Migration, Housing Constraints, and Inequality: A Quantitative Analysis of China *

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Abstract

We investigate the role of migration and housing constraints in determining income inequality within and across Chinese cities. Combining microdata and a spatial equilibrium model, we quantify the impact of the massive spatial reallocation of workers and the rapid growth of housing costs on the national income distribution. We first show several stylized facts detailing the strong positive correlation between migration inflows, housing costs, and imputed income inequality among Chinese cities. We then build a spatial equilibrium model featuring workers with heterogeneous skills, housing constraints, and heterogeneous returns from housing ownership to explain these facts. Our quantitative results indicate that the reductions in migration costs and the disproportionate growth in productivity across cities and skills result in the observed massive migration flows. Combining with the tight land supply policy in big cities, the expansion of the housing demand causes the rapid growth of housing costs, and enlarges the inequality between local housing owners and migrants. The counterfactual analysis shows that if we redistribute land supply increment by migrant flow and increase land supply toward cities with more migrants, we could lower the within-city income inequality by 14% and the national income inequality by 18%. Meanwhile, we can simultaneously encourage more migration into higher productivity cities.
Keywords: Migration, Cities, Housing Constraints, Inequality;
JEL Classification Numbers: E24, J61, R23, R31;

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1. Introduction

China has observed impressive economic growth over the last four decades after the start of economic reform and opening-up in 1978. This triggered a massive flow of migrant workers moving from under-developed more rural areas to developed coastal areas. Along with the economic growth and the migration flow, there was a huge housing boom, especially in large cities such as Beijing and Shanghai. Housing prices increased by 660% from 2003 to 2013 in Beijing (Fang et al., 2016), which can partly be attributed to the tight land supply regulatory policy. Meanwhile, the income and asset inequality rose from a level similar to the Scandinavia to a level close to the United States (Piketty et al., 2019). Much of this rise was driven by housing asset ownership inequality.

Two natural questions arise: how is the migration wave related to the housing boom in big cities, and does it widen the inequality within cities in China? If these are true, what policy can we implement to alleviate them? To answer these two questions, we first present several stylized facts about the relationship among spatial patterns of migration, housing costs, and inequality in China using household-level survey data. Then we explain these facts in a canonical spatial equilibrium model modified to incorporate heterogeneous wage income and heterogeneous private property income to quantify the effect of housing constraints on the observed income inequality in the data and evaluate the effect of several counterfactual policies. More specifically, we consider a policy that relaxes the heavily constrained land supply in developed cities. China has a very stringent land supply policy under which the central government regulates the land use quota in each region. The central government uses the distribution of quota across regions as a tool to balance the development across different regions. As a result, the distribution of quota is negatively correlated with worker flows: more land quota is distributed to cities losing workers. This leads to a shortage of land supply in developed cities but, at the same time, an excess in under-developed cities. We revisit this policy and investigate the counterfactual of distributing more land quota to more developed cities according to their migration inflows.

This paper is the first study investigating the role of migration and housing constraints in determining income inequality within and across Chinese cities. We verify the fact that rapid migration inflows into developed cities contribute to high housing demand and raise the housing rents, which benefits local real estate owners. Due to the initial distribution of housing ownership and financial constraints, migrants have limited access to the housing market and have to rent housing from local owners. Housing owners benefit as rents go up. Thus, housing ownership inequality increases income inequality in developed cities. The counterfactual analysis shows that relaxing land supply constraints could slow down the growth of housing rents in big cities and reduce income inequality.

In the first step, we show five important stylized facts from data. First, migration in China is highly concentrated in developed areas and especially in certain large cities. The concentration is accelerating across time because of the improvements in the transportation system and the relaxation of the Hukou system.[1] Second, housing costs have increased drastically over time, especially for cities with large numbers of migrant inflows. There is a positive correlation between housing costs (rent per square meter) and net migrant inflows across cities. Third, wage inequality within cities is not correlated with the net inflow of migrants. Fourth, income inequality within cities is positively correlated with net inflows, where we define income as the sum of the wage and the imputed housing asset income. Fifth, cities with higher net inflows of migrants contribute more to the national income inequality. These five stylized facts from data give us a preliminary picture of the whole story. As the economy grows, more and more migrants concentrate in large and developed cities in the coastal areas. The massive increase in housing demand, together with highly regulated land supply, push up the real estate rents and benefit all local house owners. The increasing housing rent then translates into the increasing income inequality between local housing property owners and renters.

In the second step, we construct a spatial equilibrium model to quantify all the five facts and formally explain the mechanism of how the interplay between migration and housing market could lead to the rise of within-city income inequality. The model comprises heterogeneous workers, a representative firm, and a housing sector in each city. Each worker is endowed with a skill level (either high or low skill) and a home city. Workers have to choose where to live and work among all cities in China. Their utility depends on final goods consumption, housing consumption, migration costs, and idiosyncratic unobserved location taste. We assume that the idiosyncratic location taste is Fréchet distributed, which gives us a closed-form commuting probability following the gravity equation (Eaton and Kortum, 2002). Firms produce final goods that can be traded costlessly in the country in a perfectly competitive market. The production technology is a CES function with high skill and low skill labors as the inputs. The housing sector is simplified as a government-controlled entity possessing a technology to convert the land into floor space. This setup captures the fact that in China, the land supply is heavily regulated by the government. There is a quota of land for new

[1]The Hukou system is a unique household registration system. In China, each household has to register in the place where they are initially from, and it is hard to change the registration place during the lifetime. The Hukou system is closely related to the access to public services. For instance, a family migrating from Henan to Shanghai may not be able to send their children to public schools in Shanghai. Therefore, as a result, workers are physically not constrained to move to coastal areas, but suffer from various potential constraints. For more details, please refer to Song (2014).

construction usage in each city. The quota is determined by the central government and sometimes utilized as a tool to balance the development across different regions. Thus, under-developed western regions get much more of the total national new construction land quotas than they need while land supply is severely suppressed in developed eastern regions. This potential policy distortion creates a strong spatial misallocation, as suggested by Hsieh and Moretti (2019).

We then estimate this model in multiple steps. First, we estimate the elasticity of substitution between high and low skill workers in the CES production function using China's college expansion program in the late 1990s as an exogenous shock. This paper is one of the first to investigate the elasticity of substitution between high and low skill workers in China that seriously considers the endogeneity problem. In the second step, we estimate the migration elasticity (the dispersion of the distribution for unobserved location taste) using a high-dimensional fixed effect regression resulting from the gravity equation.

After estimating all the parameters, we solve for unobserved location productivity, migration cost, and construction intensity in each city within the model using data from the years of 2005 and 2010. We show that the migration costs decreased by 42% for low-skill workers and 29% for high-skill workers during this period, which generates much more migration on both the intensive (more migrants between cities where there are already migrants) and the extensive margin (more cities are linked by migrants). In addition, both of the high-skill and low-skill augmented productivity parameters almost double in five years. Productivity growth is fast in all cities of different sizes. Large cities increase more in absolute terms, but small cities increase more in comparative terms. Furthermore, we find that land supply grows much slower in the largest cities than in other cities. Although the construction intensities in those biggest cities rocket up by 133%, the total supply of floor space grows only by 32% due to the restriction on land supply. Conversely, the average growth rate of floor space in all cities is 50%.

The central policy-relevant question then becomes what we can do to reduce income inequality and attract more migrants to highly productive cities. The main policy we impose is the land supply reform. We reallocate the increase of the land supply quota from 2005 to 2010. Rather than giving more land quota to the under-developed areas, we allocate land quota proportionally to the change in the migration inflows to different cities, while keeping the country level total land supply constant. That is, cities attracting more migrants are given more quota. We categorize cities into five tiers with tier one cities as the largest and tier five cities as the smallest in terms of the migration inflow. The model finds that after this reallocation, housing cost increase in big cities are significantly attenuated. Compared with the real world, we can reduce the housing cost in 2010 by 32%

in the first-tier cities and by 18% in the second-tier cities. The reduction of housing costs further incentivizes more workers to migrate to big cities. Finally, we find that imposing this land supply quota reallocation can substantially reduce the national level inequality (measured by the Theil Index) by 18%. Specifically, we reduce the within city level inequality by 42% in the first Tier cities and by 23% in the second Tier cities. We also implement three other counterfactuals. The first is to impose a reasonable property tax on housing owners. The second is to increase the construction intensity in cities. The third is to directly increase land supply. It shows that all of these policies do not work so well in reducing inequality.

Literature Review

Our study extends the current literature in three dimensions. First, we clarify a new mechanism for income inequality and extend knowledge about the increasing inequality in China. There are many studies on income and wage inequality all over the world. Different papers investigate many causes of the inequality, including the skill-biased technological changes and the increase in the return to human capital (Card and DiNardo, 2002; Berman et al., 1998; Moore and Ranjan, 2005), education inequality (Gregorio and Lee, 2002; Sylwester, 2002), trade liberalization (Han et al., 2012; Goldberg and Pavcnik, 2004; Verhoogen, 2008), and privatization (Cuadrado-Ballesteros and Peña-Miguel, 2018; Chao et al., 2006). The closest study is Chen et al. (2018). They find that larger cities have higher income inequality and claim that it is because the migration inflows into larger cities change the skill composition of the workers towards a higher skill premium. In this study, we investigate a new mechanism that migration and the booming housing market can also generate inequality.

Second, this paper contributes to the literature that studies the spatial distribution of labor supply using the EK-Migration framework. Since Ahlfeldt et al. (2015), the literature extends the canonical Eaton and Kortum (2002) international trade framework to introduce worker mobility to explicitly model worker location choices in the presence of migration costs and heterogeneous worker preferences regarding locations. Many of them investigate the internal migration costs, such as Morten and Oliveira (2014), Bryan and Morten (2019), Tombe and Zhu (2019), and Fan (2019). The closet studies to us are Tombe and Zhu (2019) and Fan (2019). The former focuses on how trade and migration costs affect labor productivity in China without differentiating between worker skill types, and the latter focuses on understanding how international trade affects the overall domestic wage inequality and the aggregate skill premium without considering the distribution of property ownership. Our paper aims to understand income inequality stemming from both human capital and wealth ownership differences. Guided by this target, our model is extended to introduce high/low-skill workers and heterogeneous housing ownership. Second, instead of inferring wages from the model, which is the most important ingredient for calculating inequality, we manually collect the wages by industry for as many Chinese cities as we can from individual city statistic yearbooks of each city. Combining this unique dataset with the population census, we construct a comprehensive inequality measure for China and investigate the most realistic policy reforms.

Third, this paper contributes to the literature that studies the housing and land market in China. The so-called *Great Housing Boom* of China is well documented in Fang et al. (2016), Chen and Wen (2017), and Glaeser et al. (2017). The housing boom is unevenly distributed spatially. As Fang et al. (2016) shows, the boom is not universal. More developed cities see disproportional gains in housing prices while less developed cities actually see their housing prices grow more slowly comparing to their GDP growth. Various theories attempt to explain this pattern: Garriga et al. (2017), Liang et al. (2016), and Wu et al. (2016). We contribute to this literature by showing that the inefficient land supply policy, low construction intensity, and massive migration inflows into the larger cities jointly caused the *Great Housing Boom* of China. We also provide counterfactuals on the housing sector, which could lower the housing costs as well as lower the housing inequality.

2. Data

In this study, we need a comprehensive dataset that records an individual's Hukou registration location, their current work location, wage earnings, occupation, housing ownership, and rent payment. Our interest in housing costs and spatial inequality implies that the data must be geographically representative. Moreover, since we want to estimate migration elasticity, the dataset must be large enough to record flows between all pairs of locations. Only the *Chinese Census* (*Census* for short) meets all these specifications. We also supplement the *Census* with the *City Statistic Yearbooks* and the *Urban Statistic Yearbooks* for city-level aggregate variables. Finally, we need the *Urban Household Survey* to estimate the elasticity of substitution between high and low -skill workers. We introduce these datasets sequentially as below in depth.

The *Census* is the most comprehensive household-level survey in China. It is conducted every ten years, and all residents in the territory of mainland China are surveyed. In the survey, 90% of the households report only basic demographic information, including the Hukou registration location and the current location of their work. The other 10% of the households take a so-called "long-survey," which asks additional questions including items dealing with housing conditions, rents, and jobs. Midway between two *Census* years, a *Mini-census* is conducted. The *Mini-census* randomly selects 1% of the population and asks a list of questions similar to the ones in the long survey of the decennial *Census*. In this study, we use the decennial *Census* in 2010 and the *Mini-census* in 2005 to calculate the city-level migration flows and housing rents.[2] In our sample, we have 2,585,481 observations in the year of 2005, which covers 0.2% of the whole population. We have 4,803,589 observations in the year of 2010, which covers 0.36% of the whole population.

The *City Statistic Yearbooks* are books including all collected socioeconomic data for specific cities. Each city has its own yearbook, and the data is collected by the local branch of the National Bureau of Statistics. The *Urban Statistic Yearbook* is a book with a summary of key economic indicators across all Chinese cities in a specific year. In this study, we need average wages for different skills (education levels) in different cities in 2005 and 2010. However, there is no data directly showing average high-skill (college-educated) wages and average low-skill (not college-educated) wages in each city. Fortunately, in the *City Statistic Yearbooks* of each city, they have data on average wages in different industries in this city. In addition, in the *Census* data, there is information about an individual's education level and working industry. To impute the city-skill level average wages, we first assign average city-industry level wages to individuals in the *Census* employed in a specific working industry in a specific city. Then we take the average of the wages of all individuals with a specific education level in the same city to achieve the city-skill level average wages in 2005 and 2010. In essence, what we do is to calculate city-skill-level wages using average city-industry wages, weighted by the number of workers with different education levels in each industry. Since the *City Statistic Yearbooks* are published separately by different local governments, we have to manually collect over 600 books for 2005 and 2010. There are some cities for which we cannot find for the exact years of 2005 and 2010. We replace these missing years by the closest year we could find and impute the wages using city-level GDP growth rates.[3] The replacement is less than 5% of the observations and is usually for less developed cities. The city-level GDP growth rate is derived from the *Urban Statistic Yearbook*. The land area data is also from the *Urban Statistic Yearbook* in 2005 and 2010.

The *Urban Household Survey* (UHS) is a national survey conducted by the National Bureau of Statistics in China. The survey starts in the 1980s and focuses on several aspects of Chinese house-

[2]From now on we call decennial *Census* and *Mini-census* as *Census* in general for conciseness.

[3]For example, if we cannot find the *City Statistic Yearbook* of Beijing in 2005 and can only find the one in 2004, then we use city-industry level wages for Beijing in 2004 and multiply them by Beijing's GDP growth rate in 2005 to estimate city-industry level wages for Beijing in 2005.

holds in urban areas, including their basic demographic characteristics, income, consumption, assets, and durable goods holdings. In this study, we employ surveys from 1993 to 2009 to get a long panel data of skill premium and proportion of high-skill over low-skill labors in different provinces.

3. Five Stylized Facts about Migration in China

From our data, we could calculate the migration flows between city-pairs, the net migration inflow into each city, the skill share in each city, housing costs in each city, within-city inequality, and nationwide inequality. From this, we document five stylized facts about migration in China.

Fact 1: Migration is highly & increasingly concentrated in certain large cities.

To document Fact 1, we calculate the net inflow of migration across all Chinese cities in 2005 and 2010, respectively. The net inflow for city i is calculated as follows:

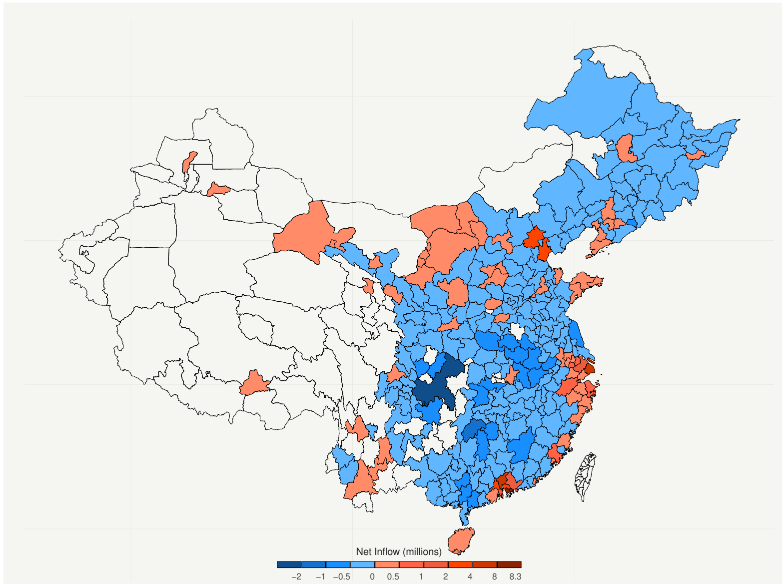
$$\text{Net Inflow}_j = \text{Current Workers}_j - \text{Hukou Workers}_j \tag{1}$$

where Current Workers_j is the total number of workers who are currently working in city i, and Hukou Workers_j is the total number of workers whose Hukou Registration is located in city j. Therefore, the net inflow reflects the net gain or loss of the working population of each city. If a city maintains its employed population, the net inflow will be zero.

