ct}$)	16.84	71.00***	63.72***	63.80***	67.74***	66.86***
	(14.40)	(7.698)	(6.723)	(7.035)	(7.340)	(7.302)
N	410	410	391	391	336	336

Standard errors in parentheses

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

the full sample into urban and rural subsamples, with the regression results reported in columns (3)-(6). The findings reveal that urban households tend to save less when faced with export slowdown, whereas rural households tend to save more in response to export slowdown. These results confirm the heterogeneous effects across urban and rural areas implied by Table 5.

3.4 Mechanism

3.4.1 Permanent Income Hypothesis

Barrot et al. (2022) highlights how international trade can result in income shocks and impact household financial behavior. They find that import competition is associated with an increase in household debt. They argue that, according to The Permanent Income Hypothesis (PIH) originally proposed by Friedman (1957), households borrow more in response to import competition only if the shock is considered transitory. To illustrate how income shocks could affect households' saving rate, we start solving a simple model with the lifetime expected utility. It sheds light on how households alter their consumption patterns depending on how they perceive the export shocks.

Households maximize lifetime expected utility

$$U_0 = \sum_{t=0}^{\infty} \mathbb{E}_0[\beta^h u(c_h)]$$

subject to the budget constraint

$$b_t + c_t \leqslant y_t + (1+r)b_{t-1} \tag{3.4}$$

where b_t represents a household's investment in risk-free bonds with an interest rate of r as savings during period t, while b_{t-1} denotes the bond holdings from the previous period, i.e., period $t-1$. y_t is the family income.

Euler equation to this utility maximization problem is

$$\mathbb{E}_t[(1+r)\beta^{1+t}u'(c_{t+1})] = \beta^t u'(c_t)$$

For simplicity, we follow Barrot et al. (2022) to assume that utility has a quadratic functional form, with $u_t = -(c_t - \gamma)^2/2$. The interest rate satisfy $(1+r) \times \beta = 1$. Under these assumptions, the Euler equation is $c_t = \mathbb{E}_t[c_{t+1}]$. Given the boundary condition in the budget constraint (3.4), the level of saving can be solved as

$$\begin{aligned}
b_t &= \Big(\sum_{k=1}^{\infty} \beta^k \mathbb{E}_t[c_{t+k}]\Big) - \Big(\sum_{k=1}^{\infty} \beta^k \mathbb{E}_t[y_{t+k}]\Big) \\
&= \frac{\beta}{1-\beta} c_t - \Big(\sum_{k=1}^{\infty} \beta^k \mathbb{E}_t[y_{t+k}]\Big) \\
&= \frac{\beta}{1-\beta}\Big((1+r)b_{t-1} + y_t - b_t\Big) - \Big(\sum_{k=1}^{\infty} \beta^k \mathbb{E}_t[y_{t+k}]\Big) \\
&= b_{t-1} - (1-\beta)\Big(\sum_{k=1}^{\infty} \beta^k \mathbb{E}_t[y_{t+k}]\Big) + \beta y_t
\end{aligned}$$

Family income is composed of income from labor, business, and subsidies y_t plus property income, or say interests from family assets rb_{t-1}. According to the budget constraint (3.4), the household saving rate can be expressed as

$$1 - \frac{c_t}{y_t + rb_{t-1}} = \frac{b_t - b_{t-1}}{y_t + rb_{t-1}} = \beta - (1-\beta)\frac{\sum_{k=1}^{\infty} \beta^k \Big(\mathbb{E}_t[y_{t+k}] + rb_{t-1}\Big)}{y_t + rb_{t-1}} \tag{3.5}$$

where $b_t - b_{t-1}$ can also be regarded as wealth accumulation in period t. $\mathbb{E}_t[y_{t+k}] + rb_{t-1}$ is the interests from current family assets rb_{t-1} plus the expected income from labor, business, and subsidies $\mathbb{E}_t[y_{t+k}]$ in period $t+k$.

