NBER WORKING PAPER SERIES

FRICTIONAL SORTING

Wenquan Liang
Ran Song
Christopher Timmins

Working Paper 27643
<http://www.nber.org/papers/w27643>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2020

We are grateful to comments from Patrick Bayer, George Borjas, Diego Restuccia, Richard Freeman, Paavo Monkkonen, Mushfiq Mobarak, Nicholas Ryan, Junfu Zhang and seminar participants at Duke University, Harvard University, Yale University, Clark University, University of Kentucky, Biennial Conference of China Development Studies and Nankai Yale Development Conference. Ran Song acknowledges financial support from Yale Research Initiative on Innovation and Scale (Y-RISE) at Yale University. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2020 by Wenquan Liang, Ran Song, and Christopher Timmins. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

Frictional Sorting
Wenquan Liang, Ran Song, and Christopher Timmins
NBER Working Paper No. 27643
August 2020
JEL No. J24,J61,R23

ABSTRACT

In many countries around the world, migration costs and housing supply restrictions interact with each other and combine to restrict workers' location decisions. Using an equilibrium sorting model and rich micro data from China, we evaluate the impacts of these dual constraints on workers' sorting behavior and quantify the resulting changes in aggregate welfare and inequality. We find strong policy interactions between the two kinds of frictions in determining welfare losses and regional inequality. Counterfactual simulations show that lowering migration costs can increase welfare and reduce regional inequality by moving workers from unproductive inland regions to productive coastal regions in China; such welfare and regional distributional impacts depend on the elasticity of housing supply in coastal regions and vice-versa. Results highlight the policy complementarities between reducing the two kinds of frictions and have general implications for countries with different levels of constraints on mobility and housing supply.

Wenquan Liang
Jinan University
No. 601 West Huangpu Road
Tianhe District
Guangzhou
P.R. China
liang.wenquan@jnu.edu.cn

Christopher Timmins
Department of Economics
Duke University
209 Social Sciences Building
P.O. Box 90097
Durham, NC 27708-0097
and NBER
christopher.timmins@duke.edu

Ran Song
Division of Social Science
Yale-NUS College
16 #01-220
College Ave West
Singapore, 138527
songr@nber.org

1. Introduction

Recent evidence has suggested the presence of large within-country gaps in productivity (Gollin et al., 2014; Moretti, 2011) and welfare (Diamond, 2016). The implication of these gaps is that moving people from unproductive to productive areas could increase total national output along with welfare. Thus, a natural question arises – why workers in underdeveloped areas do not arbitrage these opportunities? One reason may be that households face migration frictions – both administrative and informal. Another may be restrictions on housing supply in receiving destinations.

In many countries around the world, constraints on mobility and housing supply are driven by common political incentives. First, restrictions on migration and housing supply are both implemented to protect the interests of local residents¹. Second, the two restrictions are often designed to raise government “fiscal profit”². These political incentives can also, at least in part, explain the poor transportation infrastructure services which drive up migration costs in many developing countries³. Due to common incentives, constraints on migration and housing supply are likely to interact with one another and combine to inhibit workers’ spatial sorting and reduce aggregate social wellbeing. But so far, there has been little work analyzing the interplay of two kinds of frictions in driving welfare losses and regional inequality.

On the basis of the two kinds of frictions, we could roughly assign countries in the world into four groups: First, countries combining both tight constraints on mobility and housing supply like China⁴. Second, those with low migration costs but tight

¹ Migration restrictions are often aimed to increase wages and employment for local workers (Clemens et al., 2018) and housing supply regulations are designed to protect the benefits of local landowners (Glaeser and Gyourko, 2018).

² In this paper, “fiscal profit” means the difference between government fiscal income and expenditure. There are strong incentives for local government to regulate the supply of land for construction to raise fiscal revenues from land transactions (Glaeser et al., 2017) or taxes from rental income (Diamond, 2017) and restrict public services for internal migrants from other places in order to save fiscal expenditure (Bhavnani and Lacina, 2017).

³ In many developing countries, fiscal resources are highly concentrated in a few primary cities located in rich regions, because these cities have much more tax income and stronger influence on the allocation of these resources from the central government than do cities in poor regions. Local governments only care about the wellbeing of local residents rather than the aggregate national welfare and have strong incentives to minimize unnecessary fiscal expenditure. As a result, without the efficient coordination of central government, local governments of these primary cities are reluctant to invest on the transportation infrastructure linking poor to rich regions. Moreover, local governments in poor regions do not have enough money to invest on the inter-regional transportation infrastructure.

⁴ The *hukou* system in China is a typical example of institutional migration restrictions in developing countries. This system prohibits or limit internal migrants’ access to government provided benefits (Combes et al., 2020). *Hukou* restrictions are used as a policy tool to protect the interests of local residents and reduce government fiscal expenditure. Moreover, land available for construction are strongly regulated in China to raise fiscal revenues from land transactions (Glaeser et al., 2017).

constraints on housing supply like the U.S.⁵. Third, those with high migration costs but loose housing constraints like Indonesia⁶. Last, those combining both free mobility and loose housing constraints like some Nordic countries and Japan⁷.

In this paper, we use China as a laboratory to study the impacts of constraints on mobility and housing supply on workers' sorting behavior and quantify the consequent changes in aggregate welfare and regional inequality. China provides us with a good setting for this analysis, because high migration costs driven by *hukou* restrictions and stringent administrative housing supply restrictions strongly restrict the residential sorting of people and lead to huge welfare losses. We use our analysis to shed light on the economic benefits associated with reducing sorting frictions for countries with different levels of constraints on mobility and housing supply.

In order to quantify the general equilibrium welfare consequences of frictions in spatial sorting, we develop a spatial discrete choice model in which workers of different skill levels differentially sort across cities based on wages, housing costs, amenities, as well as heterogeneous migration costs. Our model builds on Rosen (1979) and Roback (1982) and has close connections to the recent spatial sorting framework of Bayer, Ferreira and MacMillan (2007), Bayer and Timmins (2007) and Diamond (2016). In our setting, workers do not sort across locations freely. They are constrained by two types of frictions – migration costs and housing supply restrictions. Migrants suffer from substantial mobility costs which differ with geographic locations and skills. Similar to Bayer, Keohane, and Timmins (2009) and Diamond (2016), we use fixed costs associated with moving various distances from one's original city to capture the physical and psychological costs of leaving home. We go beyond their approaches by further estimating overall migration costs, including utility losses due to institutional migration restrictions (i.e. *hukou* system in China) and welfare implications of migrant

⁵ Although U.S. is free-mobility country, housing supply restrictions are prevalent in its most productive coastal cities. Local landlords in those cities have strong incentives to influence local zoning policies to restrict housing supply in order to increase their rental income (Hsieh and Moretti, 2018; Glaeser and Gyourko, 2018). Moreover, tight housing supply regulations allow local governments to extract more taxes from rental income (Diamond, 2017).

⁶ High mobility costs constrain the internal migration of workers in Indonesia (Bryan and Morten, 2019). However, regulations on housing supply are loose in Indonesia.

⁷ Japan is a country with high-performance transportation infrastructure and no institutional restriction on internal migration. Moreover, zoning regulations are relatively liberal in Japan, with few density and bulk controls and limited use segregation.

specific amenities (e.g., equal economic opportunities, migrant networks). For housing constraints, we leverage the stringent restrictions on land available for construction in coastal China since 2004 (Liang et al., 2016, Liu and Xiong, 2019). Specifically, we use differences in the elasticities of housing prices with respect to population between the inland and coastal regions to capture the tight land restriction policy in coastal China.

We estimate the model using comprehensive and detailed data on workers' spatial sorting in China, which are drawn from the 2005 One-Percent Population Census of China. For each worker, our data record *hukou* location and current residential location, along with a wide range of sociodemographic and housing characteristic variables. Importantly, these are the only Chinese census data that have information about individual wages.

We use our equilibrium sorting model to quantify the impacts of reducing sorting frictions on workers' re-sorting decisions along with the consequent changes in aggregate welfare and regional inequality. We consider the U.S. as the benchmark for low migration costs (Bryan and Morten, 2019; Tombe and Zhu, 2019) and see inland China as the benchmark for elastic housing supply. In particular, when simulating the reduction in migration costs, we lower migration costs in China by 29.6%--a level of mobility costs such that the inter-province migration rate in China reaches the inter-state migration rate in the U.S.⁸. When simulating the relaxation of housing restrictions, we reduce housing price elasticities with respect to population in coastal China to the level in inland China.

In a series of quantitative exercises, we first lower migration costs under scenarios of stringent and relaxed housing constraints, respectively. The economic effects of lowering mobility costs depend on the elasticity of housing supply in coastal regions. The reduction of migration costs induces workers to re-sort to coastal Chinese cities where high productivity and good amenities are concentrated. When shifting the

⁸ Like Hsieh and Klenow (2009) and Bryan and Morten (2019), we do not analyze specific policies, but calculate the potential welfare effects of a set of policy options. Many policies can be employed to reduce moving costs. One of the most common policies is the supply of transportation infrastructure such as high-speed road or railway. Another set of policies focuses on the integration of migrants into their destination communities – e.g., increasing the supply of public services for migrants, removing discrimination against migrants in the local labor market, or offering training programs to reduce language barriers. In China, a critical policy which can lower mobility costs is to loosen *hukou* restrictions in large cities so that migrants have more access to government provided benefits.

scenario from stringent to relaxed housing supply restrictions, the fraction of worker re-sorting from the under-developed inland regions to highly developed coastal regions induced by lowering mobility costs increases from 12.55% to 14.66%. For an average worker, the resulting monetized annual welfare implication associated with the reduction in migration costs is \$338.68 under tight housing constraints and increases to \$374.12 under loose constraints. The increase in the welfare effects differs across regions of different development levels. When shifting the scenario from tight to relaxed housing constraints, the average welfare effect associated with lowering mobility costs increases by 14.9% for those in inland regions, but hardly changes for those in the coastal regions. Moreover, reducing mobility costs also drive down the wage ratio between productive coastal regions and unproductive inland regions; such spatial distributional effects are stronger under the scenario of relaxed housing constraints.

We next relax restrictions on housing supply under scenarios of high and low mobility costs, respectively. The economic returns to loosening restrictions on housing supply rely on the mobility constraints imposed on workers' spatial sorting. When relaxing housing restrictions under high mobility costs, only 1.05% of workers re-sort from inland to coastal regions, and the impact on mean monetized welfare is estimated to be \$179.04. In contrast, turning to the scenario of low mobility costs, 4.99% workers relocate to coastal cities in response to relaxing housing constraints, and the resulting monetized welfare benefits increase to \$233.77. The increase in the welfare effects is highly concentrated on those in underdeveloped inland regions. When shifting from high to low mobility costs, the mean welfare effect of loosening housing restrictions increases largely by 109% for those in inland regions, but remains almost the same for those in coastal regions. Moreover, relaxing housing constraints also lowers the coastal-inland wage ratio, the extent of which is larger when people face lower costs associated with internal migration.

The interaction of two kinds of frictions has two important policy implications. First, for countries with both tight mobility and housing constraints like China, a policy mix of lowering migration costs and relaxing housing supply restrictions

simultaneously could generate extra welfare and regional distributional effects. For either constraint on mobility or housing supply, reducing one type of friction could increase the welfare implications associated with reducing the other type of friction, and allocate the resulting extra economic gains to those living in the under-developed regions. Second, from the cross-country perspective, the impacts of lowering migration costs on welfare and regional inequality are higher in countries with fewer housing constraints like Indonesia than in countries that combine both constraints on mobility and housing supply. Similarly, the welfare and distributional effects of relaxing housing constraints are higher in a high mobility country like the U.S. than those with both frictions in mobility and housing supply.

Our paper bridges the literature on the returns to internal migration (Bryan et al., 2014; Bryan and Morten, 2019; Tombe and Zhu, 2019; Kinnan et al., 2018) and the effects of housing supply regulations (Glaeser and Gyourko, 2018; Hsieh and Moretti, 2018; Quigley and Raphael, 2005; Saiz 2010). Constraints on mobility and housing supply are likely to be induced by common incentives and interact with each other in driving welfare losses, but we are not aware of any paper studying the policy interactions associated with these constraints. Against this backdrop, we jointly analyze migration costs and housing restrictions within a unified framework of spatial sorting and quantify the policy complementarities between relaxing the two types of constraints in determining the welfare and spatial distributional effects.

A recent macro-spatial literature employs aggregate data to estimate the economic losses associated with mobility costs (Bryan and Morten, 2017; Tombe and Zhu, 2019) and housing supply restrictions (Hsieh and Moretti, 2018). Our approach differs from these “macro spatial model” papers by conducting a spatial analysis at the individual level. First, our micro analysis allows us to predict the changes in residential location and welfare for each worker in our sample due to policy shocks. However, existing macro studies mostly look at average productivity effects of policy shocks and disregard how the potential economic effects spread across heterogeneous agents. Moreover, we could account for self-selection due to observed personal attributes, e.g. highly-educated workers are more likely to sort into cities with high returns to

education, rural workers prefer to select cities with high demand for rural-migrant workers. These observed self-selections are often overlooked by macro-level studies which only explore aggregate migration flows. Last, our wage measurement is different from macro-level spatial studies that typically rely on regional average wages and overlook the Roy sorting bias⁹. Ignoring such unobserved human capital heterogeneity in estimating the costs of labor misallocation may bias results (Glaeser and Gyourko, 2018). We address Roy sorting bias using the approach proposed by Dahl (2002) and predict the counterfactual wage that each individual could earn in every potential location.