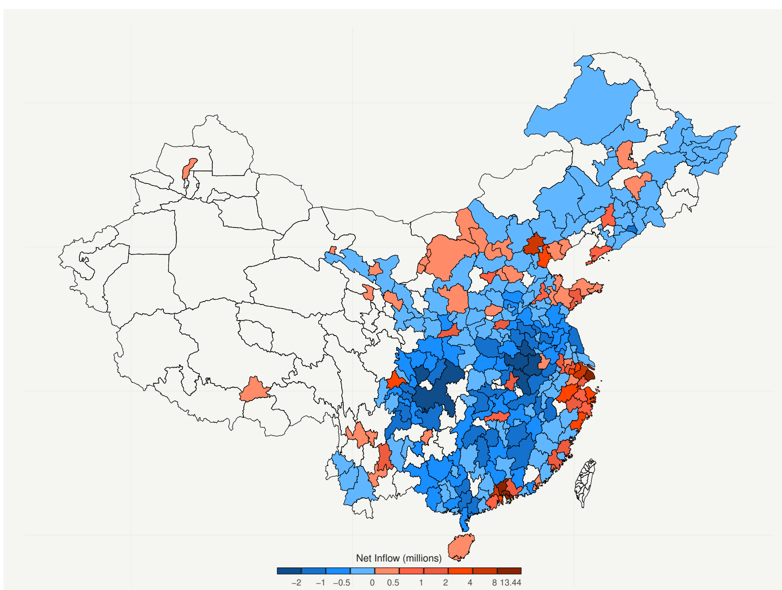
To visualize the migration patterns, we geographically plot the net inflow in 2005 by city in panel (a) of Figure 1 and the net inflow in 2010 by city in panel (b). The coloring pattern follows the cutoffs in Table 1 for both years. Each interval in the table means the range of the net migration. For instance, in 2010, there are 39 cities with a net inflow of migration between 0 to 0.5 million. It is obvious that workers are migrating from western and central regions to eastern regions, and from inner-land cities to coastal cities. Most of the big industrialized cities are located along the eastern coastline. There are four main economic zones where cities with huge migration inflows cluster: (1) the Bohai Economic Rim, led by Beijing and Tianjin; (2) the Yangtze River Delta Zone, led by Shanghai, Suzhou, and Hangzhou; (3) the Western Taiwan Straits Zone, led by Xiamen; (4) the Pearl River Delta Zone, led by Guangzhou (Canton), Shenzhen, and Hong Kong. Table 1 also shows that most of the cities lose workers, and only about one-fourth of the cities have positive net inflows.

Migration is also increasingly concentrated in certain large cities. As the colors in Figure 1 indicate, the concentration of migration grows during these five years. From 2005 to 2010, inland

Figure 1: Net Inflow of migrants by city in China



(a) Net Flow of Workers in 2005



(b) Net Flow of Workers in 2010

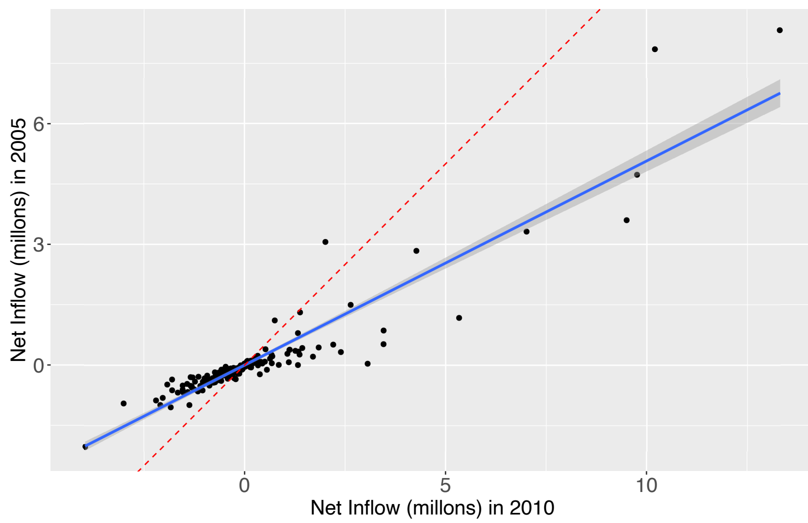
Notes: The sample only includes workers with wage income, which means that we exclude retired workers, persistently unemployed workers (zero wage income for the whole year), children, students, homemakers, and others. Net Flow of workers in city i is calculated as current workers in city i minus Hukou workers in city i. Therefore, this measure reflects the net gain in the working population for each city. We only have data on 287 cities. Though the blank parts are missing, the 287 cities with available data cover more than 95% of the Chinese population.

Table 1: **Number of Cities with Different Net Worker Migration Inflow**

Year	Total	(-4,-2)	(-2,-1)	(-1,-0.5)	(-0.5,0)	(0, 0.5)	(0.5,1)	(1,2)	(2,4)	(4,8)	(8+)
2005	287	1	1	23	188	59	4	4	4	2	1
2010	266	6	29	41	115	39	9	13	7	3	4

Notes: This Table is exactly the standard of coloring in the Map (Figure 1).

Figure 2: Correlation of Net Flow in 2005 & 2010

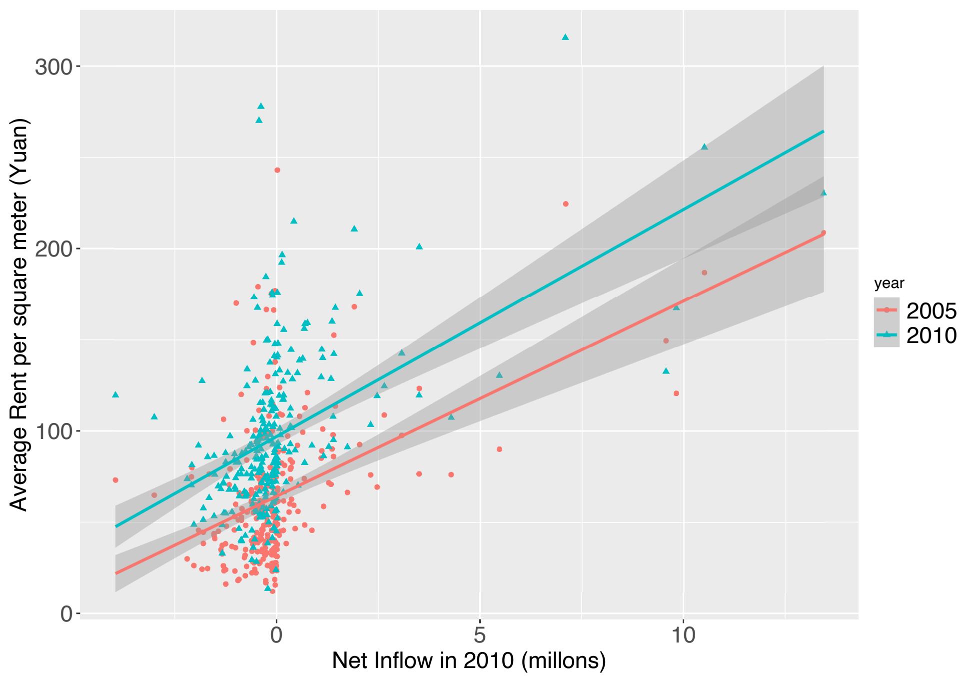


cities lose more workers, and big eastern cities gain more. To provide more intuition, we also plot the correlation between net inflows in 2005 and in 2010 in Figure 2. The red dashed line is the 45-degree line. The fitted line has a slope much smaller than one, and the big cities with a net gain of workers in 2010 are all below the 45-degree line, which means that the concentration is increasing over these years. We also show the patterns measured as the share of net inflows in Appendix A.1. The results are similar.

Fact 2: Housing costs increase drastically with the net inflow of migrants and across time.

Figure 3 shows the correlation between the net inflow of worker migration and the annual average housing rent per square meter in different cities. It is clear that net inflows in cities are positively correlated with housing rent costs. A simple regression suggests that increasing the migrant inflow by one million workers is associated with a 17.9 RMB (about 2.6 USD) increase in the annual average

Figure 3: Correlation of Net Inflow and Rent Cost



housing rent per square meter in 2005. The corresponding number in 2010 is 13.4 RMB (about 1.9 USD). The average living space for tenants in 2005 and 2010 is 43.3 and 43.9 square meters. Thus, on average, one million new migrants is associated with a 775.1 RMB (about 110.7 USD) or a 588.3 RMB (84.0 USD) increase in the annual housing rent in 2005 and 2010, respectively. In addition, the national average housing rent increases sharply from 288.6 RMB per square meter to 460.5 RMB per square meter, which corresponds to a 60% increase. The pattern in the plot and these numbers indicate that housing costs increase drastically with the net inflow of migrants and across time.

Fact 3: Wage inequality within cities is weakly correlated with net inflow.

To document Fact 3∼5, we calculate the Theil Index for wages and total income at both the national level and the city-level for all Chinese cities in 2005 and 2010, respectively. We denote each city by j, each individual worker with skill s by n, the wage of each individual worker sn currently working in city j by w^s_{jn}, and the total income of each individual worker sn currently working in city j by $i^s_{jn} = w^s_{jn} +$ housing asset income$^s_{jn}$. Housing asset income is calculated as follows. First, we calculate the housing consumption for local families owning houses by multiplying the size of their houses and the city-level average rent. Then we take the average of this housing consumption in the city and attribute it to the local residents who own houses. Thus, the income is the sum of the wage (which is the non-housing consumption) and the imputed housing consumption.[4] There could be a potential underestimation of house owners' income because housing prices have risen rapidly, and they usually have more financial assets than non-owners. Because we do not have data on other assets, we take the housing ownership imputed income as a lower bound. However, we claim that this is a decent approximation since the housing asset accounts for 74.2% of the total asset in Chinese families, according to a report by the Central Bank of China.[5] The city-level Theil Index is:

$$
\begin{aligned}
T_j^w &= \frac{1}{N_j}\sum_{n^s=1}^{N_j^s}\sum_{s=1}^{S}\frac{w_{jn}^s}{\bar{w_j}}ln\frac{w_{jn}^s}{\bar{w_j}} \text{ , for wage} \\
T_j^i &= \frac{1}{N_j}\sum_{n=1}^{N_j^s}\sum_{s=1}^{S}\frac{i_{jn}^s}{\bar{i_j}}ln\frac{i_{jn}^s}{\bar{i_j}} \text{ , for income}
\end{aligned}
\tag{2}
$$

where N_j^s is the total population of skill s workers in city j, $N_j = \sum_{s=1}^{S} N_j^s$ is the total population in city j, $\bar{w_j}$ is the average wage in city j, and $\bar{i_j}$ is the average income in city j.

The national-level Theil Index is:

$$
\begin{aligned}
T^w &= \sum_{j=1}^{J} s_j^w (T_j^w + ln\frac{\bar{w_j}}{\bar{w}}) \text{ , for wage} \\
T^i &= \sum_{j=1}^{J} s_j^i (T_j^i + ln\frac{\bar{i_j}}{\bar{i}}) \text{ , for income}
\end{aligned}
\tag{3}
$$

where $s_j = \frac{N_j}{N}\frac{\bar{x_i}}{\bar{x}}$ for $x = \{w, i\}$ is the weight of wage/income share which indicates the importance of each city's role in calculating national inequality.

With both the city-level Theil Index and the national-level Theil Index, we can easily calculate

[4]Alternatively, we investigate this correlation with two other definitions of the housing asset income. First, we calculate the housing asset income by using the actual square meters a worker owns times the per square meter rent in that city, rather than the city average. For instance, a three-person household who owns a $90m^2$ apartment in Beijing, where the average rent is $300/m^2$, then the household head's estimated housing asset income is $\frac{90}{3} \times 300 = 9000$RMB. Second, we calculate the housing asset income for all housing owners rather than just local housing owners. The basic patterns in inequality are similar in these two different definitions. The results are available upon request.

[5]Please refer to https://baijiahao.baidu.com/s?id=1664830535681198027&wfr=spider&for=pc (in Chinese).

each city's contribution to the national-level Theil Index as follows:

$$\begin{aligned} Contri_j^w &= s_j^w (T_j^w + ln\frac{\bar{w_j}}{\bar{w}})/T^w \text{ , for wage} \\ Contri_j^i &= s_j^i (T_j^i + ln\frac{\bar{i_j}}{\bar{\bar{i}}})/T^i \text{ , for income} \end{aligned} \quad (4)$$

Figure 4: Correlation of Net Inflow and Wage Inequality within Cities

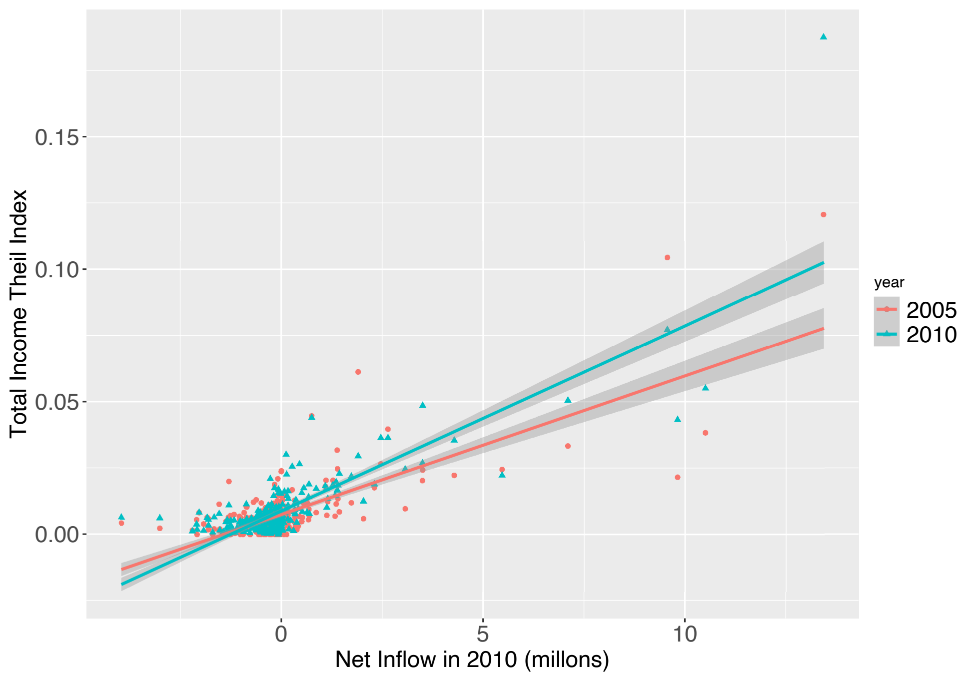
Figure 4 displays the correlation between within city inequality and the net inflow of migrants in the city. A higher Theil Index means a higher inequality level.[6] The reason why we use the Theil Index is that it can be easily decomposed into small groups. Specifically, a national level Theil Index can be decomposed into two terms. The first term is a weighted average of Theil Index scores for city-level mean wages (inequality across cities). The second term is a weighted average of the Theil Index of individual wages within different cities (inequality within cities). Therefore, it is natural to calculate the contribution of each city to the national level inequality (Novotnỳ, 2007). The figure indicates that there is only a weak positive correlation between wage inequality within cities and migrant net migrant inflows. The slope coefficient of the fitted line is also not significant statistically. Thus, wage inequality within the city is not strongly correlated with the net inflow of the city.

[6]We also try traditional Gini Index, and the results are robust.

Fact 4: Income inequality within cities is positively correlated with net inflows

Although it seems that larger cities with more migrants do not have significantly higher wage inequality, once we consider housing costs, it becomes another story. We calculate total income as the sum of the wage and the housing asset income. Figure 5 shows that income inequality within cities is positively correlated with the net inflow of migrants. Bigger cities are more unequal when housing asset income is considered. The slope coefficient of the fitted line is not zero with statistical significance.[7] This indicates that housing asset inequality contributes a lot to the income inequality in Chinese cities that have a large number of migrant workers with zero housing asset income.

Figure 5: Correlation of Net Inflow and Income Inequality within Cities

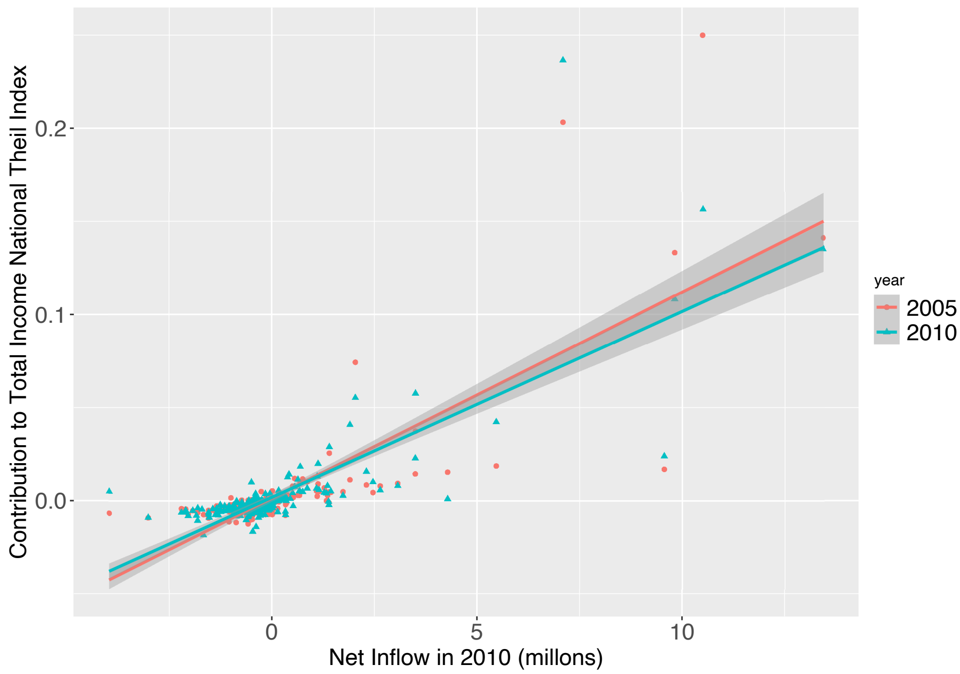


Fact 5: Cities with higher net inflows contribute more to national income inequality

When we decompose national income inequality into the two parts mentioned in equation 4, we can calculate the contribution of each city to the country's overall inequality. Figure 6 shows the correlation between cities' contributions and their net inflows of migrants. A strong positive relationship is detected, which means that larger developed cities with more migrants are contributing

[7]The financial information of households in the *Census* dataset is limited. We use another dataset called *Chinese Household Income Project* to investigate some other details about the inequality between local residents and migrants. Please refer to Appendix A.2.