Suppose a household experiences an adverse income shock, leading to a decrease in current family income ($y_t + rb_{t-1}$). If the household expects the shock to be temporary and does not adjust its expectations for future income, meaning that the expected future income $\sum_{k=1}^{\infty} \beta^k \Big(\mathbb{E}_t[y_{t+k}] + rb_{t-1}\Big)$ will not decrease, then the household saving rate will decline. This is because households tend to smooth their consumption over time and maintain a consistent level of consumption in the present.

Conversely, if households anticipate that the adverse income shock will be persistent and adjust their expectations accordingly, such that the sum of expected future income declines more dramatically than $y_t + rb_{t-1}$, then the household saving rate will increase. This is because households adapt their behavior by saving more to mitigate the prolonged negative impacts on their income.

The saving rate can be influenced by how households perceive macroeconomic shocks. During a period of export slowdown, households may maintain their confidence in the future and not adjust their future expectations downward, even if family income declines. This could result in a positive or optimistic expectation adjustment, which may lead to a decrease in the saving rate. In the following section, we will provide empirical evidence to support this mechanism of expectation adjustment.

3.4.2 Expectation Adjustment

To calculate the expectation adjustment, we first obtain the households' confidence about their future. In the CFPS survey data, each adult family member is asked to rate their confidence on a scale from 1 to 5, where 5 denotes being very confident and 1 denotes having no confidence at all. After obtaining the households' average confidence rating, we use it as the proxy for expectation term in equation (3.5), and multiple it by the inverse of family income to obtain the expectation adjustment value.

$$Confidence_{hct} \times \frac{1}{FamilyIncome_{hct}} \approx \frac{\sum_{k=1}^{\infty} \beta^k \Big(\mathbb{E}_t[y_{t+k}] + rb_{t-1}\Big)}{y_t + rb_{t-1}} = ExpectationAdj_{hct}$$

Before we test the mechanism of expectation adjustment, we want to confirm that export slowdown does influence the expectation adjustment. We estimate the impacts of export slowdown on expectation adjustment, similar to the baseline model (3.1) with expectation adjustment as dependent variable. The IV estimation results are presented in

Table 7, indicating that a negative export shock is associated with a positive expectation adjustment, or an increase in the expectation adjustment.

If we take a closer look at the expectation adjustment, we may find that the impacts of export slowdown on future confidence are insignificant, corroborated by column (2). In contrast, export slowdown is related to a significant increase in the inverse of family income, which is illustrated in column (3). It is consistent with our previous findings in subsection 3.3.4 that export slowdown decreases family income. Households do not substantially lower their expectations, though family income drops when export slowed down during 2010-2016 in China. Thus, optimistic expectation adjustments in response to export slowdown are observed.

Table 7: Export Slowdown and Expectation Adjustment

	(1)	(2)	(3)
	$1/FamilyIncome_{hct}$	$Future\ Confidence_{hct}$	$ExpectationAdj_{hct}$
$ExpSchock_{ct}$	-0.00350**	0.00441	-0.00946**
	(0.00149)	(0.00378)	(0.00442)
N	15649	16434	15634

Standard errors in parentheses

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

To examine the mechanism of expectation adjustment, we include the expectation adjustment and its interaction term with export shock in the main regression. The results are presented in Table 8.

$$y_{hct} = \alpha + \beta_1 ExpShock_{ct} + \beta_2 ExpectationAdj_{hct} + \beta_3 ExpectationAdj_{hct} \times ExpSchock_{ct} + \beta_3' Z_{hct} + \beta_4' \Gamma_{ct} + \gamma_t + \gamma_c + \epsilon_{hct}$$

In columns (2)-(4), we first control for family income and future confidence and find that the IV estimates for the impact of export slowdown on household saving rate remain unchanged. In column (5), we add the expectation adjustment term, and find that the IV coefficient becomes insignificant, with a smaller magnitude of 0.684 compared to 1.176. In column (6), we further add the interaction term, which is found to be significant, and the IV estimate becomes significantly negative.