The remainder of this paper proceeds as follows. Section 2 describes a number of important stylized facts about China. Section 3 lays out the model and Section 4 discusses the data. Section 5 presents estimation techniques and Section 6 discusses parameter estimates. Section 7 simulates the economic impacts of reducing frictions in workers' spatial sorting and Section 8 concludes.

2. Stylized Facts

In this section, we discuss three stylized facts about residential location sorting in China to guide our model setting and counterfactual analysis.

2.1 Spatial Distribution of Productivity and Amenities

According to the equilibrium sorting model, workers will sort across locations on the basis of returns in the labor market (which are driven by local productivity), local prices (particularly for housing), and amenities. We begin by plotting the spatial distribution of productivity and amenities in China, using the U.S. as a benchmark. Figure 1 plots the spread in GDP per capita across Chinese provinces along with the spread across U.S. states in 2005. It is clear that the spatial dispersion of productivity is substantially higher in China relative to the U.S.. Similarly, Figures 2 and 3 reveal that the geographical distribution of amenities is also more out of balance in China than

⁹ Roy sorting refers to the problem that individuals respond to idiosyncratic wage draws and are likely to move to a location where that wage draw is good. This means that using the average wage in a location of someone who looks like a potential migrant to that location will likely overstate what that migrant could actually earn there (Roy, 1951).

it is in the U.S.. High productivity regions usually offer desirable amenities, implying that the within-country well-being gap is very large in China. The substantial spatial differences in productivity and amenities should create strong incentives for workers to arbitrage utility through location sorting. However, the internal migration rate is much lower in China than in the U.S.. Table A1 reports that the cross-province internal migration rate in China is only 6.05% in 2005, whereas the cross-state internal migration rate in the U.S. is as large as 31.5%.¹⁰ We argue that there are two major reasons behind the larger dispersion of productivity and amenities but lower migration rate in China. One is the high migration costs that impose severe restrictions on sorting across locations within China and the other is the high housing prices driven by supply constraints at the places where migrants concentrate.

2.2 Migration Costs

The high migration costs in many developing countries are driven by institutional migration restrictions. The *hukou* system in China is a typical example of such an institutional restriction. The institution requires that each person be classified as rural or urban and be assigned a locality of *hukou* registration (typically the person's birth location). One's *hukou* registration determines one's entitlements to pursue many activities and eligibility for state-provided goods and services in a specific place. The *hukou* plays a critical role as an internal passport without which internal migrants are not entitled to the same rights and benefits as local people. The migrants who don't hold a local *hukou* have limited or no access to many government-provided benefits, including public education for children and medical care.

The difficulty of acquiring a local *hukou* is heterogenous across Chinese cities and is correlated with population and city tiers. Figure 4 illustrates a strong positive association between city population and the *hukou* index, which measures the difficulty migrants face in obtaining a local *hukou*. Figure 5 shows that the *hukou* index is highest for Beijing and Shanghai, followed by sub-provincial cities, and then by provincial

¹⁰ The cross-province migration rate in China is defined as the ratio of population who leave their *hukou* provinces, and the cross-state migration rate in U.S. is defined as the ratio of population who leave their birth states. In China, most people's *hukou* location is the same as their birth location. The China Labor-Force Dynamics Survey shows that birth province is the same as *hukou* province for 97.33% of population and 95.84% of migrants in China.

capitals in descending order¹¹. Therefore, in China today, it is relatively easy for immigrants to apply for local *hukou* in small and medium-sized cities but still very hard in large and high-tier cities.

Another prominent feature of the *hukou* system is that it is highly education-and -skill-biased. Table A2 reports the points associated with educational attainment and professional qualification that are required in the application for local *hukou* in four largest metropolitans in China, which indicate that migrant workers with a higher degree or professional qualifications can much more easily get the local *hukou* compared to those with lower education levels and less professional skills.

In China, *hukou* regulation is endogenously determined by local governments and employed to control city populations. The *hukou* restriction is more stringent in large and high-tier cities that face an influx of migrants. These cities, however, often offer desirable migrant-specific amenities – e.g., intensive migrant networks, relatively equal economic opportunities and a Mandarin-speaking (rather than local dialects) environment.¹² Figures 6 and 7 illustrate that the share of immigrants as well as the share of workers using mandarin as their working language are both higher for higher-tier cities in spite of their *hukou* restrictions.

To summarize, the overall migration costs specific for destination cities differ with city tiers in China and are driven by the combined effects associated with *hukou* regulation and migrant-specific amenities.

2.3 Housing Supply Restrictions

In the U.S., land use restrictions are implemented in the productive coastal cities. Similarly, in China, stringent restrictions are imposed on the supply of land available for construction in its highly-developed coastal regions. We give a brief introduction of China's land system here.

¹¹ We could divide prefecture-and-above level Chinese cities into four tiers – Beijing and Shanghai, sub-provincial cities, provincial capitals and ordinary prefecture cities. Tianjin and Chongqing are sub-provincial cities, but we assign the two cities to group of sub-provincial cities. The reason is that the difficulty to obtain local *hukou* and migrant-specific amenities in Tianjin and Chongqing are similar to that in the group of sub-provincial cities.

¹² Mandarin is the only official language in China, but local dialects are widely used in oral communication in many small and medium Chinese cities. It is hard for migrants to assimilate in local society and compete with local workers in labor market in a dialect-speaking environment

In China, local governments own all urban land, and state and collective ownership of land co-exist in rural areas. The land is categorized as construction land, agricultural land, and unused land. According to the *The Land Management Law of the People's Republic of China*, “construction land” is defined as “land on which buildings or other structures are built, including land used for urban and rural housing and public works.” “Agricultural land” is characterized as “land used directly in agricultural production”, and “unused land” is defined as “land other than agricultural land and construction land”.

During the period of rapid urbanization, the Chinese government set a quota system to annually specify the amount of land that can be transformed from agricultural land to construction land. Since 2004, the government has substantially reduced the construction land quota in productive coastal regions (Liang et al., 2016, Liu and Xiong, 2019). As plotted in Figure 8, before 2004, the share of coastal land supply increased annually, but since 2004, the trend of land supply reversed suddenly; the fraction of coastal land supply fell from more than 70% in 2003 to approximately 55% in 2010. The restrictions on the supply of construction land in coastal China drove up the housing price ratio between the coastal and inland regions as depicted in Figure 9. The sudden reduction in coastal land supply was not due to non-availability of land, but rather to the stringent restrictions on the amount of construction land that can be converted from agricultural land in coastal regions imposed by the government since 2004. For example, Shanghai has reserved up to about one-third of its land for agricultural use, even though transforming those land to construction use could largely drive down unaffordable housing prices in Shanghai.

Despite restricted land supply, coastal regions are still experiencing high economic growth and receiving an influx of immigrants, which cause a large and increasing housing demand. The three major economic circles, i.e. the Circum-Bohai-Sea Region, the Yangtze River Delta and the Pearl River Delta, are all located in coastal China, and Table A3 reports that about 67.97% of Chinese internal migrants are residing in these three economic circles. We further plot the spatial distribution of internal migrants across Chinese provinces in Figure 10. It is clear that internal migrants are concentrated

in coastal China. The imbalance between the supply of and demand for construction land raises housing prices in coastal China, which consequently inhibits the movement of workers from inland cities to those productive and livable coastal cities and reduces the aggregate well-being.

3. A Residential Sorting Model Incorporating Frictions

This section presents a residential sorting framework where workers choose locations based on wages, housing prices, amenities as well as mobility costs. Our model shares features with recent work on spatial sorting, particularly Bayer, Ferreira and McMillan (2007), Bayer and Timmins (2007) and Diamond (2016). We build upon their frameworks by incorporating constraints on mobility and housing, as well as externalities associated with city size and the share of high-skilled people.

3.1 Residential Location Sorting

Worker i with skill-level s chooses residential city j , along with consumption of a numeraire commodity $C_{i,j}$ and housing services $H_{i,j}$, to maximize their utility subject to a budget constraint:

$$\max_{\{C_{i,j}, H_{i,j}, X_j\}} U(C_{i,j}, H_{i,j}, X_j, N_j, \Delta_j, M_{i,j,s}, \xi_{j,s}, \eta_{i,j,s}; \bar{\beta}_s) \quad s.t. \quad C_{i,j} + \rho_j H_{i,j} = I_{i,j} \quad (1)$$

where X_j denotes exogenous amenities in city j (e.g. temperature, distance to seaports) and $s = low$ indicates “less than high school”, while mid and $high$ indicate “high school” or “some college and above”.

N_j and Δ_j are, respectively, the number of workers and the share of high-skilled workers, which are endogenous attributes of city j that are determined by the aggregate location choice decisions of individuals. The payoff from choosing a place depends partially on the number and the characteristics (here, educational attainment) of the other individuals who choose the same place. For example, people might prefer to live in large metropolitan areas because of the urban amenities that only large cities could provide, but congestion operating through increased commuting times and

crowded public services may distract the well-being in large cities. People might also have a direct preference for highly educated neighbors, and an indirect preference for the services and urban amenities that come along with them^{13,14}. $\xi_{j,s}$ captures the utility effects of all the unobserved characteristics of city j that are common to workers of the educational level s , and $\eta_{i,j,s}$ is the idiosyncratic unobserved taste for city j . $M_{i,j,s}$ denotes the disutility to individual i of moving from their original city to city j . $M_{i,j,s}$ not only captures the physical and psychological costs of living far from one's original city, but also the utility loss due to institutional migration restrictions that are prevalent in many developing countries. Migration costs are heterogeneous across education groups; we expect that high-skilled workers will generally face lower migration costs.

We allow utility parameters to vary with skill, and assume the utility function for worker i of skill level s residing in city j is:

$$U_{i,j,s} = C_{i,j}^{\beta_{C,s}} H_{i,j}^{\beta_{H,s}} X_j^{\beta_{X,s}} N_j^{\beta_{N,s}} \Delta_j^{\beta_{\Delta,s}} e^{M_{i,j,s} + \xi_{j,s} + \eta_{i,j,s}} \quad (2)$$

Individual utility maximization produces the optimum housing consumption:

$$H_{i,j}^* = \frac{\beta_{H,s}}{\beta_{H,s} + \beta_{C,s}} \cdot \frac{I_{i,j}}{\rho_j} \quad (3)$$

Denoting $\beta_{I,s} = \beta_{H,s} + \beta_{C,s}$, substituting $H_{i,j}^*$ for $H_{i,j}$ back into equation (2) and using the budget constraint yields the following individual indirect utility function:

$$V_{i,j,s} = B_s e^{\beta_{I,s} \ln I_{i,j} + M_{i,j,s} - \beta_{H,s} \ln \rho_j + \beta_{X,s} \ln X_j + \beta_{\Delta,s} \ln N_j + \beta_{\Delta,s} \ln \Delta_j + \xi_{j,s} + \eta_{i,j,s}} \quad (4)$$

¹³ Locations with a large share of high-educated people may contain certain amenities (e.g. theaters and museums) and certain city services (e.g., trash removal, sewage) that require a sufficient number of high-income residences to supply.

¹⁴ Diamond (2016) incorporates an index of observable amenities into the utility function which are endogenously determined by the skill mix of the city. Instead of modelling the effects of skill mix on amenities, we here treat the number and the skill mix of workers directly as endogenous amenities which capture both people's direct preference for city population and education composition and indirect preference for the services and amenities that only provided by cities with larger population or higher fraction of high-educated households.

where $B_s = \beta_{H,s}^{\beta_{H,s}} \beta_{C,s}^{\beta_{C,s}} / (\beta_{H,s} + \beta_{C,s})^{(\beta_{H,s} + \beta_{C,s})}$ is a constant across locations.

We can only observe workers' wages in the locations where they actually live. Thus, we must predict each worker i 's counterfactual wage in other locations that were not chosen. We decompose the would-be wage each worker would earn in every location into a predicted mean and an idiosyncratic error term that represents the unobserved individual ability in a particular city — i.e., $\ln I_{i,j} = \ln \hat{I}_{i,j} + \varepsilon_{i,j}^I$.

Substituting back into equation (4) and taking logs yields:

$$\ln V_{i,j,s} = \theta_{j,s} + \beta_{I,s} \ln \hat{I}_{i,j} + M_{i,j,s} + v_{i,j,s}, \quad v_{i,j,s} = \beta_I \varepsilon_{i,j}^I + \eta_{i,j,s} \quad (5)$$

$$\theta_{j,s} = \ln B_s + \beta_{H,s} \ln \rho_j + \beta_{X,s} \ln X_j + \beta_{\Delta,s} \ln N_j + \beta_{\Delta,s} \ln \Delta_j + \xi_{j,s} \quad (6)$$

where $\theta_{j,s}$ denotes city-and-skill specific mean utility that is common to all workers of skill level s in city j and captures all the utility-relevant attributes of the city, and $\xi_{j,s}$ is the unobservable component of $\theta_{j,s}$. $\theta_{j,s}$ could be considered as city quality of life, which is independent of wages and migration costs.

