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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 flows, 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 reductions in migration costs and the divergent growth in productivity across cities and skills result in the observed massive migration to developed areas. Combined with tight land supply policies in big cities, the expansion of housing demand caused the rapid growth of housing costs and increased inequality between local housing owners and migrants. The counterfactual analysis shows that a migration-based land supply reform with regional transfers or a US-level property tax can lower within-city income inequality by 34% and 21%, respectively. Meanwhile, both reforms lower national income inequality by 20%. However, only the land supply reform encourages more workers to migrate to higher productivity cities.

1. Introduction

As documented by Piketty et al. (2019), Chinese income and asset inequality rose from a level similar to that of Scandinavia to approaching that of the United States. More importantly, much of this rise was driven by the uneven ownership of the dramatically appreciating housing assets in developed cities. This housing boom in developed cities has been accompanied by massive inflows of migrant workers as well as tightening housing constraints.[1] Could this massive migration inflow and tight housing constraints in these developed cities explain rapidly rising inequality in China? If so, is there any policy we could implement to alleviate this rising inequality?

In this paper, we take two approaches to answer both questions. First, using various sources of data, we document that housing costs and income inequality are significantly positively correlated with the number of migrant workers in different cities. Second, we construct a spatial equilibrium model incorporating both heterogeneous wage income and heterogeneous housing asset income to quantify the effects of migra-

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[1] China has experienced impressive economic growth over the last four decades after the start of economic reforms and opening-up in 1978. This triggered a massive wave of migrant workers moving from under-developed areas to developed areas. There was also 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.

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tion and housing constraints on the observed income inequality. In the counterfactual analysis, we find that easing the housing constraints in developed cities can reduce income inequality in China.

In the first step, we show four main stylized facts from the data. First, migration in China is overwhelmingly into developed areas. The concentration is accelerating across time because of improvements in the transportation system and the relaxation of the Hukou system.[2] Second, housing costs have increased drastically over time, especially for cities with large numbers of migrants. There is a positive correlation between housing costs and the net stock of migrant workers across cities. Third, income inequality within cities is positively correlated with the net stock of migrant workers. Fourth, it is housing ownership inequality, rather than wage inequality that caused the observations in stylized fact 3. These four stylized facts give us a preliminary picture of the whole story. As the economy grew, more and more migrants concentrated in large and developed coastal cities. The massive increase in housing demand, together with a highly regulated land supply, pushed up real estate rents in big cities to the benefit of local housing owners. Increasing housing rents then translated into increasing income inequality between local property owners and migrant renters.

In the second step, we construct a spatial equilibrium model to quantify the facts, explain the mechanism, and conduct counterfactual analysis. The model comprises heterogeneous workers making migration choices, a representative firm, and a state-regulated housing sector in each city. The key mechanism is that with the universal drop in migration costs and uneven productivities, workers migrate from under-developed cities to developed cities with higher wages. Since housing supply is heavily regulated and inelastic in these developed cities, housing costs increase dramatically, which drives up local property owners housing income. However, due to various frictions, migrant workers cannot participate in their local property market or share any increases in housing values in the living city. They can only earn housing returns in their under-developed home city. As more and more migrants move into developed cities, the housing ownership gap between locals and migrants results in rapidly rising income inequality.

Using various sources of data from 2005 and 2010, we solve the model quantitatively. We find that from 2005 to 2010, the average migration costs decreased by 35% for low-skill workers and 21% for high-skill workers. Meanwhile, productivity growth was faster in absolute terms in large cities, which attracted large numbers of migrant workers. These large, developed cities also have slower growth in land supply. Construction land supply increased by only 10% in the largest cities, which together attracted more than twenty million workers. While at the same time, average land supply growth was 40% for cities which lost almost half of their working population. This inefficient land supply policy causes severe housing constraints in developed cities and increases income inequality.[3]

Finally, we conduct counterfactual policy reforms to ease housing constraints in developed cities and reduce income inequality. The main counterfactual we impose is a migration-based land supply reform. The idea is straightforward and intuitive: to allocate new land quotas by migration flows. We reallocate the increment of the total land supply quota from 2005 to 2010. Instead of giving more land quota to under-developed areas, we allocate land quota proportionally to the change in the migration inflows to different cities, while keeping the national total land supply constant. That is, cities attracting more migrants are given more quota.[4] Meanwhile, all revenues from additional lands in developed cities are collected and transferred to under-developed cities who lost quota as compensation. This policy mimics a ”land quota transfer market” (Lu, 2016) where developed cities can buy land quota from under-developed cities and compensate them with direct transfers. Thus, we can achieve balanced development between regions and simultaneously avoid policy distortion. With the counterfactual land supply policy, housing cost increases in big cities are significantly attenuated. Compared with the real world, this policy reduces housing costs in 2010 by 30% in first-tier cities and by 25% in second-tier cities, and also incentivizes more workers to migrate to these developed cities. Simultaneously, within-city income inequality falls by 34% and national inequality by 20%. In another counterfactual policy, we show that a US-level property tax and redistribution policy could also help to reduce income inequality.

Literature Review Our study extends the current literature in three dimensions. First, we investigate a new mechanism for income inequality and extend knowledge about increasing inequality in China. There are many studies on income and wage inequality. Different papers investigate many causes of inequality, including skill-biased technological change and the increase in the return to human capital (Berman et al., 1998; Card and DiNardo, 2002; Moore and Ranjan, 2005), education inequality (Gregorio and Lee, 2002; Sylwester, 2002), trade liberalization (Goldberg and Pavcnik, 2004; Han et al., 2012; Verhoogen, 2008), and privatization (Chao et al., 2006; Cuadrado-Ballesteros and Peña-Miguel, 2018). The closest study to ours is Chen et al. (2018). They find that larger cities have higher income inequality and claim that this is because migration inflows into larger cities change the skill composition of the workers, yielding a higher skill premium. In this study, we investigate a new mechanism of migration interacting with housing constraints that can also increase income 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 has extended 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 these contributions investigate internal migration costs, such as Morten and Oliveira (2014), Bryan and Morten (2019), Ma and Tang (2020), Tombe and Zhu (2019), Yu (2019), Wu and You (2020) 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 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 introduces both 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 statistical yearbooks. Combining this unique dataset with the population census, we construct a compre-

[2] 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 locale during one's lifetime. The Hukou system is closely related to 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. For more details, please refer to Song (2014).

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

[4] A main concern here is whether big cities like Shanghai and Beijing have reached their natural limits for land supply or not. Wu and You (2020) shows that, in 2005, only 23% of the land was developed in tier-1 cities (the most developed).

hensive and spatially decomposable 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 Garriga et al. (2020), Garriga et al. (2017), 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 have seen disproportionate gains in housing prices while less developed cities have seen their housing prices grow more slowly than GDP. 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 and massive migration inflows into larger cities jointly caused the *Great Housing Boom*. We also provide counterfactual policies for the housing sector, which could lower housing costs and reduce housing inequality.

Layout This paper is organized as follows. Section 2 describes the data and variables. Section 3 documents five stylized facts of migration, housing, and inequality in China. Section 4 shows the spatial equilibrium model. Section 5 quantifies the model and shows the quantitative results. Section 6 shows counterfactual policy reforms. Section 7 concludes.

2. Data and variables

2.1. Data sources

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 elasticities, the dataset must be large enough to record flows between all pairs of locations. Only the *Chinese Population 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. We introduce these datasets sequentially below in depth.

We use the *Census* as the main dataset in this study. It is the most comprehensive household-level survey in China. It is conducted every ten years, and all residents in mainland China are surveyed. In the survey, 90% of households report only basic demographic information, including their Hukou registration location and current living location. The other 10% of households take a so-called "long-survey," which asks additional questions including items dealing with housing conditions, housing rents, and job details. 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 city-level migration flows and housing rents for individuals with different education levels.[5] In our sample, we have 2,585,481 observations in the year 2005, which covers 0.2% of the Chinese population. Additionally, we have 4,803,589 observations in the year 2010, which covers 0.36% of the population.

We supplement the *Census* data with the *City Statistic Yearbooks* and the *Urban Statistic Yearbook*. *City Statistic Yearbooks* contain 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. We derive industry level average wages in each city from these yearbooks. They will be used to impute the city-skill level wages as we will explain in the next section. The *Urban Statistic Yearbook* is a book with a summary of key economic indicators across all Chinese cities in a specific year. We derive city-level GDP growth rates and construction land area data from it.

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

2.2. Imputing city-skill level wages

In the model part of 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. Ideally, if we have wages for all individuals in the *Census* data, we can calculate city-skill level average wages as:

$$w_j^s = \frac{1}{N_j^s} \sum_i w_{ij}^s \tag{1}$$

where w_j^s is the average wage of workers with skill s in city j, N_j^s is the number of workers in city j with skill s, and w_{ij}^s is the wage of individual worker i with skill s, working in city j. However, the *Census*data contains wage information only for the year 2005 and not 2010. Fortunately, in the *City Statistic Yearbooks* of each city, they have average wages in different industries in this city. In addition, in the *Census* data, there is information about an individual's education and industry. Thus, we can first impute an individual's wage by using the average wage in the industry-city the individual is working in. Then we use Eq. (1) to calculate city-skill level average wages. 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 data 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.[6] This replacement is less than 5% of the observations.