Figure 6: Correlation of Net Inflow and Contribution to National Inequality



much more to the national income inequality. This pattern is further strengthened when large cities become even larger. For instance, at the corner of the figure, three cities: Shanghai, Shenzhen, and Beijing collectively contribute almost 60%, 40%, and 50%, respectively, to national income inequality in 2010[8]. These numbers were much lower in 2005 (45%, 30%, and 37%, respectively). This indicates that certain Chinese cities with sizeable net inflows of workers are much more unequal in income than other cities.

Remarks of the Stylized Facts

We have shown five important patterns about migration, housing costs, and income inequality in China[9]. It illustrates that as China continues to urbanize, more and more workers are migrating from rural inland areas to developed coastal areas. Because of the restrictive land supply regulations in China, the huge inflow of working-age migrants lifts the housing demand in big industrialized cities and results in a rapid increase in housing costs. Because most of the property-owners are local residents, incumbent locals benefit a lot from the rising rents at the expense of renting migrants.

[8]The majority of small cities contribute negatively to national income inequality. That is why the total contribution still sums up to 100% even though the collectively contribution of larger cities is larger than 100%.

[9]Additional results dealing with the stylized facts are presented in Appendix A.

This yields the observed positive relation between within city income inequality and the net inflows, even without any correlation between within city wage inequality and net inflows. We now ask that how can we alleviate income inequality and motivate more migration flows from less developed/productive areas to more developed/productive areas? This is the main target of this study. To answer this, we construct a spatial equilibrium model with a housing sector and evaluate different policy counterfactuals.

4. The Model

Our general equilibrium model of migration builds on the strand of work by Eaton and Kortum (2002), Ahlfeldt et al. (2015), and Tombe and Zhu (2019). We extend the literature by introducing workers with heterogeneous skills, which interacts with endogenous housing constraints as in Ahlfeldt et al. (2015) and local-only return from land factor income as in Tombe and Zhu (2019)[10].

The economy consists of a set of discrete locations, specifically in this paper, **cities**, which are indexed by $j = 1, ..., K$. The economy is populated by an exogenous measure of H workers, who are imperfectly mobile within the economy subject to migration costs. Each worker is either low skill $s = l$ or high skill $s = h$ and the total labor in a city is the sum of the two skills, that is, $H_j = H_j^l + H_j^h$. Each location j has an effective supply of floor space S_j, which is produced by combining capital K_j and a fixed amount of land supply L_j.

Workers decide whether or not to move after observing an idiosyncratic utility shock for each possible destination location. Firms produce a single final good, which is costlessly traded within the city and across the country which we take as the numeraire. Locations differ in terms of their final goods productivity (A_j) and the supply of floor space (S_j).

4.1 Worker Preferences

The utility of a worker o with skill s, originating from region i and migrating to region j is an aggregation of final good consumption (c_{ijo}), residential space consumption (s_{ijo}), migration costs

[10]This assumption is largely consistent with China's reality. According to national statistics, 75% of household wealth is housing assets. Meanwhile, only a small number of migrants could buy an apartment in the city where they are currently working due to financial constraints and housing market regulations.

(τ_{ij}^s), and an idiosyncratic shock (z_{ijo}) in a Cobb-Douglas form:

$$U_{ijo} = \frac{z_{ijo}}{\tau_{ij}^s}\left(\frac{c_{ijo}}{\beta}\right)^{\beta}\left(\frac{s_{ijo}}{1-\beta}\right)^{1-\beta} \tag{5}$$

We model the heterogeneity in the utility that workers derive from working in different parts of the economy following Eaton and Kortum (2002). For each worker o originating from city i and migrating to city j, the idiosyncratic component of utility (z_{ijo}) is drawn from an independent Fréchet distribution:

$$F(z_{ijo}) = e^{-z_{ijo}^{-\epsilon}},\ \epsilon > 1 \tag{6}$$

where the shape parameter $\epsilon > 1$ controls the dispersion of the idiosyncratic shock. We assume that the migration costs can be separated into two parts:

$$\tau_{ij}^s = \bar{\tau}_i^s d_{ij} \tag{7}$$

where d_{ij} captures the physical distance and institutional costs, due to the Hukou system and other potential frictions, in migrating from city i to city j, and $\bar{\tau}_i^s$ captures the difference in the cost across individuals with different skills. It may include skill-biased migration policies, differences in their preferences for specific types of amenities such as education for children, entertainment, transportation, and many others.

After observing the realizations for idiosyncratic utility for each employment location, each worker chooses his location of employment to maximize his utility, taking as given residential amenities, goods prices, factor prices, and the location decisions of other workers and firms. Each worker is endowed with one unit of labor that is supplied inelastically with zero disutility. Combining our choice of the final good as numeraire with the first-order conditions for the consumer, we obtain the following demands for the final good and residential land for worker o with skill s from location i who is migrating to location j:

$$c_{ijo} = \beta v_{ij}^s \tag{8}$$

$$s_{ijo} = (1-\beta)\frac{v_{ij}^s}{Q_j} \tag{9}$$

where v_{ij}^s is the total income, including wage income and return from owning floor space, received by workers in city j. Q_j is the unit rent of residential floor space in city j.

Floor space is not tradable and is commonly owned by local incumbent (Hukou) residents. This assumption is broadly consistent with the institutional features of China[11] and implies that migrant workers have no claim to this fixed factor income of their current working city. Therefore, the income v_{ij}^s is a combination of the wage income of skill s workers and the equally-divided rent income among local Hukou residents:

$$v_{ij}^s = w_j^s + \frac{Q_i S_i}{H_{ii}^R} \cdot \mathbb{1}(i = j) \tag{10}$$

where H_{ii}^R is the number of local Hukou residents staying in their origination city i and S_i is the residential floor space in city i. Families migrating to other cities cannot benefit from the rent in their hometowns or in their destination cities. This is one of the frictions that hinders workers' migration activities, especially those originating rural areas. Since this equation determines the gap between wage income and total income, we also construct an alternative model with the residential floor space revenue redistributed among all Hukou registered residents, including those who migrate out, as a robustness check in Appendix C.

Substituting equilibrium consumption of the final good and residential land use into the utility function, we obtain the following expression for the indirect utility function:

$$U_{ijo} = \frac{z_{ijo} v_{ij}^s Q_j^{\beta-1}}{\tau_{ij}^s} \tag{11}$$

4.2 Distribution of Utility and Migration Flow

Using the monotonic relationship between the utility and the idiosyncratic shock, the distribution of utility for a worker migrating from city i to city j is also Fréchet distributed:

$$G_{ij}^s(u) = Pr[U \leq u] = F\Big(\frac{u \tau_{ij}^s Q_j^{1-\beta}}{v_{ij}^s}\Big) \tag{12}$$

$$G_{ij}^s(u) = e^{-\Phi_{ij}^s u^{-\epsilon}}, \ \Phi_{ij}^s = (\tau_{ij}^s Q_j^{1-\beta})^{-\epsilon} (v_{ij}^s)^{\epsilon} \tag{13}$$

Since the maximum of a sequence of Fréchet distributed random variables is itself Fréchet dis-

[11]Many migrants own local properties in their Hukou city (mostly rural countryside houses), which are hard to be rented out. Therefore, when they leave their hometown, they lose all the revenue from these properties, even imputed rent through self-consumption.

tributed, the distribution of utility across all possible destinations is:

$$1 - G_i^s(u) = 1 - \prod_{k=1}^{K} e^{-\Phi_{ik}^s u^{-\epsilon}} \tag{14}$$

we have

$$G_i^s(u) = e^{-\Phi_i^s u^{-\epsilon}},\ \Phi_i^s = \sum_{k=1}^{K} \Phi_{ik}^s \tag{15}$$

Let π_{ij}^s denote the share of workers with skill s registered in city i who migrate to city j. The proportion of workers who migrate to city j is:

$$\pi_{ij}^s = \frac{(\tau_{ij}^s Q_j^{1-\beta})^{-\epsilon}(v_{ij}^s)^{\epsilon}}{\sum_{k=1}^{K}(\tau_{ik}^s Q_k^{1-\beta})^{-\epsilon}(v_{ik}^s)^{\epsilon}} = \frac{\Phi_{ij}^s}{\Phi_i^s} \tag{16}$$

4.3 Production

We assume there is a single final good that is costlessly traded in the economy. It is produced with perfect competition and constant returns to scale with the following technology:

$$X_j = [(A_j^h H_j^h)^{\frac{\sigma-1}{\sigma}} + (A_j^l H_j^l)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \tag{17}$$

where X_j is a CES combination of high skill labor H_j^h and low skill labor H_j^l multiplied by their corresponding city-level efficiency A_j^h and A_j^l respectively.

Firms choose their inputs of workers with different skills to maximize profits, taking as given the final goods productivity ($\{A_j^h, A_j^l\}$), the distribution of idiosyncratic utility, factor prices, and the location decisions of other firms and workers. From the first-order conditions for profit maximization, we obtain:

$$w_j^l = {A_j^l}^{\frac{\sigma-1}{\sigma}} X_j^{\frac{1}{\sigma}} {H_j^l}^{-\frac{1}{\sigma}} \tag{18}$$

$$w_j^h = {A_j^h}^{\frac{\sigma-1}{\sigma}} X_j^{\frac{1}{\sigma}} {H_j^h}^{-\frac{1}{\sigma}} \tag{19}$$

This also gives us a measure of the skill premium ω in city j:

$$\omega_j = \frac{w_j^h}{w_j^l} = \left(\frac{A_j^h}{A_j^l}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{H_j^h}{H_j^l}\right)^{-\frac{1}{\sigma}} \tag{20}$$

The zero profit assumption gives us:

$$X_j = w_j^l H_j^l + w_j^h H_j^h \tag{21}$$

4.4 Land Market Clearing

The standard approach in the urban literature is to assume that floor space S is supplied by a competitive construction sector that uses a Cobb-Douglas technology with geographic land L and construction intensity K as inputs. However, the Chinese land market is highly regulated. The central government restrictively determines both the construction intensity and land supply. Therefore, we assume the following floor space production function with regulated intensity ϕ_j and regulated land supply L_j in each city j:

$$S_j = \phi_j L_j \tag{22}$$

where ϕ_j represents the allowed density of development (the ratio of floor space to land).

Residential land market clearing implies that the demand for residential floor space equals the supply of residential floor space in each location. Using utility maximization for each worker and taking expectations over the distribution for idiosyncratic utility, this residential land market clearing condition can be expressed as:

$$S_j = E[s_j]H_j = (1-\beta)\frac{E[v_j]H_j}{Q_j} \tag{23}$$

4.5 Definition of Spatial General Equilibrium

We define and characterize the properties of this spatial general equilibrium given the model's fixed parameters $\{\beta, \epsilon, \sigma, \eta\}$.

*A **Spatial General Equilibrium** for this economy is defined by a list of exogenous economic conditions $\{\tau_{ij}^s, A_j^s, \phi_j, L_j, H_i^s\}$, a list of endogenous prices $\{Q_j, w_j^s\}$, quantities $\{v_{ij}^s, y_j, H_j^s, S_j\}$, and proportions $\{\pi_{ij}^s\}$ that solve the firm's problem, the worker's problem, the floor space producer's problem, and market clearing such that:*

> *(i).**[Worker Optimization]** Taking the exogenous economic conditions $\{\tau_{ij}^s\}$ and the aggregate prices $\{Q_j, w_j^s\}$ as given, the optimal migration choices of workers pins down the equilibrium labor supply in each city H_j^s and the migration flow between each city pairs π_{ij}^s.*

*(ii).**[Firm Optimization]** Taking the exogenous economic conditions $\{A_j^s\}$ and the aggregate prices $\{w_j^s\}$ as given, firms' optimal production choices pin down the equilibrium labor demand H_j^s.*

*(iv).**[Market Clearing]** For all cities, labor supply equals labor demand and floor space supply equals floor space demand. This pins down the equilibrium aggregate prices $\{Q_j, w_j^s\}$, the equilibrium floor space S_j, and the equilibrium output y_j.*

5. Estimation

5.1 Worker Preferences

We first match $(1-\beta)$ to the share of residential floor space cost in consumer expenditure to pin down the share parameters in the worker preferences (β).

We use the average accommodation expenditure share of total consumption from UHS to match $(1-\beta)$. The survey is conducted by the National Bureau of Statistics of China with a change in statistics standard in 2012. We think the new standard is more realistic which give us an average around 23% from 2013 to 2017.[12] Hence, we choose (β) to be equal to 0.77.

5.2 Elasticity of Substitution between H/L-skills

The estimation results of the elasticity of substitution between high and low-skill labor in China are mixed in previous studies (Dong et al., 2013; Song et al., 2010). We follow the canonical model of Katz and Murphy (1992) to estimate the elasticity of substitution between high-skill labors and low-skill labor. Recall from the skill premium equation that

$$ln(\omega_j) = \frac{\sigma - 1}{\sigma} ln\Big(\frac{A_j^h}{A_j^l}\Big) - \frac{1}{\sigma} ln\Big(\frac{H_j^h}{H_j^l}\Big)$$

We estimate this equation using panel data from the UHS. Productivity A_{jt} varies by location and

[12] According to the old statistical standard, the average housing expenditure share ranges from 11.7% in 2012 to 14.3% in 2002 which is very low because they did not include the converted rent costs of self-owned houses and apartments. From 2013, the converted rent costs of self-owned houses and apartments are added to housing costs, which results in a range of 22.7% in 2017 to 23.3% in 2013. We find that the average expenditure share is very stable across time within both periods.

time, so do the supply of high-skill and low-skill workers and the high-skill/low-skill wage ratio. We observe wages and thus can calculate the wage premium. Hence, the unknowns are σ and A^h_{jt}/A^l_{jt}. Therefore, we can estimate this model as:

$$ln(\omega_{jt}) = \gamma_0 + \gamma_1 ln\Big(\frac{H^h_{jt}}{H^l_{jt}}\Big) + \epsilon_{jt} \tag{24}$$

where γ_0 is a constant and $\hat{\gamma_1}$ is an estimate of $-1/\sigma$. σ can be derived when γ_1 is estimated. Here we use the subscript j to denote province rather than city since we do not have enough data to recover city-level skill premium and labor ratio for a long period.

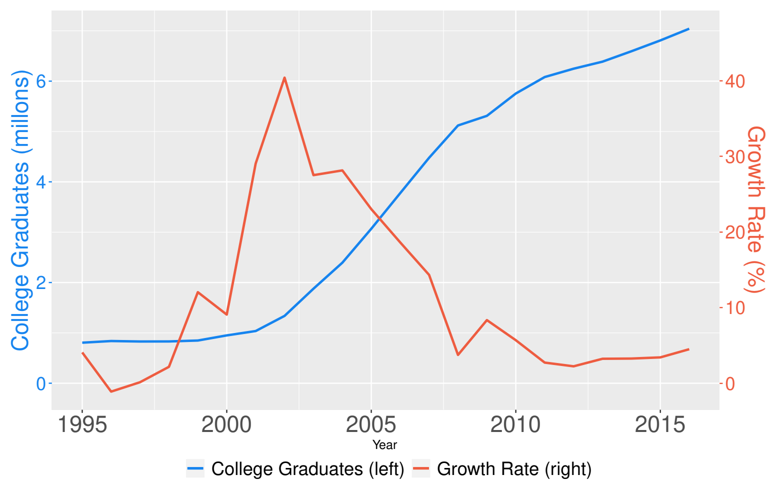
In equation (24), the error term includes location-time variant part of the ratio of high-skill labor-augmented and low-skill labor augmented-productivities $\frac{A^h_{jt}}{A^l_{jt}}$. As this ratio determines the relative wages of high-skill and low-skill workers in a city, it is correlated with the ratio of the number of high-skill to low-skill workers in that city. Thus, σ cannot be identified by a naive OLS regression.

To solve the identification difficulty in equation (24), we employ a national-level higher education expansion in China in the late 1990s as a quasi-experiment. In China, the quota of new students in colleges is set by the Ministry of Education. The Ministry makes five-year plans for student enrollment for each school according to their capacity and reputation. However, in 1999, the State Council announced an ambitious project to expand the higher education system and increase the number of students admitted to colleges. To meet the new edict, the Ministry of Education had to abruptly revise the planned quota just two weeks before the College Entrance Exam, which was considered to be a huge unexpected labor market shock.[13] The allocation of the increased quota was mainly proportional to the original plan[14] (Feng et al., 2018) though it tended to slightly favor underdeveloped areas (Kang, 2000). Approximately 300,000 more new students are admitted to colleges in 1999 compared to 1998, which corresponds to a 43% increase. In 2000 the expansion continued, and another 220,000 more new students were enrolled compared to 1999. The magnitude of the increase then declined and growth in enrollments returned to a normal level after the mid-2000s. The time span of higher education in China ranges from two to four years. Thus, the first wave of additional college graduates flooded into the labor market in 2001 and reshaped the ratio of high-skill to low-skill workers. This episode of college expansion is shown in Figure 7. We can clearly detect a huge positive shock after 2001.

[13]For more details, see Li et al. (2014) and Feng et al. (2018).

[14]That is, the Ministry of Education imposed the same growth rate for all cities.