The combined idiosyncratic unobservable, $v_{i,j,s}$, in equation (5) captures both worker i 's idiosyncratic ability ($\varepsilon_{i,j}^I$) in city j and idiosyncratic taste ($\eta_{i,j,s}$) for the city. It accounts for the selection of workers into locations where their personal abilities have comparative advantage or their personal preferences are unusually high. Assuming that $v_{i,j,s}$ is independently and identically distributed Type I extreme value, the probability that worker i of type s chooses to reside in city j can be expressed as:

$$P(\ln V_{i,j,s} \geq \ln V_{i,l,s}, \forall l \neq j) = \frac{\exp(\theta_{j,s} + \beta_{I,s} \ln \hat{I}_{i,j,s} + M_{i,j,s})}{\sum_{q=1}^J \exp(\theta_{q,s} + \beta_{I,s} \ln \hat{I}_{i,q,s} + M_{i,q,s})} \quad (7)$$

Given the total number of skill-level- s workers (N_s) in China, the equilibrium number of workers of skill level s choosing to settle in city j is determined by:

$$N_{j,s} = \sum_{i=1}^{N_s} P(\ln V_{i,j,s} \geq \ln V_{i,l,s} \forall l \neq j) \quad (8)$$

Thus, the number of workers and the share of high-skilled workers choosing to live in city j can be written as:

$$N_j = \sum_s N_{j,s} \quad (9)$$

$$\Delta_j = \frac{N_{j,high}}{\sum_s N_{j,s}} \quad (10)$$

Without loss of generality, each worker provides one unit of labor in the local labor market. Therefore, the equilibrium of residential sorting equates the labor supply in a given location and the number of workers choosing to live there.

3.2 Labor Market

We use city specific Mincer wage equations to recover the local labor market equilibrium for each city. The wage that worker i could earn in city j is given by:

$$\ln I_{i,j} = \alpha_{j,low} + \alpha_{j,mid} Mid_Skill + \alpha_{j,high} High_Skill + \gamma_j' \Gamma_i + \varepsilon_{i,j}^I \quad (11)$$

where *Mid_Skill* and *High_Skill* are education attainment dummies for high school and some college or above, respectively. $\alpha_{j,low}$ is the average wage of low-skilled workers (i.e., less than high school), and $\alpha_{j,mid}$ and $\alpha_{j,high}$ are the wage ratios between middle- and low-skilled workers (returns to high school education) and between high- and low-skilled workers (returns to some college or above education), respectively, conditional upon individual attributes. Γ_i is a vector of other individual attributes. $\varepsilon_{i,j}^I$ is the unobserved worker i 's location-specific ability¹⁵.

Increasing the number of high-skilled workers may increase the demand for low- and middle-skilled workers. For example, college-educated residents take more taxi rides and hire more housekeepers. Additionally, a higher agglomeration of high-skilled

¹⁵ For example, a worker who is talented at finance would have a comparative advantage in New York, and a worker who is talented at computer science would have a relative higher skill in California bay area.

workers raises the productivity of all workers through knowledge spillovers.¹⁶ For example, the concentration of highly-educated people might result in a better spread of ideas and more intensive innovation activities. Thus, changes in the number and the skill mix of workers affects wages in the local market both by moving along workers' labor demand curves (i.e., a shift in labor supply) and by directly impacting workers' marginal products (i.e., a shift in labor demand). Therefore, we use three flexible linear equations to model the average wages of low-skilled workers and the returns to middle- and high-skill:

$$\alpha_{j,low} = \ln \bar{I}_{j,low} = \pi_0 + \pi_1 \ln N_{j,low} + \pi_2 \ln N_{j,high} \quad (12)$$

$$\alpha_{j,mid} = \ln \left(\frac{\bar{I}_{j,mid}}{\bar{I}_{j,low}} \right) = \varphi_0 + \varphi_1 \ln \left(\frac{N_{j,mid}}{N_{j,low}} \right) + \varphi_2 \ln N_{j,high} \quad (13)$$

$$\alpha_{j,high} = \ln \left(\frac{\bar{I}_{j,high}}{\bar{I}_{j,low}} \right) = \delta_0 + \delta_1 \ln \left(\frac{N_{j,high}}{N_{j,low}} \right) \quad (14)$$

where $\bar{I}_{j,low}$, $\bar{I}_{j,mid}$, and $\bar{I}_{j,high}$ denote average wage for low-, middle- and high- skilled workers, respectively, conditional upon other personal attributes. Equation (12) indicates that, as is illustrated in Figure A1, increasing the number of low-skilled workers in city j reduces their average wage by shifting the labor supply curve outward, whereas increasing the number of high-skilled workers raises low-skilled wages through shifting the labor demand curve for low-educated workers outward. Similarly, equation (13) indicates that, as shown in Figure A2, increasing the ratio between middle- and low-skilled workers decreases their wage ratio, i.e., the return to middle-education, by shifting their relative labor supply curve outward. Changes in the number of high-skilled workers impact the demand for low- and middle-skilled workers differentially. If the impacts are higher for the demand for middle-skilled workers, increasing the number of high-skilled workers will shift the relative labor demand curve of middle- and low-skilled workers outward and increase their wage ratio and vice versa.

We then turn to equation (14). The increase in high-skilled workers impacts their wages through not only labor supply but also their positive knowledge spillovers (e.g.,

¹⁶ See the survey of Rosenthan and Strange (2004) and Moretti (2011).

sharing of ideas, the agglomeration of innovation activities, etc.). Thus, Figure A3 shows that increasing the ratio between high- and low-skilled workers affects their wage ratio, i.e., the return to high-education, through shifting both the relative labor supply curve and the relative labor demand curve outward. If the movement of the relative labor demand curve is larger than that of the relative labor supply curve, the high-skill wage premium will go up.

3.3 Housing Market

We implicitly assume all housing is owned by an absentee landlord. The unit price of housing services ρ_j in city j is given by:

$$\ln \rho_j = \gamma_0 + \gamma_j N_j \quad (15)$$

where γ_j represents the elasticity of house price with respect to population in the city, and is determined by the land supply regulation. Cities with stringent land use restrictions have a higher housing price elasticity γ_j , and cities with highly elastic land supply have a smaller γ_j . Since 2004, the Chinese government has strengthened land-use administration and strictly restricted the construction land supply in coastal regions. Therefore, we assume γ_j differs between the coastal and the inland region of China.

3.4 Spatial Equilibrium

Spatial equilibrium is defined by a menu of wages $\hat{l}_{i,j}^*$, housing price ρ_j^* , and education-specific population $N_{j,s}^*$ in each location j :

1. Labor demand equals labor supply:

$$\ln \hat{l}_{i,j}^* = \alpha_{j,low} + \alpha_{j,mid} Mid_Ed + \alpha_{j,high} High_Ed + \gamma_j' \Gamma_i \quad (16)$$

$$\alpha_{j,low} = \pi_0 + \pi_1 N_{j,low}^* + \pi_2 N_{j,high}^*$$

$$\alpha_{j,mid} = \varphi_0 + \varphi_1 (N_{j,mid}^* / N_{j,low}^*) + \varphi_2 N_{j,high}^*$$

$$\alpha_{j,high} = \delta_0 + \delta_1 (N_{j,high}^* / N_{j,low}^*)$$

$$N_{j,s}^* = \sum_{i=1}^{N_s} \frac{\exp(\theta_{j,s} + \beta_{I,s} \ln \hat{l}_{i,j}^* + M_{i,j,s})}{\sum_{q=1}^J \exp(\theta_{q,s} + \beta_{I,s} \ln \hat{l}_{i,q}^* + M_{i,s,q})} \quad s = \{low, mid, high\}$$

$$\theta_{j,s} = \ln B_s + \beta_{H,s} \ln \rho_j^* + \beta_{X,s} \ln X_j + \beta_{\Delta,s} \ln N_j^* + \beta_{\Delta,s} \ln \Delta_j^* + \xi_{j,s}$$

2. Housing supply equals housing demand:

$$\ln \rho_j^* = \gamma_0 + \gamma_j N_j^* \quad (17)$$

$$N_j^* = \sum_s N_{j,s}^* \quad s = \{low, mid, high\}$$

Here, migration costs $M_{i,j,s}$ and different housing price elasticities with respect to population γ_j capture frictions in workers' spatial sorting. We do not solve for wages, housing prices, and skill-specific population analytically, but rather use our model to simulate the re-sorting decisions that workers make in response to policy changes, and the re-equilibration of labor and housing market adjusted to the relocation of workers. Thus, our framework provides the basis for analyzing the impacts of reducing frictions in residential location sorting and quantifying the consequent welfare changes.

4. Data

We estimate our equilibrium sorting model using the 2005 One-Percent Population Census of China. The census data not only contains very detailed information about housing conditions, but also includes a long list of variables about demographic and economic characteristics of workers, such as age, gender, education attainment, employment status, occupation, *hukou* type (rural/urban), *hukou* city and current residential city. The most important variable in the data is the individual wage. The 2005 One-Percent Population Census of China is the only census dataset that records the information about wages.

Without loss of generality, we use the household head sample in our analysis, and we use workers' *hukou* locations and current residential locations to define their migration status¹⁷. We drop the observation if a worker has been away from their *hukou* city for less than six months because we are uncertain whether they have made a long-term migration decision. We use data from age groups between 25 to 54 years of age

¹⁷ This definition is consistent with recent work on internal migration in China (Combes et al., 2020; Tombe and Zhu, 2019). Only 7% of individuals have a *hukou* city that is not their birth city.

and drop observations with missing values in wage and education attainment. Because China's real estate market was not established until 1991¹⁸, we drop observations if houses were built before 1991 before we compute the city-specific housing price¹⁹. We classify skill levels into three categories: low-skill (i.e. below high school), middle-skill (i.e. high school), and high-education (i.e. some college or above).

Our amenity data come from various sources. We collect city area from the China City Statistical Yearbook. Weather amenity data come from China Meteorological Data Service Center. We calculate the minimum distance to the three large seaports (i.e. Tianjin seaport, Shanghai seaport and Shenzhen seaport) by hand.

We combine our individual data and city amenity data. Our final data set includes 341,413 workers in 285 Chinese cities. The geographical distribution of the 285 cities in our sample is illustrated in Figure A4. The 285 cities contain 91.04% of the Chinese population in 2005.

Table A4 reports the summary statistics and a full description of the key variables used in our analysis. In 2005, only 6.7% of workers leave their *hukou* city, indicating high mobility costs in China. Table A5 further compares some key variables between the inland and coastal regions. The average wage is 89.44% higher in coastal regions than in inland regions; the fraction of high skilled workers and the fraction of migrant workers are both significantly higher in coastal regions compared to inland regions. Thus, the level of economic development is substantially higher in coastal China than that in inland China. Largely driven by constraints on housing supply, city-level housing price is significantly higher in coastal cities in comparison with inland cities.

¹⁸ Prior to 1991, housing was mainly allocated to employees at state owned enterprises, public institutions and government departments through a planned system; therefore, there was no housing market, and one cannot observe transaction values. In 1991, the central government authorized a comprehensive reform of the housing sector in China. Since then, the housing market in China has matured, allowing people to exchange their housing through the price system. This has made it possible for us to observe transaction prices since that time.

¹⁹ See Appendix C for the detailed procedure to calculate city-specific housing price.

5. Estimation

5.1 Counterfactual Wage

We first recover the city-specific wage equation – equation (11) in section 3.2 – by estimating an augmented Mincer wage regression separately for each city. A key advantage of conducting micro-level analysis using our equilibrium sorting model is that we could use detailed personal information to account for Roy sorting bias. We follow the semi-parametric approach proposed by Dahl (2002) to deal with Roy sorting problem. This is described in Appendix B. After that, we use the coefficients on individual characteristics in a city-specific Mincer wage equation to recover the counterfactual wage each worker would earn in every city.

5.2 Residential Location Sorting

We employ the two-step approach proposed by Berry et al. (1995) to infer the parameters underlying the residential location decision. In the first step, we use a discrete-choice model incorporating moving costs to estimate marginal utilities of wages and migration costs, as well as city-and-skill specific mean utilities. In the second step, we regress the estimated city-and-skill specific mean utilities on the number and the skill mix of workers, as well as exogenous amenities. We conduct our two-step estimation separately for each education group.

5.2.1 First-Step Estimation

The residential sorting model introduced in Section 3 can capture the migration disutility in the sorting process by incorporating fixed costs that vary with alternative locations. In order to capture the heterogeneity in the barrier to obtaining a local *hukou* and migrant-specific amenities across Chinese cities, we use six dummy variables and their interactions to model migration costs. Following Freeman, Liang, Song and Timmins (2019), we first classify the cities into four categories: Beijing and Shanghai, sub-provincial cities along with Tianjin and Chongqing, provincial capitals, and ordinary cities. It is hardest for migrants to obtain local *hukou* in Beijing and Shanghai, followed by sub-provincial cities, and then by provincial capitals and ordinary cities. Regarding migrant-specific desirable amenities, the pattern is entirely different. Large cities like Beijing and Shanghai offer much better migrant-specific amenities relative

to those small cities, including economic opportunities that are more similar to those offered to locals,²⁰ intensive migrant social ties and a Mandarin speaking environment. Therefore, we use the following equation to model the overall migrant costs due to *hukou* regulation and migrant-specific amenities:

$$M_{i,j,s} = \sum_{k=1}^3 \mu_{k,s} D_{k,ij} + \sum_{k=4}^6 \mu_{k,s} D_{1,ij} D_{k,ij} \quad (18)$$

$D_{1,ij} = 1$ if location j is outside of worker i 's *hukou* city ($= 0$ otherwise).

$D_{2,ij} = 1$ if location j is outside of worker i 's *hukou* province ($= 0$ otherwise).

$D_{3,ij} = 1$ if location j is outside of worker i 's *hukou* macro-region²¹ ($= 0$ otherwise).

$D_{4,ij} = 1$ if location j is Beijing/Shanghai ($= 0$ otherwise).

$D_{5,ij} = 1$ if location j is a sub-provincial city/ Tianjin/ Chongqing ($= 0$ otherwise).

$D_{6,ij} = 1$ if location j is a provincial capital ($= 0$ otherwise).