There is another concern that the wages from *City Statistic Yearbooks* may not be representative since the National Bureau of Statistics usually does not include informal jobs when it collects the data. Thus, we try another imputation of the city-skill level average wages to check the robustness of our results. In this method, we directly use individual wages in 2005 and calculate city-skill level wages using Eq. (1) in 2005. We then impute the city-skill level wages in 2010 by multiplying the city-skill level wages in 2005 with GDP growth from 2005 to 2010 in each city. We repeat all the analysis using this method and the results are robust. They are available upon request. We do not use this measure for our main results because by multiplying city-level GDP growth with wages in 2005, we assume that wages of people with high and low skills in each city evolved in the same way from 2005 to 2010.

3. Stylized facts: migration, housing, and inequality

From our data, we calculate the net stock of migrant workers, the skill share, and housing costs in each city. We then calculate within-city inequality for each city and nationwide inequality. From these observations, we document four major and one supplementary stylized facts of migration, housing and inequality in China.

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

To document Fact 1, we calculate the net stock of migrant workers and the share of the net stock of migrant workers across all Chinese cities in 2005 and 2010, respectively. The net stock (in numbers N) and share of the net stock (in percentage %) for city j are calculated as follows:

$$\text{Net Stock}_j(N) = \text{Current Workers}_j - \text{Hukou Workers}_j$$

[6] 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.

(a) Net stock of migrant workers in 2005 (b) Net stock of migrant workers in 2010

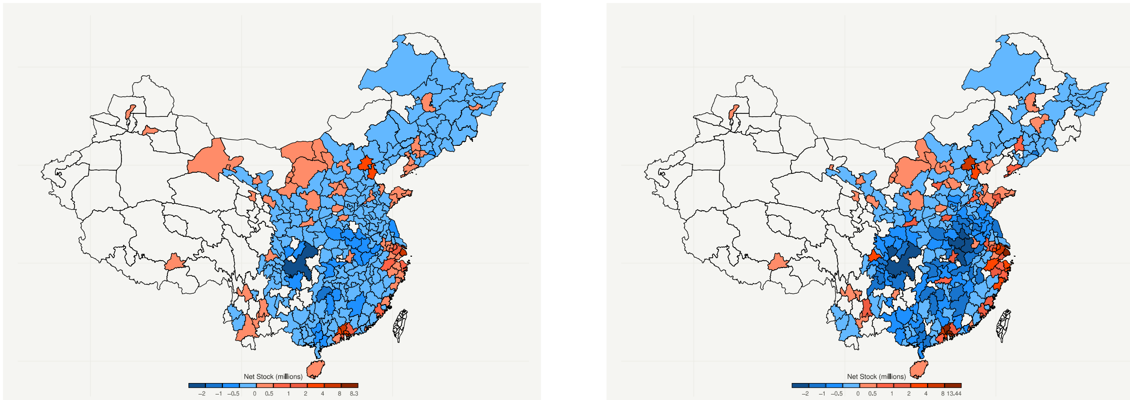

Fig. 1. Net stock (Numbers N) of migrant workers by city in China. Notes: The sample only includes workers with wage income, which means that we exclude retired workers, persistently unemployed workers (zero wage income for the whole year), children, students, homemakers, and others. The net stock of 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 and 266 cities in 2005 and 2010, respectively. Though the blank parts are missing, our available data covers more than 95% of the Chinese population. The map of *Net Stock (%)* which shows a similar pattern, as well as the summary table of the underlying numbers, are presented in Appendix.

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

where Current Workers$_j$ is the total number of workers who are currently working in city j, and Hukou Workers$_j$ is the total number of workers whose Hukou registration is located in city j. Therefore, the net stock reflects the net gain or loss in the working population of each city and the share of net stock reflects the net gain or loss proportional to the Hukou registered working population of each city.[7] The former measure avoids potential outliers when measuring in percentages and the latter measure avoids the potential city size effect when measuring in absolute numbers.

First, migration is highly concentrated in certain large cities. Our analysis here extends Ma and Tang (2020)'s study from 2005 to 2010. To visualize the migration patterns, we also geographically plot the *Net Stock(N)* by cities in both 2005 and 2010 in Fig. 1,[8] where colors demonstrate the pattern of net migration. For instance, in 2010, there were 34 cities with a net stock of more than 8 million migrants. Most cities lose workers, and only about one-fourth of cities have positive net stocks. From the map, it is obvious that workers are migrating from western and central regions to eastern regions, and from inland cities to coastal cities.[9]

Second, migration is increasingly funneled into certain large cities. As the colors in Fig. 1 indicate, the concentration of migration has grown during these five years. From 2005 to 2010, inland cities lost more workers to large eastern cities. To provide more intuition, we also plot the correlation between the net stock of migrants in 2005 and in 2010 in Fig. 2. The red dashed line is the 45-degree line. The fitted line has a slope much larger than one, and the big cities with a net gain of workers in 2010 are all above the 45-degree line, which means that migration concentration was rapidly increasing over these five years.

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

To document Fact 2, we calculate housing costs for each city in both 2005 and 2010 using micro data from the *Chinese Population Census*. We first calculate the annual individual housing rent per square meter, then take the average for each city.

Fig. 3 plots housing costs against the net stock of migrant workers for both 2005 and 2010 in both absolute number and percentage measures, respectively. Red dots are values in 2010 and blue dots are values in 2005. We fix the x-axis using the 2010 value for each city so we can easily compare changes in housing costs across cities over the five-year period. For instance, the highest dot (>300 Yuan) in sub-figure (a) is Beijing's average housing cost in 2010; we can then easily identify Beijings average housing cost in 2005 as roughly 220 Yuan, right below the highest dot. We keep this plotting format for all figures in the rest of this paper.

The message is twofold. First, housing costs increase drastically with the net stock of migrants. It is clear that the net stock of migrants is positively correlated with housing rent costs. The fitted lines for both net stock measures and both years are significantly upward sloping. Second, housing costs increased drastically over time. The national average annual housing rent per square meter increased sharply from 74 RMB per square meter to 113 RMB per square meter, which corresponds to a 53% increase.

We illustrate the positive correlation between migration and housing cost in more detail in Appendix A2. The first concern is that cities may systematically differ in their housing qualities and the correlation may be caused by better qualities in developed cities with more migrants. We solve this issue by running a household-level regression and controlling for house characteristics. We find that conditional on house quality, an additional 1 million migrants within the city is associated with an increase in the annual housing rent of 7.7 (4.6) RMB per square meter in 2005 (2010), which corresponds to a 10.3% (4.1%) increase. Second, we further attempt to identify the causal effect of migration on housing costs by employing a Bartik-style instrument inspired by Card (2009) and Bartik (1991). Using this approach, we find that an increase of 1 million migrants raises the annual housing rent by 1.4 RMB per square meter. In general, our evidence indicates that housing costs increase significantly with the net stock of migrants and across time.

[7] We do not choose a percentage measure such as {(Current Workers$_j$ − Hukou Workers$_j$)/Current Workers$_j$} which is strictly bounded between 0 and 1 because we do not want to capture just the relative share of migrant workers among working populations in each city. We emphasize each city's net gain or loss relative to its Hukou registrations.

[8] For the sake of space, the map of *Net Stock* (%) which shows similar pattern as well as the summary table of underlying numbers are presented in Appendix.

[9] Most of the big industrialized cities are located along the eastern coastline. There are four main economic zones containing cities with huge numbers of migrant workers: (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.