Figure 7: College Expansion in China (1995-2016)



This shock on the labor market can be regarded as exogenous. Consider the following regression:

$$ln(\omega_{jt}) = \gamma_0' + \gamma_1 ln\Big(\frac{H_{jt}^h}{H_{jt}^l}\Big) + year_t + province_j + \epsilon_{jt} \tag{25}$$

where $year_t$ is the year fixed effect and $province_j$ is the province fixed effect. After controlling for the time and the province fixed effects, we may still have the endogeneity problem since the shocks to productivity and the composition of the labor force, captured by $ln\Big(\frac{H_{jt}^h}{H_{jt}^l}\Big)$, in the same year for the same province are correlated. To resolve this, we construct an instrument for the ratio of high-skill workers to low-skill workers. The basic idea is that the college expansion had different effects on different provinces. On one hand, provinces with more colleges may have more newly-graduate college students. On the other hand, even if shocks are similar in absolute scale across all provinces, the initial skill composition of the labor market could result in different changes in $ln\Big(\frac{H_{jt}^h}{H_{jt}^l}\Big)$. Provinces with fewer high-skill workers initially, could be affected more.[15] We construct the IV as the interaction between the indicator of whether the observation (province-year) is within the period of the expansion and the province indicators. We select the period of the expansion to be

[15]For instance, assume simply that all students will work in the province where their colleges is located. In province A, we assume that the initial level of H^h is 10, and the initial level of H^l is 100. Then the initial skill ratio is $\frac{1}{10}$. In province B, we assume that the initial level of H^h is 20, and the initial level of H^l is 90. Then the initial skill ratio is $\frac{2}{9}$. If the college expansion results in an increase of 10 new high-skill workers in both provinces, the skill ratio in province A would change from $\frac{1}{10}$ to $\frac{1}{5}$, which corresponds to a 100% change. Then change in province B is from $\frac{2}{9}$ to $\frac{1}{3}$, which corresponds to a 50% change. It is obvious that the same scale increase in the expansion of college graduates, leads to very different changes in the skill composition in the local labor market.

between 2001 to 2004. There are two reasons why we do not want to include years after 2004. First, firms can adjust to this shock, and after several years they can form the expectations of a growing high skill labor force, which will contaminate the IV. Second, in Figure 7 we can see that the growth rate of the number of college graduates starts to decline to a normal level after 2005. We also check the results when the policy window is extended to 2005 or 2006. There is no significant change in the point estimation.[16]

Mathematically, we can write the instrument for $ln\left(\frac{H^h_{jt}}{H^l_{jt}}\right)$ in province j in year t, as $\mathbf{1}(2001 \leq t \leq 2004) \times \mathbf{1}(Province_j)$. We call the time indicator variable $\mathbf{1}(2001 \leq t \leq 2004)$ "expansion". The exclusion restriction we impose is that the provincial differences in the college expansion affect local wages only through the channel of changing the high-skill/low-skill labor ratio in the local labor market. In other words, the different effects of college expansion in different provinces are not correlated with province-year productivity shocks. We claim that this is true since the allocation of the quota is proportional to the original plan and unlikely to be correlated with future shocks.[17]

The wage information and high-skill/low-skill ratio information are derived from the UHS (Urban Household Survey) dataset from 1993 to 2009 in urban areas in China. In this dataset, we have information about individuals' wages and educational attainments in six provinces (Beijing, Liaoning, Zhejiang, Guangdong, Sichuan, and Shaanxi). We use only currently employed workers and define high-skill workers as those currently working who have college degrees (both two/three-year and four-year colleges). From 1993 to 2001, there are 1000 to 2000 workers for each province in each year. After 2001, we have 2000 to 8000 workers for each province in each year.

With this micro-level data, we calculate the mean wages of each province j in each year t, for both high-skill and low-skill workers. The skill premium is the corresponding wage ratio. We also calculate the high-skill to low-skill worker ratio in each province and year by counting the number of workers with and without at least a college degree. We have data of six provinces over seventeen years. Thus, in the provincial level regression, we have $6 \times 17 = 102$ observations.

The results are shown in Table 2 and 3. In the first stage regression, the positive relationship between the college expansion and the high-skill over low-skill labor ratio is statistically and economically significant.[18] In addition, we can detect very different effects of college expansion across

[16]We check different policy window cutoffs (2001 to 2005, 2001 to 2006, 2001 to 2007, 2002 to 2004, 2002 to 2005, 2002 to 2006, 2002 to 2007) for the college expansion and find no significant change in the qualitative conclusion.

[17]In a paper written by a main leader of the Ministry of Education, he admits that even if they want to allocate enrollment quota based on the predicted future changes in the labor market in different locations, it is impossible to implement it in reality due to the institutional reasons. See Kang (2000) for more details.

[18]Due to the multi-collinearity, the dummy for the year of 2004 is omitted in the regression.

Table 2: First Stage Regression Estimating the Elasticity of Substitution

Variables	OLS
expansion	0.645***
	(0.0904)
expansion $\times$ $\mathbf{1}(province = Beijing)$	-0.192**
	(0.0841)
expansion $\times$ $\mathbf{1}(province = Liaoning)$	-0.0947
	(0.0646)
expansion $\times$ $\mathbf{1}(province = Zhejiang)$	-0.198***
	(0.0548)
expansion $\times$ $\mathbf{1}(province = Guangdong)$	-0.0710
	(0.0545)
expansion $\times$ $\mathbf{1}(province = Sichuan)$	-0.131**
	(0.0657)
Province FE	YES
Year FE	YES
Observations	102
R-squared	0.898
Prob > F	0.0000

Notes: The dependent variable is the skilled/unskilled labor ratio in each province in each year. In this table, we show the results from the first stage regression when we utilize the interaction of the college expansion with province indicator as the instrumental variable. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

provinces. The reference group is Shaanxi Province. The effect of the college expansion is 19.2 percentage points smaller in Beijing and 19.8 percentage points smaller in Zhejiang, compared with that in Shaanxi. The F-statistic of this first stage regression is large, and most of the coefficients are statistically significant. When we consider a joint Wald test of all the interaction terms, we also

Table 3: IV & OLS Regression of
Estimating the Elasticity of Substitution

Variables	2SLS	OLS
Skilled/Unskilled Ratio	-0.333**	-0.00984
	(0.160)	(0.0409)
Province FE	YES	YES
Year FE	YES	YES
Observations	102	102
R-squared	0.726	0.836
Prob > F	0.0000	0.0000

Notes: The dependent variable is the skill premium in each province in each wave. In this table, we show the results from the IV regression when we utilize the interaction of the college expansion with province indicator as the instrumental variable for the skilled over unskilled worker ratio. In column (2), we show the results from the Naive OLS regression to estimate equation (24).
*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

reject the null hypothesis. Consequently, the instrument is not weak. Table 3 gives a point estimation of γ_1 of -0.333, which means that the elasticity of substitution between high-skill and low-skill worker σ is 3.0. We will use this estimate in the model. This result is a little larger than the estimates in the U.S. but still comparable.[19] The overidentification test of this IV regression gives a p-value of 0.41, which supports the validity of the instrument. In Table 3 column (2), we also check the results from the naive OLS regression and find that there is some upward bias due to the positive correlation between the ratio of high-skill to low-skill labor augmenting technologies and the ratio of the high-skill to low-skill workers. In Appendix B.1, we conduct some robustness checks and get similar results.

[19]The estimates of the elasticity of substitution between high-skill and low-skill labor in the U.S. ranges between 1 and 2 (Heckman et al., 1998; Katz and Murphy, 1992; Autor et al., 1998).

5.3 Migration Elasticity

From the gravity equation (16), we estimate the migration elasticity (ϵ). Rewrite (16) as:

$$\pi_{ij}^s = \frac{(\tau_{ij}^s Q_j^{1-\beta})^{-\epsilon}(v_{ij}^s)^{\epsilon}}{\Phi_i^s}$$

To estimate ϵ, we assume $\tau_{ij}^s = \tau_i^s d_{ij}$, where τ_i^s is the origination-skill fixed component and d_{ij} is the distance index between location i and j. Also, we use the income $v_{ij}^s = w_j^s + \frac{Q_j S_j}{H_{jj}^R} \cdot \mathbb{1}(i=j)$ as in the stylized facts section. Under these assumptions and given data on migration shares and real incomes, we estimate ϵ using the fixed effect regression:

$$ln(\pi_{ij}^s) = \epsilon ln(v_j^s) + \psi_{ij} + \gamma_{is} + \zeta_j + \phi_{ijs}, \text{ for } i \neq j \tag{26}$$

where $\psi_{ij} = -\epsilon ln(d_{ij})$ is the origination-destination pair fixed effect, $\gamma_{is} = -\epsilon ln(\tau_i^s) - ln(\Phi_i^s)$ is the origination-skill fixed effect, $\zeta_j = -\epsilon(1-\beta)ln(Q_j)$ is the destination fixed effect, ϕ_{ijs} is the measurement error term. We assume that the error term ϕ_{ijs} is not correlated with $ln(v_j^s)$ after controlling for all these fixed effects.

To estimate ϵ, we need to run a regression estimating (26) with origination-destination pair fixed effects ψ_{ij}, origination-skill fixed effects γ_{is}, and destination fixed effects ζ_j. We use migration flows and housing rent data from the *Census* in 2005 and city-skill level average wage data imputed from City Statistic Yearbooks. To calculate π_{ij}^s for each origination-destination city pair, we sum up the number of current workers who migrated from each origination city to each destination city by skill groups (with/without a college degree). $ln(v_j^s)$ are different for residents with a local Hukou registration and migrant residents without local Hukou registration. For migrants, income is only their wages. However, for local incumbents with housing assets, it will be a combination of wages and housing rent incomes. To calculate local residents' $ln(v_j^s)$, we first calculate the average rental income for local residents and then add the rental incomes to their wages. Rent incomes are calculated as follows. First, we calculate the total housing rent in the living city j. Second, we divide this city-level total rent by the number of local Hukou registered house owners, to get the average housing rent income of local residents. Adding up the wage and the rental income, we have v_j^s. Because there are many zero migration flows between small city pairs, $ln(\pi_{ij}^s)$ actually contains many missing values which are not used in the regression. Hence, we construct $\widehat{ln(\pi_{ij}^s)}$ by assigning an extremely small value (i.e., 1e-7) to the migration flow and then estimating the same regression with $\widehat{ln(\pi_{ij}^s)}$[20]. In the estimation, the origination-destination pair fixed effect cannot be distinguished from the destination fixed effect, so we will only add a set of origination-destination fixed effects in the regression shown in column (1) of Table 4.

Table 4: Regression of Estimating the Migration Elasticity

Variables	(1)	(2)
$ln(v_j^s)\{Census\}$	1.847***	
	(0.0761)	
$ln(v_j^s)\{CSYB\}$		1.926***
		(0.138)
Origin-Destination FE	YES	YES
Origin-Skill FE	YES	YES
Observations	164,738	137,186
R-squared	0.568	0.577

Notes: Column 1 shows the results when the independent variable is $ln(_j^s)$. Column 2 shows the results when the independent variable is $\widehat{ln(v_j^s)}$, which includes the rebate of housing costs back to local residents. ***p<0.01, **p<0.05, and *p<0.1.

The results are shown in Table 4. Column 1 shows the results of directly regressing migration flows from city i to city j with skill s $\widehat{ln(\pi_{ij}^s)}$ on destination-skill average income $ln(v_j^s)\{Census\}$ with wages measured from the individual wage in the original *Census 2005*. This gives us a statistically significant estimate of the migration elasticity of 1.847 with a standard error of 0.0761. However, to closely match the model, we run a second regression, which uses the destination-skill average income $ln(v_j^s)$ with wages measured from the City Statistic Yearbook *CSYB 2005*. The results are in column (2) of Table 4, which gives us an estimate of 1.926 with a standard error of 0.138. Our estimates are slightly larger than the estimate of around 1.5 in Tombe and Zhu (2019), which uses province-level data. As our model actually uses the wage data from City Statistics Yearbooks, we prefer to choose ϵ towards the estimation from the second regression using $ln(v_j^s)\{CSYB\}$, therefore, we pick $\epsilon = 1.90$[21].

[20]The estimation results are robust to the choice of the extreme small value.

[21]The true parameter should be between very likely to be somewhere between the two estimators. Also, as robustness

5.4 Summary of Parameters

Table 5 below summarizes our parameters. The first parameter is quite standard, as in the literature, such as Ahlfeldt et al. (2015). Chinese citizen has a slightly higher share of consumption in utility (β). However, the number is generally inline.

Table 5: **Estimated Parameters**

Parameter	Description	Value
β	share of consumption in utility	0.77
σ	elasticity of substitution between H/L-skills	3.0
ϵ	migration elasticity	1.90

What is new here is the estimation of the elasticity of substitution between H/L-skills (σ) and the city pair migration elasticity (ϵ). Our estimations use a large sample dataset across many locations in China. We are the first to estimate the elasticity of substitution between high and low skill labors in China using the college expansion shock. The estimated $\sigma = 3$ is higher than the literature using U.S. data, which ranges between 1 and 2. Since China in the early 2000s was still a low-tech intensive industrial country, a lot of high-skill occupations were substitutable with a combination of imported machines and low-skill workers, the result is reasonable. We also solve the quantitative analysis with the value of $\sigma = 1.4$, which is usually used in previous studies in the U.S. and the results are inline as in Appendix D. As for migration elasticity, Tombe and Zhu (2019) estimates at province-sector pair and ends with a number of 1.5. Since cities are more substitutable than provinces, we expect the migration elasiticity between cities to be slightly larger. In this paper, we show that the city pair migration elasticity is around 1.9.

6. Quantitative Analysis

In this section, we quantify productivities, housing construction intensities, and migration costs for each of the Chinese cities in our sample (which is 233 cities for both years). We first solve the model

checks, we actually solved several models under a variety of parameter choices from 1.5 as in Tombe and Zhu (2019) to 2.0 which is slightly higher than our estimation. In all cases, all the results hold as in the paper, though the magnitudes changes slightly. The results are available upon request.

with the estimated parameters in Section 5, and the Census data we have in 2005 and 2010. We then show the model results and calculate the unobserved variables and how the migration costs, productivity, and housing markets change during these five years.

6.1 Solving the model

Based on our observed variables $\{H_i^s, H_j^s, \pi_{ij}^s, w_j^s, Q_j\}$, we can calculate all the unobserved variables: productivity $\{A_j^l, A_j^h\}$, migration cost $\{\tau_{ij}^s\}$, floor spaces $\{S_j\}$, and construction density $\{\phi_j\}$ for both 2005 and 2010.

A. Productivity

From profit maximization and zero profits, we can infer productivity from the data on employment and wages. First, we solve for productivity A_j^h as a function of A_j^l using first order conditions.

$$A_j^h = A_j^l \Big(\frac{H_j^h}{H_j^l}\Big)^{\frac{1}{\sigma-1}} \Big(\frac{w_j^h}{w_j^l}\Big)^{\frac{\sigma}{\sigma-1}} \tag{27}$$

Plug A_j^h into the production function of y_j and apply the zero profit condition to yield:

$$X_j = A_j^l H_j^l \Big[\frac{w_j^h H_j^h + w_j^l H_j^l}{w_j^l H_j^l}\Big]^{\frac{\sigma}{\sigma-1}} = w_j^h H_j^h + w_j^l H_j^l \tag{28}$$

Define $\Xi_j^l = \frac{w_j^l H_j^l}{w_j^h H_j^h + w_j^l H_j^l}$ the share of labor income distributed to low-skill workers. We can then calculate the productivities:

$$A_j^l = w_j^l (\Xi_j^l)^{\frac{1}{\sigma-1}} \tag{29}$$

$$A_j^h = w_j^h (1 - \Xi_j^l)^{\frac{1}{\sigma-1}} \tag{30}$$

B. Land Market Clearing

From the workers' first order conditions for floor space and the summation over all workers residing in each city j, we are able to calculate the total amount of floor space S_j:

$$
\begin{aligned}
S_j = E[s_j]H_j &= (1-\beta)\frac{E[v_j]H_j}{Q_j} \\
&= \frac{1-\beta}{Q_j}\left[w_j^l H_j^l + w_j^h H_j^h\right] + (1-\beta)S_j \\
&= \frac{1-\beta}{\beta}\frac{w_j^l H_j^l + w_j^h H_j^h}{Q_j}
\end{aligned}
\tag{31}
$$

and then back out the construction intensity ϕ_j:

$$\phi_j = S_j / L_j \tag{32}$$

C. Migration Costs

To compute migration costs, we need first to compute the city-level rent income which we assume to be equally divided among local residents $\frac{Q_j S_j}{H_{jj}}$ from the floor space S_j we calculated above. Starting with the value of a skill s worker moving from i to j:

$$v_{ij}^s = w_j^s + \frac{Q_j S_j}{H_{jj}} \cdot \nVdash(i = j) \tag{33}$$

From the gravity equations, we can calculate the migration costs between all city pairs. We assume that the iceberg migration cost for staying in the original city is one, that is $\tau_{ii}^s = 1$. With data on Q_i, v_{ij}^s and π_{ij}^s, and the gravity equation, we have:

$$\Phi_i^s = \sum_{k=1}^{K} (\tau_{ik}^s Q_k^{1-\beta})^{-\epsilon} (v_{ik}^s)^{\epsilon} = \frac{(Q_j^{1-\beta})^{-\epsilon}(v_{ii}^s)^{\epsilon}}{\pi_{ii}^s} \tag{34}$$

Then by inserting Φ_i^s into the original gravity equation, we have:

$$\tau_{ij}^s = \frac{v_{ij}^s}{Q_j^{1-\beta}(\pi_{ij}^s \Phi_i^s)^{1/\epsilon}}\text{ , for } i \neq j \tag{35}$$

For city pairs with zero migration flow, we assign a migration probability $\pi_{ij}^s \sim 0$, resulting in a huge migration cost approaching infinity, which we will not include while calculating the changes in migration costs.

6.2 What does the model tell us about the unobservables?

In this subsection, we show how the unobserved variables changed, including the dynamics of migration costs, productivities, and housing construction intensities for each of the 233 Chinese cities in our model between 2005 and 2010.

A. Migration Costs

Table 6 reports the share of migrants relative to the total working population, the mean value of τ_{ij}^{s}, and the number of city pairs which have at least one recorded migrant in our sample. On average, in 2005, migrants comprised 11% of total employment in China, along with an average migration cost of 9.2 and the active linkage is 12,640, which is less than 25% of the total amount of city-pair linkages. That is, less than 25% of the city pairs have at least one migrant in the sample. As for workers by skill type, the statistics for low-skill workers are very similar to the overall statistics since they are the majority. However, high-skill workers do not experience as much change as low-skill workers do, even though their migration costs are lower on average.

