Online Appendix for "Migration, Housing Constraints, and Inequality: A Quantitative Analysis of China" by Min Fang and Zibin Huang (Not for Publication)

A Empirical Appendix

A.1 Supplementary Results for Stylized Fact 1

Table A1 below shows the distribution of the net stock of migrant workers across cities measured in both absolute numbers and percentages. This summarizes the visualization of the migration patterns in the geographically plot the *Net Stock(N)* and *Net Stock(%)*, respectively, by cities in both 2005 and 2010 in Figure 1 for absolute numbers and Figure A1 for percentages.

Table A1: **Distribution of Net Stock of Migrant Workers**

Panel A: Net Stock (measured in numbers, Unit: million)											
Year	No.	(-4,-2)	(-2,-1)	(-1,-0.5)	(-0.5,0)	(0, 0.5)	(0.5,1)	(1,2)	(2,4)	(4,8)	(8+)
2005	287	1	1	23	188	59	4	4	4	2	1
2010	266	6	29	41	115	39	9	13	7	3	4
Panel B: Net Stock (measured in percentage, Unit: %)											
Year	No.	(-80, -45)	(-45,-30)	(-30,-15)	(-15,0)	(0, 15)	(15,30)	(30,45)	(45,60)	(60,75)	(75+)
2005	287	0	11	63	139	48	9	5	3	3	6
2010	266	12	47	61	71	19	17	14	6	4	15

Notes: This table shows the distribution of the net stock of migrant workers across Chinese cities. There are 287 and 266 cities available in 2005 and 2010, respectively in our data. Panel A is the standard of coloring in the Figure 1 map. Panel B is the standard of coloring in the Figure A1 map.

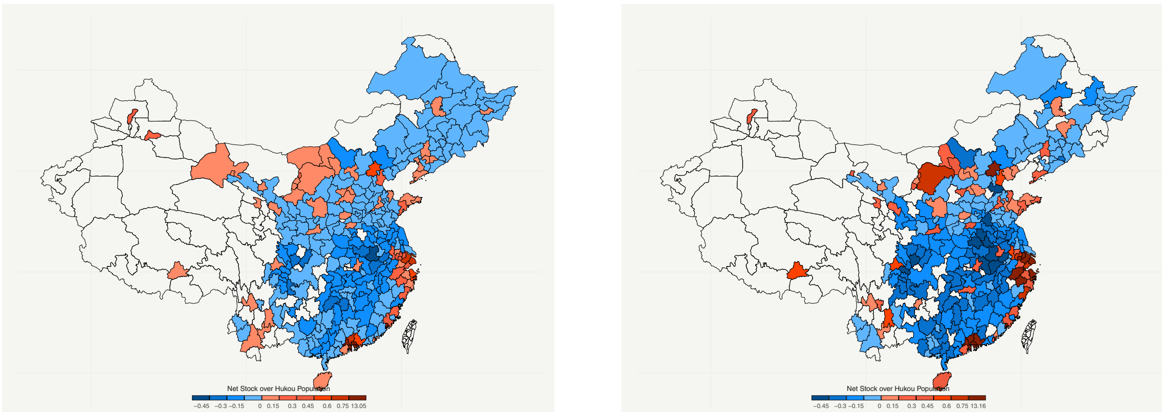
Figure A1 visualizes the geographic migration patterns in percentage of net migrant stock (%), geographically plot the *Net Stock(N)* by cities in both 2005 and 2010. Each color corresponds to a level of net migration. For instance, in 2010, there are 34 cities with a net stock of more than 8 million migrants. Most cities lose workers, and only about one-fourth of cities have positive net stocks. From the map, it is obvious that workers are migrating from western and central regions to eastern regions, and from inland cities to coastal cities.[20]

[20]Most of the big industrial cities are located along the eastern coastline. There are four main economic zones comprising most cities attracting huge numbers of migrant workers: (1) the Bohai Economic Rim, led by Beijing and Tianjin; (2) the Yangtze River Delta Zone, led by Shanghai, Suzhou, and Hangzhou; (3) the Western Taiwan Straits Zone, led by Xiamen; (4) the Pearl River Delta Zone, led by Guangzhou (Canton), Shenzhen, and Hong Kong.