The first three dummies of equation (18) measure the disutility with respect to the physical and psychological costs of leaving one's *hukou* city.²² The interactions between "outside of *hukou* city" dummy and three city group dummies capture overall utility effects of the difficulty of obtaining local *hukou* and migrant-specific amenities, which are relative to migration costs in ordinary cities.²³ We allow migration cost parameters to differ with educational attainment.

We next estimate parameters of the discrete choice model of equation (7) by maximizing the following likelihood function:

²⁰ Here, economic opportunities not only refer to job opportunities, but also include other opportunities, such as assimilate into local society, learn and improve personal ability, and invest in profitable projects etc.

²¹ There are seven macro-regions in China: East China, North China, Central China, South China, Southwest China, Northwest China and Northeast China.

²² In China, most people's *hukou* city is the same as their birth city. The China Labor-force Dynamics Survey shows that only 7% of individuals have a *hukou* city that is not their birth city. Additionally, it usually takes a long time for migrants to obtain local *hukou*. Some local governments' official documents require that migrants must work in the city for more than 3 years before applying for local *hukou*. If a migrant moved out from his hometown and obtains *hukou* in a second city, he must have worked in this city for a long period and got used to the life there. Overall, there exists a significant moving disutility for households leaving their *hukou* city.

²³ We assume that migration disutility is heterogeneous across the four group of cities. Ordinary cities are considered as the benchmark group in the empirical specification of equation (18), therefore we don't add the interaction between "outside of *hukou* city" dummy and "ordinary city" dummy.

$$L(\theta_{j,s}, \beta_{I,s}, \mu_{1,\dots,6,s}) = \prod_i \prod_j \left[\frac{\exp(\theta_{j,s} + \beta_{I,s} \ln \hat{I}_{i,j,s} + \sum_{k=1}^3 \mu_{k,s} D_{k,ij} + \sum_{k=4}^6 \mu_{k,s} D_{1,ij} D_{k,ij})}{\sum_{q=1}^J \exp(\theta_{q,s} + \beta_{I,s} \ln \hat{I}_{i,q} + \sum_{k=1}^3 \mu_{k,s} D_{k,iq} + \sum_{k=4}^6 \mu_{k,s} D_{1,ij} D_{k,iq})} \right]^{\chi_{i,j}} \quad (19)$$

where $\chi_{i,j,s}$ is an indicator that takes the value of one if worker i of skill level s is observed to settle in city j , and 0 otherwise. City-and-education-fixed effect $\theta_{j,s}$ recovered from equation (19) represents city- and skill-specific mean utility independent of wages and moving costs. $\theta_{j,s}$ is constant to both natives and migrants of skill level s living in city j , and it captures the overall effects of all the utility-relevant city attributes. Our migration cost variables represent the heterogeneity in utility difference between natives and migrants across Chinese cities. Since we have controlled for $\theta_{j,s}$ which fully absorbs the utility effects of any city features, our migration cost variables are orthogonal to any city characteristics including both city-level observables and unobservables.

5.2.2 Second-Step Estimation

In the second step of our estimation, we regress city- and education-specific mean utilities obtained from the first-step estimation on housing price, population, the share of high educated workers and other local amenities. Two identification problems arise in this estimation stage.

First, the price of housing services (ρ_j) will be correlated with unobserved city characteristics in ξ_j . Following Bayer, Keohane and Timmins (2009), we address this issue by using information provided by the model to parameterize $\beta_{H,s}$. In particular, from equation (3), we have that $\beta_{H,s} = \beta_{I,s}(\rho_j H_{i,s}^* / I_{i,j,s})$; the parameter $\beta_{I,s}$ can be estimated from the first step estimation and we set $\rho_j H_{i,s}^* / I_{i,j,s}$ equal to the average share of housing expenditure over wage for cohorts with skill level s ,²⁴ which is 0.336, 0.290, and 0.223 for low-, middle- and high-skilled workers, respectively. We then solve the endogeneity issue by moving observed $\beta_H \ln \rho_j$ to the left-hand side of

²⁴ Following Bayer et al. (2007), for the purchased houses and self-built houses, we use the coefficients of housing price regression of equation (30) (see Appendix C) to convert the housing values into a measure of annual costs in 2005, and then calculate the share of housing expenditure in household income.

equation (20). The new dependent variable $\theta_{j,s} + \beta_{H,s} \ln \rho_j$ could be considered as housing price adjusted city quality of life. Thus, we use equation (20) to perform our second step estimation:

$$\theta_{j,s} + \beta_{H,s} \ln \rho_j = \ln B_s + \beta_{X,s} X_j + \beta_{\Delta,s} N_j + \beta_{\Delta,s} \Delta_j + \xi_{j,s} \quad (20)$$

We control for exogenous amenities involving winter and summer temperature, humidity, wind speed, and the minimum distance to the three large seaports in China (i.e. Shenzhen, Shanghai and Tianjin seaport) in the estimation of equation (20).

Second, we confront the fact that the number and skill mix of workers that choose each location is determined endogenously as part of the sorting equilibrium. In particular, N_j and Δ_j are likely to be correlated with $\xi_{j,s}$ due to the logic of the sorting process itself—unobserved natural advantages in a place affect the demand of individuals of different educational attainments for that place and, subsequently, population and skill mix. Therefore, it is hard to distinguish between local spillovers of the number and the skill mix of workers choosing city j and the unobserved attractiveness of the city.

Following Bayer and Timmins (2005, 2007), we propose an instrumental variables strategy to deal with the endogeneity of N_j and Δ_j . In developing our instrumental variables, we exploit the nature of the sorting process—that the overall demand for a particular location is affected by not only the features of location itself, but also by the way these features fit into a broader landscape of available alternatives. In particular, the exogenous attributes of other locations influence the sorting equilibrium (and, thereby, the number and skill mix of individuals who choose a given location), but do not have a direct effect on utility from a location choice once made. In this case, measures of a location's ‘isolation’ in exogenous attribute space make ideal instruments for the number and the skill mix of individuals who choose that location. Therefore, we leverage variations coming from exogenous amenities and migration

costs in all other alternative locations, and use the following predicted values as instrumental variables for N_j and Δ_j :

$$N_j: \ln \left(\sum_s \sum_{i=1}^{N_s} \frac{\exp(M_{i,j,s} + \beta_s X_j)}{\sum_{q=1}^J \exp(M_{i,q,s} + \beta_s X_q)} \right) \quad (21)$$

$$\Delta_j: \left(\sum_{i=1}^{N_{high}} \frac{\exp(M_{i,j,high} + \beta_{high} X_j)}{\sum_{q=1}^J \exp(M_{i,q,high} + \beta_{high} X_q)} \right) / \left(\sum_s \sum_{i=1}^{N_s} \frac{\exp(M_{i,j,s} + \beta_s X_j)}{\sum_{q=1}^J \exp(M_{i,q,s} + \beta_s X_q)} \right) \quad (22)$$

We only use exogenous local amenities (winter temperature, summer temperature, humidity, wind speed) and migration costs variables to predict individual location choices before aggregating those choice probabilities at the city level to get the predicted population and predicted share of highly educated workers. Since we have controlled for the migration costs (in the first step estimation) and exogenous amenities (in the second step estimation) in the same city (city j) when we estimate the effects of N_j and Δ_j , the variation of our instrumental variables only comes from the migration costs and exogenous amenities in all other locations that were not chosen. The migration costs and amenities of alternative locations influence the sorting equilibrium (and, thereby, the number and skill mix of workers who settle in city j), but do not have a direct effect on utility from a location choice once made²⁵. Therefore, our IV strategy satisfies the exclusion restriction assumption.

One may be concerned that migration cost variables $M_{i,j,s}$ (in city j) might be correlated with city-level unobservables in the same city. However, this is not the case. Since we have accounted for city-and-skill specific fixed effects $\theta_{j,s}$ when we estimate $M_{i,j,s}$ in the first step estimation, $M_{i,j,s}$ will be uncorrelated with any city-level characteristics in city j , including both city-level observables and unobservables.

²⁵ We can use a simple story to explain the logic of our IV construction. For instance, there are three cities in workers' location choice set—Boston, New York City and New Haven. Workers of different education attainment make location choices among the three cities. The attributes in New York City and New Haven strongly affect the probability that each worker choose to reside in Boston, and then affects the number and skill mix of workers in Boston. However, once location choice decisions have been made, the attributes in New York City and New Haven do not have any direct effect on the utility of residents settled in Boston.

Given the number of workers of each skill level in the country and their location choice set, the nature of the sorting equilibrium ensures that attributes in all other locations in the choice set strongly affect the number and the skill mix of workers choosing location j . Table A6 shows the results from first-stage IV estimation. The coefficients on the two instruments are highly statistically significantly different from zero, and the F-statistics are all larger than ten.

5.3 Labor Demand

The city-specific Mincer wage equation (discussed in section 3.2 and estimated in section 5.1) represents the equilibrium between labor supply and labor demand. Conditional upon workers' personal characteristics, all the determinants of skill-specific labor demand are residing in the average wage of low-educated workers $\alpha_{j,low}$, the return to middle education $\alpha_{j,mid}$, and the return to high education $\alpha_{j,high}$. Recall that equations (12)-(14) in section 3.2 indicate that the number and skill mix of workers impact $\alpha_{j,low}$, $\alpha_{j,mid}$ and $\alpha_{j,high}$. We then quantify these impacts by estimating the following equations:

$$\alpha_{j,low} = \pi_0 + \pi_1 \ln N_{j,low} + \pi_2 \ln N_{j,high} + \epsilon_j^{low} \quad (23)$$

$$\alpha_{j,mid} = \varphi_0 + \varphi_1 \ln(N_{j,mid}/N_{j,low}) + \varphi_2 \ln N_{j,high} + \epsilon_j^{mid} \quad (24)$$

$$\alpha_{j,high} = \delta_0 + \delta_1 \ln(N_{j,high}/N_{j,low}) + \epsilon_j^{high} \quad (25)$$

The independent variables in equation (23)-(25) tend to be correlated with unobserved city attributes, e.g. productivity-enhancing unobservable features could attract workers to settle in the city and subsequently affect population and the skill composition of workers. Thus, we need to distinguish the wage effects of the number and skill mix of workers from those of productivity-related unobservable features that are tied to locations. We use the instrumental variables strategy derived from the internal logic of the equilibrium sorting model in section 5.2 to deal with the endogeneity issue. Our instrumental variables provide an exogenous source of variation in labor supply by skill level in each city and thus identify equation (23)-(25) as labor

demand curves. Importantly, we take this procedure one step further and exploit the spillovers from high-skilled workers on the marginal products of labor of other groups. Thus, we include $N_{j,high}$ in the labor demand curve of low-skilled workers of equation (24), and in the relative labor demand curve of middle- and low-skilled workers in equation (25).

5.4 Housing Supply

Recall that cities with stringent land use restriction have a higher housing price elasticity with respect to population. Since 2004, the supply of construction land has been strongly restricted in coastal regions of China. We thus regress housing price $\ln p_j$ on city population separately for the coastal and inland regions:

$$\begin{aligned} \ln p_{j,coastal} &= \gamma_{0,coastal} + \gamma_{1,coastal} N_j + \epsilon_j \\ \ln p_{j,inland} &= \gamma_{0,inland} + \gamma_{1,inland} N_j + \epsilon_j \end{aligned} \tag{26}$$

We also employ the IV strategy derived from the internal logic of equilibrium sorting model to address the endogeneity of N_j . Our instrumental variables strategy provides an exogenous source of variation in housing demand across cities and thus identifies equation (26) as a housing supply curve. Recall that the ratio of construction land supply between the inland and coastal regions increases dramatically since 2004. Thus, we consider inland China as a benchmark of elastic housing supply in our next counterfactual exercise.

6. Parameter Estimates

6.1 Mincer Wage Regressions

Table A7 presents the summary statistics of coefficient estimates from the city-specific wage regressions described in section 5.1. The average return to middle education and high education is 24.06% and 58.18%, respectively. On average, wages increase with age, but do so at a decreasing rate. Female workers earn less than male workers, and urban *hukou* holders earn more than rural *hukou* holders. After getting city-specific coefficients on worker attributes, we use these coefficients to predict the

counterfactual wage that each worker could earn in every city, which will be employed when we estimate residential location sorting of workers.

6.2 Estimates from Residential Location Sorting

Table 1 reports parameter estimates from the first-step discrete choice model. Marginal utilities of wage are significantly positive for all three educational cohorts. Since we have included city fixed effects in the first-stage estimation, the six migration cost variables represent the difference in utility between migrants and natives independent of city characteristics. The first three dummies measure the disutility with respect to the physical and psychological costs of leaving one's original city, and their coefficient estimates are all significantly negative. The coefficient on $D_{1,ij}$ is larger than $D_{2,ij}$ and $D_{3,ij}$ in magnitude, which reflects that there exists a fixed cost associated with internal migration and migration costs rise with distance at a decreasing rate.

The three interactions between “out of *hukou* city” dummy and the three city group dummies capture the overall utility effects associated with *hukou* restriction and migrant-specific amenities across cities of different tiers. The coefficient estimates of the three interactions indicate that migration disutility is lowest for those moving to the two largest metropolitan areas of China-Beijing and Shanghai, followed by sub-provincial level cities, and then by provincial capitals and ordinary cities. It is extremely hard for migrants to apply for local *hukou* in Beijing and Shanghai, however, the two cities offer much better migrant-specific amenities in comparison with small cities, including more equal economic opportunities, intensive migration networks, and a more inclusive attitude toward migrants. The benefits from desirable migrant-specific amenities outweigh the disutility from *hukou* regulation, thus the consequence of combining these factors is that the overall migration costs are relatively lower in large metropolitan areas of China. Our results are in accordance with the geographic distribution of internal migrants in China – the 2005 One-Percent Population Census of China shows that about 31.8% of internal migrants live in the 10 largest cities of China. Our estimates of mobility costs are consistent with recent work on residential location sorting in China (Freeman, Liang, Song and Timmins, 2019; Liang, Song, Timmins, 2020).