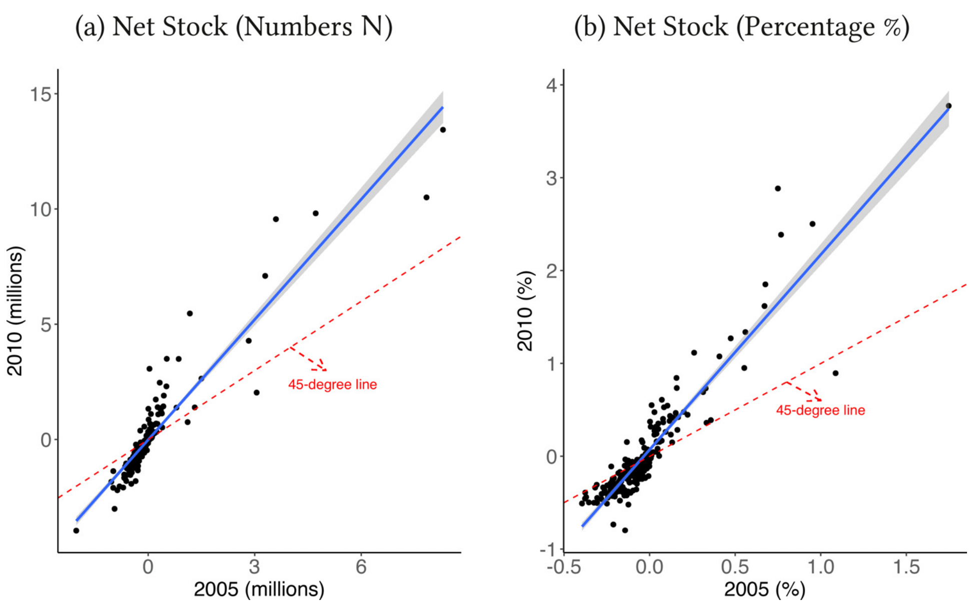

Fig. 2. Correlation of Net Stock of Migrants in 2005 and 2010. Notes: In plot (b), 1 means 100%. The percentage plot (b) excludes two outlier new cities Shenzhen and Dongguan which do not fit the scale of the plot but still fit the pattern. Both cities were established in the 1980s. Because of low initial stocks of Hukou population and high appeal to migrants, both cities have *Net Stock (%)* measures larger than 500% in 2005, growing to larger than 1000% in 2010.

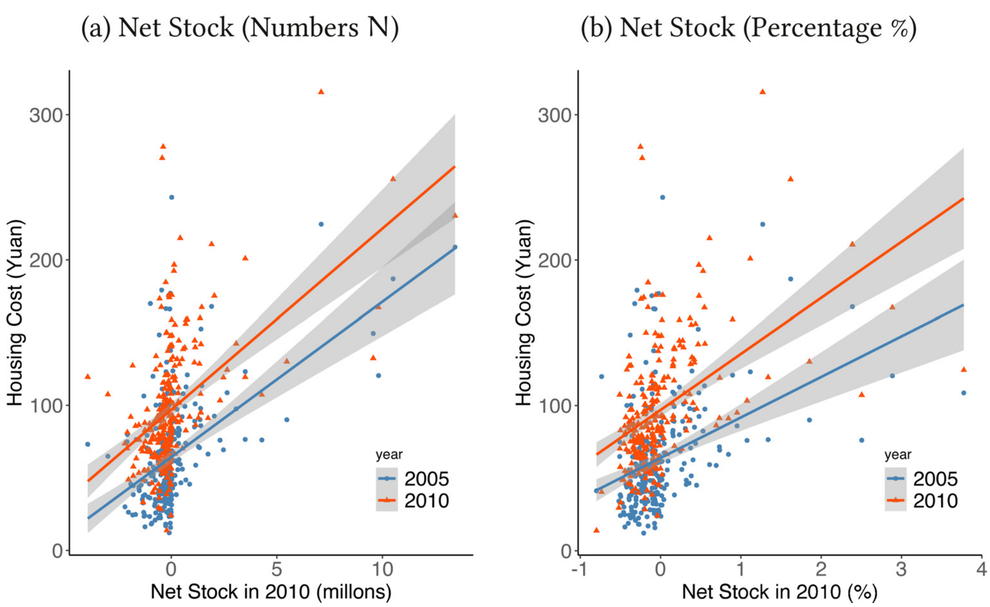

Fig. 3. Net Stock of Migrants and Housing Cost. Notes: Housing cost is measured as monthly rent per square meter using the micro data from the *Chinese Population Census*. In plot (b), 1 means 100%. The percentage plot (b) excludes two outlier new cities Shenzhen and Dongguan which do not fit the scale of the plot but still fit the pattern. Both cities were established at the end of 1980s. Because of low initial stocks of Hukou population and high appeal to migrants, both cities have *Net Stock (%)* measures larger than 1000% in 2010 and almost the highest housing costs among all Chinese cities.

Fact 3: Income inequality increases drastically with net stock of migrants and across time

To document Fact 3, we calculate the Theil Index[10] for total income at city-level for all Chinese cities in 2005 and 2010, respectively. Each worker's income consists of wage income and capital income. For wage income, we directly take the imputed city-skill wages as each individual workers' wage income, which is explained in Section 2.2.[11] For capital income, however, there is no available data for each city. Therefore, we adopt a lower bound imputation through some compromises using the *Census* data. For brevity, we relegate this technical discussion and associated robustness checks to the end of this section.

We calculate housing incomes for local workers owning houses by multiplying the size of their houses by city-level average rent divided by family sizes.[12] Then we take the average of this housing income for each city and attribute it to the local residents who own houses. Thus, an individual worker's total income is the sum of the city-skill wage and the imputed housing asset income (including both self-consumed housing and actual rental income from migrant renters). This construction is more consistent with our model.[13] We would like to emphasize

[10] We use the Theil Index because 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 means (inequality across cities). The second term is a weighted average of the Theil Index of individuals within different cities (inequality within cities). Therefore, it is natural to calculate the contribution of each city to national level inequality (Novotnỳ, 2007). We also try the traditional Gini Index, and the results are robust.

[11] One concern is that when we use city-skill level imputed wages, we may erase a large portion of heterogeneity. Thus, we also check the results using real individual level wages in 2005. The results are robust, consistently finding that cities with more migrant workers have higher inequality. We stick with imputed city-skill level wages in the main paper for two reasons. First, there is no real individual wage data available in the 2010 *Census*. Second, we want to present data that is the most consistent with the model.

[12] In calculating the family size, we only consider adults.

[13] Alternatively, we investigate this correlation with two other definitions of housing asset income. First, we calculate housing asset income by using the

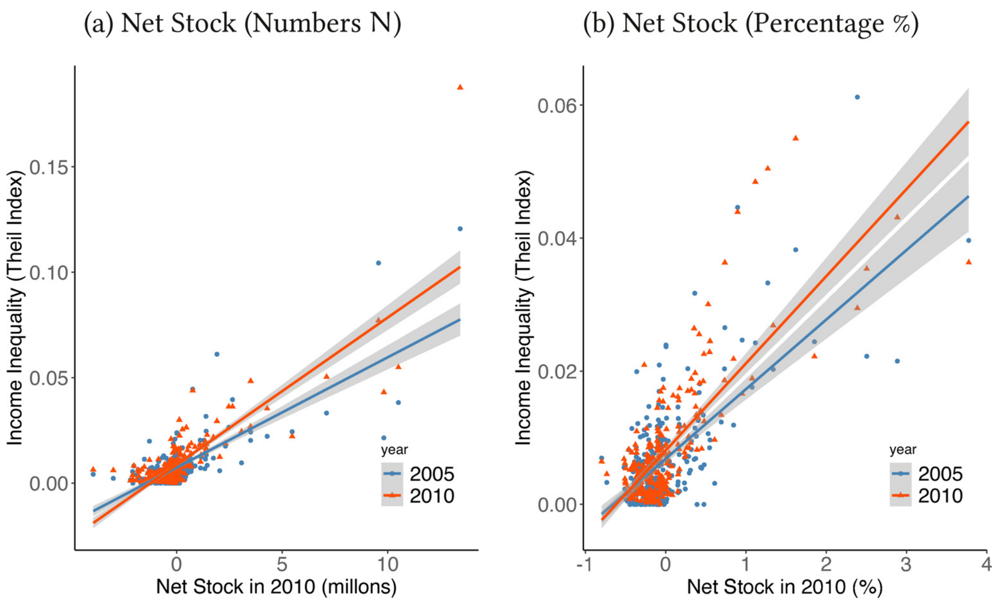

Fig. 4. Net Stock of Migrants and Income Inequality. Notes: Income Theil Index for each city is calculated by Eq. (2) using the micro data from the *Chinese Population Census*. In plot (b), 1 means 100%. The percentage plot (b) excludes two outlier new cities Shenzhen and Dongguan which do not fit the scale of the plot but still fit the pattern. Both cities were established at the end of 1980s. Because of low initial stocks of Hukou population and high appeal to migrants, both cities have *Net Stock (%)* measures larger than 1000% in 2010 and the highest levels of income inequality among all Chinese cities.

that the inequality documented here is inequality between several major groups: high-skill vs low-skill workers in wage income, interacting with housing-owner vs non-housing-owner in housing asset income.

The city-level Income Theil Index for city j is then:

$$T_j^{\text{Inc}} = \frac{1}{N_j} \sum_{n=1}^{N_j^s} \sum_{s=1}^{S} \frac{i_{jn}^s}{\bar{i}_j} ln \frac{i_{jn}^s}{\bar{i}_j}, \quad i_{jn}^s = w_{jn}^s + \text{housing asset income}_{jn} \tag{2}$$

where j, n, s indicate city, worker, and skill, respectively. N_j is the total number of current workers in city j, N_J^s is the total number of current workers with skill s in city j, $\bar{i}_j$ is the average income in city j, i_{jn}^s is the income of each individual n with skill s in city j, and w_{jn}^s is the wage of each individual n with skill s in city j.