Figure A1: Net Stock (%) of migrants by city in China

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

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



Notes: The sample only includes workers with wage income, which means that we exclude retired workers, persistently unemployed workers (zero wage income for the whole year), children, students, homemakers, and others. The net stock of workers in city i is calculated as current workers in city i minus Hukou workers in city i. Therefore, this measure reflects the net gain in the working population for each city. We only have data on 287 and 266 cities in 2005 and 2010 respectively. Though the blank parts are missing, our available data covers more than 95% of the Chinese population. The summary table of underlying numbers are presented in the appendix A.1.

A.2 Supplementary Results for Stylized Fact 2

A.2.1 Quality-adjusted Housing Rents and Migration

In this subsection, we investigate the relation between quality-adjusted housing rents and migration. Using *Census* data, we run a simple household-level regression as follows:

$$rent_{ij} = \beta_0 + \beta_1 NetMig_j + \mathbf{Z_{ij}}'\alpha + \epsilon_{ij} \tag{23}$$

$rent_{ij}$ is the per square meter housing rent of house i in city j. $NetMig_j$ is the net stock of migrant workers in city j, with a unit of 10k. $\mathbf{Z_{ij}}$ is a vector of housing characteristics for house i, including the total area of the house, the number of rooms, the number of floors, the type of house, the year of construction, the main cooking resource, whether it has tap water, whether it has an independent kitchen, the type of restroom, and the type of showering system. We run the same regression separately for the years 2005 and 2010. The results in Table A2 show that a 1 million increase in net stock of migrant workers is correlated with a 7.7 RMB (about 1.2 USD) increase in the annual rent per square meter in 2005, which corresponds to a 10.3% increase. Similarly, a 1 million increase in the number of net stock of migrant workers is correlated with a 4.6 RMB (about 0.7 USD) increase in the annual rent per square meter in 2005, which corresponds to a 4.1% increase. This shows that the positive relation between housing rents and the net stock of migrant workers in the city is robust even when we control for the quality of the houses.

Table A2: The Relation between Housing Rents and Migration

Variables	(1) OLS-2005	(2) OLS-2010
Net Stock of Migrant Workers (10k)	0.0765***	0.0464***
	(0.00130)	(0.000881)
Observations	70,774	130,909
R-squared	0.208	0.163

Notes: This table shows the correlation between the city-level number of migrants and the household-level housing rent, after controlling for a set of housing characteristics. The control variables include the total area of the house, the number of rooms, the number of floors, the type of house, the year of construction, the main cooking resource, whether it has a tap water system, whether it has an independent kitchen, the type of restroom, and the type of the showering system. Column 1 shows the results in 2005. Column 2 shows the results in 2010. ***p<0.01, **p<0.05, and *p<0.1.

A.2.2 Causal Effect of Migration on Housing Costs

We have established a positive correlation between migration and housing costs in the main context. In this section, we try to further identify the causal effect of the city-level number of migrants on household-level housing rents. The main method is we apply is a Bartik-style instrument.

Let's consider a naive two-way fixed effects setting. When we directly regress housing rents on the number of migrants in the city, we have:

$$y_{ijt} = \beta_0 + X'_{ijt}\beta_1 + C'_{jt-1}\beta_2 + Mig_{jt}\beta_3 + city_j + Year_t + u_{ijt} \tag{24}$$

where y_{ijt} refers to the rental rate (RMB per square meter) of house i in city j at time t. X_{ijt} represents the characteristics for house i. C_{jt-1} refers to the lagged characteristics of city j (containing house i) at time t. Mig_{jt} is the variable of interest which represents the number of migrants in city j at time t. $city_j$ denotes the city dummy. $Year_t$ is the year dummy. u_{ijt} is the unobservable term.