The city-and-skill-specific fixed effects obtained from the first-step discrete choice estimation represent the mean utility from living in every location, regardless of migration status and wages. We next use housing price adjusted city-and-skill-specific fixed effects as the dependent variable in our second step estimation of equation (20). Panel A of Table 2 shows the OLS results from our second-step estimation. The variables of interest here are the two endogenous amenities, i.e., the number of workers $\ln N_j$ and the share of high-skilled workers $\ln \Delta_j$. At first sight, the coefficients on $\ln N_j$ and $\ln \Delta_j$ are both significantly positive for all three educational cohorts. It is, however, difficult to apply a causal interpretation to these estimates. $\ln N_j$ and $\ln \Delta_j$ are likely to be correlated with desirable unobservables, thus their naïve OLS estimates might be biased.

Our instrumental strategy proposed in section 5.2.2 affords us the opportunity to deal with the endogeneity issue. We employ exogenous attributes in all other alternative locations to leverage variations in the number and the skill mix of workers in city j . Panel B of Table 2 shows the IV results from our second step estimation. Comparing the OLS and IV estimates, the coefficients on $\ln N_j$ change from significantly positive to significantly negative for all three skill groups, highlighting the importance of addressing the endogeneity problem. Recall that coefficients on $\ln N_j$ combine the agglomeration effects (e.g. services and amenities that only large cities can provide) and congestion effects (e.g. environmental costs, commuting costs, and higher prices of local traded commodities) of increasing city size, thus the estimated negative marginal utility of population from our IV regression indicates that the latter outweighs the former. The results are consistent with Bayer and Timmins (2005, 2007), which show that correlation between population and attractive local unobservables can cause severe upward bias in favor of mistakenly inferring agglomeration effects. Conversely, the impacts of our instrumental strategy on $\ln \Delta_j$ is to increase the positive spillover from high-skilled residents for all the education cohorts. This positive spillover could be attributed to a direct preference for living with high-educated neighbors, and an indirect preference for the business, services and public good that only accompany high-educated residences.

6.3 Estimates from Labor Demand

Panel A and Panel B of Table 3 present the OLS and IV results, respectively, from the estimation of equations (23) - (25). As reported in Column (1), an increase in the number of low-skilled workers reduces their mean wage, but is statistically insignificant. The number of high-skilled workers has a significantly positive impact on the mean wage of low-skilled workers, and the coefficient estimates from the IV regression are larger than the corresponding OLS estimates in magnitude.

Column (2) presents estimates of relative labor demand for middle- and low-skilled workers. Increasing the ratio between middle- and low-skilled workers significantly reduces their wage differential. However, increasing high-skilled workers significantly raises the wage ratio between middle- and low-skilled workers, which indicates that the productivity spillovers from high-skilled workers is more pronounced for the middle-skilled group relative to the low-skilled group.

We next turn to the relative labor demand for high- and low-skilled workers. As reported in column (3), both OLS and IV results show that the ratio between high- and low-skilled workers is significantly positively associated with their wage ratio. The reason is that increasing the ratio between high- and low-skilled workers shifts their relative labor demand and supply curves outward simultaneously, but the labor demand curve moves further.

Overall, our results indicate that a higher concentration of high-skilled workers could raise the productivity of all education groups. The IV estimates of labor demand parameters are typically larger than the corresponding OLS estimates in magnitude, because our instrumental variables provide an exogenous source of variation in skill-specific labor supply across locations.

6.4 Estimates from Housing Supply

We use equation (26) in section 5.4 to estimate the housing price elasticity with respect to population in the inland and coastal regions, respectively. Panel A of Table 4 shows the OLS results and Panel B presents IV estimates. Both OLS and IV estimates show that the coefficient on city population $\ln N_j$ is statistically insignificant for the inland region but significant and positive for the coastal region. Moreover, the IV

estimate of $\ln N_j$ for the coastal region is substantially higher in magnitude and significance than the corresponding OLS estimates. Our instrumental variables offer an exogenous source of variation in housing demand across cities and thus identify equation (26) as a housing supply curve. Therefore, the difference in housing price elasticity with respect to population between coastal and inland China, to a large extent, captures the heterogeneous housing supply restriction between the two regions.

7. Counterfactual Welfare Analysis

High migration costs and stringent housing supply restrictions induced by common policy incentives inhibit the spatial sorting of workers and reduce the aggregate social welfare. Two questions naturally arise. What are implications of reducing migration costs and relaxing housing supply restrictions on welfare and regional inequality? How do the two kinds of frictions interact with each other in determining welfare losses? To answer these questions, in this section, we do counterfactual simulations to quantify the general equilibrium effects associated with constraints on mobility and housing supply.

7.1 Simulation Procedure

7.1.1 Specifications in Policy Experiments

In a series of quantitative exercises, we consider the U.S. as a benchmark for low mobility costs (Bryan and Morten, 2019; Tombe and Zhu, 2019) and see inland China as the benchmark for elastic housing supply. In particular, when simulating the reduction in migration costs, we lower migration costs in China by 29.6%—a level of migration costs such that the inter-province migration rate in China reaches the inter-state migration rate in the U.S.. When simulating the loosening of housing restrictions, we reduce housing price elasticities with respect to population in coastal China to the level in inland China²⁶.

²⁶We acknowledge that, the difference of internal migration rate between China and the U.S. is not only driven by high mobility costs in China and the difference of housing price elasticities with respect to population between coastal and inland regions is not only determined by the stringent construction land restrictions in coastal regions. These differences might also be influenced by other factors. However, we only consider the U.S. as a benchmark for low mobility costs and see inland China as a benchmark of elastic housing supply. Our approach is similar to Bryan and Morten (2019) and Tombe and Zhu (2019),

We will conduct four counterfactual simulations:

(i) Reduced migration costs under the current scenario of tight housing constraints. Specifically, we lower migration costs by 29.6%; we keep current housing price elasticities with respect to population unchanged both before and after the change in migration costs.

(ii) Reduced migration costs under the alternative scenario of loose housing constraints. In particular, we lower migration costs by 29.6%; we let housing price elasticities with respect to population in coastal regions equal to those in inland regions both before and after the change in migration costs.

(iii) Relaxed housing supply restrictions under the current scenario of high migration costs. Specifically, we reduce housing price elasticities with respect to population in coastal China to the level in inland China; we keep current high mobility costs unchanged both before and after the change in housing constraints.

(iv) Relaxed housing supply restrictions under the alternative scenario of lowered migration costs. In particular, we reduce housing price elasticities with respect to population in coastal China to the level in inland China; we lower mobility costs by 29.6% both before and after the change in housing constraints.

7.12 General Equilibrium Welfare Calculation

We exploit individuals' re-sorting and the re-equilibration of labor and housing markets to calculate the Hicksian compensating surplus CV_i and the wage change $\Delta I_i/I_i$ for each individual associated with the policy change in constraints on mobility and housing supply:

$$\begin{aligned} & \max_j^{0*} \{ \theta_{js}^0 + \beta_I \ln \hat{l}_{ijs}^0 + M_{ijs}^0 + v_{ijs} \} \\ & = \max_{j'}^{1*} \{ \theta_{j's}^1 + \beta_I \ln (\hat{l}_{ij's}^1 - CV_i) + M_{ij's}^1 + v_{ij's} \} \end{aligned} \quad (27)$$

$$\Delta I_i/I_i = (\hat{l}_{ij's}^1 - \hat{l}_{ijs}^0)/\hat{l}_{ijs}^0 \quad (28)$$

who consider the U.S. as high mobility benchmark and evaluate the counterfactual reduction in migration costs in Indonesia and China to the level of the U.S. and Hsieh and Klenow (2009) who use the U.S. as a high efficiency benchmark and exploit the counterfactual reduction in resource misallocation in China and India through raising marginal factor products in the two countries to the level of the U.S..

Where $(\theta_{js}^0, \hat{I}_{ijs}^0, M_{ijs}^0)$ and $(\theta_{js}^1, \hat{I}_{ijs}^1, M_{ijs}^1)$ denote equilibrium location-and-skill-specific mean utilities (which incorporate housing prices, city population, the share of high-skilled people and all other amenities), equilibrium wages and migration costs before and after the policy change, respectively²⁷. Please note that worker i 's new location j' may or may not be same as their initial location j .

We calculate the expected value of CV_i conditional on the individual's location choice -- that is, using the distributions of $\{v_{ijs}\}$ that are conditional on the individual's observed location choice (von Haefen, 2003; Timmins, 2005, 2007). In particular, we take a 5% random sample of workers and simulate CV_i by taking a draw from the conditional distributions of the vector of error terms v_{ijs} and calculating CV_i using Eq. (27) for each draw. We average these values across 50 draws to calculate the individual's expected Hicksian welfare measure. To make the welfare effects more comparable across different cohorts, we also use the status-quo wage to normalize the individual Hicksian welfare measure CV_i/I_i^0 .

7.2 Reduced Migration Costs under Different Scenarios of Housing Restrictions

We firstly lower migration costs under the current scenario of stringent housing constraints in China. As shown in Panel A of Table 5, 33.32% of workers relocate to other cities in response to the decline in migration costs, and 12.55% of workers re-sort from under-developed inland regions to highly-developed coastal regions. Therefore, lowering mobility costs allows more workers to have access to the high productivity and good amenities in coastal cities. Turning to heterogeneity in skills, 14.32% of low-skilled workers and 12.81% of middle-skilled workers relocate from inland cities to coastal cities as a result of the reduction of migration costs, whereas only 5.29% of high skilled workers re-sort from inland to coastal areas. The *hukou* policy in China is strongly education-and-skill biased, so that migration costs are substantially higher for low- and middle-skilled groups. This strongly prevents unskilled workers in under-

²⁷ Bayer and Timmins (2005) prove that the equilibrium is unique if all endogenous population effects are congestive, as is the case with the number of workers N_j in the utility function (entering directly through both a direct congestion effect and through housing prices, and own education-specific population entering through labor demand for low and middle education workers). This is not the case, however, with the share of highly educated workers, Δ_j , which has an agglomerative impact. Given the possibility of multiple equilibria, we use observed (i.e., pre-policy) city-and-education specific populations as a starting point and take the first equilibrium that arises in an iterative algorithm.

developed regions from sorting into developed regions to gain access to higher wages and better amenities²⁸. Therefore, the re-sorting effects of lowering mobility costs are more pronounced for those with lower education attainment.

We then lower migration costs to the same level under the alternative scenario of loose housing constraints. Panel B of Table 5 presents the resulting re-sorting effects. When shifting from stringent to relaxed housing supply restrictions, the fraction of workers resorting from inland to coastal regions in response to lowering mobility costs increases from 12.55% to 14.66%. With respect to heterogeneity in skills, relaxing housing constraints magnifies the re-sorting effects of reducing migration costs for low- and middle-skilled workers but attenuates the effects for the high-skilled group. The reason is that under elastic housing supply, the re-sorting of people is less likely to drive up housing prices in those migrant-inflow cities so more under-educated workers are able to move to those places. The situation is different for high-skilled workers. Their location choice is less likely to be constrained by housing costs, but their disutility associated with the congestion effects owing to increased population is stronger than their under-educated counterparts. Therefore, under relaxed housing constraints, high-skilled workers are less likely to re-sort to coastal cities.

In Panel A of Table 6, we calculate workers' Hicksian welfare measures and wage changes due to the targeted reduction in migration costs under current tight constraints on housing supply in China. On average, the monetized welfare gain is as large as \$338.68 which accounts for 38.33% of the status-quo wage. We also see a 22.3% increase in an average worker's wage. The consequent welfare implications incorporate the direct utility gain from reducing migration costs for current migrants, and the indirect utility improvement resulting from expanding the number of workers who have access to high productivity and good amenities in those developed cities. Our findings are consistent with Au and Henderson (2006) who find that a large fraction of Chinese

²⁸ Figure A5 illustrates the relationship between local *hukou* policy and the changes in city population resulting from lowering mobility costs. The first graph shows that the city *hukou* index, which measures the difficulty for migrants to obtain local *hukou*, is positively associated with our predicted population changes. In China, *hukou* policy is endogenously determined by local government. The threshold to apply for a local *hukou* is usually high in populated and productive cities which often offer desirable migrant-specific amenities. In other words, the difficulty of obtaining a local *hukou* can, to a large extent, capture the level of wages and migrant-specific amenities, thus cities with a higher *hukou* index receive a larger inflow of immigrants in response to lowering migration barriers, even though we reduce the migration costs for all the cities by the same proportion. The rest of the graphs show that the positive association between *hukou* index and population changes only exists for low- and middle- skilled groups, while for the high-skilled workers, we observe no relationship between them. It is much easier for high-skilled migrants to get a local *hukou* compared to their unskilled counterparts, thus their location choice is less likely to be affected by city *hukou* policy.

cities are undersized due to stringent constraints on mobility, resulting in substantial economic losses.