Table 6: **Average Migration Costs and Active Linkage**

	Share of Emp.		Migration Costs				Active Linkage			
	2005	2010	2005	2010	Relative	Changes	2005	2010	Relative	Changes
Overall	11%	22%	9.2	5.8	63%	-3.4	12,640	26,335	208%	+13,695
Low-skill	11%	23%	9.3	5.8	62%	-3.5	9,173	18,477	201%	+9,304
High-skill	9%	17%	7.6	5.7	75%	-1.9	3,467	7,858	227%	+4,391

*This table displays migration-weighted harmonic means of migration costs in 2005 and 2010.
*Share of Employment among high-skill is high-skill migrants over high-skill population.
*τ_{ij}^{s} is proportional in the model, so we show % changes.
*The total amount of city pair linkage is 54,289 (233 cities) in the model.

In 2010, the overall migration costs dropped dramatically by 37% relative to 2005, to the level of 5.8. For low-skill workers, the changes are similar on average. While for high-skill workers, the drop on average is smaller (75%). With these huge drops in migration costs, we observe the share of migrants relative to the total working population doubling to 22%. More importantly, high-skill workers started to move more, which gives us a 227% increase in the relative active linkages comparing to 2005. These results indicate that the decreasing migration costs contribute a lot to the increasing migration flows.[22]

As documented in Bryan and Morten (2019), the dramatic drops in migration costs are essential for the massive flow of migrant workers in developing countries. Tombe and Zhu (2019) also shows that province-sector level migration costs drop a lot between 2000 and 2005. Our results indicate that the same pattern holds at the city-skill level as well. Though these changes are not the key we want to address in this paper, it is still important to capture them in the model so that the model will not overestimate other components.

B. Productivity

Table 7 presents the average productivities A_j^s for both high-skill and low-skill workers, for all cities j by migration net inflow groups. On average, the overall productivity for all the cities grows by 87% for high-skill and by 94% for low-skill. To show the results in a more compact way, we group cities by their total amount of net inflow workers. (6,13) means the cities have between 6 million and 13 million net inflows of workers while (-4,-1) means the cities have between -4 million and -1 million net inflows of workers. First, by net inflow groups, cities with larger net inflows have much higher productivities than cities with smaller or negative net inflows for both high-skill and low-skill workers. For instance, Tier 1 cities, including Beijing, Shanghai, Shenzhen, Guangzhou, and Dongguan, had more than thirty million workers migrate in on net in 2010. These cities have much higher productivity for both high-skill and low-skill workers in both 2005 and 2010. In 2005, their average high-skill productivity was 1.94, which was 90% higher than the national average, 84% higher than Tier 2 cities, 122% higher than Tier 3 cities, 288% higher than Tier 3 cities, and more than 350% higher than Tier 5 cities. The same pattern holds for low-skill, but the differences between city groups are smaller. Tier 1 cities' average low-skill productivity is 2.22, which is 79% higher than the national average, 31% higher than Tier 2 cities, 60% higher than Tier 3 cities, 126% higher than Tier 4 cities, and 143% higher than Tier 5 cities.

Second, there is a strong city size skill premium, as documented by Baum-Snow and Pavan (2012) across city tiers. Take the same comparison between Tier 1 cities and other groups above[23]. We see

[22]Another possible reason for the increase in the linkages is that the sample size of the *Census* data is larger in 2010, which could capture more city pairs with very few migrants. In addition, this could result in underestimating the decline in the average migration cost shown in this table. The reason is that in 2010, more cities with very few migrants are captured, and their migration costs in the model change from infinity to a very big number. This increases the average migration cost for city pairs with positive linkage. Consequently, the reduction of the migration cost should be even larger than the values we show here.

[23]One thing to keep in mind is that the absolute value of high-skill and low-skill productivities are not directly comparable. Because there are more low-skill workers than high-skill workers, the CES production function may naturally

Table 7: **Average Productivity Growth**

Net Inflow Range(2010)	No. of Cities	High-skill				Low-skill			
		2005	2010	Relative	Changes	2005	2010	Relative	Changes
Average	233	1.02	1.91	187%	+0.89	1.24	2.41	194%	+1.17
(6,13)	5	1.94	3.48	179%	+1.54	2.22	3.55	159%	+1.33
(1,6)	19	1.05	2.19	208%	+1.14	1.69	2.98	176%	+1.28
(0, 1)	45	0.87	1.84	211%	+0.97	1.38	2.53	183%	+1.15
(-1,0)	134	0.50	1.10	220%	+0.60	0.98	2.08	212%	+1.10
(-4,-1)	30	0.43	0.99	230%	+0.56	0.91	1.88	206%	+0.97

*This table displays population-weighted means in 2005 and 2010. Unit of Productivity is $1e4$.
*The Net Inflow Range Groups are classified by net inflow in 2010 (unit: millions).
*Each Net Inflow Range Group consists of the same cities in 2005 and 2010.
*The total amount of cities is 233 in the model.

that the productivity gain of moving from a lower to a higher tier is much larger for high-skill workers than low-skill workers. For instance, when moving to Tier 1, the gain is 84% for high-skill and 31% for low-skill from Tier 2, 122% versus 60% from Tier 3, 288% versus 126% from Tier 4, and 350% versus 143% from Tier 5. Third, productivities improved massively from 2005 to 2010 and especially the high-skill productivities in larger cities. The national average improved by 87% for high-skill and 94% for low-skill. While smaller (outflow) cities' productivity improved more in percentage terms because they had a smaller base in 2005, if we focus on the changes in absolute value, it is easy to spot that the improvement of high-skill productivity is much larger in cities with larger net inflows of workers. The improvement between Tier 1 and Tier 5 in high-skill is three times (+1.54 vs. +0.56) while the improvement in low-skill is only one and one third (+1.33 vs. +0.97).

All these results indicate that the reallocation of workers, especially high-skill workers, from these lower productive cities to higher productive cities, will significantly improve national productivity and therefore improve the national level of welfare.

C. Housing Constraints

Table 8 shows the supply of construction land and how it changes from 2005 to 2010. The national

give us a higher low-skill productivity even though the low-skill workers' wage is much lower. For level, the meaningful comparison is within skill group; For relative changes, it is also meaningful to compare across skill groups.

total land supply increased by 31%. However, the total land supply in Tier 1 cities only increased by 10% despite their massive migration net inflows. The Tier 2 cities increased their total land supply the most (55%). Combing this with their large increments in construction intensity, it leads to the massive growth in floor space, as in Table 9. Given that all the Tier 1 cities are located on plains, their construction land supply is essentially less than 10% of their administrative districts (except Shenzhen). This leaves substantial room for increasing or spatially reallocating the total land supply in/to larger cities to loosen the housing constraints. The land supply is determined administratively.

Table 8: **Construction Land Supply**

Net Inflow Range(2010)	No. of City	Total Land Supply 2005	2010	Relative	Changes
Overall	233	24,277	31,705	131%	+7,428
(6,13)	5	5,135	5,648	110%	+513
(1,6)	19	3,801	5,912	155%	+2,111
(0, 1)	45	5,555	7,250	131%	+1,695
(-1,0)	134	7,950	10,363	130%	+2,413
(-4,-1)	30	1,836	2,532	138%	+696

*This table displays total land supply within group (unit: km^2).
*The Range are classified by net inflow in 2010 (unit: millions).
*Each Net Inflow Range Group consists of same cities in 2005 and 2010.
*Total amount of cities is 233 in the model.

Table 9 shows the average housing construction intensity, floor space, and their changes from 2005 to 2010 by the same migration net inflow groups as in the previous section. On average, the housing construction intensity for all the cities decreased by -2%, and the floor space grew by 50%. First, by net inflow groups, cities with larger net inflows have much lower construction intensity than cities with smaller or negative net inflows, which contradicts the literature. Unlike the US situation, China has a lot of construction land assigned to villages and towns[24], even in large cities such as Shanghai and Beijing. The construction intensity, also known as plot ratio, of these construction land is super low even though the plot ratio of the central urban construction lands is much higher, just miles away. Given the massive migration net inflows, Tier 1's, Tier 2's, and Tier 3's cities'

[24]In China, a city is a administrative collection of a city center and counties around the city. Each county consists of a county center, villages, and towns. Each province consists usually ten to twenty cities and while each city, there is a city center and several counties.

construction intensity are only two-third of the national average. These differences in construction intensity result in similar differences in the total residential floor space. The tightening conditions in construction intensity and floor space supply limit the migration flow into higher productivity cities.

Table 9: **Construction Intensity and Floor Space**

Net Inflow	No. of	Construction Intensity				Floor Space			
Range(2010)	City	2005	2010	Relative	Changes	2005	2010	Relative	Changes
Average	233	2.63	2.58	98%	-0.05	2.19	3.30	150%	+1.11
(6,13)	5	0.72	1.68	233%	+0.96	5.92	7.84	132%	+1.92
(1,6)	19	1.57	1.91	122%	+0.34	1.79	4.10	229%	+2.31
(0, 1)	45	2.05	1.41	69%	-0.64	1.53	2.48	162%	+0.95
(-1,0)	134	3.21	3.27	102%	+0.06	1.48	2.17	147%	+0.69
(-4,-1)	30	3.61	3.38	94%	-0.23	2.55	3.12	122%	+0.57

*This table displays population-weighted means in 2005 and 2010. Intensity Unit is $1e6$; Floor Space Unit is $1e8$.
*The Net Inflow Range Groups are classified by net inflow in 2010 (unit: millions).
*Each Net Inflow Range Group consists of the same cities in 2005 and 2010.
*The total amount of cities is 233 in the model.

These results show that the construction intensity is lower in larger cities with massive migration net inflows, and the land supply market is not endogenously responding to the market demands. Land supply and construction intensity are highly restricted by central and local governments. Therefore, the floor space supply is not very responsive to the rising housing costs.

6.3 Wage Inequality & Income Inequality

In this subsection, we show wage inequality and income inequality measured by the Theil Index in our model in both 2005 and 2010. To keep the results consistent, we also summarize them by city groups of different migration net inflows.

Table 10 shows the within-city Theil Index for both wages and income. The average Wage Theil Index is 0.0072 in 2005 and declined slightly to 0.0070 in 2010. Larger cities with more incoming migration have slightly higher wage inequality, and their wage inequality increased slightly from

2005 to 2010. On the other hand, during the same period, wage inequality in smaller cities with negative net workers inflows of workers decreased. However, the differences and the changes in wage inequality across cities and across time is not comparable to these patterns of income inequality. First, the average within-city Income Theil Index was much higher than the average within-city Wage Theil Index, and it doubled from 2005 to 2010. If we break down the statistics by city groups, we could easily observe that this huge jump is attributable to cities with positive net inflows, especially Tier 1 and Tier 2 cities with more than 100% increases.

Table 10: **Within-city Theil Index**

Net Inflow	No. of	Wage Theil Index			Income Theil Index		
Range(2010)	City	2005	2010	Relative	2005	2010	Relative
Average	233	0.0072	0.0070	97%	0.0126	0.0247	196%
(6,13)	5	0.0087	0.0097	111%	0.0575	0.1215	211%
(1,6)	19	0.0065	0.0079	122%	0.0154	0.0363	235%
(0, 1)	45	0.0075	0.0083	111%	0.0083	0.0144	173%
(-1,0)	134	0.0071	0.0058	82%	0.0049	0.0051	104%
(-4,-1)	30	0.0072	0.0058	80%	0.0047	0.0045	96%

Notes: This table displays population-weighted means in 2005 and 2010. Each column sums up to 100%.

Table 11 shows contribution shares to national Theil Indexes. The first row shows the national Wage Theil Index and Income Theil Index for both 2005 and 2010. At the national level, income inequality is still higher than wage inequality. Both measures dropped as more workers migrated from lower productivity areas to higher productivity areas.[25] Moreover, if we examine by city groups, we could observe that larger cities with positive migration net inflows contribute massively to both national Theil Index measures. For instance, for the Wage Theil of Tier 1 cities in 2005, +1.49 means that if we do not account for all workers in Tier 1 cities, the national Wage Theil will decrease by 149%. This pattern holds for both inequality measures and does not change much from 2005 to 2010.

To further indicate how housing constraints play an essential role, we show the skill premium and the housing premium and their changes in Table 12. The national average skill premium and the city groups' skill premiums are very similar and do not change much over time. However, the

[25]The trend is similar to the Gini Index published by the National Bureau of Statistics. The Gini Index in 2010 is 0.481 and the Gini Index in 2005 is 0.485.

Table 11: **Share of Contribution to National Theil Index**

Net Inflow Range(2010)	No. of City	Share of Wage Theil 2005	Share of Wage Theil 2010	Share of Wage Theil Relative	Share of Income Theil 2005	Share of Income Theil 2010	Share of Income Theil Relative
National	233	0.0972	0.0622	64%	0.1080	0.0873	81%
(6,13)	5	+1.49	+1.41	97%	+1.43	+1.21	84%
(1,6)	19	+0.58	+0.83	143%	+0.53	+0.66	125%
(0, 1)	45	+0.22	+0.26	118%	+0.20	+0.20	100%
(-1,0)	134	-0.92	-1.00	108%	-0.83	-0.71	86%
(-4,-1)	30	-0.37	-0.49	132%	-0.34	-0.35	103%

Notes: This table displays city groups' contribution to the national Theil Index in 2005 and 2010. The first row displays the national wage/income Theil Index in 2005 and 2010.

average housing premium increased from 0.39 in 2005 to 0.56 in 2010, resulting in a 43% jump. For an "average" worker, housing asset income is more than 50% of his wage income. Furthermore, if we break down by city groups, we could observe that in Tier 1 cities, the housing premium increased from 0.94 to 2.03, which is substantially above the average rate of growth. Given that houses in these large cities are almost all owned by locals and many more migrants are moving into these cities, it is not hard to understand the astonishing income inequality measures in income in Table 10.

6.4 Remarks on the Quantitative Analysis

In this section, we showed that the dramatic migration cost reductions and the fast productivity growth are the major drivers of the massive migration flows in China. Further, the restrictive housing constraints in the larger/high-productivity cities with positive net inflows are much tighter. These housing constraints increase income inequality in larger cities and also dissuade more migrants from entering these higher productivity cities.

7. Counterfactual Analysis

Given the restrictive housing constraints we found in the quantitative analysis, we want to discover if there could be potential improvements through examining some policy counterfactuals. In this

Table 12: **Skill Premium & Housing Premium**

Net Inflow	No. of	Skill Premium			Housing Premium		
Range(2010)	Cities	2005	2010	Relative	2005	2010	Relative
Average	233	1.47	1.40	95%	0.39	0.56	143%
(6,13)	5	1.35	1.39	103%	0.94	2.03	216%
(1,6)	19	1.40	1.40	100%	0.41	0.62	151%
(0, 1)	45	1.42	1.39	97%	0.33	0.39	118%
(-1,0)	134	1.50	1.40	93%	0.31	0.31	100%
(-4,-1)	30	1.57	1.45	92%	0.30	0.30	100%

Notes: This table displays population-weighted means in 2005 and 2010. Skill Premium is measured as annual high-skill wage over annual low-skill wage for each city, and Housing Premium is measured as average annual housing return over the average annual wage for each city.

section, we change some parameters of the model to represent some policies recommended in previous literature and try to recover how the policies could change the spatial distribution of workers with different skills in China. Most importantly, we investigate the effect of relaxing the housing constraint on migration flows on national and within-city inequality.

7.1 Algorithm

Given exogenous variables and parameters, we need to calculate the response of the endogenous variables resulting from policy changes. As we have mentioned, we will select the equilibrium that is the closest to the one in the real world. Thus, the variables' initial values will be set to be equal to the model result in 2010.

We first specify the exogenous variables and the model equation system. The exogenous variables are $\{H_i^s, A_j^s, \tau_{ij}^s, L_j, \phi_j\}$ where i indexes origination cities, j indexes destination cities, and s indexes skill. The equation system consists of three blocks. The migration block consists of worker income equation (10), and gravity equation (16), the production block consists of production equation (17) and wage equations (18, 19), and the housing block consists of construction equation (22) and market clearing equation (23).

To calculate the policy counterfactuals, we start with the block in which changes occur and then iterate block by block to update the endogenous variables until all endogenous variables converge. We present the process of calculating a counterfactual, using the relaxation of construction intensity as an example.

Suppose a policy that increases construction intensity by 20%. That is, $\hat{\phi}_j = 1.2 \times \phi_j$ for every city j. We have the following process of updating variables ($\{\hat{X}_j\}^t$ indicates t's iteration of variable X). Starting with the housing block:

$$\{\hat{S}_j\}^1 = \hat{\phi}_j L_j \text{ from eq.(22)} \tag{36}$$

$$\{\hat{Q}_j\}^1 = \frac{1-\beta}{\beta}\frac{w_j^l H_j^l + w_j^h H_j^h}{\{\hat{S}_j\}^1} \text{ from eq.(23)} \tag{37}$$

Now we move to worker's migration choices (migration block):

$$\{\hat{v_{ij}^s}\}^1 = w_j^s + \frac{\{\hat{Q}_i\}^1\{\hat{S}_i\}^1}{H_i^R} \text{ from eq.(10)} \tag{38}$$

$$\{\hat{\pi_{ij}^s}\}^1 = \frac{(\tau_{ij}^s \{\hat{Q}_j\}^{1^{1-\beta}})^{-\epsilon}(\{\hat{v_{ij}^s}\}^1)^{\epsilon}}{\sum_{k=1}^{K}(\tau_{ik}^s \{\hat{Q}_k\}^{1^{1-\beta}})^{-\epsilon}(\{\hat{v_{ik}^s}\}^1)^{\epsilon}} \text{ from eq.(16)} \tag{39}$$

Then, combining $\{\hat{\pi_{ij}^s}\}^1$ with $\{H_i^s\}$, we are able to calculate $\{\hat{H_j^s}\}^1$. Finally, we move to the production block to calculate wages:

$$\{\hat{X}_j\}^1 = [(A_j^h\{\hat{H_j^h}\}^1)^{\frac{\sigma-1}{\sigma}} + (A_j^l\{\hat{H_j^l}\}^1)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \text{ from eq.(17)} \tag{40}$$

$$\{\hat{w_j^l}\}^1 = A_j^{l\,\frac{\sigma-1}{\sigma}}\{\hat{X}_j\}^{1\frac{1}{\sigma}}\{\hat{H_j^l}\}^{1^{-\frac{1}{\sigma}}} \text{ from eq.(18)} \tag{41}$$

$$\{\hat{w_j^h}\}^1 = A_j^{h\,\frac{\sigma-1}{\sigma}}\{\hat{X}_j\}^{1\frac{1}{\sigma}}\{\hat{H_j^h}\}^{1^{-\frac{1}{\sigma}}} \text{ from eq.(19)} \tag{42}$$

So far we have updated all the endogenous variables once. We calculate how far $\{\hat{x_j}\}^1$ is from $\{\hat{x_j}\}^0$, where x means any specific variable. If the distance is large, we go back to eq.(36) and eq.(37) to iterate until the distance is small enough. For other counterfactuals, the starting block of iteration may differ, but the general algorithm is identical. The key is to update all the endogenous variables in a loop.