The endogeneity issue comes from the possible existence of correlation between the unobserved city-level shock and the migration inflow. For instance, if a city is experiencing a good economic shock, rents will naturally rise, and also more migrants will be attracted. To deal with this problem, we construct a predicted migration inflow as an instrument for the number of migrants, which is inspired by Card (2009) and Bartik (1991). To build our prediction instrument, for migration into city j at time t, we subtract the total migration of all cities other than j at time t from the counterpart at time $t-1$, and multiply it by the proportion of the number of migrants in city j, compared with the national aggregate migrants in all cities at time $t-2$. This is a typical shift-share IV which we multiply the leave-one-out total migration change by the migration share in the initial year. The instrument can be written as follows:

$$\delta^{j1990} = \frac{n_{j1990}}{n_{1990}} \tag{25}$$

$$z_{j2010} = \delta^{j1990}[Mig_{-j2010} - Mig_{-j2000}] \tag{26}$$

$$z_{j2000} = \delta^{j1990}[Mig_{-j2000} - Mig_{-j1990}] \tag{27}$$

where n_{j1990} is the number of migrants in city j in 1990; n_{1990} is the total number of migrants in all cities in 1990; δ^{j1990} is equal to the the proportion of the number of migrants in city j in 1990; and Mig_{-jt} is the number of migrants migrating in all cities other than j at time t.

We use the *Census* data in 1990, 2000 and 2010 to estimate this IV regression. Table A3 shows the first stage result. It illustrates a clear positive correlation between the number of migrants and the predicted migration inflow. The t-statistic and the F-statistic are both large enough to address the weak IV concern. Table A4 shows the results of the 2SLS estimation. We find that a 1 million increase in the number of migrants is associated with a 1.4-4.8 RMB increase in the annual rent per square meter. This result further confirms that migrant inflows push up local housing costs.

A.3 Supplementary Results for Stylized Fact 3

Additional Results of Inequality from CHIP In this section, we investigate the inequality between migrants and local residents in more detail. The *Census* is a comprehensive survey, but it does not contain too much information about a household's financial status, income, or expenditure. In the main context, we only have housing rents and wages, which are imputed from the *City Statistic Yearbooks*. We now introduce another dataset called the *Chinese Household Income Project (CHIP)* to further consider this inequality.[21] In 2013, CHIP covers 18,948 households in 15 provinces. After data cleaning in which we keep only urban observations, we have a sample size of 7,400 households. In these 7,400 households, there are 344 rural migrant families (migrant families from rural areas), 223 urban migrant families (migrant families from urban areas), and 6,833 local families.

[21] For more details of this dataset, please refer to Li, Sato, and Sicular (2013).

Table A3: First Stage

Variables	(1)	(2)
Predicted Migration Flow	1.188***	0.983***
	(0.000992)	(0.00153)
City FE	YES	YES
Year FE	YES	YES
Lagged City Characteristics	NO	YES
House Characteristics	NO	YES
Observations	308,805	308,805
R-squared	0.960	0.974
F>Prob	0.000	0.000

Notes: This table shows the first stage regression of the IV method. The dependent variable is the net stock of migrant workers. The set of lagged city characteristics includes the total population, the GDP growth rate, the share of the agricultural sector, and the share of the manufacturing sector. The set of house characteristics includes the total area of the house, the number of rooms, the number of floors, the type of house, the year of construction, the main cooking resource, whether it has a tap water system, whether it has an independent kitchen, the type of restroom, and the type of the showering system. ***p<0.01, **p<0.05, and *p<0.1.