We then quantify welfare effects for different educational cohorts. The average fraction of monetized welfare gain in wage and the average change in wage are both higher for low- and middle- skilled workers relative to the high-skilled group. Lower-education people suffer substantial welfare losses due to the education-and-skill biased *hukou* restriction in China, thus they benefit more from reducing migration barriers. Regarding heterogeneity across regions, the residents who originally live in underdeveloped inland regions get larger welfare gains than those in coastal regions. The reason is that, in response to the reduction in migration costs, a large number of workers who originally reside in inland regions re-sort into coastal regions, where high productivity and better amenities are centralized.

Panel B of Table 6 reports the welfare effects of lowering migration costs under the alternative scenario of relaxed housing supply restrictions. The economic returns to lowering migration costs depend on the elasticity of housing supply in coastal regions, which are popular destinations for migrants. The monetized welfare gain associated with the reduction in migration costs increases significantly from \$338.68 under stringent housing constraints to \$374.12 under relaxed housing constraints. The increase in the welfare improvement is concentrated on those who live in unproductive inland regions. When shifting from inelastic to elastic housing supply, the welfare benefits of lowering migration costs increase substantially from \$506.53 to \$582.78 for those living in inland regions, but hardly change for those in coastal regions.

We further quantify the distributional effects associated with lowering mobility costs in Panel A and B of Table 7. Owing to the targeted reduction in migration costs, the 90-10 percentile wage ratio decreases by 16.84% under stringent housing constraints and by 17.47% under relaxed housing constraints, and the coastal-inland wage ratio decreases by 22.81% under inelastic housing supply and by up to 27.34% under elastic housing supply. Therefore, lowering mobility costs could reduce wage inequality in China, especially for the inequality driven by the regional differences between unproductive inland and productive coastal regions; such distributional effects are stronger when restrictions on housing supply are relaxed in coastal cities.

Both the welfare and distributional impacts of reducing migration costs are more pronounced under the scenario of elastic housing supply, because relaxing housing constraints can expand the number of workers re-sorting from unproductive to productive regions in response to lowering mobility costs and provide more affordable housing for those re-sorting workers in coastal regions²⁹.

The interaction of two kinds of frictions in determining the economic effects of lowering mobility costs have two policy implications. First, in countries with both tight constraints on mobility and housing supply like China, there are extra welfare gains and distributional effects from reducing the two kinds of frictions together. Relaxing housing constraints could increase the welfare benefits of lowering migration costs and allocate the additional welfare effects to those in underdeveloped areas³⁰. Second, from the cross-country perspective, the implications of lowering migration costs on welfare and regional inequality are higher in countries with less stringent housing constraints like Indonesia than those with both stringent constraints on mobility and housing supply.

As mentioned before, political incentives to provide benefits to local residents could drive up mobility costs. We take examples of Beijing and Shanghai, which experience the most stringent *hukou* restrictions, to see how the welfare implications of lowering mobility costs differ between natives and migrants. We divide people into three groups--natives, incumbent migrants and newly arriving migrants induced by lowering mobility costs. Figure A6 illustrates the changes in welfare associated with lowering mobility costs for workers by migration status. Local people suffer from large welfare losses, because the inflow of migrant workers drives down their wages and causes increased congestion. Measured in terms of the fraction of the wage, the

²⁹ Unaffordable housing is among the most serious concerns for internal migrants in China. Take examples of Beijing and Shanghai, which are the most popular destination cities for migrants. The annual growth rate of housing price between 2001 and 2005 is 10.42% in the two cities. Due to the stringent restrictions on housing supply, the annual housing price growth rate increases sharply to 20% during the period from 2006 to 2010 in Beijing and Shanghai. The rising housing prices, driven by inelastic housing supply functions, prevent the entry of workers from underdeveloped areas and inflict large welfare losses on immigrants who choose to settle in the two cities.

³⁰ Recently, the Chinese National Development and Reform Commission has promulgated the policy of encouraging the migrants in urban areas to obtain local *hukou* and enjoy the local public services. Meanwhile, another policy released by the State Council has emphasized that the construction land quota should be allocated to those migrant-inflow cities, the majority of which are located in coastal China. Our counterfactual calculation here clarifies the potential economic benefits of the recent policy mix in China. For background information, see http://www.ndrc.gov.cn/zcfb/zcfbtz/201810/t20181010_900750.html and http://www.gov.cn/xinwen/2019-04/08/content_5380457.htm.

monetized welfare losses are large and more pronounced for low-skilled natives. However, the reduction in migration costs improves the welfare for incumbent migrants, even though their wages are still driven down by the increased labor supply. The reason is that their welfare losses due to stringent *hukou* restrictions decrease substantially when we simulate the reduction in migration costs. For newly arriving migrants, we see an even larger increase in their welfare, because they have access to higher wages and better amenities by moving to Beijing and Shanghai. The pattern of changes in utility is similar under different levels of housing constraints. Natives suffer from large welfare losses due to increased numbers of migrant workers. Moreover, the influx of immigrants in Beijing and Shanghai will drive up the fiscal burden for local governments. Political incentives to protect the interests of local people and reduce fiscal expenditures induce local governments in the two cities to impose the most stringent migration restrictions in China, even though encouraging internal migration could increase total national welfare.

7.3 Relaxed Housing Constraints under Different Scenarios of Migration Costs .

We simulate the relaxation of restrictions on housing supply in coastal cities, which are most productive in China. Panels C and D of Table 5 report the resulting effects on workers' resorting decisions under scenarios of high and low migration costs, respectively. In response to the relaxation of housing constraints, only 1.05% of workers re-sort from unproductive inland regions to productive coastal regions under current high migration costs, whereas 3.95% of workers relocate to coastal cities under lowered migration costs. Therefore, lowering migration costs allows more workers to re-sort from under- to highly-developed regions induced by loosening housing constraints.

In both scenarios of high and low mobility costs, the re-sorting implications of relaxing housing constraints are more pronounced for low- and middle-skilled groups compared to those with high educational attainment. Unskilled cohorts spend much more on housing services compared to their high-skilled counterparts, thus their initial location choice decisions are more restricted by housing constraints, and consequently they are more likely to re-sort somewhere else due to decreased housing prices.

Moreover, lowering mobility costs increases the re-sorting responses to relaxing housing supply restrictions for all of the education cohorts.

The relaxation of housing supply restrictions in coastal China yields a large welfare improvement but a small wage increase. Panel C of Table 6 shows that, under current high migration costs, the average monetized welfare gain owing to the relaxation of housing constraints is \$179.04, which consists of approximately 11.61% of the status-quo wage. However, workers' wages rise by only 0.51% on average, because, restricted by high mobility costs, only a small fraction of workers re-sort from unproductive to productive areas in response to the simulated housing policy. The welfare boost is mostly due to the reduction in housing prices in high density coastal cities rather than the relocation of workers.

The economic returns to loosening restrictions on housing supply depend on the mobility constraints imposed on workers' spatial sorting. By comparison of Panel C and D in Table 6, we see that, when shifting the scenario from high to low mobility costs, the average monetized welfare implication of relaxing housing restrictions rises from \$179.04 to \$233.77, and only those who live in under-developed inland regions receive the extra benefits. In the current scenario of high mobility costs, people originally living in inland regions receive an average monetized welfare gain of \$67.41 and a wage increase of only 1.33% due to relaxing housing constraints. However, when turning to the alternative scenario of low mobility costs, the monetized welfare effect associated with loosening housing constraints more than doubles for those originally in inland regions (from \$67.41 to \$140.613) and the wage effect almost quintuples for them (from a wage increase of 1.33% to 6.30%). Under the scenario of fewer mobility restrictions, more people from under-developed inland regions are able to move to developed coastal regions in response to the relaxation in housing constraints and experience larger increases in wages and welfare. By contrast, lowering mobility costs hardly changes the welfare benefits of relaxing housing constraints received by those coastal residents while having them suffer more wage losses.

Panel C and D of Table 7 shows the distributional impacts of relaxing housing constraints. As a result of loosening restrictions on housing supply, the 90-10 percentile

wage ratio decreases by only 0.69% under current high mobility costs and by 3.37% under low mobility costs, and the coastal-inland wage ratio decreases by 0.79% under tight mobility constraints and by as large as 11.32% under less mobility constraints. Therefore, relaxing housing constraints could reduce wage inequality in China, especially for the inequality driven by the spatial heterogeneity between underdeveloped inland and developed coastal regions. Moreover, lowering mobility costs could increase the effects of relaxing restrictions on housing supply on wage inequality.

The impacts of relaxing housing constraints on welfare and inequality are both much stronger under the scenario of low mobility costs. The reason is that lowering migration costs expands the number of workers who migrate from unproductive to productive areas in response to the relaxation of housing constraints and has those re-sorting workers suffer less disutility from the costs associated with migration.

The interaction of the two kinds of frictions in determining the welfare and distributional effects of loosening housing constraints provides two policy implications. First, there are additional welfare gains and stronger distributional effects from reducing the two types of frictions simultaneously in countries with stringent constraints on both mobility and housing supply. In particular, lowering migration costs could increase the welfare impact of relaxing housing constraints, yielding additional gains to those in the underdeveloped regions. Second, from the cross-country perspective, the impacts of relaxing housing constraints on welfare and regional inequality are higher for a free-mobility country like the U.S. compared to countries with both tight constraints on mobility and housing supply.

8. Conclusion

In many countries in the world, constraints on mobility and housing supply are driven by common policy incentives and combine to inhibit workers' spatial sorting. In this paper, we evaluate the impacts of reducing migration costs and relaxing housing constraints on workers' re-sorting decisions and quantify the consequent changes in welfare and regional inequality in the case of China.

We find strong policy interactions between the two kinds of frictions in determining the welfare and regional distributional consequences. The implications of lowering mobility costs on welfare and regional inequality depend on the elasticity of housing supply in coastal regions which are the popular destinations of internal migrants. Similarly, the welfare and spatial distributional impacts of relaxing housing supply restrictions depend upon the mobility constraints imposed on workers. For either constraint on mobility or housing supply, reducing one type of friction can increase the welfare and distributional impacts of reducing the other type of friction and allocate the additional welfare returns to those in under-developed inland regions.

The interaction of two types of friction has broad policy implications. First, a policy mix of simultaneously lowering migration costs and relaxing housing supply restrictions can bring extra economic returns for countries with tight mobility and housing constraints like China. Second, the implications of lowering migration costs on welfare and regional inequality are higher in countries with less stringent housing constraints like Indonesia than they are in countries that combine tight constraints on mobility with similarly tight constraints on housing supply. Finally, the welfare and distributional effects of relaxing housing constraints are stronger in a high mobility country like the U.S. than in countries with both types of frictions.

References:

- Au, C. C. and Henderson, J. V., 2006, "Are Chinese Cities Too Small?", *The Review of Economic Studies*, 73(3): 549-576.
- Bayer, P. and Timmins, C., 2005, "On the Equilibrium Properties of Locational Sorting Models", *Journal of Urban Economics*, 57(3): 462-477.
- Bayer, P. and Timmins, C., 2007, "Estimating Equilibrium Models of Sorting Across Locations", *The Economic Journal*, 117(March): 353-374.
- Bayer, P., Ferreira, F. and Mcmillan, R., 2007, "A Unified Framework for Measuring Preferences for Schools and Neighborhoods", *Journal of Political Economy*, 115(4): 588-638.
- Bayer, P., Keohane, N. and Timmins, C., 2009, "Migration and Hedonic Valuation: The Case of Air Quality", *Journal of Environmental Economics and Management*, 58(1): 1-14.
- Berry, S., Levinsohn, J. and Pakes, A., 1995, "Automobile Prices in Market Equilibrium", *Econometrica*, 63(4): 841-890.
- Bhavnani, R.R. and Lacina, B., 2017. "Fiscal Federalism at Work? Central Responses to Internal Migration in India", *World Development*, 93(May): 236-248.
- Bryan, G., Chowdhury, S. and Mobarak, A.M., 2014. "Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh", *Econometrica*, 82(5): 1671-1748.
- Bryan, G. and Morten, M., 2019, "The Aggregate Productivity Effects of Internal Migration: Evidence from Evidence From Indonesia", *Journal of Political Economy*, 127(5):2229-2268.
- Card, D. and Lemieux, T., 2001, "Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis. ", *The Quarterly Journal of Economics*, 116(2): 705-746.
- Clemens, M. A., Lewis, E. G. and Postel, H. M., 2018, "Immigration Restrictions as Active Labor Market Policy: Evidence from the Mexican Bracero Exclusion", *American Economic Review*, 108(6): 1468-1487.
- Combes, P.P., Démurger, S., Li, S. and Wang, J., 2020. "Unequal Migration and Urbanisation Gains in China", *Journal of Development Economics*, 142(1): 102328.
- Dahl, G., 2002, "Mobility and the Return to Education: Testing a Roy Model with Multiple Markets", *Econometrica*, 70(6): 2367-2420.
- Diamond, R., 2016, "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000", *American Economic Review*, 106(3): 479-524.
- Diamond, R., 2017. "Housing Supply Elasticity and Rent Extraction by State and Local Governments", *American Economic Journal: Economic Policy*, 9(1), pp.74-111.
- Freeman, R., Liang, W., Song, R. and Timmins, C., 2019, "Willingness to Pay for Clean Air in China", *Journal of Environmental Economics and Management*, 94(3): 188-216.
- Glaeser, E. L., Huang, W., Ma, Y. and Shleifer, A., 2017. "A Real Estate Boom with Chinese Characteristics", *Journal of Economic Perspectives*, 31(1): 93-116.
- Glaeser, E. and Gyourko, J., 2018, "The Economic Implications of Housing Supply", *The Journal of Economic Perspectives*, 32(1): 3-30.
- Gollin, D., Lagakos, D. and Waugh, M. E., 2014, "The Agricultural Productivity Gap", *The Quarterly Journal of Economics*, 129(2): 939-993.
- Hsieh, C. and Klenow, P. J., 2009, "Misallocation and Manufacturing TFP in China and India", *Quarterly Journal of Economics*, 124(4): 1403-1448.
- Hsieh, C. and Moretti, E., 2018, "Housing Constraints and Spatial Misallocation", *American Economic Journal: Macroeconomics*, 11(2): 1-39.