Fig. 4 shows that income inequality is positively correlated with the net inflow of migrants. When net stock is measured in levels as in sub-figure (a), bigger cities with more migrants are much more unequal. When net stock is measured as a percentage as in sub-figure (b), cities with a larger proportional net gain of migrant workers are much more unequal even though we excluded the two most unequal cities in sub-figure (a). This indicates that cities with more migrants and higher housing costs also exhibit higher income inequality, due to the high housing asset income inequality between local Hukou residents and migrant workers.

Compromises and Robustness Checks: This income measure has two compromises. The first is assuming that housing assets are the only assets. Housing accounts for the majority (74.2%) of total assets in Chinese families,[14] and families with more housing assets usually own more financial assets. This compromise potentially underestimates income inequality due to the exclusion of financial assets. Our second compromise is to assume that housing returns are totally captured by the flow of rental income (homologous to the dividend of an always fairly priced stock). Since housing prices in larger and more developed Chinese cities have increased much faster than rents, this compromise also potentially underestimates the housing income of property owners in these larger and more developed cities. In general, our inequality measure is a lower bound and focuses on housing assets. To address concerns that the assumptions of our measure maybe too strong.[15], we use another dataset called the *Chinese Household Income Project* to investigate other details about inequality between local residents and migrants. We find rural migrants (the majority of migrants), hold significantly less non-housing assets and earn less net asset income, which is similar to their pattern of housing asset ownership relative to locals. The results are in Appendix A3.

Fact 4: Housing asset income inequality rather than wage inequality accounts for the patterns in stylized fact 3

We show that wage inequality is not the major source of the observed income inequality patterns in Fact 3, but housing asset income inequality is. Fig. 5 displays the correlation between wage inequality and the net stock of migrants in the city. The figure indicates that there is only a weak positive correlation between wage inequality within cities and the net migrant inflows. The slope coefficient of the fitted line is also not statistically significant.

Fig. 6 displays the correlation between housing asset income inequality and the net stock of migrants in the city. The figure indicates that there is only a strong positive correlation between housing asset income inequality within cities and net migrant inflows. The slope coefficient of the fitted line is also statistically significant. These indicates that housing asset income inequality rather than wage inequality accounts for the patterns in stylized fact 3.

Fact 5: Supplementary stylized facts on city shares of national inequality

Though not the focus of this paper, we calculate national income inequality and then decompose it by calculating each city's contribution to national income inequality. We find that national inequality drops from 2005 to 2010, but developed city's contribution remains high. Larger cities contribute more than small cities to the overall national income inequality in both 2005 and 2010. We show the detailed results in Appendix A4.

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

[14] This is according to a report by the People's Bank of China. Please refer to this hyperlink (in Chinese). An average urban family owns 1.5 houses/apartments and only 43% of Chinese families carry a mortgage.

[15] The financial information of households in the *Census* dataset is limited

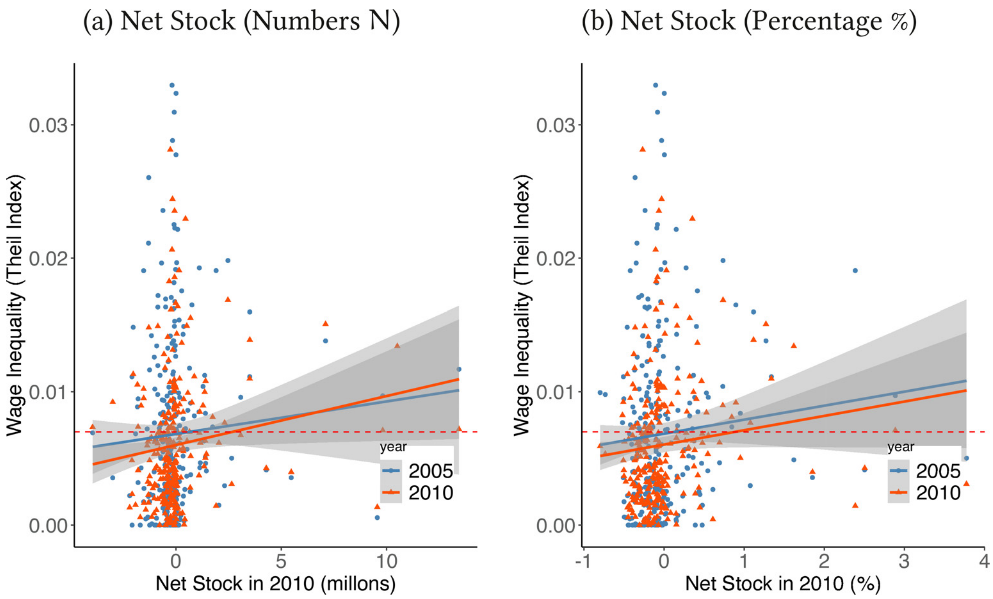

Fig. 5. Net Stock of Migrants and Wage Inequality. Notes: The Income Theil Index for each city is calculated by Eq. (2) using micro data from the *Chinese Population Census*. In plot (b), 1 means 100%. The percentage plot (b) excludes two outlier new cities, Shenzhen and Dongguan, which do not fit the scale of the plot but still fit the pattern. Both cities were established at the end of the 1980s. Because of low initial stocks of Hukou registrants and high appeal to migrants, both cities have *Net Stock (%)* measures larger than 1000% in 2010. However, they do not have much higher Wage Theil Indexes than other cities.

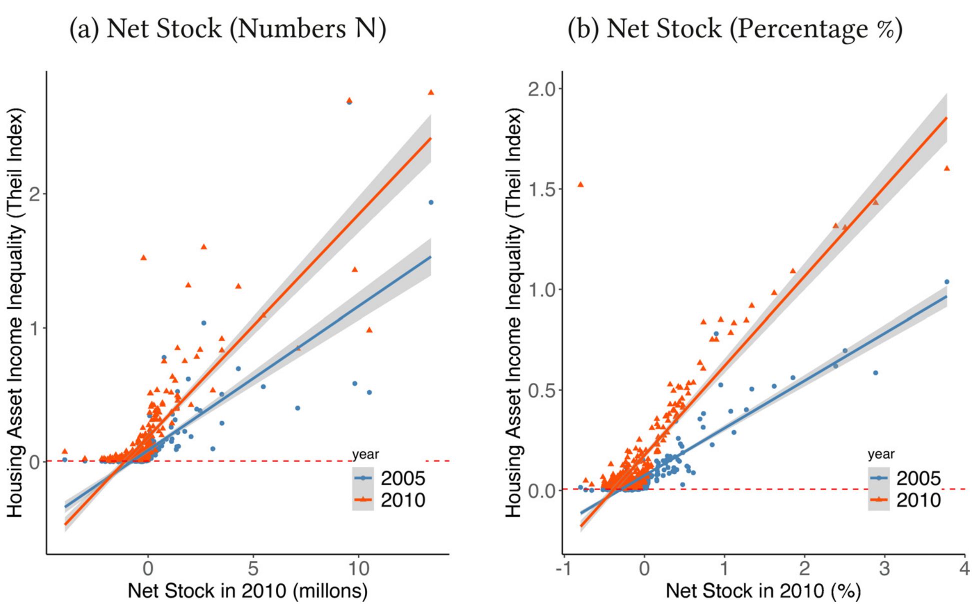

Fig. 6. Net Stock of Migrants and Housing Asset Income Inequality. Notes: The Income Theil Index for each city is calculated by Eq. (2) using micro data from the *Chinese Population Census*. In plot (b), 1 means 100%. The percentage plot (b) excludes two outlier new cities, Shenzhen and Dongguan, which do not fit the scale of the plot but still fit the pattern. Both cities were established at the end of the 1980s. Because of low initial stocks of Hukou registrants and high appeal to migrants, both cities have *Net Stock (%)* measures larger than 1000% in 2010. However, they do not have much higher Wage Theil Indexes than other cities.

Remarks on the Stylized Facts

We have shown important patterns about migration, housing costs, and income inequality in China. They illustrate that as China continues to grow, more and more workers are migrating from under-developed inland areas to developed coastal areas. Because of the restrictive land supply regulations in China, the huge stock of working-age migrants lifts housing demand in big industrialized cities and results in a rapid increase in housing costs. Because most property-owners are local residents, incumbent locals benefit a lot from the rising rents at the expense of the migrant tenants. This yields the observed positive relation between income inequality and the net stock of migrants, even without any correlation between wage inequality and the net stock of migrants. One natural question then arises. 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

This section describes how we construct the spatial equilibrium model, which will be used in the quantitative analysis and the policy counterfactual analysis.