Table 8: The Mechanism of Expectation Adjustment

	(1)	(2)	(3)	(4)	(5)	(6)
$ExpSchock_{ct}$	1.176**	1.193**	1.181**	1.201**	0.684	-5.251**
	(0.572)	(0.557)	(0.571)	(0.557)	(0.453)	(2.291)
$FamilyIncome_{hct}$		1.257**		1.257**		
		(0.535)		(0.535)		
$Future\ Confidence_{hct}$			-0.0453	-0.864		
			(1.733)	(1.741)		
$ExpectationAdj_{hct}$					-58.29***	-61.57***
					(5.877)	(6.552)
$ExpectationAdj_{hct}$						-83.22***
$\times ExpSchock_{ct}$						(30.61)
N	14792	14792	14778	14778	14778	14778

Standard errors in parentheses

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

The empirical evidence supports the hypothesis that an export slowdown decreases the household saving rate through the mechanism of optimistic expectation adjustment. After controlling for this adjustment, an export slowdown may increase household saving rates in response to income decline and unemployment risk, as suggested by the precautionary saving theory in the literature.

3.4.3 Consumption

Our results are consistent with Barrot et al. (2022) which suggests that households may not lower their future expectations and may maintain their consumption level even if trade shocks reduce family income. In their study, households borrowed more in the United States during 2001-2007. In parallel, our study shows that households saved less in China during 2010-2016.

Barrot et al. (2022) proposes a novel mechanism that households may consider the shocks as transitory. However, the consumer credit panel data they use for the main results does not have information on agents' income, consumption, their expectations about the future, and their demographic characteristics. To supplement their paper, we provide more direct and rich empirical evidence on households' expectations. We also confirm this mechanism with evidence on households' consumption.

We estimate the impacts of export slowdown on consumption, similar to the baseline model (3.1), with consumption as the dependent variable. The results are presented in Table 9. We re-estimate the impacts separately for urban and rural households and display the estimates in columns (3)-(6).

Overall, export slowdown is associated with an increase in family consumption, although the coefficient is not significant. This impact is more pronounced in urban households. In rural households, however, export slowdown reduces family consumption. There are three potential explanations: (1) rural households are more pessimistic about the future; (2) as discussed in subsection 3.3.4, export slowdown correlates with an increase in family income of rural households because of government subsidies; (3) rural households experience a higher unemployment risk and consume less according to precautionary saving theory.

Comparing the empirical results for urban households in Table A3.1 and A3.2, and for rural households in Table A3.3 and A3.4, we find that precautionary saving theory can explain rural households' lower consumption and higher saving rate in response to export slowdown.

Urban households maintain or even increase their consumption in response to export slowdown, as they remain confident about the future despite the adverse income shock. In the next section, we investigate the timing of households' expectation adjustment behavior to determine whether they completely ignore the macroeconomic shock or gradually adjust their expectations. We also explore whether this inertia of expectation adjustment applies to the period of export expansion.

Table 9: Export Slowdown and Family Consumption

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	Urban-OLS	Urban-IV	Rural-OLS	Rural-IV
$ExpSchock_{ct}$	-0.0355	-0.0551	-0.0355	-0.0634	0.0469	0.147***
	(0.0247)	(0.0333)	(0.0267)	(0.0397)	(0.0272)	(0.0490)
N	16202	16202	7791	7791	8353	8353