Table A4: Effect of Migration on Housing Cost (IV)

Variables	(1) 2SLS	(2) 2SLS
Net Stock of Migrant Workers (10k)	0.0479***	0.0141***
	(0.00244)	(0.00317)
City FE	YES	YES
Year FE	YES	YES
Lagged City Characteristics	NO	YES
House Characteristics	NO	YES
Observations	308,805	308,805
R-squared	0.201	0.266
F>Prob	0.000	0.000

Notes: This table shows the IV results. The dependent variable is the housing rent. The set of lagged city characteristics includes the total population, the GDP growth rate, the share of the agricultural sector, and the share of the manufacturing sector. The set of house characteristics includes the total area of the house, the number of rooms, the number of floors, the type of house, the year of construction, the main cooking resource, whether it has tap water, whether it has an independent kitchen, the type of restroom, and the type of the showering system. ***p<0.01, **p<0.05, and *p<0.1.

Table A5: Quantile Statistics

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

Table A5 shows the distributions of different household-level variables. Non-housing assets is the total value of the non-housing assets of a household. Net asset income is defined as the difference between total disposable income and wages of the household members. Savings rate is calculated as the ratio of income less expenditure to income. Rural migrants have fewer non-housing assets, less net asset income, and less expenditure. Nevertheless, they save more compared with urban migrants and local residents. In addition, although urban migrants have more non-housing assets, they still have much less net asset income than local residents. This indicates that a very important part of the net asset income of local residents is their housing rent, which results in significant gaps and inequalities in the income and expenditure between local residents and rural migrants.

A.4 Supplementary Stylized Fact: National Inequality Drops but Remains Driven by Developed Cities.

To document this supplementary stylized fact, we calculate a national Income Theil Index and then calculate each city's contribution to the national Income Theil Index as follows:

$$T = \sum_{j=1}^{J} s_j (T_j + \ln \frac{\bar{i_j}}{\bar{i}}), \quad s_j = \frac{N_j}{N} \frac{\bar{i_j}}{\bar{i}}$$

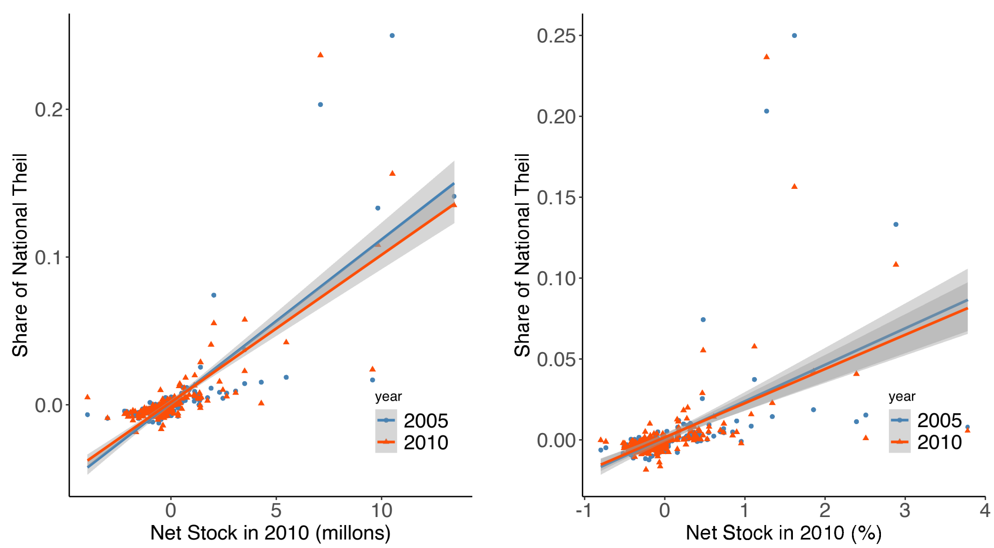
$$Contri_j = s_j (T_j + \ln \frac{\bar{i_j}}{\bar{i}})/T$$

where j indicates city, T is the national Theil Index, T_j is the Theil Index of city j, N_j is the total number of current workers in city j, N is the national total number of workers, $\bar{i_j}$ is the average income in city j, and $\bar{i}$ is the average national income.