7.2 Land Supply Reform

China has had a very restrictive construction land supply policy since the 1950s. The central government decides the total amount and the distribution of the total land supply for all Chinese cities year by year. The local governments follow the instructions to increase or decrease their city-level land supply to match their city quotas. These quotas cannot be traded between cities. Therefore, land deficient cities and land abundant cities co-exist at the same time, even though some of them share land borders.

Current Land Supply Policy in China

Since 2003, the central government changed its principles of land supply policy. The purpose is to balance regional developments. This is documented by a large urban literature (Han and Lu, 2018; Liang et al., 2016; Han and Lu, 2017). There are two purposes. First, redistributing land supply from favoring the coastal areas (more developed) to favoring the inland areas (less developed). The inland's share of the national land supply quota rose from 30% in 2003 to 60% in 2014. Second, redistributing land supply from favoring large cities (more developed) to favoring smaller cities (less developed). The small cities' share of the national land supply increased from 49% in 2003 to 64% in 2014. This trend has persisted until today.

However, from the stylized facts of migration flows and housing costs, we think the current land supply policy is inefficient. It is increasing land supply in cities which are less productive and losing workers while restricting land supply in cities which are much more productive and gaining workers. Therefore, we propose an alternative land supply policy that favors high productivity and population net inflow cities.

Migration-Based Land Supply Policy Reform

We propose a counterfactual policy of redistributing the total land supply increment from 2005 to 2010 according to net migration inflows. More specifically, the rule for land supply redistribution is as follows. We denote the total land supply increment from 2005 to 2010 as ΔL, the net inflow for each city with positive changes of inflow as $\Delta^+ H_j$ which sums up to total worker population growth $\Delta^+ H$. Then city $j's$ counterfactual land supply increment is: $\Delta^+ L_j = \Delta L \times \frac{\Delta^+ H_j}{\Delta^+ H}$. Since it is very costly to revoke current land supply, for cities with negative migration inflow changes, we assign $\Delta^0 L_j = 0$. The counterfactual land policy changes are summarized in Table 13.

We think this counterfactual is a more reasonable comparison to the data because it is feasible

Table 13: **Counterfactual Construction Land Supply**

Net Inflow Range(2010)	No. of Cities	Land Supply (Data) 2005	2010	Relative	Changes	Counterfactual $\widehat{2010}$	$\widehat{Relative}$	$\widehat{Changes}$
National	233	24,277	31,705	131%	+7,428	31,705	131%	+7,428
(6,13)	5	5,135	5,648	110%	+513	7,762	151%	+2,627
(1,6)	19	3,801	5,912	155%	+2,111	7,131	188%	+3,330
(0, 1)	45	5,555	7,250	131%	+1,695	6,829	123%	+1,274
(-1,0)	134	7,950	10,363	130%	+2,413	7,988	100.5%	+38
(-4,-1)	30	1,836	2,532	138%	+696	1,836	100%	+0

Notes: This table displays the total land supply data by group in 2005 and 2010, as well as the counterfactual land supply in 2010 (unit: km^2). The Range is classified by net inflow in 2010 as in the data (unit: millions). Each Net Inflow Range Group consists of the same cities in 2005 and 2010.

to implement. To guarantee that the redistribution of construction land supply does not change inequality through land ownership changes, we subtract land income from the additional land allocated to land-gaining cities and compensate land-losing cities for their losses. This mechanism mimics a policy called the ”land quota market”, which has been recommended by previous literature (Lu, 2016). The basic idea is that central government can balance the development of different regions by transferring revenues in housing markets from big cities to small cities, rather than allocating the land supply directly. Since the land income in land-gaining cities is higher than the land income in land-losing cities and the total amount of land supply is unchanged, this redistribution is feasible, and the central government receives additional revenue surplus after the redistribution.

Land Supply Policy Reform Results

The results of the land supply policy reform are summarized in Table 14 to Table 17. To keep the results intuitive and easy to compare, we maintain the city grouping as in the quantitative analysis section 6.3. Table 14 shows how this counterfactual policy changes the net migration inflows and housing costs. First, the policy motivates 9% more workers to move from low productivity cities to high productivity cities, and the increases are the highest in the most productive cities (Tier 1: 118% > Tier 2: 108% > Tier 3: 85%). Meanwhile, because of the land supply redistribution, more land is distributed to cities with larger net inflows of workers, and the housing costs in these higher productivity cities drop a lot. For Tier 1 and Tier 2 cities, the costs drop to only 68% and 82% of the ones in the original equilibrium.

Table 14: **Migration Flow and Housing Cost**

Net Inflow Range(2010)	No. of Cities	Net Inflow 2010	Net Inflow $\widehat{2010}$	Net Inflow Relative	Housing Cost 2010	Housing Cost $\widehat{2010}$	Housing Cost Relative
Overall	233	96m	105m	109%	114	121	106%
(6,13)	5	+45m	+53m	118%	226	154	68%
(1,6)	19	+38m	+41m	108%	136	112	82%
(0, 1)	45	+13m	+11m	85%	118	129	109%
(-1,0)	134	-48m	-53m	110%	87	117	134%
(-4,-1)	30	-48m	-52m	108%	80	105	131%

Notes: This table displays total net migration inflows and population weighted average housing costs for each city groups. In the first raw(Overall), we show the number of workers who have migrated flow and the national population weighted average housing cost. The unit of migration net inflow is millions, and the unit of housing costs is Chinese Yuan (RMB) per square meters per year.

We then show how within-city inequality changes in Table 15. We list the original equilibrium and the counterfactual (with a hat) side-by-side for the ease of comparison. The first thing to notice is that the Wage Theil Index effectively does not change. The only noticeable change is that the Theil Index in Tier 1 cities drops by 7%. This is mainly because that more high-skill workers move to Tier 1 cities due to the dramatic drop in housing costs. Nevertheless, for any other city group, the Wage Theil Index is almost identical. However, the population-weighted mean Income Theil Index drops significantly from 0.0246 to 0.0214 (14% drop). Moreover, if we divide by city groups, the drops are much larger for Tier 1 and Tier 2 cities. Since almost 30% of all workers live in these cities, it significantly lowers the average within-city Income Theil Index even though the Income Theil Index raises in cities losing workers. Therefore, the land supply reform helps to reduce within-city income inequality.

We also want to show how the policy changes national inequality and each city's contribution to the national inequality in Table 16. Similar to the pattern of within-city inequality, the counterfactual policy does not have much effect on the national wage inequality or cities' contributions to the national wage inequality. The national Wage Theil Index drops by 1%, and each Tier's contribution changes by roughly 2%. However, the counterfactual policy significantly lowers the national income

Table 15: **Within-city Theil Index**

Net Inflow	No. of	Wage Theil Index			Income Theil Index		
Range(2010)	Cities	2010	$\widehat{2010}$	Relative	2010	$\widehat{2010}$	Relative
Average	233	0.0070	0.0070	100%	0.0247	0.0214	86%
(6,13)	5	0.0096	0.0089	93%	0.1215	0.0709	58%
(1,6)	19	0.0079	0.0080	101%	0.0363	0.0279	77%
(0, 1)	45	0.0083	0.0083	100%	0.0144	0.0151	105%
(-1,0)	134	0.0058	0.0058	100%	0.0051	0.0081	158%
(-4,-1)	30	0.0058	0.0058	100%	0.0045	0.0155	344%

Notes: This table displays population-weighted means of both inequality measures. The original equilibrium is 2010 and the counterfactual equilibrium is $\widehat{2010}$. Relative is calculated via dividing $\widehat{2010}$ by 2010.

inequality by 18% measured by the Income Theil Index. By city groups, the positive contributions of Tier 1 and Tier 2 cities are lowered by roughly 15%, and the negative contributions of Tier 4 and Tier 5 cities are lowered by 25% and 9%, respectively. All these results indicate that the land supply reform lowers national income inequality as well as cross-city income inequality.

Finally, we show the skill premium and the housing premium in Table 17. The skill premium is the high-skill wage over low-skill wage, and the housing premium is the average housing return over the average wage return. The underlying reason why any measures of wage inequality do not change much is that the skill premium does not move at all. The only changes come from the location choices of high-skill workers relative to low-skill, which changes the composition of workers in each city. However, for the housing premium, it is another story. Since the government increases land supply in cities with insufficient land quotas, the housing costs drop massively, which dilutes the asset return from property ownership. As a result, these give us 41% and 24% drops in housing premia in Tier 1 and Tier 2 cities. These results help us to better understand the changes in the Theil Indexes.

Table 16: **Share of National Theil Index**

Net Inflow Range(2010)	No. of Cities	Share of Wage Theil 2010	Share of Wage Theil $\widehat{2010}$	Share of Wage Theil Relative	Share of Income Theil 2010	Share of Income Theil $\widehat{2010}$	Share of Income Theil Relative
National	233	0.0622	0.0615	99%	0.0873	0.0717	82%
(6,13)	5	+1.41	+1.45	103%	+1.21	+1.05	87%
(1,6)	19	+0.83	+0.84	101%	+0.66	+0.57	86%
(0, 1)	45	+0.26	+0.23	88%	+0.20	+0.23	115%
(-1,0)	134	-1.00	-1.02	102%	-0.71	-0.53	75%
(-4,-1)	30	-0.49	-0.48	98%	-0.35	-0.32	91%

Notes: This table displays city groups' contribution to the national Theil Index in 2005 and 2010. The first row display the national wage/income Theil Index in 2005 and 2010.

Table 17: **Skill Premium & Housing Premium**

Net Inflow Range(2010)	No. of Cities	Skill Premium 2010	Skill Premium $\widehat{2010}$	Skill Premium Relative	Housing Premium 2010	Housing Premium $\widehat{2010}$	Housing Premium Relative
Average	233	1.40	1.40	100%	0.56	0.53	95%
(6,13)	5	1.39	1.39	100%	2.03	1.20	59%
(1,6)	19	1.40	1.40	100%	0.62	0.47	76%
(0, 1)	45	1.39	1.38	99%	0.39	0.41	105%
(-1,0)	134	1.40	1.39	99%	0.31	0.44	142%
(-4,-1)	30	1.45	1.44	99%	0.30	0.42	140%

Notes: This table displays population-weighted means in 2005 and 2010. Skill Premium is measured as annual high-skill wage over annual low-skill wage for each city, and Housing Premium is measured as average annual housing return over the average annual wage for each city.

7.3 Additional Counterfactual Analysis

In this section, we present three additional counterfactual policy changes. The tables of these additional counterfactuals are shown in appendix E. For brevity, we only briefly discuss these results here.

The first counterfactual is applying a property tax and redistributing the tax revenue to all city residents, including migrants. China does not have a property tax on housing ownership. As a large part of the income inequality stems from house ownership inequality, we think this may be a possible way to reduce income inequality. Could a reasonable property tax and redistribution give us desirable reductions in income inequality? The answer is no. This policy cannot effectively lower income inequality because even though we redistribute part of the property income to migrants who do not receive any own housing income, it also pushes up housing costs and attracts more migrants to more productive cities. As a result, property owners capture more returns from the additional floor space.

The second is reforming the construction intensity restriction. As we document in the quantitative analysis section, the underlying construction intensity is not higher in larger cities because of the existence of a lot of construction land assigned to villages and towns. Is there also a potential income inequality reduction from more efficient uses of construction land? The answer is also no. This policy cannot lower the income inequality because even though relaxing construction intensity could lower the housing costs and attract more migrants to more productive cities, property owners still capture all the returns from the additional floor space. Therefore, directly increasing the construction intensity without redistribution of the additional returns from floor space in these larger cities cannot help to lower income inequality.[26]

The third is through directly increasing the land supply based on migration inflow. Instead of promoting the trade of land quotas across cities, we directly double the land supply increment from 2005 to 2010 and redistribute the additional land supply to cities with positive net inflows. We examine two cases: One where all the revenue from additional land supply goes to the central government; two where we redistribute the revenue from additional land supply among the local Hukou holders. The results depend on this. If all the revenue from additional land supply goes to local Hukou holders, this will only worsen income inequality, otherwise, income inequality is reduced.

[26]We reproduce all tables in the same form as for the land supply reform in the appendix E.

8. Conclusion

Migration and housing constraints shape the income inequality within and across Chinese cities. Along with the nationwide reduction of migration costs and the rapid growth of productivity in more developed cities, we observe a massive reallocation of workers towards these more developed cities, a rapid growth of housing costs in these more developed cities, and a stark increase in income inequality within these more developed cities. In a spatial equilibrium model, we explain the mechanism behind these observations and quantify the impacts of the interactions of the massive spatial reallocation of workers with the rapid growth of housing costs on income inequality. The rapid migration inflows to more developed cities and a highly regulated land supply system contribute to high housing demand and lift the housing costs (rent), which benefits local real estate owners. Housing owners gain more from the rents, and tenants spend more by paying rents. Thus, housing ownership inequality increases inequality in disposable income in developed cities.

With the understanding of the mechanism, we conduct several feasible counterfactual experiments. Among all counterfactuals, we show that a land supply reform that allows regions to trade construction land usage quotas could lower the within-city income inequality by 14% and national income inequality by 18%. This also encourages more migration to higher productivity cities and improves nationwide productivity.

References

Ahlfeldt, Gabriel M, Stephen J Redding, Daniel M Sturm, and Nikolaus Wolf, "The economics of density: Evidence from the Berlin Wall," *Econometrica*, 2015, *83* (6), 2127–2189.

Autor, David H, Lawrence F Katz, and Alan B Krueger, "Computing Inequality: Have Computers Changed the Labor Market?," *The Quarterly Journal of Economics*, 1998, *113* (4), 1169–1213.

Baum-Snow, Nathaniel and Ronni Pavan, "Understanding the City Size Wage Gap," *The Review of Economic Studies*, 2012, *79* (1), 88–127.

Berman, Eli, John Bound, and Stephen Machin, "Implications of Skill-biased Technological Change: International Evidence," *The Quarterly Journal of Economics*, 1998, *113* (4), 1245–1279.

Bryan, Gharad and Melanie Morten, "The aggregate productivity effects of internal migration: Evidence from indonesia," *Journal of Political Economy*, 2019, *127* (5), 2229–2268.

Card, David and John E DiNardo, "Skill-biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles," *Journal of Labor Economics*, 2002, *20* (4), 733–783.

Chao, Chi-Chur, Bharat R Hazari, and Eden SH Yu, "Rising Wage Inequality in Developing Economies: Privatization and Competition," *Journal of International Trade & Economic Development*, 2006, *15* (3), 375–385.

Chen, Binkai, Dan Liu, and Ming Lu, "City Size, Migration and Urban Inequality in China," *China Economic Review*, 2018.

Chen, Kaiji and Yi Wen, "The great housing boom of China," *American Economic Journal: Macroeconomics*, 2017, *9* (2), 73–114.

Cuadrado-Ballesteros, Beatriz and Noemí Peña-Miguel, "The Socioeconomic Consequences of Privatization: An Empirical Analysis for Europe," *Social Indicators Research*, 2018, *139* (1), 163–183.

Dong, Zhiqing, Fangling Wang, and Qingkun Gao, "Does Skill Premium Derive from Biased Technical Change?," *Statistical Research*, 2013, *6*.

Eaton, Jonathan and Samuel Kortum, "Technology, Geography, and Trade," *Econometrica*, 2002, *70* (5), 1741–1779.

Fan, Jingting, "Internal Geography, Labor Mobility, and the Distributional Impacts of Trade," *American Economic Journal: Macroeconomics*, 2019, *11* (3), 252–88.

Fang, Hanming, Quanlin Gu, Wei Xiong, and Li-An Zhou, "Demystifying the Chinese Housing Boom," *NBER Macroeconomics Annual*, 2016, *30* (1), 105–166.

Feng, Shuaizhang, Xiaoyu Xia et al., "Endogenous Skill-biased Technology Adoption: Evidence from China's College Enrollment Expansion Program," Technical Report 2018.

Garriga, Carlos, Aaron Hedlund, Yang Tang, and Ping Wang, "Rural-urban Migration, Structural Transformation, and Housing Markets in China," Technical Report, National Bureau of Economic Research 2017.

Glaeser, Edward, Wei Huang, Yueran Ma, and Andrei Shleifer, "A Real Estate Boom with Chinese Characteristics," *Journal of Economic Perspectives*, 2017, *31* (1), 93–116.

Goldberg, Pinelopi K and Nina Pavcnik, "Trade, Inequality, and Poverty: What Do We Know? Evidence from Recent Trade Liberalization Episodes in Developing Countries," Technical Report, National Bureau of Economic Research 2004.

Gregorio, Jose De and Jong-Wha Lee, "Education and Income Inequality: New Evidence from Cross-country Data," *Review of Income and Wealth*, 2002, *48* (3), 395–416.