Standard errors in parentheses

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

3.5 Inertia of Expectation Adjustment

3.5.1 Future Income Confidence Index

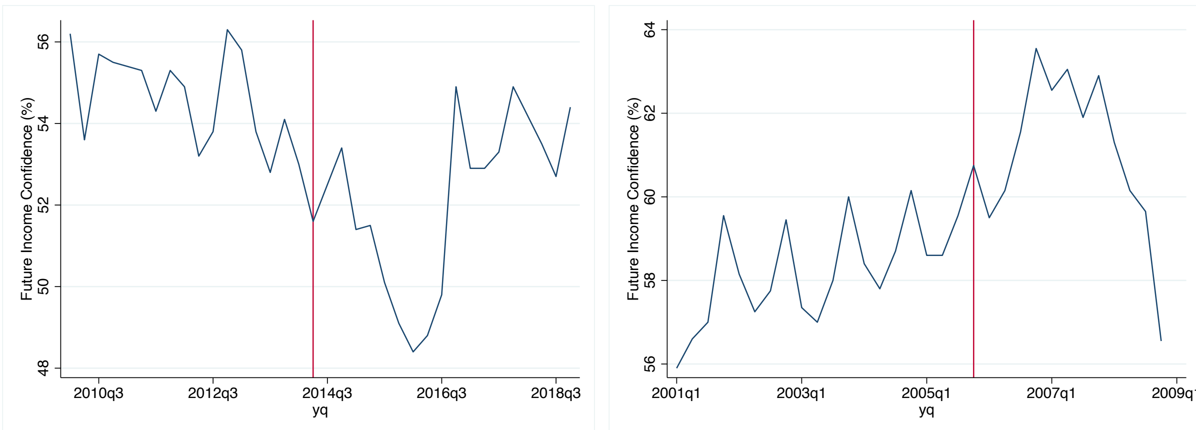
Individuals' expectations can deviate from reality. Barrot et al. (2022) show that in areas highly exposed to import competition, individuals' expected probability of finding a job after becoming unemployed is higher than the actual probability. We find that individuals may not fully perceive the adverse macroeconomic shock and may exhibit inertia in adjusting their expectations about the future.

It may take several years for individuals to adapt their expectations to the new macroeconomic environment. To provide empirical evidence for this, we collect data on expectations regarding future income from the Urban Depositor Survey (UDS) established by the People's Bank of China in 1999[7]. Unlike the longitudinal survey data used by Barrot et al. (2022), the UDS provides a quarterly time-series Future Income Confidence Index at the national level during 2000-2020, allowing us to observe individuals' adjustment of

[7]Each quarter, 50 depositors are randomly selected from 50 (large, medium, and small) survey cities and 400 bank branches nationwide, for a total of 20,000 depositors surveyed. For questions about future income, depositors can choose among the "good/growth" option (assigned a weight of 1), the "general/unchanged" option (assigned a weight of 0.5), and the "poor/decreasing" option (assigned a weight of 0). The proportion of each option is multiplied by the corresponding weight and then added up to calculate the final index. All index values are between 0% and 100%.

expectations in a more frequent and long-term manner. We begin by examining the period of export slowdown during 2010-2018, as presented in Figure 4.

Figure 4: Future Income Confidence and Structural Breaks



(a) The Export Slowdown Period

(b) The Export Expansion Period

Though exports slowed down since 2010, depositors' future income confidence kept fluctuating around 54% during 2010-2013 and then collapsed after 2014. Individuals adjust their expectations on the future income in a sluggish response to export slowdown.

We further confirm individuals' inertia of expectation adjustment. Specifically, we find empirical evidence that export slowdown is associated with a reduction in future income confidence. We conduct a regression analysis, estimating the impact of the national export growth rate[8] on future income confidence index. The OLS estimate is 0.123 with a standard error of 0.02 and a p-value smaller than 0.001, as shown in Table 10 column (1).

We also conduct a test for a structural break in the relationship between future income expectation and export growth rate. The null hypothesis of no structural break is rejected, with a Supremum Wald statistic of 15.5747 and a p-value of 0.0088. The estimated break date is identified as 2014 Q2, which is highlighted in Figure 4 panel (a). Subsequently, we divide the sample period of 2010-2018 into two subsamples: 2010-2013, prior to the structural break, and 2014-2018, after the structural break. Table 10 column (2) reveals that the correlation between export growth rate and future income confidence is weak and

[8]We collect quarterly data for export value of goods from Federal Reserve Economic Data (FRED). The export growth rate is the percentage change in export compared to the same period last year.

insignificant during 2010-2013, but becomes strong and significant during 2014-2018.