4.1. Environment

The economy consists of a set of discrete locations, specifically in this paper, **cities**, which are indexed by $j = 1, \ldots, K$. 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 $s = h$. 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 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, and which we take as the numeraire. Locations differ in terms of their final goods productivity A_j^s and the supply of floor space S_j.

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

$$U_{ijo} = \frac{z_{ijo}}{\tau_{ij}^s}\left(\frac{c_{ijo}}{\beta}\right)^{\beta}\left(\frac{s_{ijo}}{1-\beta}\right)^{1-\beta} \tag{3}$$

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:

$$F(z_{ijo}) = e^{-z_{ijo}^{-\epsilon}},\ \epsilon > 1 \tag{4}$$

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:

$$\tau_{ij}^s = \bar{\tau}_i^s d_{ij} \tag{5}$$

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 differences in high/low skill workers' preferences for amenities such as education for children, entertainment, transportation, among many other possibilities.

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:

$$c_{ijo} = \beta v_{ij}^s \tag{6}$$

$$s_{ijo} = (1-\beta)\frac{v_{ij}^s}{Q_j} \tag{7}$$

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 all workers whose Hukou is registered in that city. This assumption is broadly consistent with the institutional features of China and is the key component of the observed income inequality. Many migrants only own local properties in their Hukou cities and do not have access to the local housing market in their current city of employment due to financial frictions and policy regulations. We discuss this assumption in more detail and provide some supporting empirical evidence in Appendix B.1. 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:

$$v_{ij}^s = w_j^s + \frac{Q_i S_i}{H_i^R} \tag{8}$$

where H_i^R is the number of Hukou residents registered in their origination city i and S_i is the residential floor space in city i.

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:

$$U_{ijo} = \frac{z_{ijo} v_{ij}^s Q_j^{\beta-1}}{\tau_{ij}^s} \tag{9}$$

4.3. 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:

$$G_{ij}^s(u) = Pr[U \le u] = F\left(\frac{u\tau_{ij}^s Q_j^{1-\beta}}{v_{ij}^s}\right) \tag{10}$$

$$G_{ij}^s(u) = e^{-\Phi_{ij}^s u^{-\epsilon}},\ \Phi_{ij}^s = (\tau_{ij}^s Q_j^{1-\beta})^{-\epsilon}(v_{ij}^s)^{\epsilon} \tag{11}$$

Since the maximum of a sequence of Fréchet distributed random variables is itself Fréchet distributed, the distribution of utility across all possible destinations is:

$$1 - G_i^s(u) = 1 - \prod_{k=1}^{K} e^{-\Phi_{ik}^s u^{-\epsilon}} \tag{12}$$

we have

$$G_i^s(u) = e^{-\Phi_i^s u^{-\epsilon}},\ \Phi_i^s = \sum_{k=1}^{K}\Phi_{ik}^s \tag{13}$$

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:

$$\pi_{ij}^s = \frac{(\tau_{ij}^s Q_j^{1-\beta})^{-\epsilon}(v_{ij}^s)^{\epsilon}}{\sum_{k=1}^{K}(\tau_{ik}^s Q_k^{1-\beta})^{-\epsilon}(v_{ik}^s)^{\epsilon}} = \frac{\Phi_{ij}^s}{\Phi_i^s} \tag{14}$$

4.4. 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:

$$X_j = [(A_j^h H_j^h)^{\frac{\sigma-1}{\sigma}} + (A_j^l H_j^l)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \tag{15}$$

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 efficiencies 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:

$$w_j^l = A_j^{l\,\frac{\sigma-1}{\sigma}} X_j^{\frac{1}{\sigma}} H_j^{l\,-\frac{1}{\sigma}} \tag{16}$$

$$w_j^h = A_j^{h\,\frac{\sigma-1}{\sigma}} X_j^{\frac{1}{\sigma}} H_j^{h\,-\frac{1}{\sigma}} \tag{17}$$

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

$$\omega_j = \frac{w_j^h}{w_j^l} = \left(\frac{A_j^h}{A_j^l}\right)^{\frac{\sigma-1}{\sigma}}\left(\frac{H_j^h}{H_j^l}\right)^{-\frac{1}{\sigma}} \tag{18}$$

The zero profit assumption gives us:

$$X_j = w_j^l H_j^l + w_j^h H_j^h \tag{19}$$

4.5. Floor space 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:

$$S_j = \phi_j L_j \tag{20}$$

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:

$$S_j = E[s_j]H_j = (1-\beta)\frac{E[v_j]H_j}{Q_j} \tag{21}$$

4.6. Definition of spatial general equilibrium

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

Definition 4.1. *A **Spatial General Equilibrium**for this economy is defined by a list of exogenous economic conditions $\{\tau^s_{ij}, A^s_j, \phi_j, L_j, H^s_i\}$, a list of endogenous prices $\{Q_j, w^s_j\}$, quantities $\{v^s_{ij}, y_j, H^s_j, S_j\}$, and proportions $\{\pi^s_{ij}\}$ 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 $\{\tau^s_{ij}\}$ and the aggregate prices $\{Q_j, w^s_j\}$ as given, the optimal migration choices of workers pins down the equilibrium labor supply in each city H^s_j and the migration flow between each city pairs π^s_{ij}.*
(ii) ***[Firm Optimization]****Taking the exogenous economic conditions $\{A^s_j\}$ and the aggregate prices $\{w^s_j\}$ as given, firms' optimal production choices pin down the equilibrium labor demand H^s_j.*
(iii) ***[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 $\{Q_j, w^s_j\}$, the equilibrium floor space S_j, and the equilibrium output y_j.*

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

5.1. Parameterization

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 who changed their measurement approach in 2012. We think the new approach is more realistic which gives us an average around 23% from 2013 to 2017.[16] Hence, we choose β to be equal to 0.77.

Elasticity of Substitution between Skills: The estimation results for 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). Therefore, we choose to follow the canonical model of Katz and Murphy (1992) to calibrate the elasticity of substitution between high-skill and low-skill labor (σ) to be equal to 1.4. We also test the model results using alternative calibrations from 1.2 to 3 to ensure the results are robust to our parameter choice.

Migration Elasticity: We estimate the migration elasticity (ϵ) from the gravity equation of migration flow (14). We assume $\tau^s_{ij} = \tau^s_i d_{ij}$, where τ^s_i is the origination-skill fixed component and d_{ij} is the distance index between location i and j. Under these assumptions and given data on migration shares and real incomes, we estimate ϵ using the fixed effect regression:

$$ln(\pi^s_{ij}) = \epsilon ln(v^s_j) + \psi_{ij} + \gamma_{is} + \zeta_j + \phi_{ijs}, \text{ for } i \neq j \tag{22}$$

where $\psi_{ij} = -\epsilon ln(d_{ij})$ is the origination-destination pair fixed effect, $\gamma_{is} = -\epsilon ln(\tau^s_i) - ln(\Phi^s_i)$ is the origination-skill fixed effect, $\zeta_j = -\epsilon(1-\beta)ln(Q_j)$ is the destination fixed effect, and ϕ_{ijs} is the measurement error term. We assume that the error term ϕ_{ijs} is not correlated with $ln(v^s_j)$ after controlling for all these fixed effects. Given our estimation, we choose ϵ to be equal to 1.90. The details of the estimation are in Appendix B.2.

Summary of Parameters: We calibrate three main parameters. The first parameter $\beta = 0.77$ is quite standard, as in literature such as Ahlfeldt et al. (2015). Chinese citizens have a slightly higher share of final consumption in utility. However, the number is generally similar. As for the migration elasticity, Tombe and Zhu (2019) estimates at the province-sector level and ends with a magnitude of 1.5. We have $\epsilon = 1.9$ which is similar but slightly larger, since cities are more substitutable than provinces. The elasticity of substitution between skills is calibrated to be 1.4 based on Katz and Murphy (1992).

5.2. Solving the model

Based on our parameterization and the observed data variables $\{H^s_i, H^s_j, \pi^s_{ij}, w^s_j, Q_j, L_j\}$, we can now calculate all the unobserved variables in each city: productivity $\{A^l_j, A^h_j\}$, migration cost $\{\tau^s_{ij}\}$, floor space $\{S_j\}$, and construction density $\{\phi_j\}$ for both 2005 and 2010. **A. Productivity**

From profit maximization and the zero profit conditions, we can infer productivity for each city from the data on employment and wages. First, we solve for productivity A^h_j as a function of A^l_j using first order conditions $A^h_j = A^l_j (H^h_j/H^l_j)^{1/(\sigma-1)}(w^h_j/w^l_j)^{\sigma/(\sigma-1)}$. Second, we plug A^h_j into the production function of X_j and apply the zero profit condition to yield:

$$X_j = A^l_j H^l_j \left[\frac{w^h_j H^h_j + w^l_j H^l_j}{w^l_j H^l_j}\right]^{\frac{\sigma}{\sigma-1}} = w^h_j H^h_j + w^l_j H^l_j$$

Defining $\Xi^l_j = \frac{w^l_j H^l_j}{w^h_j H^h_j + w^l_j H^l_j}$ as the share of labor income of low-skill workers, we can then calculate the productivities for both skill types as follows:

$$A^l_j = w^l_j (\Xi^l_j)^{\frac{1}{\sigma-1}}$$

[16] According to the old statistical standard, the average housing expenditure share ranged 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.