Han, Jun, Runjuan Liu, and Junsen Zhang, "Globalization and Wage Inequality: Evidence from Urban China," *Journal of International Economics*, 2012, *87* (2), 288–297.

Han, Libin and Ming Lu, "Housing Prices and Investment: An Assessment of China's Inland-favoring Land Supply Policies," *Journal of the Asia Pacific Economy*, 2017, *22* (1), 106–121.

_ and _ , "Supply-Demand Mismatch: Solving the Puzzle of China's Housing Price Divergence," *The Journal of World Economy*, 2018, (10), 7.

Heckman, James J, Lance Lochner, and Christopher Taber, "Explaining Rising Wage Inequality: Explorations with a Dynamic General Equilibrium Model of Labor Earnings with Heterogeneous Agents," *Review of Economic Dynamics*, 1998, *1* (1), 1–58.

Hsieh, Chang-Tai and Enrico Moretti, "Housing Constraints and Spatial Misallocation," *American Economic Journal: Macroeconomics*, 2019, *11* (2), 1–39.

Kang, Ning, "On the Education Policy and Institutional Reform: A Case Study of the College Expansion in 1999 (in Chinese)," *Journal of Higher Education*, 2000, (2), 31–38.

Katz, Lawrence F and Kevin M Murphy, "Changes in Relative Wages, 1963–1987: Supply and Demand Factors," *The Quarterly Journal of Economics*, 1992, *107* (1), 35–78.

Li, Shi, Hiroshi Sato, and Terry Sicular, *Rising Inequality in China: Challenges to a Harmonious Society*, Cambridge University Press, 2013.

_ , John Whalley, and Chunbing Xing, "China's Higher Education Expansion and Unemployment of College Graduates," *China Economic Review*, 2014, *30*, 567–582.

Liang, Wenquan, Ming Lu, and Hang Zhang, "Housing Prices Raise Wages: Estimating the Unexpected Effects of Land Supply Regulation in China," *Journal of Housing Economics*, 2016, *33*, 70–81.

Lu, Ming, *Great Nation Needs Bigger City*, Shanghai People's Press, 2016.

Moore, Mark P and Priya Ranjan, "Globalisation vs Skill-biased Technological Change: Implications for Unemployment and Wage Inequality," *The Economic Journal*, 2005, *115* (503), 391–422.

Morten, Melanie and Jaqueline Oliveira, "Migration, Roads and Labor Market Integration: Evidence from a Planned Capital City," *Unpublished manuscript*, 2014.

Novotnỳ, Josef, "On the Measurement of Regional Inequality: Does Spatial Dimension of Income Inequality Matter?," *The Annals of Regional Science*, 2007, *41* (3), 563–580.

Piketty, Thomas, Li Yang, and Gabriel Zucman, "Capital Accumulation, Private Property, and Rising Inequality in China, 1978–2015," *American Economic Review*, 2019, *109* (7), 2469–96.

Song, Donglin, Linhui Wang, and Zhiqing Dong, "Is There Skill Biased Technological Change? Evidence from China," *Economic Research Journal*, 2010, *5*, 68–81.

Song, Yang, "What Should Economists Know About the Current Chinese Hukou System?," *China Economic Review*, 2014, *29*, 200–212.

Sylwester, Kevin, "Can Education Expenditures Reduce Income Inequality?," *Economics of Education Review*, 2002, *21* (1), 43–52.

Tombe, Trevor and Xiaodong Zhu, "Trade, Migration, and Productivity: A Quantitative Analysis of China," *American Economic Review*, 2019, *109* (5), 1843–72.

Verhoogen, Eric A, "Trade, Quality Upgrading, and Wage Inequality in the Mexican Manufacturing Sector," *The Quarterly Journal of Economics*, 2008, *123* (2), 489–530.

Wu, Jing, Joseph Gyourko, and Yongheng Deng, "Evaluating the Risk of Chinese Housing Markets: What We Know and What We Need to Know," *China Economic Review*, 2016, *39*, 91–114.

Appendix

A. Additional Results of Stylized Facts

A.1 Migration measured by relative net inflow

We document five stylized facts about migration in China measured by the relative magnitude of their net inflows (Share of Net Inflows). These results are consistent with what we show in the main text. The alternative measure is defined as a city's percentage gain in workers from migration:

$$\text{Net Inflow}_j(\%) = \frac{\text{Current Workers}_j - \text{Hukou Workers}_j}{\text{Hukou Workers}_j} \tag{43}$$

where Current Workers$_j$ is the total number of workers who are currently working in city i and Hukou Workers$_j$ is the total number of workers whose Hukou registrations are located in city j. Therefore, the *Net Inflow(%)* reflects the percentage gain or loss of workers in each city. If a city maintains its worker population, the *Net Inflow(%)* will be zero.

Figure 8: Correlation of Net Inflow(%) in 2005 & 2010

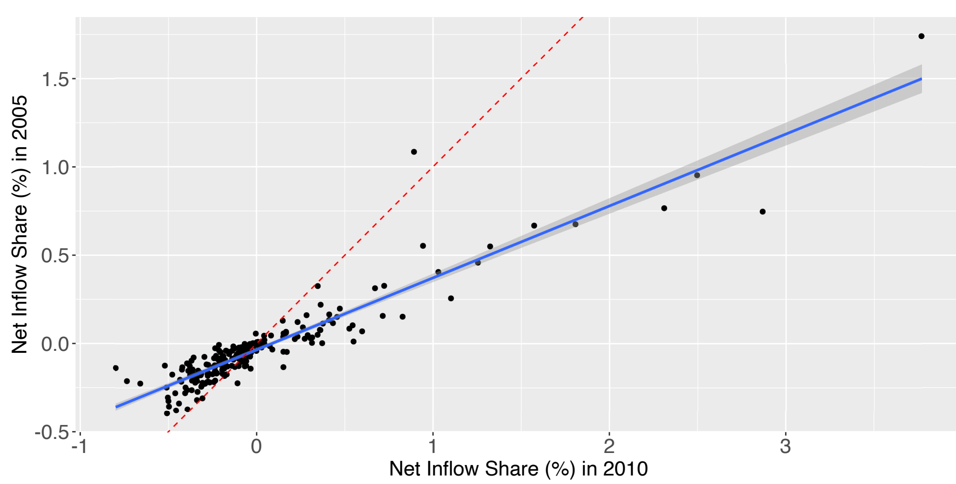
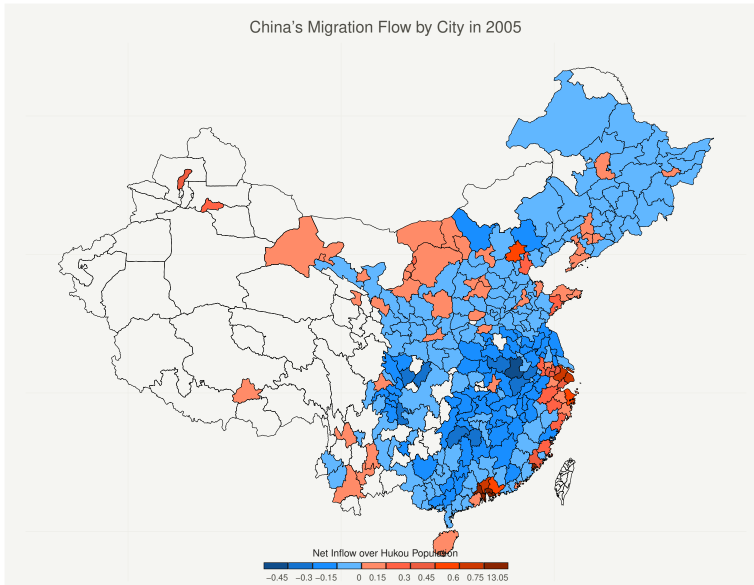
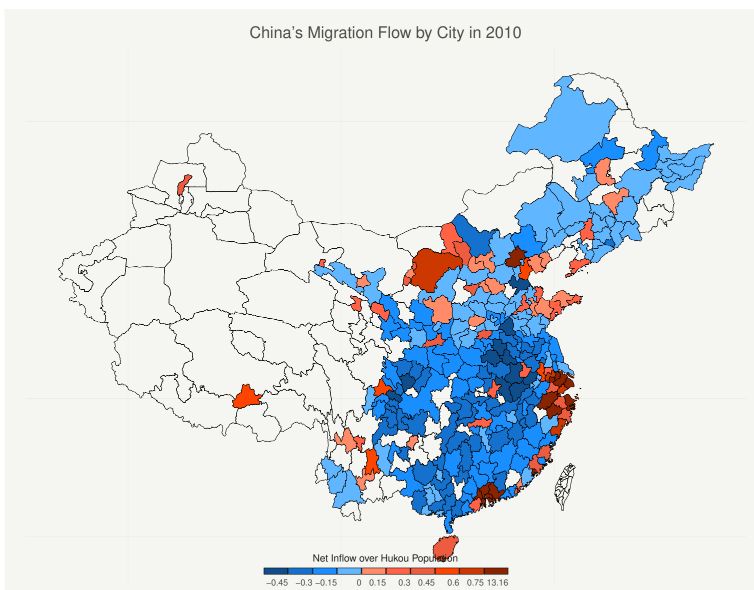


Figure 9: Net Inflow(%) of migrants by city in China



(a) Net Inflow(%) of Workers in 2005



(b) Net Inflow(%) of Workers in 2010

Notes: The sample only includes workers with wage income, which means we exclude retired workers, persistent unemployed workers (zero wage income for the whole year), children, students, homemakers, and others. The net inflow is calculated as following. Net Flow of city i is current workers of city i minus Hukou workers of city i. Therefore, this measure reflects the net gain of working population of each city. We only have data on 287 cities. Though the blank parts are missing, the data on 287 cities we have includes more than 95% of Chinese population.

A.2 Additional Results of Inequality from CHIP

In this section, we investigate the inequality between migrants and local residents in more detail. The *Census* is a comprehensive survey, but it does not contain too much information about a household's financial status, income, or expenditure. In the main context, we only have housing rents and wages, which are imputed from the *City Statistic Yearbooks*. We now introduce another dataset called the *Chinese Household Income Project (CHIP)* to further consider this inequality.[27] In 2013, CHIP covers 18,948 households in 15 provinces. After data cleaning in which we keep only urban observations, we have a sample size of 7,400 households. In these 7,400 households, there are 344 rural migrant families (migrant families from rural areas) , 223 urban migrant families (migrant families from urban areas), and 6,833 local families.

Table 18 shows the distributions of different household-level variables. Non-housing assets is the total value of the non-housing asset of a household. Net asset income is defined as the difference between total disposable income and wages of the household members. Savings rate is calculated as the ratio of income less expenditure to income. Rural migrants have fewer non-housing assets, less net asset income, and less expenditure. Nevertheless, they save more compared with urban migrants and local residents. In addition, although urban migrants have more non-housing assets, they still have much less net asset income than local residents. This indicates that a very important part of the net asset income of local residents is their housing rent, which results in significant gaps and inequalities in the income and expenditure between local residents and rural migrants.

B. Estimation

B.1 Robustness Checks in the Elasticity of Skill Substitution

We address three concerns about the IV strategy used in this paper in estimating the elasticity of substitution in the production function.

The first concern is that at the same time of the college expansion, China joined the WTO in December 2001. This was a demand shock varying across provinces which changed the skilled/unskilled labor ratio in different provinces. Moreover, it resulted in changes in productivity in different provinces. Thus, it could violate the exclusion restriction and contaminate our IV estimation. To

[27] For more details of this dataset, please refer to Li et al. (2013).

Table 18: Quantile Statistics

Variable	10%	25%	50%	75%	90%
Non-housing Asset Distribution (RMB)					
Locals	12000	30000	69700	154800	304500
Rural Migrants	7000	18925	40750	98400	185500
Urban Migrants	15000	32500	70000	140000	372000
Net Asset Income Distribution (RMB)					
Locals	-13000	0	10000	39600	66444
Rural Migrants	-10000	0	0	1000	20000
Urban Migrants	-12634	0	0	24000	60000
Expenditure Distribution (RMB)					
Locals	17000	25000	38000	56000	80000
Rural Migrants	12000	20000	30000	48548	77250
Urban Migrants	15200	28000	40500	74000	95000
Savings Rate Distribution					
Locals	3.2%	19.5%	37.4%	53.2%	65.3%
Rural Migrants	11.1%	25.0%	43.2%	60.1%	72.7%
Urban Migrants	6.3%	23.6%	41.4%	53.8%	66.7%

check the robustness of our estimating method, we redefine the IV to be $\mathbf{1}(t = 2001) \times \mathbf{1}(Province_j)$. That is, we consider only the shock before China joined the WTO and net out that demand shock. Results are shown in Table 19 and 20. We can see that the qualitative conclusion is not altered, but the point estimation is now smaller and less accurate than the one in the original IV regression.

Another method to alleviate the WTO shock is not only to control for province fixed effects and year fixed effects, but also some measure of the openness of the province's economy. We run the IV regression and additionally control for the ratio of trade to GDP in the province in different years. The results are shown in Table 21 and 22. The point estimation is not changed.

The second concern is that the shock of college expansion is unexpected in the initial years, but firms can then adjust their expectation of the labor supply and improve their productivity accordingly. In fact, (Feng et al., 2018) does find some evidence of skill-biased technology adoption. If this is the case, the exclusion restriction will be again violated. To eliminate this effect as much as possible, we redefine the IV to be $\mathbf{1}(t = 2001, 2002) \times \mathbf{1}(Province_j)$ which only considers the first two years of the stock with huge inflows of high-skill workers. The results from this estimation are shown in Table 23 and 24. We still reach the same conclusion qualitatively though the point estimation shrinks.

The third concern is that whether these provinces have different time trends before the college expansion. That is, for some intrinsic reasons, the skilled/unskilled labor ratio in these provinces had different growth patterns even without the college expansion. To test this, we define a before expansion time period dummy $\mathbf{1}(t < 2001)$ and multiply it by province fixed effects to yield $\mathbf{1}(t < 2001) \times \mathbf{1}(Province_j)$. Then we run the same regression as the original first stage, that is, a regression of the skilled/unskilled labor ratio on this interaction, year fixed effects, and province fixed effects. If the estimates of these interaction terms are different from each other, then there may have been different time trends before the expansion. The results are shown in Table 25. The baseline group is the interaction of the pre-expansion period with Shaanxi province. The results show that none of the interaction terms is statistically significant from zero, which means that there is no differential pre-trend between Shaanxi province and other provinces. Furthermore, we check the differences of the coefficients between each pair of the provinces. For instance, we check whether there are significantly different pre-trends between Beijing and Liaoning by substracting Beijing's coefficient (-0.0539) from Liaoning's coefficient (0.107) and implementing a Wald test. It shows that none of the differences between these pairs are statistically significant from zero. It means that we can rule out the possibility of contamination caused by pre-trends.

Table 19: First Stage Regression: Only Considering Shocks Before WTO

Variables	OLS
expansion	0.593***
	(0.0840)
expansion $\times$ $\mathbf{1}(province = Beijing)$	-0.328***
	(0.0486)
expansion $\times$ $\mathbf{1}(province = Liaoning)$	0.0151
	(0.0355)
expansion $\times$ $\mathbf{1}(province = Zhejiang)$	-0.111***
	(0.0382)
expansion $\times$ $\mathbf{1}(province = Guangdong)$	-0.0631
	(0.0396)
expansion $\times$ $\mathbf{1}(province = Sichuan)$	-0.200***
	(0.0439)
Province FE	YES
Year FE	YES
Observations	102
R-squared	0.897
Prob > F	0.0000

Notes: The dependent variable is the skilled/unskilled labor ratio in each province in each year. In this table, we show the results from the first stage regression when we utilize the interaction of the 2001 indicator with province indicator as the instrumental variable. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 20: IV Regression: Only Considering Shocks Before WTO

Variables	2SLS
Skilled/Unskilled Ratio	-0.161
	(0.129)
Province FE	YES
Year FE	YES
Observations	102
R-squared	0.812

Notes: The dependent variable is the skill premium in each province in each wave. In this table, we show the results from the IV regression when we utilize the interaction of the 2001 indicator with province indicator as the instrumental variable of the skilled over unskilled labor ratio. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 21: First Stage Regression: Controlling for Province Openness

Variables	OLS
expansion	0.656***
	(0.0898)
expansion × $\mathbf{1}(province = Beijing)$	-0.196**
	(0.0812)
expansion × $\mathbf{1}(province = Liaoning)$	-0.0937
	(0.0656)
expansion × $\mathbf{1}(province = Zhejiang)$	-0.196***
	(0.0550)
expansion × $\mathbf{1}(province = Guangdong)$	-0.0777
	(0.0563)
expansion × $\mathbf{1}(province = Sichuan)$	-0.131*
	(0.0657)
Trade over GDP	-0.0748
	(0.0779)
Province FE	YES
Year FE	YES
Observations	102
R-squared	0.898
Prob > F	0.0000

Notes: The dependent variable is the skilled/unskilled labor ratio in each province in each year. In this table, we show the results from the first stage regression when we utilize the interaction of the 2001 indicator with province indicator as the instrumental variable. We additionally control for the ratio of trade to GDP in different provinces in various years in this regression. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 22: IV Regression: Controlling for Province Openness

Variables	2SLS
Skilled/Unskilled Ratio	-0.330**
	(0.144)
Province FE	YES
Year FE	YES
Province Openness	YES
Observations	102
R-squared	0.739

Notes: The dependent variable is the skill premium in each province in each wave. In this table, we show the results from the IV regression when we utilize the interaction of the 2001 indicator with province indicators as the instrumental variable of the skilled over unskilled labor ratio. We additionally control for the ratio of trade over GDP in different provinces in various years in this regression. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 23: First Stage Regression: Only Consider Shocks Before 2002