Table 10: Export Growth Rate and Future Income Confidence

	(1)	(2)	(3)	(4)	(5)
	2010-2018	2010-2013	2014-2018	2001-2009	2001-2018
Export Growth Rate	0.123***	0.0387	0.162***	0.0791***	0.150***
	(0.0212)	(0.0240)	(0.0401)	(0.0213)	(0.0220)
N	36	16	20	36	72

Standard errors in parentheses

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

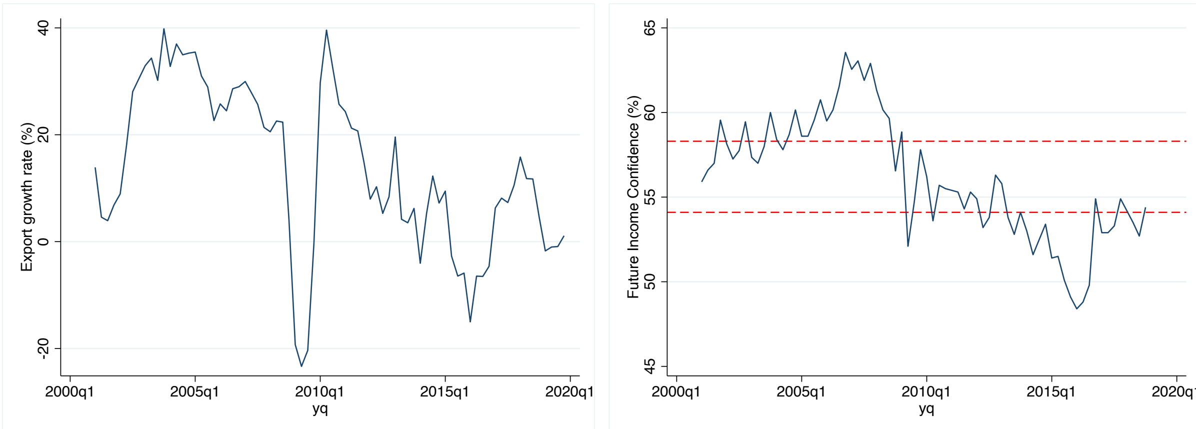
We find evidence that households' expectations exhibit inertia not only in response to export slowdown shocks that occurred after the Great Recession in 2009, but also in response to trade liberalization shocks that took place after China's accession to the World Trade Organization (WTO) in 2001. Table 10 column (4) reveals that export expansion is associated with an increase in individuals' future income confidence during 2001-2009. We also conduct a test for a structural break during this period. The null hypothesis of no structural break is rejected, with a Supremum Wald statistic of 43.3745 and a p-value of 0.0000. The estimated break date is identified as 2005q4, which is highlighted in Figure 4 panel (b).

We conduct a regression analysis using the entire sample period from 2001-2018, and the results are presented in Table 10 column (5). Overall, we observe a positive correlation between export growth rate and future income confidence. Following each major international trade shock in 2001 and 2009, there was a period of fluctuation in future income confidence around a certain level, implying inertia expectation adjustment. Figure 5 panel (b) illustrates this, where the top dashed line indicates 58.3% for the period 2001-2005, and the bottom dashed line indicates 54.1% for the period 2010-2013.

3.5.2 Year-Over-Year Analysis

Besides the macro-level index in the last subsection, we examine the effect of export slowdown on households' confidence about the future using the CFPS waves of 2010, 2012,

Figure 5: Export Growth Rate and Future Income Confidence



(a) Export Growth Rate (b) Future Income Confidence

2014, and 2016 separately. We perform cross-sectional regression analyses on the data for each year to obtain year-specific estimates.