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

B. Construction Intensity

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:

$$S_j = E[s_j]H_j = (1-\beta)\frac{E[v_j]H_j}{Q_j} = \frac{1-\beta}{Q_j}\left[w_j^l H_j^l + w_j^h H_j^h\right] + (1-\beta)S_j = \frac{1-\beta}{\beta}\cdot\frac{w_j^l H_j^l + w_j^h H_j^h}{Q_j}$$

and then back out the construction intensity ϕ_j by dividing the land supply data:

$\phi_j = S_j / L_j$

C. Migration Costs

To compute migration costs, we first need to compute city-level rent incomes which we assume to be equally divided among local residents $\frac{Q_i S_i}{H_i^R}$ from the floor space S_i we calculated above. Then, we can calculate individual worker incomes $v_{ij}^s = w_j^s + \frac{Q_i S_i}{H_i^R}$. From the gravity equations, we can then calculate the destination-origination-skill-specific migration costs between all city pairs. We normalize the iceberg migration cost for staying in ones original city as unity, that is $\tau_{ii}^s = 1$. With data on rents Q_i, incomes v_{ij}^s, and migration flows π_{ij}^s, via the gravity equation we have:

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

Inserting Φ_i^s into the original gravity equation, we have the migration cost as follows:[17]

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

5.3. What does the model tell us about the unobservables?

In this subsection, we solve for the unobserved fundamentals of the model and how they change over time, including migration costs, productivities, and housing construction intensities.

A. Universal Reduction in Migration Costs

Using our model, we find that there was a universal reduction in migration costs from 2005 to 2010. In 2010, overall migration costs dropped dramatically by 35% relative to 2005. For low-skill workers, the changes were similar to the national average, while for high-skill workers, the drop on average was smaller (21%). 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. These results indicate that decreasing migration costs contributed substantially to increasing migration flows. Detailed summary statistics on the migration cost structure is provided in Appendix B.3.

As documented in Bryan and Morten (2019), the dramatic drop in migration costs is essential for the observed massive flow of migrant workers in developing countries. Tombe and Zhu (2019) also shows that province-sector level migration costs dropped 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 the contribution of other elements.

Table 1
Parameters.

Parameter	Description	Value
β	share of consumption in utility	0.77
ϵ	migration elasticity	1.9
σ	elasticity of substitution between H/L-skills	1.4

Notes: This table displays the summary of parameters. We match $(1-\beta)$ to the share of residential floor space cost in consumer expenditure. The elasticity of substitution between H/L-skills (σ) is as in Katz and Murphy (1992) and the city pair migration elasticity (ϵ) is estimated using the log form of the gravity Eq. (14).

B. Uneven Productivities and Uneven Growth in Productivities

Table 2 presents the average productivities A_j^s for both high-skill and low-skill workers, for all cities j grouped by net stock of migrant workers. On average, overall productivity for all cities grows by 87% for high-skill and by 94% for low-skill workers. To show the results in a more compact way, we group cities by their net stock of migrant workers. (6,13) refers to cities having a net stock of migrant workers between 6 million and 13 million. Similarly, (-4,-1) refers to cities having a net stock of migrant workers between -4 million and -1 million. We will use these groupings throughout the paper.

We find that, first, cities with larger net stocks of migrant workers have much higher productivities than cities with smaller or negative net stocks 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 net stock of migrant workers in 2010. These cities had much higher productivity for both high-skill and low-skill workers in both 2005 and 2010. In 2005, their average high-skill productivity was 19.2, which was 200% higher than the national average, 290% higher than Tier 2 cities. However for low-skill, the differences between city groups are smaller. Tier 1 cities' average low-skill productivity is 12.6, which is 34% higher than the national average and only 3% higher than Tier 2 cities.

Second, productivities improved massively from 2005 to 2010 and especially high-skill productivities in developed cities with more migrants. National average productivity improved by 119% for high-skill and 82% for low-skill workers. While smaller 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 was much larger in cities with more migrant workers. High-skill productivity increased by 26.5 in Tier 1 cities but only increased by 1.2 in Tier 5 cities.

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

C. Tightening Housing Constraints in Developed Cities

The land supply for each city in China is determined administratively by the central government. Table 3 shows the supply of construction land and floor space and how they change from 2005 to 2010. The national total land supply increased by 31%. However, the total land supply in Tier 1 cities only increased by 10% despite the massive migration. Tier 2 cities increased their total land supply the most (55%). Meanwhile, Tier 4 and 5 cities, which were losing massive numbers of workers, gained construction land, 30% and 38% respectively. This leaves substantial room for increasing or spatially reallocating the total land supply to larger cities to loosen housing constraints. A relevant concern is whether these tight land constraints are due to government regulation or natural limitations. According to Wu and You (2020), in 2005, only

[17] 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 when calculating the changes in migration costs.

Table 2
Average productivity growth.

Net Migrants	No. of	High-skill				Low-skill			
(2010)	Cities	2005	2010	Relative	Changes	2005	2010	Relative	Changes
Average	233	6.4	14.0	219%	+7.6	9.4	17.1	182%	+7.7
(6,13)	5	19.2	45.7	240%	+26.5	12.6	21.2	168%	+8.6
(1,6)	19	3.9	12.0	308%	+8.1	12.2	19.5	160%	+7.3
(0, 1)	45	3.7	10.5	184%	+6.8	10.2	16.3	160%	+6.1
(-1,0)	134	0.9	2.3	256%	+1.4	8.2	16.3	199%	+8.1
(-4,-1)	30	0.4	1.6	400%	+1.2	7.8	15.2	195%	+7.4

Notes: This table displays population-weighted means in both 2005 and 2010 and their changes. The levels of high-skill and low-skill productivity are not directly comparable. For readability, we normalize both numbers. The unit of high-skill productivity is $1e2$ and the unit of low-skill productivity is $1e3$. The net stock of migrant worker range groups are classified by net stock of migrant workers in 2010 (unit: millions). Each net migrant range group consists of the same cities in 2005 and 2010. There are 233 cities in the model. We also show the changes in standard deviations in Appendix B.3, which shows similar increasing patterns as does average productivity.

Table 3
Construction land supply and floor space.

Net migrants	No. of	Total land supply				Total floor space			
(2010)	Cities	2005	2010	Relative	Changes	2005	2010	Relative	Changes
Overall	233	24,277	31,705	131%	+7,428	2.19	3.30	150%	+1.11
(6,13)	5	5,135	5,648	110%	+513	5.92	7.84	132%	+1.92
(1,6)	19	3,801	5,912	155%	+2,111	1.79	4.10	229%	+2.31
(0, 1)	45	5,555	7,250	131%	+1,695	1.53	2.48	162%	+0.95
(-1,0)	134	7,950	10,363	130%	+2,413	1.48	2.17	147%	+0.69
(-4,-1)	30	1,836	2,532	138%	+696	2.55	3.12	122%	+0.57

Notes: This table displays total land supply within groups (unit: km^2) and total floor space (unit: $1e8\ m^2$). Net migrant range is classified by the net stock of migrant workers in 2010 (unit: millions). Each net migrant range group consists of the same cities in 2005 and 2010. There are 233 cities in the model.

Table 4
Within-city Theil Index.

Net Migrants	No. of	Wage Theil Index			Income Theil Index		
(2010)	Cities	2005	2010	Relative	2005	2010	Relative
Average	233	0.0072	0.0070	97%	0.0100	0.0184	184%
(6,13)	5	0.0087	0.0097	111%	0.0442	0.0908	205%
(1,6)	19	0.0065	0.0079	122%	0.0092	0.0223	242%
(0, 1)	45	0.0075	0.0083	111%	0.0060	0.0092	153%
(-1,0)	134	0.0071	0.0058	82%	0.0049	0.0052	106%
(-4,-1)	30	0.0072	0.0058	80%	0.0054	0.0062	115%

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

23% of all land was developed in Tier-1 cities. Given that most of the Tier 1 and 2 cities are located on plains, these constraints are unlikely to represent natural limitations.

5.4. Wage inequality and income inequality

In this subsection, we examine wage inequality and income inequality, measured by the Theil Index in our model for both 2005 and 2010.

Table 4 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 migrant workers 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 decreased in smaller cities with negative net migration. However, the differences and the changes in wage inequality across cities and across time are not comparable to these patterns of income inequality. The average within-city Income Theil Index was much higher than the average within-city Wage Theil Index, doubling from 2005 to 2010. If we break down the statistics by city groups, we easily observe that this huge jump is attributable to cities with positive net migrants, especially Tier 1 and Tier 2 cities, with more than 100% increases in migrant stocks.