- Katz, F. L. and Murphy, M. K., 1992, "Changes in Relative Wages, 1963-1987: Supply and Demand Factors", *The Quarterly Journal of Economics*, 107(1): 35-78.
- Kinnan, C., Wang, S. and Wang, Y., 2018, "Access to Migration for Rural Households", *American Economic Journal: Applied Economics*, 10(4): 79-119.
- Liang, W., Lu, M. and Zhang, H., 2016, "Housing Prices Raise Wages: Estimating the Unexpected Effects of Land Supply Regulation in China", *Journal of Housing Economics*, 33(C): 70-81.
- Liang, W., Song, R. and Timmins, C., 2020, "The Role of Migration Costs in Residential Sorting", *Duke University Working Paper*.
- Liu, C. and Xiong, W., 2019, "China's Real Estate Market", *The Handbook of China's Financial System*, edited by Marlene Amstad, Guofeng Sun, and Wei Xiong, Princeton University Press, forthcoming.
- Molloy, R., Smith, L. C., and Wozniak, A. 2011, "Internal Migration in the United States." *Journal of Economic Perspectives*, 25 (3): 173-96.
- Moretti, E., 2011, "Local Labor Markets", In Card D. and Ashenfelter O.(eds.), *Handbook of Labor Economics*, Vol.(4b), New York, Elsevier, 1237-1313.
- Quigley, J. M. and Raphael, S., 2005, "Regulation and the High Cost of Housing in California", *American Economic Review*, 95(2): 323-328.
- Roback, J., 1982, "Wages, Rents, and the Quality of Life ", *Journal of Political Economy*, 90(6): 1257-1278.
- Rosen, S., 1979, "Wages-Based Indexes of Urban Quality of Life", In Mieszkowski P. and Straszheim M.(eds.), *Current Issues in Urban Economics*, Baltimore, John Hopkins University Press, 74-104.
- Rosenthal, S. S. and Strange, W. C., 2004, "Evidence On the Nature and Sources of Agglomeration", In Henderson J. V. and Thisse J.(eds.)(4), Amsterdam, North-Holland, 211902171.
- Roy, D. A., 1951, "Some Thoughts On the Distribution of Earnings", *Oxford Economic Papers*, 3(2): 135-146.
- Saiz, A., 2010, "The Geographic Determinants of Housing Supply", *The Quarterly Journal of Economics*, 125(3): 1253-1296.
- Timmins, C., 2005, "Estimable Equilibrium Models of Locational Sorting and Their Role in Development Economics." *Journal of Economic Geography*, 5(1): 83-100.
- Timmins, C., 2007, "If You Cannot Take The Heat, Get Out Of The Cerrado ... Recovering The Equilibrium Amenity Cost Of Nonmarginal Climate Change In Brazil", *Journal of Regional Science*, 47(1):1-25.
- Tombe, T. and Zhu, X., 2019, "Trade, Migration, and Productivity: A Quantitative Analysis of China", *American Economic Review*, 109(5): 1843-1872.
- Trostel, P.A., Ronca, J.M., 2009, "A Simple Unifying Measure of State Support for Postsecondary Education", *Research in Higher Education*, 50(3): 215-247.
- von Haefen, R., 2003, "Incorporating Observed Choice into the Construction of Welfare Measures From Random Utility Models", *Journal of Environmental Economics and Management*, 45(2): 145-165.
- Wu, K., Zhang, L., 2010, "Developmentalist Government and Urban Hukou Threshold: Rethinking Hukou System Reform", *Sociological Studies* (In Chinese) 25(6):59-86.

Figure 1: The Comparison between China and the U.S.: GDP per Capita in 2005
Data Source: GDP per Capita in U.S. are drawn from Bureau of Economic Analysis (BEA), GDP per Capita in China are drawn from Comprehensive Statistical Data and Materials on 55 Years of New China.

Figure 2: The Comparison between China and the U.S.: Students per School in 2005
Data Source: The raw data of students per school in U.S. are drawn NCES Education Statistics and Trostel and Ronca (2009), the raw data of students per school in China are drawn from Comprehensive Statistical Data and Materials on 55 Years of New China.

Figure 3: The Comparison between China and U.S.: Doctors per capita
Data Source: The raw data of doctors per capita in U.S. are drawn from Annual American Hospital Association (AHA) Survey and Bureau of Economic Analysis (BEA), The raw data of doctors per capita in China are drawn from Comprehensive Statistical Data and Materials on 55 Years of New China.

Figure 4: City population and *Hukou* index
Data Source: *Hukou* index data are drawn from Wu and Zhang (2010), city population data are drawn from China City Statistical Yearbook.

Figure 5: Average *Hukou* index for cities of different hierarchies
Notes: We assign Tianjin and Chongqing to the group of sub-provincial city
Data Source: Wu and Zhang (2010)

Figure 6: Average share of migrants for cities of different hierarchies
Notes: We assign Tianjin and Chongqing to the group of sub-provincial city
Data Source: 2005 One-Percent Population Census of China

Figure 7: Average share of workers using Mandarin as working languages
Notes: We assign Tianjin and Chongqing to the group of sub-provincial city
Data Source: China Labor Dynamic Survey 2014

Figure 8: Coastal share of the total construction land supply
Data source: China Land and Resource Statistical Yearbook

Figure 9: The ratio of average housing price between inland region and coastal region
Data source: China Regional Economics Statistical Yearbook

Figure 10: The share of internal migrants across Chinese provinces in 2005
Notes: The narrow region on the right of regional boundary is coastal region, the rest is inland region. Dark reds indicate larger share of migrants in population.
Data Source: 2005 One-Percent Population Census of China

Table 1: Results from the first step discrete choice model of residential location decision

	Low skill (1)	Middle skill (2)	High skill (3)
$\ln(\text{Counter-factual Income } \hat{I}_{i,j})$	2.088*** (0.104)	1.525*** (0.126)	2.350*** (0.225)
Out of <i>hukou</i> city dummy ($D_{1,ij}$)	-7.685*** (0.037)	-7.411*** (0.063)	-7.890*** (0.086)
Out of <i>hukou</i> province dummy ($D_{2,ij}$)	-1.914*** (0.046)	-2.066*** (0.082)	-2.535*** (0.106)
Out of <i>hukou</i> macro-region dummy ($D_{3,ij}$)	-2.109*** (0.042)	-1.777*** (0.075)	-1.456*** (0.088)
Out of <i>hukou</i> city dummy ($D_{1,ij}$) $\times$ Beijing/Shanghai dummy ($D_{4,ij}$)	2.551*** (0.580)	3.761*** (0.295)	5.777*** (0.198)
Out of <i>hukou</i> city dummy ($D_{1,ij}$) $\times$ Sub-provincial city dummy ($D_{5,ij}$)	1.672*** (0.094)	2.118*** (0.128)	3.400*** (0.126)
Out of <i>hukou</i> city dummy ($D_{1,ij}$) $\times$ provincial capital dummy ($D_{6,ij}$)	1.296*** (0.105)	1.235*** (0.173)	2.638*** (0.169)
City-specific fixed effects	Yes	Yes	Yes

Notes: Low skill denotes workers whose highest degree is below high school. Middle skill denotes workers whose highest degree is high school. High skill denotes workers whose highest degree is some college or above. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Results from the second step estimation

Dependent variable: $\theta_j + \beta_H \ln \rho_j$	Low skill (1)	Middle skill (2)	High skill (3)
Panel A: OLS regression			
$\ln N_j$	0.517*** (0.114)	0.496*** (0.110)	0.0456 (0.124)
$\ln \Delta_j$	0.295** (0.138)	0.483*** (0.132)	0.112 (0.154)
City controls	Yes	Yes	Yes
Observations	285	285	285
R-squared	0.314	0.355	0.120
Panel B: IV regression			
$\ln N_j$	-1.111*** (0.420)	-1.004** (0.393)	-2.075*** (0.474)
$\ln \Delta_j$	1.605*** (0.537)	1.529*** (0.476)	1.132** (0.505)
City controls	Yes	Yes	Yes
Observations	285	285	285
R-squared	-0.290	-0.150	-0.867

Notes: N_j denotes the number of workers. Δ_j denotes the share of high-skilled workers. Low skill denotes workers whose highest degree is below high school. Middle skill denotes workers whose highest degree is high school. High skill denotes workers whose highest degree is some college or above. City controls include winter temperature, summer temperature, humidity, wind speed, the log of minimum distance to three large seaports and the log of city area. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Results from labor demand function estimation

Dependent variable:	Mean wage of low-skilled workers (1)	Return to middle skill (2)	Return to high skill (3)
Panel A: OLS regression			
$\ln N_{j,low}$	-0.0911 (0.0626)		
$\ln(N_{j,mid}/N_{j,low})$		-0.0434*** (0.0132)	
$\ln(N_{j,high}/N_{j,low})$			0.0435*** (0.0141)
$\ln N_{j,high}$	0.164*** (0.0478)	0.0222*** (0.00661)	
City controls	Yes	Yes	Yes
Observations	285	285	285
R-squared	0.121	0.062	0.048
Panel B: IV regression			
$\ln N_{j,low}$	-0.0870 (0.143)		
$\ln(N_{j,mid}/N_{j,low})$		-0.136*** (0.0280)	
$\ln(N_{j,high}/N_{j,low})$			0.123*** (0.0274)
$\ln N_{j,high}$	0.252*** (0.0696)	0.0652*** (0.0123)	
City controls	Yes	Yes	Yes
Observations	285	285	285
R-squared	0.105	-0.182	-0.087

Notes: $N_{j,low}$ denotes the number of low-skilled workers. $N_{j,high}$ denotes the number of high-skilled workers. $N_{j,mid}/N_{j,low}$ denotes the ratio of middle-skilled to low-skilled workers. $N_{j,high}/N_{j,low}$ denotes the ratio of high-skilled to low-skilled workers. Low skill denotes workers whose highest degree is below high school. Middle skill denotes workers whose highest degree is high school. High skill denotes workers whose highest degree is some college or above. City controls include the log of minimum distance to three large seaports and the log of city area. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Results from housing supply function estimation

Dependent variable: $\ln \rho_j$	Inland	Coastal
	(1)	(2)
Panel A: OLS regression		
$\ln N_j$	0.0382 (0.0325)	0.0738* (0.0425)
City controls	Yes	Yes
Observations	184	101
R-squared	0.019	0.357
Panel B: IV regression		
$\ln N_j$	-0.0328 (0.0764)	0.211*** (0.0704)
City controls	Yes	Yes
Observations	184	101
R-squared	-0.012	0.281

Notes: Inland denotes cities in inland China, and coastal denotes cities in coastal China. N_j denotes the number of workers. City controls include the log of minimum distance to three large seaports and the log of city area. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Re-sorting of workers: reducing frictions

	Share of relocation workers (%)	Share of relocation workers from inland regions to coastal regions (%)
Panel A. Reducing migration costs under <i>inelastic</i> housing supply		
All workers	33.321	12.547
Low skill	32.726	14.317
Middle skill	34.054	12.807
High skill	34.798	5.290
Panel B. Reducing migration costs under <i>elastic</i> housing supply		
All workers	34.680	14.663
Low skill	34.525	17.099
Middle skill	35.269	14.937
High skill	34.600	4.776
Panel C. Relaxing housing constraints under <i>high</i> migration costs		
All workers	1.384	1.051
Low skill	1.575	1.300
Middle skill	1.366	1.040
High skill	0.653	0.088
Panel D. Relaxing housing constraints under <i>low</i> migration costs		
All workers	4.987	3.950
Low skill	5.776	4.870
Middle skill	4.706	3.935
High skill	2.216	0.352

Notes: Low skill denotes workers whose highest degree is below high school. Middle skill denotes workers whose highest degree is high school. High skill denotes workers whose highest degree is some college or above.

Table 6: Changes in wage and utility: reducing frictions

		<i>CV</i> (\$)	<i>CV</i> / wage (%)	Δ Wage /Wage (%)
Panel A. Reducing migration costs under <i>inelastic</i> housing supply				
All workers		338.683	38.328	22.298
By skill	Low skill	290.691	41.936	25.316
	Middle skill	493.149	44.883	25.768
	High skill	346.290	16.482	6.380
By region	Coastal region	143.851	19.652	7.380
	Inland region	506.527	54.418	35.151
Panel B. Reducing migration costs under <i>elastic</i> housing supply				
All workers		374.120	39.968	21.779
By skill	Low skill	317.030	43.562	24.495
	Middle skill	533.590	46.557	25.174
	High skill	411.603	18.138	7.140
By region	Coastal region	146.172	19.180	5.769
	Inland region	582.780	58.999	36.437
Panel C. Relaxing housing constraints under <i>high</i> migration costs				
All workers		179.037	11.608	0.505
By skill	Low skill	123.801	11.162	0.871
	Middle skill	320.410	16.938	0.694
	High skill	230.430	7.118	-1.155
By region	Coastal region	308.598	19.405	-0.450
	Inland region	67.413	4.890	1.326
Panel D. Relaxing housing constraints under <i>low</i> migration costs				
All workers		233.774	14.273	0.985
By skill	Low skill	161.285	13.873	1.266
	Middle skill	389.293	19.849	0.234
	High skill	336.360	9.318	0.763
By region	Coastal region	308.556	19.061	-3.282
	Inland region	140.613	8.310	6.302

Notes: Low skill denotes workers whose highest degree is below high school. Middle skill denotes workers whose highest degree is high school. High skill denotes workers whose highest degree is some college or above. Coastal region denotes workers who live in the coastal region in the status-quo. Inland region denotes workers who live in the inland region in the status-quo.