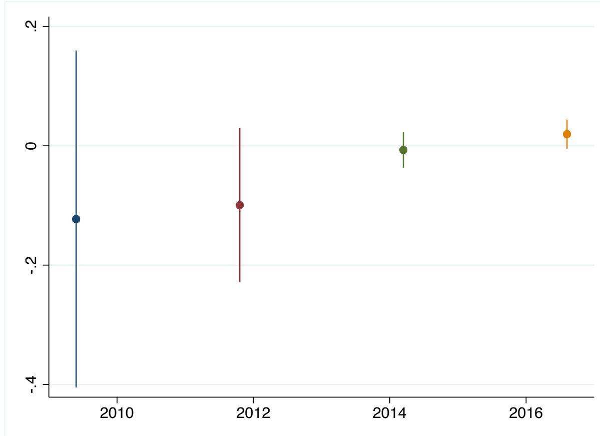
$$ExpectationAdj_{hct} = \alpha + \beta_{1,t} ExpShock_{ct} + \beta_{2,t}^{'} Z_{hct} + \beta_{3,t}^{'} \Gamma_{ct} + \gamma_p + \epsilon_{hct}$$

where γ_p is the dummy variable for provinces. Standard errors are clustered at the province level.

The instrumental variable estimates are presented in Figure 6 and Table A3.5. We observe that households gradually adjust their future expectations since 2010, the onset of the export slowdown. Notably, the most significant adjustment occurs in 2014, consistent with the pattern suggested by the future income confidence index in Figure 4.

To summarize, our findings provide empirical evidence for the inertia of expectation adjustment at both the national and household levels. We observe that people adjust their expectations about the future sluggishly in response to negative trade shocks, resulting in households maintaining optimistic expectation adjustments in the face of export slowdown. In the future, we plan to investigate whether households exhibit similar inertia in expectation adjustment during periods of export expansion. It may shed light on whether households exhibit pessimistic expectation adjustment and increase their saving rate in response to positive trade shocks. This analysis could potentially help to explain the puzzle regarding the high Chinese saving rate observed during 2001-2007.

Figure 6: 95% CI for the Impact of Export Slowdown on Expectation Adjustment



3.6 Extensions

High household saving rate during 2001-2007 is a puzzle and widely explored in the literature. Explanation candidates include demographic forces including the sex ratio in Wei and Zhang (2011), number of brothers in Zhou (2014), and one child policy in Choukhmane et al. (2023). Though not intentionally contribute to this literature, He et al. (2018) show that high unemployment risk brought by the shut down of state-owned enterprises increases household saving rate in China.

This paper shows that, besides the nationwide one-child policy and institutional change, the macro-level trade shocks can also influence household saving behavior. In addition, this paper not only contribute to the high saving rate puzzle in the first decade of 21st century, but also explore the decade following Global Financial Crisis in 2009.

A reduction in household saving rate is observed after 2010. As a result of rapid aging and rises in governmental spending on healthcare, Zhang et al. (2018) expect a continued decline in household savings by 2022. They conduct a comprehensive analysis and list up all the potential forces that determine household saving rates: social safety net, housing reform, rising income and widening inequality, and demographics. They provide a brilliant benchmark to track the trends of saving rate. This paper supplement their study with a new factor: macro-level income shock. At the same time, the inertia expectation adjustment proposed by this paper help to explain the observed bounce-back of household saving rate in China since 2016.

Going forward, we plan to investigate the interaction effects of export slowdown and the demographic and social safety net factors studies previously. We want to re-estimate the impact of export slowdown on saving rate in different sub-samples of households. We consider various scenarios based on whether the household (1) has more than one child; (2) has boys and is located in a city with a high sex ratio; (3) has access to retirement insurance; (4) head work in government and has high job security.

3.7 Conclusion

Export slowdown is a global trade shocks following the Global Financial Crisis in 2009. We analyze the effect of export slowdown on household saving rates using data from Chinese Family Panel Studies (CFPS). We exploit cross-city variation in exposure to the trade shocks to study households' saving behavior in response to the adverse income shock induced by export slowdown. We show that household saving rates are lower in cities that experience a more severe export slowdown.