Variables	OLS
expansion	0.475***
	(0.0860)
expansion $\times$ $\mathbf{1}(province = Beijing)$	-0.254***
	(0.0751)
expansion $\times$ $\mathbf{1}(province = Liaoning)$	-0.0102
	(0.0553)
expansion $\times$ $\mathbf{1}(province = Zhejiang)$	-0.144**
	(0.0569)
expansion $\times$ $\mathbf{1}(province = Guangdong)$	-0.0629
	(0.0476)
expansion $\times$ $\mathbf{1}(province = Sichuan)$	-0.116
	(0.0728)
Province FE	YES
Year FE	YES
Observations	102
R-squared	0.897
Prob > F	0.0000

Notes: The dependent variable is the skilled/unskilled labor ratio in each province in each year. In this table, we show the results from the first stage regression when we utilize the interaction of the 2001 and 2002 indicators with province indicators as the instrumental variable. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 24: IV Regression: Only Consider Shocks Before 2002

Variables	2SLS
Skilled/Unskilled Ratio	-0.187*
	(0.113)
Province FE	YES
Year FE	YES
Observations	102
R-squared	0.803

Notes: The dependent variable is the skill premium in each province in each wave. In this table, we show the results from the IV regression when we utilize the 2001 and 2002 indicators with province indicator as the instrumental variable of the skilled over unskilled labor ratio. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 25: Pre-trend Testing

Variables	OLS
$\mathbf{1}(t < 2001)$	-0.990***
	(0.0959)
$\mathbf{1}(t < 2001) \times \mathbf{1}(province = Beijing)$	-0.0539
	(0.0974)
$\mathbf{1}(t < 2001) \times \mathbf{1}(province = Liaoning)$	0.107
	(0.0651)
$\mathbf{1}(t < 2001) \times \mathbf{1}(province = Zhejiang)$	0.0226
	(0.0748)
$\mathbf{1}(t < 2001) \times \mathbf{1}(province = Guangdong)$	0.0151
	(0.0786)
$\mathbf{1}(t < 2001) \times \mathbf{1}(province = Sichuan)$	-0.0271
	(0.0868)
Province FE	YES
Year FE	YES
Observations	102
R-squared	0.896
Prob > F	0.0000

Notes: The dependent variable is the skilled/unskilled labor ratio in each province in each year. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

C. Alternative Model: $v_{ij}^s = w_j^s + \frac{Q_i S_i}{H_i^R}$

In this appendix, we calculate an alternative model in which the income from the residential floor space market is redistributed among all the Hukou-registered workers regardless of whether they remain in their hometown or migrate to other cities. In this case, even workers who migrate to another city will still enjoy the housing revenue created in his or her hometown. This requires a modification of the individual income equation (10) as following:

$$v_{ij}^s = w_j^s + \frac{Q_i S_i}{H_i^R} \tag{44}$$

where H_i^R is the number of Hukou residents registered in origination city i and S_i is the residential floor space in city i. Families migrating to other cities benefit from the rent rebate in their hometowns but not the destination cities.

We show how this will change the key model and counterfactual results. The main conclusion is that all properties remain identical qualitatively but slightly change quantitatively.

C.1 Model Results: Wage Inequality & Income Inequality

Table 26: **Within-city Theil Index**

Net Inflow	No. of	Wage Theil Index			Income Theil Index		
Range(2010)	Cities	2005	2010	Relative	2005	2010	Relative
Average	233	0.0073	0.0070	96%	0.0099	0.0184	186%
(6,13)	5	0.0087	0.0096	110%	0.0439	0.0908	206%
(1,6)	19	0.0065	0.0079	122%	0.0091	0.0222	243%
(0, 1)	45	0.0076	0.0083	109%	0.0060	0.0092	153%
(-1,0)	134	0.0071	0.0058	82%	0.0049	0.0052	106%
(-4,-1)	30	0.0074	0.0058	78%	0.0054	0.0062	115%

Notes: This table displays population-weighted means in 2005 and 2010.

Table 27: **Share of Contribution to National Theil Index**

Net Inflow Range(2010)	No. of Cities	Share of Wage Theil 2005	Share of Wage Theil 2010	Share of Wage Theil Relative	Share of Income Theil 2005	Share of Income Theil 2010	Share of Income Theil Relative
National	233	0.0985	0.0622	63%	0.1156	0.0921	80%
(6,13)	5	+1.47	+1.41	95%	+1.43	+1.27	89%
(1,6)	19	+0.58	+0.83	143%	+0.53	+0.70	132%
(0, 1)	45	+0.22	+0.26	118%	+0.19	+0.20	105%
(-1,0)	134	-0.90	-1.00	111%	-0.81	-0.78	96%
(-4,-1)	30	-0.37	-0.49	132%	-0.34	-0.39	115%

Notes: This table displays city groups' contributions to the national Theil Index in 2005 and 2010. Each column sums up to 100%. The first row display the national wage/income Theil Index in 2005 and 2010.

Table 28: **Skill Premium and Housing Premium**

Net Inflow Range(2010)	No. of City	Skill Premium 2005	Skill Premium 2010	Skill Premium Relative	Housing Premium 2005	Housing Premium 2010	Housing Premium Relative
Average	233	1.47	1.40	95%	0.36	0.49	136%
(6,13)	5	1.35	1.39	103%	0.92	1.89	205%
(1,6)	19	1.40	1.40	100%	0.39	0.56	144%
(0, 1)	45	1.43	1.39	97%	0.32	0.35	109%
(-1,0)	134	1.50	1.40	93%	0.27	0.25	93%
(-4,-1)	30	1.58	1.45	92%	0.24	0.19	79%

Notes: This table displays population-weighted means in 2005 and 2010. Skill Premium is measured as annual high-skill wage over annual low-skill wage for each city, and Housing Premium is measured as average annual housing return over the average annual wage for each city.

C.2 Counterfactual Results: Land Supply Reform

We conduct the same migration-based land supply policy reform as in the main text. The results of land supply policy reform are summarized in Table 29 to Table 32.

Table 29: **Migration Flow and Housing Cost**

Net Inflow Range(2010)	No. of City	Net Inlow 2010	Net Inlow $\widehat{2010}$	Net Inlow Relative	Housing Cost 2010	Housing Cost $\widehat{2010}$	Housing Cost Relative
Overall	233	96m	110m	115%	111	117	105%
(6,13)	5	+45m	+54m	120%	223	156	70%
(1,6)	19	+38m	+44m	116%	131	109	83%
(0, 1)	45	+13m	+12m	92%	118	129	109%
(-1,0)	134	-48m	-56m	117%	85	112	132%
(-4,-1)	30	-48m	-54m	113%	69	87	126%

Notes: This table displays total net inflow of migration flow and population weighted average housing cost for each city groups. In the first overall raw, we show the number of workers who have moved for migration flow and the national population weighted average housing cost. The unit of migration net inflow is millions, and the unit of housing costs is Chinese Yuan (RMB) per square meters per year.

Table 30: **Within-city Theil Index**

Net Inflow Range(2010)	No. of Cities	Wage Theil Index 2010	Wage Theil Index $\widehat{2010}$	Wage Theil Index Relative	Income Theil Index 2010	Income Theil Index $\widehat{2010}$	Income Theil Index Relative
Average	233	0.0070	0.0071	101%	0.0246	0.0119	48%
(6,13)	5	0.0096	0.0091	94%	0.1215	0.0425	34%
(1,6)	19	0.0079	0.0083	105%	0.0363	0.0134	37%
(0, 1)	45	0.0083	0.0080	96%	0.0144	0.0097	67%
(-1,0)	134	0.0058	0.0058	100%	0.0051	0.0045	88%
(-4,-1)	30	0.0058	0.0059	102%	0.0045	0.0053	118%

Notes: This table displays population-weighted means of both inequality measures. The original equilibrium is 2010 and the counterfactual equilibrium is $\widehat{2010}$. And the Relative is dividing $\widehat{2010}$ by 2010.

Table 31: **Share of national Theil Index**

Net Inflow Range(2010)	No. of Cities	Share of Wage Theil 2010	Share of Wage Theil $\widehat{2010}$	Share of Wage Theil Relative	Share of Income Theil 2010	Share of Income Theil $\widehat{2010}$	Share of Income Theil Relative
National	233	0.0622	0.0618	99%	0.0873	0.0739	85%
(6,13)	5	+1.41	+1.46	102%	+1.21	+1.27	105%
(1,6)	19	+0.83	+0.84	101%	+0.66	+0.65	98%
(0, 1)	45	+0.26	+0.23	88%	+0.20	+0.30	150%
(-1,0)	134	-1.00	-0.97	97%	-0.71	-0.75	106%
(-4,-1)	30	-0.49	-0.56	114%	-0.35	-0.47	134%

Notes: This table displays city groups' contribution to national Theil Index in 2005 and 2010. The first row display the national wage/income Theil Index in 2005 and 2010.

Table 32: **Skill Premium and Housing Premium**

Net Inflow Range(2010)	No. of Cities	Skill Premium 2010	Skill Premium $\widehat{2010}$	Skill Premium Relative	Housing Premium 2010	Housing Premium $\widehat{2010}$	Housing Premium Relative
Average	233	1.40	1.40	100%	0.56	0.44	79%
(6,13)	5	1.39	1.39	100%	2.03	1.10	54%
(1,6)	19	1.40	1.42	101%	0.62	0.40	65%
(0, 1)	45	1.39	1.38	99%	0.39	0.40	102%
(-1,0)	134	1.40	1.39	99%	0.31	0.33	106%
(-4,-1)	30	1.45	1.44	99%	0.30	0.27	90%

Notes: This table displays population-weighted means in 2005 and 2010. Skill Premium is measured as annual high-skill wage over annual low-skill wage for each city, and Housing Premium is measured as average annual housing return over the average annual wage for each city.

D. Alternative Model: $\sigma = 1.4$

In this appendix, we calculate an alternative model with the elasiticity of substitution between high and low skill workers to be $\sigma = 1.4$ as in the classic literature for the U.S.. We show how this will change the key model and counterfactual results. The main conclusion is that all properties remain identical qualitatively but slightly change quantitatively.

D.1 Model Results: Wage Inequality and Income Inequality

Table 33: **Average Productivity Growth**

Net Inflow	No. of	High-skill				Low-skill			
Range(2010)	Cities	2005	2010	Relative	Changes	2005	2010	Relative	Changes
Average	233	0.06	0.14	233%	+0.08	0.94	1.71	182%	+0.77
(6,13)	5	0.19	0.46	242%	+0.27	1.26	2.12	168%	+0.86
(1,6)	19	0.04	0.12	300%	+0.08	1.21	1.94	160%	+0.73
(0, 1)	45	0.04	0.10	250%	+0.06	1.02	1.63	160%	+0.61
(-1,0)	134	0.01	0.02	200%	+0.01	0.82	1.63	199%	+0.81
(-4,-1)	30	0.004	0.015	375%	+0.011	0.78	1.52	194%	+0.74

D.2 Counterfactual Results: Land Supply Reform

We conduct the same migration-based land supply policy reform as in the main text. The results are as following.

Table 34: **Migration Flow and Housing Cost**

Net Inflow Range(2010)	No. of Cities	Net Inflow 2010	Net Inflow $\widehat{2010}$	Net Inflow Relative	Housing Cost 2010	Housing Cost $\widehat{2010}$	Housing Cost Relative
Overall	233	96m	104m	115%	111	118	106%
(6,13)	5	+45m	+52m	116%	223	152	68%
(1,6)	19	+38m	+41m	108%	131	108	82%
(0, 1)	45	+13m	+11m	85%	118	129	109%
(-1,0)	134	-48m	-52m	108%	85	116	136%
(-4,-1)	30	-48m	-52m	108%	69	91	132%

Table 35: **Within-city Theil Index**

Net Inflow Range(2010)	No. of Cities	Wage Theil Index 2010	Wage Theil Index $\widehat{2010}$	Wage Theil Index Relative	Income Theil Index 2010	Income Theil Index $\widehat{2010}$	Income Theil Index Relative
Average	233	0.0070	0.0070	100%	0.0246	0.0208	85%
(6,13)	5	0.0096	0.0089	93%	0.1215	0.0694	57%
(1,6)	19	0.0079	0.0081	103%	0.0363	0.0276	75%
(0, 1)	45	0.0083	0.0082	99%	0.0144	0.0151	105%
(-1,0)	134	0.0058	0.0058	100%	0.0051	0.0078	152%
(-4,-1)	30	0.0058	0.0057	99%	0.0045	0.0142	315%

Table 36: **Share of national Theil Index**

Net Inflow Range(2010)	No. of Cities	Share of Wage Theil 2010	Share of Wage Theil $\widehat{2010}$	Share of Wage Theil Relative	Share of Income Theil 2010	Share of Income Theil $\widehat{2010}$	Share of Income Theil Relative
National	233	0.0622	0.0616	99%	0.0873	0.0712	82%
(6,13)	5	+1.41	+1.44	102%	+1.21	+1.05	87%
(1,6)	19	+0.83	+0.84	101%	+0.66	+0.57	86%
(0, 1)	45	+0.26	+0.23	88%	+0.20	+0.23	115%
(-1,0)	134	-1.00	-1.03	103%	-0.71	-0.53	75%
(-4,-1)	30	-0.49	-0.48	98%	-0.35	-0.32	91%

Table 37: **Skill Premium and Housing Premium**

Net Inflow	No. of	Skill Premium			Housing Premium		
Range(2010)	Cities	2010	$\widehat{2010}$	Relative	2010	$\widehat{2010}$	Relative
Average	233	1.40	1.40	100%	0.56	0.53	95%
(6,13)	5	1.39	1.39	100%	2.03	1.18	58%
(1,6)	19	1.40	1.41	101%	0.62	0.47	76%
(0, 1)	45	1.39	1.38	99%	0.39	0.41	105%
(-1,0)	134	1.40	1.39	99%	0.31	0.44	142%
(-4,-1)	30	1.45	1.44	99%	0.30	0.42	140%

E. Additional Counterfactual Analysis

E.1 Property Tax and Redistribution

China currently has no property tax on housing ownership so far. There is a recent heated debate on whether China should adopt a property tax and redistribution policy. It is widely documented that more than 75% of Chinese household wealth is in housing. Given the approximate ratio of a property tax to rent revenue is roughly 20% in the U.S., this counterfactual taxes property owners' housing income by 20% and redistributes the proceeds to all residences in the same city (think about using the tax revenue on building city amenities which benefits all residents equally.). The results are presented in Table 38 to Table 41.

Table 38: **Migration Flow & Housing Cost**

Net Inflow	No. of	Net Inlow			Housing Cost		
Range(2010)	Cities	2010	$\widehat{2010}$	Relative	2010	$\widehat{2010}$	Relative
Overall	233	96m	101m	105%	114	116	102%
(6,13)	5	+45m	+48m	107%	226	235	104%
(1,6)	19	+38m	+40m	105%	136	139	102%
(0, 1)	45	+13m	+14m	108%	118	119	101%
(-1,0)	134	-48m	-51m	106%	87	86	99%
(-4,-1)	30	-48m	-50m	104%	80	78	98%

Notes: This table displays total net migration inflows and population weighted average housing cost for each city groups. In the first overall raw, we show the number of workers who have migrated and the national population weighted average housing cost. The unit of net migration net inflow is millions, and the unit of housing costs is Chinese Yuan (RMB) per square meters per year.

Table 39: **Within-city Theil Index**

Net Inflow	No. of	Wage Theil Index			Income Theil Index		
Range(2010)	Cities	2010	$\widehat{2010}$	Relative	2010	$\widehat{2010}$	Relative
Average	233	0.0070	0.0071	101%	0.0247	0.0319	129%
(6,13)	5	0.0096	0.0100	104%	0.1215	0.1399	115%
(1,6)	19	0.0079	0.0081	103%	0.0363	0.0432	119%
(0, 1)	45	0.0083	0.0085	102%	0.0144	0.0181	126%
(-1,0)	134	0.0058	0.0058	100%	0.0051	0.0092	180%
(-4,-1)	30	0.0058	0.0058	100%	0.0045	0.0112	248%

Notes: This table displays population-weighted means of both inequality measures. The original equilibrium is 2010 and the counterfactual equilibrium is $\widehat{2010}$. And the Relative is calculated via dividing $\widehat{2010}$ by 2010.

Table 40: **Share of national Theil Index**

Net Inflow	No. of	Share of Wage Theil			Share of Income Theil		
Range(2010)	Cities	2010	$\widehat{2010}$	Relative	2010	$\widehat{2010}$	Relative
National	233	0.0622	0.0624	100%	0.0873	0.0954	109%
(6,13)	5	+1.41	+1.43	101%	+1.21	+1.16	96%
(1,6)	19	+0.83	+0.82	99%	+0.66	+0.61	92%
(0, 1)	45	+0.26	+0.24	92%	+0.20	+0.18	90%
(-1,0)	134	-1.00	-1.01	101%	-0.71	-0.65	92%
(-4,-1)	30	-0.49	-0.48	98%	-0.35	-0.31	89%

Notes: This table displays city groups' contributions to the national Theil Index in 2005 and 2010. The first row display the national wage/income Theil Index in 2005 and 2010.

Table 41: **Skill Premium and Housing Premium**

Net Inflow	No. of	Skill Premium			Housing Premium		
Range(2010)	Cities	2010	$\widehat{2010}$	Relative	2010	$\widehat{2010}$	Relative
Average	233	1.40	1.40	100%	0.56	0.60	107%
(6,13)	5	1.39	1.40	101%	2.03	2.19	108%
(1,6)	19	1.40	1.41	101%	0.62	0.64	103%
(0, 1)	45	1.39	1.39	100%	0.39	0.40	102%
(-1,0)	134	1.40	1.39	99%	0.31	0.32	103%
(-4,-1)	30	1.45	1.44	99%	0.30	0.31	103%

Notes: This table displays population-weighted means in 2005 and 2010. Skill Premium is measured as annual high-skill wage over annual low-skill wage for each city, and Housing Premium is measured as average annual housing return over the average annual wage for each city.