Table 7: Changes in wage inequality: reducing frictions

	Status-quo	Post-change	Percent Change (%)
Panel A. Reducing migration costs under <i>inelastic</i> housing supply			
90-10 percentile wage ratio	5.375	4.470	-16.836
Coastal inland wage ratio	1.386	1.070	-22.819
Panel B. Reducing migration costs under <i>elastic</i> housing supply			
90-10 percentile wage ratio	5.300	4.373	-17.473
Coastal inland wage ratio	1.349	0.980	-27.343
Panel C. Relaxing housing constraints under <i>high</i> migration costs			
90-10 percentile wage ratio	5.375	5.338	-0.692
Coastal inland wage ratio	1.386	1.375	-0.792
Panel D. Relaxing housing constraints under <i>low</i> migration costs			
90-10 percentile wage ratio	4.377	4.229	-3.373
Coastal inland wage ratio	1.061	0.941	-11.322

Appendix A: Additional Tables and Figures

Figure A1: Labor demand and labor supply for low-educated workers

Figure A2: Relative labor demand and relative labor supply for middle educated and low educated workers

Figure A3: Relative labor demand and labor supply for high educated and low educated workers

Figure A4: 285 Cities in our sample

Figure A5: *Hukou* index and the ratio of population change to status-quo city population
Data source: Hukou index data are drawn from Wu and Zhang (2010)

Figure A6a: The share of monetized welfare benefits in status-quo wage associated with lowering mobility costs for workers in Beijing and Shanghai: Under *inelastic* housing supply

Notes: Low, middle and high denote low-, middle- and high-skilled workers, respectively

Figure A6b: The share of monetized welfare benefits in status-quo wage associated with lowering mobility costs for workers in Beijing and Shanghai: Under *elastic* housing supply

Notes: Low, middle and high denote low-, middle- and high-skilled workers, respectively

Table A1: The comparison between U.S. and China: Internal migration rates in 2005

China		U.S.	
Leave <i>hukou</i> province	6.05%	Leave birth state	31.5%
Leave province living one year ago	0.97%	Leave state living one year ago	2.8%
Leave province living five years ago	4%	Leave state living five years ago	8.9%

Notes: According to China Labor Dynamic Survey 2014, birth province is the same as *hukou* province for 97.33% of population and 95.84% of migrants in China.

Data Source: Migration rates in China are drawn from 2005 One-Percent Population Census of China and migration rates in U.S. are drawn from Molloy et al. (2011).

Table A2: The comparison of points-based *hukou* policy across Chinese metropolitans

City	Beijing	Shanghai	Guangzhou	Shenzhen
Total points required to obtain local <i>hukou</i>	It depends on the population policy	72	60	100
Education	Doctoral degree:37 point Master degree:26 point College degree:15 point Some college degree: 10.5 point	Doctoral degree:27 point Master degrees:24 point College degree:21 point	College degree and above: 60 point Some college:40 point High school degree: 40 point	Doctoral degree:100 point Master degrees:90 point College degree:80 point Some college:60 point
Skills		College English Test Band 6 or 8: 8 point College English Test Band 4: 7 point	Junior workers: 10 point Middle-level workers: 30 point High-level workers: 50 point	Junior workers: 20 point Middle-level workers: 40 point High-level workers: 70 point Senior technical worker: 100point Junior-level professional skill: 70 point middle-level professional skill: 90 point high-level professional skill: 100 point

Data source: The official government websites of Beijing, Shanghai, Guangzhou and Shenzhen

Table A3: The share of total migrants living in the three major economic circles

Region	The share of total migrants (%)
<i>Circum-Bohai-Sea Region</i>	12.77
<i>Yangtze River Delta</i>	27.43
<i>Pearl River Delta</i>	27.77

Notes: The Circum-Bohai-Sea Region includes 13 cities; the Yangtze River Delta includes 26 cities and the Pearl River Delta includes 9 cities. The share of total migrants is defined as the share of total cross-city migrants in China living in one particular economic circle.

Table A4: Summary statistics

Variable	Description	Mean	SD
Panel A. Individual characteristics			
<i>I</i>	Annual wage (dollar)	1223.588	1391.818
<i>Low skill</i>	Dummy =1 for below high school, =0 otherwise	0.679	0.467
<i>Middle skill</i>	Dummy=1 for high school, =0 otherwise	0.173	0.378
<i>High skill</i>	Dummy=1 for some college or above, =0 otherwise	0.148	0.355
<i>Migrant</i>	Dummy=1 if the worker leave <i>hukou</i> city for more than 6 months, =0 otherwise	0.067	0.250
Panel B. City characteristics			
<i>lnp</i>	log (Housing price) (dollar)	4.204	0.293
<i>N_j</i>	The number of workers	584.439	659.003
<i>Δ_j</i>	The share of workers with some college or above education (%)	13.962	7.349
<i>Winter temperature</i>	The average temperature in winter (° F)	9.054	89.70
<i>Summer temperature</i>	The average temperature in summer (° F)	255.7	29.13
<i>Humidity</i>	The yearly average of humidity (%)	277.0	1698
<i>Wind</i>	The yearly average of wind speed (0.1m/s)	203.6	1252
<i>Distance to seaport</i>	The minimum distance to three large sea ports in the mainland of China (km)	651.476	415.567
<i>Area</i>	City area (km ²)	16428.63	21831.57

Notes:

(1) *I*, *lnp* are translated from RMB into 2005 U.S. dollars.

(2) The three large seaports in the mainland of China are Tianjin seaport, Shanghai seaport, and Shenzhen seaport. These seaports are located at the three major economic circles of China: *The Circum-Bohai-Sea Region*, *The Yangtze River Delta*, *the Pearl River Delta*.

Data Source:

(1) The raw data of household income, *I*, and housing price, *lnp*, are drawn from the 2005 One-Percent Population Census of China.

(2) The raw data of *temperature*, *wind speed*, *humidity* is collected by National Meteorological Information Center in China. We calculate these variables based on monthly data.

(3) The data of *Area* are drawn from *China City Statistical Yearbook*.

Table A5: Summary statistics by region and city size

Variable Name	Inland cities	Coastal cities	Difference
<i>I</i>	869.123 (849.858)	1646.499 (1748.685)	-777.376*** (4.594)
<i>Low skill</i>	0.723 (0.448)	0.627 (0.484)	0.096*** (.002)
<i>Middle skill</i>	0.151 (0.358)	0.199 (0.399)	-0.048*** (.002)
<i>High skill</i>	0.126 (0.332)	0.174 (0.379)	-0.047*** (0.001)
<i>Migrant</i>	0.018 (0.133)	0.125 (0.331)	-0.107*** (0.001)
<i>lnp</i>	4.097 (0.253)	4.398 (0.260)	-0.301*** (0.032)
<i>Population</i>	490.174 (395.278)	756.168 (949.371)	-265.995*** (80.21)

Notes: This table shows the heterogeneities of key variables between inland cities and coastal cities, as well as between small cities and large cities. The definition of each variable is reported in Table A4. *I*, *Low.edu*, *Mid.edu*, *High.edu* and *Migrant* are individual level variables, *lnp* and *Population* are city level variables.

Table A6: Results from first Stage IV regression

Dependent variable:	$\ln N_j$ (1)	$\ln N_j$ (2)	$\ln \Delta_j$ (3)	$\ln \Delta_j$ (4)
<i>IV for $\ln N_j$</i>	-6.925*** (0.620)	-13.93*** (3.201)		8.332** (3.335)
<i>IV for $\ln \Delta_j$</i>		8.012** (3.458)	-6.632*** (0.582)	-15.71*** (4.077)
City controls	Yes	Yes	Yes	Yes
F-statistic	91.08	85.82	89.43	72.64
Observations	285	285	285	285
R-squared	0.518	0.526	0.487	0.520

Notes: N_j denotes the number of workers. Δ_j denotes the share of high education workers. City controls include *ln Distance*, *Seaport*, *Winter. temperature*, *Summer. temperature*, *Humidity*, *Wind*, and *ln Area*. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Summary of estimated coefficients from mincer wage regressions

Variables	Mean	Std. dev
High school education	0.241	0.086
Some college or above education	0.582	0.233
Age	0.040	0.024
Age2	-0.001	0.000
Female	-0.391	0.159
Urban <i>hukou</i>	0.582	0.151
Constant	6.151	0.572

Notes: This table presents the summary statistics of coefficient estimates from city-specific mincer wage regression for 285 Chinese cities.

Appendix B: Roy Sorting

We define $\omega_{i,j}$ as the probability of worker i selecting to live in city j , and infer the selection probability in the context of China. We first divide the data into two categories: stayers, or those who live in their *hukou* cities, and movers, who have moved into other cities. We also allocate workers into one of the three education classes: less than high school, high school, some college or above. We next allocate workers into two *hukou* type cells: urban *hukou* and rural *hukou*. Within each education-*hukou* type cell, we divide stayers into 6 age groups: 25-29, 30-34, 35-49, 40-44, 45-49, 50-54. Within each education-by-*hukou* type-by-age cell, we further assign stayers into 285 residential cities. Finally, we assign 10,260 data cells for stayers. Since there are fewer observations for movers, their groupings are relatively more coarse by necessity (Dahl, 2002). We continue to assign movers into one of the six education-by-*hukou* type classes. Within each class, we finally allocate movers into one of thirty original provinces. Overall, we have 180 data cells for movers. Selection probability $\omega_{i,j}$ is calculated as the fraction of the population in worker i 's cell that chooses to live in city j . Then we augment mincer wage equation by adding selection probability $\omega_{i,j}$, and estimate the wage regression separately for each city using the following equation:

$$\ln I_{i,j} = \alpha_{j,low} + \alpha_{j,mid} Mid_edu + \alpha_{j,high} High_edu + \gamma_j' \Gamma_i + \phi_{1,j} \omega_{i,j} + \phi_{2,j} \omega_{i,j}^2 + \varepsilon_{i,j}^I \quad (29)$$

Γ_i is a vector of individual attributes, including age, age squared, dummy variables for *hukou* types (rural *hukou* or urban *hukou*), and dummy variables for gender (male or female). We calculate the counterfactual wage $\hat{I}_{i,j}$ that each individual could earn in every potential location using coefficients estimated by equation (29). Note that we don't include the Dahl correction terms, $\omega_{i,j}$ and $\omega_{i,j}^2$ when computing $\hat{I}_{i,j}$, because they only serve as controls for Roy sorting bias. Individual counterfactual wage will be employed to exploit workers' location sorting in section 6.2.

Appendix C: City-Specific Housing Price

We define the value of the home occupied by individual i in city j , $P_{i,j}$, as the value of the house (for owner-occupied units) or annual rent (for rental units) in our census data. We assume that $P_{i,j}$ is a function of a scaling parameter ρ_j specific to city j and a vector of housing characteristics H_i . Then, we estimate the following regression:

$$\ln P_{i,j} = \ln \rho_j + \lambda_{1,pro,purchase} \Omega_{i,purchase} + \lambda_{2,pro,purchase} \Omega_{i,purchase} house_age_i + \lambda_{1,j,build} \Omega_{i,build} + \lambda_{2,j,build} \Omega_{i,build} house_age_i + H_i' \tau + \varepsilon_{i,j}^H \quad (30)$$

where $\Omega_{i,purchase}$ is a dummy variable that takes the value of 1 for a purchased home and 0 otherwise; $\Omega_{i,build}$ is a dummy variable that takes the value of 1 for self-built home and 0 otherwise, and $house_age_i$ represents a vector of house age-specific fixed effects. We allow the parameters on the dummies for purchased home and self-built home, as well as the two interactions of the dummies with house age to vary with province (*pro*). The 2005 One-Percent Population Census of China records the current rent in the census year, but the past price of owner-occupied housing if the house was purchased or self-built. Dwelling characteristics H_i describe house age, the number of rooms, floor area, whether the housing structure is a storied building, whether tap water is provided, whether a kitchen is provided, and whether there is a bathroom. The city fixed effect $\ln \rho_j$ measures the effective “price of housing services” in city j independent of ownership and housing attributes.

Table C1 reports the results from the housing price regression of equation (30). Housing prices decrease with house age and increase with the number of rooms and floor area. The price of storied buildings is higher than single-story houses. Houses with tap water, kitchen and bathrooms are more expensive. The city-specific scaling parameter $\ln \rho_j$ measures the city average price of housing services independent of housing attributes and ownership.

Table C1: Estimated coefficients from housing price regression

Dependent variable: $\ln P_{i,j}$	
House age	-0.0122*** (0.00124)
The number of rooms	0.0465*** (0.00133)
Floor area	0.00561*** (0.0000408)
Storied building	0.486*** (0.00508)
Tap water	0.243*** (0.00466)
Kitchen	0.0800*** (0.00643)
Restroom	0.107*** (0.00557)
City specific scaling parameter $\ln \rho_j$	Yes
Province dummy $\times$ House age dummy $\times$ Purchase dummy	Yes
Province dummy $\times$ House age dummy $\times$ Self-build dummy	Yes
Observations	166565
R-squared	0.994

Notes: Standard errors clustered at city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.