We find that export slowdown is associated with a decrease in family income and an increase in consumption. Based on Permanent Income Hypothesis, we propose that during a period of export slowdown, households may maintain their confidence in the future even if their family income declines, and they may maintain or increase their consumption level. This optimistic expectation adjustment can lead to a decrease in the household saving rate in response to export slowdown. We test the expectation adjustment mechanism using the data for households' confidence about the future from CFPS. We confirm that export slowdown decreases household saving rate mainly through the optimistic expectation adjustment mechanism. We further provide empirical evidence that households exhibit inertia in expectation adjustment in response to trade shocks.

In the future study, we will explore the interaction effects of export slowdown and demographic factors on household savings. Demographic characteristics are proposed as the potential explanations for China's high household saving rate puzzle. Whether the number of children or the number of household heads' brothers can hedge the income risk induced by export slowdown remains an unexplored research question.

Appendix

Tables

Table A3.1: Export Slowdown and Expectation Adjustment in Urban Households

	(1)	(2)	(3)
	$1/FamilyIncome_{hct}$	$Future\ Confidence_{hct}$	$ExpectationAdj_{hct}$
$ExpSchock_{ct}$	-0.00301**	0.00450	-0.00926***
	(0.00117)	(0.00564)	(0.00320)
N	7429	7790	7425

Standard errors in parentheses

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

Table A3.2: The Mechanism of Expectation Adjustment in Urban Households

	(1)	(2)	(3)	(4)	(5)	(6)
$ExpSchock_{ct}$	1.313*	1.301*	1.322*	1.314*	0.770	-1.437
	(0.682)	(0.662)	(0.686)	(0.667)	(0.495)	(1.384)
$FamilyIncome_{hct}$		1.456**		1.458**		
		(0.581)		(0.581)		
$Future\ Confidence_{hct}$			-0.989	-1.986		
			(2.890)	(2.984)		
$ExpectationAdj_{hct}$					-64.91***	-68.53***
					(9.414)	(10.41)
$ExpectationAdj_{hct}$						-52.67*
$\times ExpSchock_{ct}$						(30.89)
N	6982	6982	6978	6978	6978	6978

Standard errors in parentheses

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

Table A3.3: Export Slowdown and Expectation Adjustment in Rural Households

	(1)	(2)	(3)
	$1/FamilyIncome_{hct}$	$Future\ Confidence_{hct}$	$ExpectationAdj_{hct}$
$ExpSchock_{ct}$	-0.00509	0.0160	-0.00422
	(0.00543)	(0.0105)	(0.0194)
N	8167	8589	8156

Standard errors in parentheses

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

Table A3.4: The Mechanism of Expectation Adjustment in Rural Households

	(1)	(2)	(3)	(4)	(5)	(6)
$ExpSchock_{ct}$	-1.314	-1.221	-1.294	-1.192	-1.020	-10.72***
	(2.596)	(2.535)	(2.577)	(2.515)	(1.537)	(3.665)
$FamilyIncome_{hct}$		1.107		1.108		
		(0.760)		(0.760)		
$Future\ Confidence_{hct}$			-0.145	-0.772		
			(2.544)	(2.478)		
$ExpectationAdj_{hct}$					-55.59***	-54.22***
					(4.094)	(3.366)
$ExpectationAdj_{hct}$						-48.73***
$\times ExpSchock_{ct}$						(14.53)
N	7758	7758	7748	7748	7748	7748

Standard errors in parentheses

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

Table A3.5: Year-Over-Year Analysis: Export Slowdown and Expectation Adjustment

	(1)	(2)	(3)	(4)
exp_shock	-0.123	-0.0995	-0.00697	0.0195
	(0.137)	(0.0626)	(0.0144)	(0.0118)
N	4552	4447	4573	4441

Standard errors in parentheses

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

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