Figure A2: Net Stock of Migrants and Share of Contribution to National Inequality

(a) Net Stock (Numbers N)

(b) Net Stock (Percentage %)



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

The calculated national Income Theil Index dropped by 16% from 0.19 in 2005 to 0.16 in 2010. However, the contributions of developed cities to national income inequality remains high. Figure

A2 shows the correlation between cities' contributions and their net stock of migrants. The strong positive relationship indicates that larger developed cities with more migrants are contributing much more to national income inequality. This pattern is especially salient for the largest cities. For instance, at the corner of the figure, Shanghai, Shenzhen, and Beijing contribute almost 60%, 40%, and 50%, respectively, to national income inequality in 2010[22]. These numbers were much lower in 2005 (45%, 30%, and 37%, respectively). This indicates that certain Chinese cities with sizeable net stocks of migrant workers contribute much more to national income inequality than other cities.

B Model Appendix

B.1 Validation of Model Assumption: Housing Ownership of Migrants

One assumption in the model is that migrants get housing income from their hometown but not their migration destination. We claim that this reflects reality in China.

First, migrants cannot get housing income from their migration destination. In China, migrant workers are usually poorer and not able to afford down payments in their destination cities. Even if (rarely) some workers could manage a down payment, they still face much regulation to purchase real estate because they do not own a Hukou registration in the city where they currently reside. In many developed cities, banks are restricted from providing migrants with mortgage services. As a result, only a very small fraction of migrants are able to participate in the local housing market as locals. We calculate the housing ownership of local and migrant residents using the Census data in 2010. Panel A in Table B1 illustrates that the housing ownership rate of local residents is more than 90%. On the contrary, only 27.1% of the migrants own their houses.[23] Panel B further investigates the housing ownership of migrants with different migration durations. We can find that the rate is very stable no matter how long the migrant has been away from home. The only change is that for migrants who have left their hometown more than six years ago, their housing ownership rate rises to 32%. This may result from a top coding issue.

Second, migrants can get housing income from their hometown. Most of the migrants in China are temporary migrants. They usually go to big cities to work (in Chinese, *Dagong*) when they are young, and then come back home in their 50s. Their usually still keep their hometown

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

[23]Local residents in rural areas usually build their houses by themselves, which are different from houses available in the housing market. We double check the results by dropping these self-built houses and find that the ownership rate for locals is still as high as 81%. Meanwhile, the rate for migrants is about 25%.

Table B1: Housing Ownership Rate

Individual Type	Housing Ownership Rate
Panel A: Local vs Migrant	
Local	93.2%
Migrant	27.1%
Panel B: Migrants by Migrating Years	
Migrant less than half year	26.2%
Migrant half to one year	24.5%
Migrant one to two years	25.6%
Migrant two to three years	25.7%
Migrant three to four years	25.2%
Migrant four to five years	24.6%
Migrant five to six years	24.2%
Migrant more than six years	32.0%

Notes: This table displays housing ownership rate by individual types. The numbers are calculated from the *Census* data in 2010.

houses in their hometown. Using the *Census* data in 2010, we find that the housing ownership rate of migrants in their hometown is 99%. However, we have to mention that although the real ownership rate is very high, this number is overestimated due to the survey scheme of the *Census*. Usually, migrants without houses at home will attach (*guakao*) their Hukou registration to houses of their relatives. In these cases, such migrants will appear as members of home-owning households, even though they are not. Tombe and Zhu (2019) makes a stronger assumption that migrant workers have no claim to any fixed factor income from land in either their current working city or their Hukou city. In their model, whenever a worker migrates, she loses all fixed factor income from her previously owned local property in her Hukou city. We also solve a variation of our model using their assumption. Our mechanism that "migration interacting with housing constraints can increase income inequality" is further amplified with this assumption. The results are available upon request.