Table B.6 in Appendix B.4 shows city contributions to the 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.[18] Moreover, if we examine by city groups, we observe that larger cities with positive net migration 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 did not account for all workers in Tier 1 cities, the national Wage Theil would 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 (measured as the average annual housing return over the average annual wage) and their changes in Table B.7 in Appendix B.4. The national average skill premium and the city groups' skill premiums are very similar and do not change much over time. However, the average housing premium in-

[18] 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.

creased from 0.36 in 2005 to 0.49 in 2010, resulting in a 36% jump. For an "average" worker, housing asset income is almost 50% of their wage income. Furthermore, if we check by city groups, we observe that in Tier 1 cities the housing premium increased from 0.93 to 1.89, 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 rise income inequality in Table 4.

5.5. Remarks on the quantitative analysis

In this section, we showed that the universal reduction in migration costs, the uneven productivities, and the uneven growth in productivities are the major drivers of the massive migration flows within China. Furthermore, the restrictive housing constraints in cities with positive net stocks of migrants are much tighter. These housing constraints increase income inequality in these larger cities and dissuade more migrants from entering these cities with higher productivities.

6. Counterfactual analysis

In this section, we simulate various policies recommended in previous literature using our model. We try to recover how these policies could change the spatial distribution of workers with different skills in China. Most importantly, we investigate the effect of these policies on the housing market in different regions, and on national and within-city inequality. We employ an iteration algorithm to compute the counterfactuals. The details of the algorithm are in Appendix C1.

6.1. A migration-based land supply policy reform

The most important reason that housing constraints are very tight in larger cities is because 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. Local governments follow these instructions to change 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. In this section, we propose a policy to allocate more land to large cities with more migrants.

A. Current Land Supply Policy in China

In 2003, the central government changed the principles of its land supply policy. The purpose is to balance regional development using land quotas as a regional income redistribution device. This is documented by a large urban literature (Han and Lu, 2017; 2018; Liang et al., 2016). There are two general guidelines. First, redistributing extra land supply away from the coastal areas (more developed) to favoring the inland areas (less developed). The inland 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 since the beginning of 2003 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. Even though workers in less developed cities do receive additional land income just due to having more land, this policy is economically poor in terms of both productivity and equality. Therefore, we propose an alternative land supply policy that favors high productivity cities with a cross-city transfer based on migration flows.

B. Migration-Based Land Supply Policy Reform

We propose a counterfactual policy of redistributing the total land supply increment from 2005 to 2010 according to the changes in the net stock of migrant workers. More specifically, the proposed rule for land supply redistribution is as follows. Call the total national land supply increment from 2005 to 2010 as ΔL, and the increase in the net stock of migrant workers in each city as $\Delta^+ H_j$ which sums up to total worker population growth $\Delta^+ H$. Then set city $j's$ counterfactual land supply increment as: $\widehat{\Delta^+ L_j} = \Delta L \times (\Delta^+ H_j / \Delta^+ H)$ instead of its actual increment $\Delta^+ L_j$. Since it is very costly to revoke existing zoned land, for cities with negative migrant changes we assign $\Delta^+ L_j = 0$. It is important to point out that the change of the quota is exogenously based on actual, not model, migration flows. It will not endogenously respond in the model. The counterfactual land policy changes are summarized in Table 5.

This counterfactual is feasible to implement and still fulfills the central government's goal of balancing regional development. We subtract land income from the additional land allocated to land-gaining cities $(\hat{Q}_j \phi_j (\widehat{\Delta^+ L_j} - \Delta^+ L_j))$ and compensate land-losing cities $(\hat{Q}_j \phi_j (\Delta^+ L_j - \widehat{\Delta^+ L_j}))$ for their losses to achieve the redistribution motive. 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 from developed cities to under-developed 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 can even profit from it.

C. Land Supply Policy Reform Results

The results of the land supply policy reform are summarized in Tables 6 and 7. We list the original equilibrium and the counterfactual (with a hat) side-by-side for ease of comparison. Table 6 shows how this counterfactual policy changes net migration and housing costs. First, the policy motivates 17% 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: 22% > Tier 2: 16% > Tier 3: 0%). Meanwhile, because of the land supply redistribution, more land is distributed to cities with more incoming migrants, and housing costs in these cities drop a lot. For Tier 1 and Tier 2 cities, the costs drop to only 70% and 75% of the original equilibrium.

We then show how within-city inequality changes in Table 7. Row 3 shows the overall national Theil Index. Row 4 shows the population-weighted mean Theil Index. Row 5-9 show the within-city Theil Index for each city group. 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 2 cities increases by 13%. This is mainly because more high-skill workers move to Tier 1 and Tier 2 cities due to the dramatic drop in housing costs. Nevertheless, for any other city group and for the whole country, the Wage Theil Index is almost identical.

However, the counterfactual policy significantly lowers national income inequality by 20% measured by the Income Theil Index. The population-weighted mean Income Theil Index also drops significantly from 0.0184 to 0.0121 (34% 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 rises in cities losing workers. Therefore, the land supply reform helps to reduce within-city and overall national level income inequality.

Additionally, we show how the policy changes each city's contribution to national inequality in Table C1 in the Appendix. Similar to the pattern of within-city inequality, the counterfactual policy does not have much effect on national wage inequality or cities' contributions to national wage inequality. By city groups, the positive contributions of Tier 1, 2 and 3 cities and the negative contributions of Tier 4 and Tier 5 cities all increase in magnitude. All these results indicate that the land supply reform lowers national income inequality but not cross-city income inequality since we motivated more high-skill migrants to go to more productive cities. We also show the skill premium and the housing premium in Table C2 in the Appendix.

Table 5
Counterfactual Construction Land Supply.

Net Migrants	No. of	Land Supply (Data)				Counterfactual		
(2010)	Cities	2005	2010	Relative	Changes	$\widehat{2010}$	$\widehat{Relative}$	$\widehat{Changes}$
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 total land supply data by city group in 2005 and 2010, as well as the counterfactual migration-based land supply in 2010 (unit: km^2). Net Migrants classifies cities by net stock of migrant workers in 2010 as in the data (unit: millions). Each net migrant group consists of the same cities in 2005 and 2010.

Table 6
Migration Flow and Housing Cost: Land Supply Reform.

Net Migrants	No. of	Net Migrants			Housing Cost		
(2010)	Cities	2010	$\widehat{2010}$	Relative	2010	$\widehat{2010}$	Relative
Overall	233	96m	112m	117%	114	119	104%
(6,13)	5	+45m	+55m	122%	226	158	70%
(1,6)	19	+38m	+44m	116%	136	102	75%
(0, 1)	45	+13m	+13m	100%	118	132	112%
(-1,0)	134	-48m	-48m	100%	87	115	132%
(-4,-1)	30	-48m	-65m	135%	80	105	131%

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

Furthermore, we decompose the dominant role of housing prices for rising income inequality into two channels: i) migrants push up housing prices in destination locations; ii) population outflows reduce the income of migrants from their housing assets within their origin city. Table C3 in the Appendix shows such a decomposition of the effect of housing asset income changes on the Income Theil Index. The results show that migrants pushing up housing prices in more developed cities is the main channel of the observed counterfactual changes in income inequality.

Finally, though not the focus of this paper, motivating more migrants into productive cities could generate higher measured productivities even when the city-skill-specific fundamental productivities are unchanged. In Table C4 in the Appendix, we show that the land supply reform does increase measured producitivities in cities with migration inflows as well as the national average producitivities, but not for high-skill workers in developed cities.

6.2. Property tax and redistribution

Currently, China has no property tax on housing ownership. There is a heated debate on whether China should adopt a property tax as 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 rental revenue is roughly 20% in the U.S.,[19] this counterfactual taxes property owners' housing income by 20% and redistributes the proceeds equally to all residences in the same city (such as using the tax revenue to build infrastructure which benefits all residents equally). In this counterfactual, the government budget constraint of each city is automatically satisfied since all the tax revenue generated from the property tax is redistributed equally to all residents currently living in the city regardless of residents' Hukou registration. For brevity, we only discuss the key results for migration, housing costs, and inequality. Tables with detailed results are presented in Appendix C3.

Could a reasonable property tax and corresponding redistribution give us desirable reductions in income inequality? The answer is yes. This policy can effectively lower income inequality because migrant workers pay property tax for their house in their Hukou city but gain redistribution income from their current working city. The former is usually much lower than the latter for migrants moving from underdeveloped cities to developed cities. Therefore, property taxation allows migrants to share the benefits of the floor space market returns even though they do not own any property in their current working cities.

From Tables C.5–C.7, we can see that even though a property tax cannot motivate much more migration, and barely changes housing costs, it still lowers income inequality (20% drops in the national Theil Index). It

[19] According to a report from www.mortgagecalculator.org, U.S. national average property tax rate in 2020 is about 1.1%. Meanwhile, a report from www.smartasset.com indicates a national average price to rent ratio of 18.27. These give us an average property tax to rent ratio of about 20.

Table 7
Within-city Theil Index: Land Supply Reform.

Net Migrants	No. of	Wage Theil Index			Income Theil Index		
(2010)	Cities	2010	$\widehat{2010}$	Relative	2010	$\widehat{2010}$	Relative
National Theil	233	0.062	0.062	100%	0.092	0.074	80%
Average	233	0.0070	0.0072	103%	0.0184	0.0121	66%
(6,13)	5	0.0097	0.0093	97%	0.0908	0.0428	47%
(1,6)	19	0.0079	0.0089	113%	0.0223	0.0139	62%
(0, 1)	45	0.0083	0.0082	99%	0.0092	0.0098	106%
(-1,0)	134	0.0058	0.0059	101%	0.0052	0.0045	86%
(-4,-1)	30	0.0058	0.0056	97%	0.0062	0.0051	82%

Notes: This table displays population-weighted means of both inequality measures, except for row 3. Row 3 shows the overall national level Theil Index. The original equilibrium is 2010 and the counterfactual equilibrium is $\widehat{2010}$. Relative is calculated via dividing $\widehat{2010}$ by 2010.

works almost exclusively as a redistribution device between local property owners and migrant workers. Therefore, even though it lowers income inequality substantially, it will face much opposition from local property owners in big cities.

6.3. Additional counterfactual analysis

Another policy counterfactual that we consider is directly increasing land supply in developed cities based on migration flows. Instead of promoting the trade of land quotas across cities, we simply double the national land supply increment from 2005 to 2010 and redistribute the additional land supply to cities with positive net migrants. Could we lower income inequality from increasing land supply everywhere? The answer is no. Because revenue from additional land supply is only redistributed among local Hukou holders, this policy will only worsen income inequality even though housing costs are dramatically reduced. Detailed results are presented in Appendix C4.

We also extend our model with an agglomeration effect as in Combes et al. (2008) and implement our main counterfactual analysis using this model. The results are shown in Appendix C5 and we find that incorporating a moderate agglomeration effect does not yield significantly different effects of counterfactual policies. We do not use this model in our main context we could not find a feasible way to estimate the agglomeration coefficient for China, nor do we find consistent and reliable estimates from existing literature.

7. Conclusion

Migration and housing constraints shape 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. 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 to more developed cities and the highly regulated land supply system contribute to housing demand and lift 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 within developed cities and across the whole country.

With this understanding of the mechanism, we conduct several feasible counterfactual experiments. Among all counterfactuals, we show that a migration-based land supply reform that allows regions to ”trade” construction land usage quotas could lower within-city income inequality by 34% and national income inequality by 20%. This also encourages more migration to higher productivity cities and improves nationwide productivity.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.labeco.2022.102200

References

Ahlfeldt, G.M., Redding, S.J., Sturm, D.M., Wolf, N., 2015. The economics of density: evidence from the berlin wall. Econometrica 83 (6), 2127–2189.
Bartik, T. J., 1991. Who benefits from state and local economic development policies?.
Berman, E., Bound, J., Machin, S., 1998. Implications of skill-biased technological change: international evidence. Q. J. Econ. 113 (4), 1245–1279.
Bryan, G., Morten, M., 2019. The aggregate productivity effects of internal migration: evidence from indonesia. J. Polit. Economy 127 (5), 2229–2268.
Card, D., 2009. Immigration and inequality. Am. Econ. Rev. 99 (2), 1–21.
Card, D., DiNardo, J.E., 2002. Skill-biased technological change and rising wage inequality: some problems and puzzles. J. Labor Econ. 20 (4), 733–783.
Chao, C.-C., Hazari, B.R., Yu, E.S., 2006. Rising wage inequality in developing economies: privatization and competition. J. Int. Trade Econ. Dev. 15 (3), 375–385.
Chen, B., Liu, D., Lu, M., 2018. City size, migration and urban inequality in china. China Econ. Rev..
Chen, K., Wen, Y., 2017. The great housing boom of china. Am. Econ. J. 9 (2), 73–114.
Combes, P.-P., Duranton, G., Gobillon, L., 2008. Spatial wage disparities: Sorting matters!. J. Urban Econ. 63 (2), 723–742.
Cuadrado-Ballesteros, B., Peña-Miguel, N., 2018. The socioeconomic consequences of privatization: an empirical analysis for europe. Social Indicators Res. 139 (1), 163–183.
Dong, Z., Wang, F., Gao, Q., 2013. Does skill premium derive from biased technical change? Stat. Res. 6.
Eaton, J., Kortum, S., 2002. Technology, geography, and trade. Econometrica 70 (5), 1741–1779.
Fan, J., 2019. Internal geography, labor mobility, and the distributional impacts of trade. Am. Econ. J. 11 (3), 252–288.
Fang, H., Gu, Q., Xiong, W., Zhou, L.-A., 2016. Demystifying the chinese housing boom. NBER Macroecon. Ann. 30 (1), 105–166.
Garriga, C., Hedlund, A., Tang, Y., Wang, P., 2017. Rural-urban Migration, Structural Transformation, and Housing Markets in China. Technical Report. National Bureau of Economic Research.
Garriga, C., Hedlund, A., Tang, Y., Wang, P., 2020. Rural-urban migration and house prices in china. Reg. Sci. Urban Econ. 103613.
Glaeser, E., Huang, W., Ma, Y., Shleifer, A., 2017. A real estate boom with chinese characteristics. J. Econ. Perspect. 31 (1), 93–116.
Goldberg, P.K., Pavcnik, N., 2004. Trade, Inequality, and Poverty: What Do We Know? Evidence from Recent Trade Liberalization Episodes in Developing Countries. Technical Report. National Bureau of Economic Research.
Gregorio, J.D., Lee, J.-W., 2002. Education and income inequality: new evidence from cross-country data. Rev. Income Wealth 48 (3), 395–416.
Han, J., Liu, R., Zhang, J., 2012. Globalization and wage inequality: evidence from urban china. J. Int. Econ. 87 (2), 288–297.
Han, L., Lu, M., 2017. Housing prices and investment: an assessment of china's inland-favoring land supply policies. J. Asia Pacific Economy 22 (1), 106–121.
Han, L., Lu, M., 2018. Supply-demand mismatch: solving the puzzle of china's housing price divergence. J. World Economy (10) 7.
Hsieh, C.-T., Moretti, E., 2019. Housing constraints and spatial misallocation. Am. Econ. J. 11 (2), 1–39.
Katz, L.F., Murphy, K.M., 1992. Changes in relative wages, 1963–1987: supply and demand factors. Q. J. Econ. 107 (1), 35–78.
Liang, W., Lu, M., Zhang, H., 2016. Housing prices raise wages: estimating the unexpected effects of land supply regulation in china. J. Housing Econ. 33, 70–81.
Lu, M., 2016. Great Nation Needs Bigger City. Shanghai People's Press.
Ma, L., Tang, Y., 2020. Geography, trade, and internal migration in china. J. Urban Econ. 115, 103181.
Moore, M.P., Ranjan, P., 2005. Globalisation vs skill-biased technological change: Implications for unemployment and wage inequality. Econ. J. 115 (503), 391–422.
Morten, M., Oliveira, J., 2014. Migration, roads and labor market integration: evidence from a planned capital city. Unpublished manuscript.
Novotnỳ, J., 2007. On the measurement of regional inequality: does spatial dimension of income inequality matter? Ann. Reg. Sci. 41 (3), 563–580.
Piketty, T., Yang, L., Zucman, G., 2019. Capital accumulation, private property, and rising inequality in China, 1978–2015. Am. Econ. Rev. 109 (7), 2469–2496.
Song, D., Wang, L., Dong, Z., 2010. Is there skill biased technological change? Evidence from china. Econ. Res. J. 5, 68–81.
Song, Y., 2014. What should economists know about the current chinese Hukou system? China Econ. Rev. 29, 200–212.
Sylwester, K., 2002. Can education expenditures reduce income inequality? Econ. Educ. Rev. 21 (1), 43–52.
Tombe, T., Zhu, X., 2019. Trade, migration, and productivity: a quantitative analysis of china. Am. Econ. Rev. 109 (5), 1843–1872.
Verhoogen, E.A., 2008. Trade, quality upgrading, and wage inequality in the mexican manufacturing sector. Q. J. Econ. 123 (2), 489–530.
Wu, J., Gyourko, J., Deng, Y., 2016. Evaluating the risk of chinese housing markets: what we know and what we need to know. China Econ. Rev. 39, 91–114.
Wu, W., You, W., 2020. The welfare implications of internal migration restrictions: evidence from china. Available at SSRN 3637557.
Yu, Y., 2019. Land-use regulation and economic development: evidence from the farmland red line policy in china. Working Paper.