B.2 Estimation of Migration Elasticity

We estimate the migration elasticity (ϵ) from the gravity equation for migration flows (14). We assume $\tau_{ij}^s = \tau_i^s d_{ij}$, where τ_i^s is the origination-skill fixed component and d_{ij} is the distance index between location i and j. Under these assumptions and given data on migration shares and real incomes, we estimate ϵ using the fixed effect regression:

$$\ln(\pi_{ij}^s) = \epsilon \ln(\nu_j^s) + \psi_{ij} + \gamma_{is} + \zeta_j + \phi_{ijs}, \text{ for } i \neq j \tag{28}$$

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

To estimate ϵ, we need to run a regression estimating (28) with origination-destination pair fixed effects ψ_{ij}, origination-skill fixed effects γ_{is}, and destination fixed effects ζ_j. We use migration flows and housing rent data from the *Census* in 2005 and city-skill level average wage data imputed from the *City Statistic Yearbooks.* To calculate π_{ij}^s for each origination-destination city pair, we sum up the number of current workers who migrated from each origination city to each destination city by skill groups (with/without a college degree). $\ln(\nu_j^s)$ are different for residents with a local Hukou registration and migrant residents without a local Hukou registration. For migrants, income is the sum of their wages and their housing incomes in their Hukou locations. However, for local incumbents with housing assets, income is a combination of wages and local housing rent incomes. Housing rent incomes are constructed as explained in section 3. Because there are many zero migration flows between small city pairs, $\ln(\pi_{ij}^s)$ actually contains many missing values which are not used in the regression. Hence, we construct $\widehat{\ln(\pi_{ij}^s)}$ by assigning an extremely small value (i.e., 1e-7) to the migration flow and then estimating the same regression with $\widehat{\ln(\pi_{ij}^s)}$[24].

Table B2: Regression of Estimating the Migration Elasticity

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

Notes: Column 1 shows the results when the independent variable is calculated from the Census. Column 2 shows the results when the independent variable is calculated from the yearbook. ***p<0.01, **p<0.05, and *p<0.1.

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

The results are shown in Table B2. Column 1 shows the results of directly regressing migration flows from city i to city j with skill s $\ln(\widehat{\pi^s_{ij}})$ on destination-skill average income $\ln(\nu^s_j)\{Census\}$ with wages measured from the individual wage in the original *Census 2005*. This gives us a statistically significant estimate of the migration elasticity of 1.847 with a standard error of 0.0761. However, to closely match the model, we run a second regression, which uses the destination-skill average income $\ln(\nu^s_j)$ with wages measured from the City Statistic Yearbook *CSYB 2005*. The results are in column (2) of Table B2, which gives us an estimate of 1.926 with a standard error of 0.138. Our estimates are slightly larger than the estimate of around 1.5 in Tombe and Zhu (2019), which uses province-level data. As our model actually uses the wage data from City Statistics Yearbooks, we prefer to choose ϵ towards the estimation from the second regression using $\ln(\nu^s_j)\{CSYB\}$, therefore, we pick $\epsilon = 1.90$[25].

A concern is that even though we have controlled for various fixed effects, there may be an endogeneity issue. That is, there can be shocks at the ijs level that affect both wages and migrations. A possible solution is to use an instrumental variable. However, it is very hard to find a clean IV that will affect migration only through wages. We adopt an instrument similar as in Tombe and Zhu (2019). That is, we use the average wages of cities within 150km as to instrument for wages in city j. The average number of neighboring cities within the 150 km radius is about 5 for each city in China. The first stage is strong, though we omit these results for brevity. The 2SLS results are given in Table B3. There is no significant change.

Table B3: IV Regression of Estimating the Migration Elasticity

Variables	(1) 2SLS	(2) 2SLS
$\ln(\nu^s_j)\{Census\}$	1.418***	
	(0.139)	
$\ln(\nu^s_j)\{CSYB\}$		1.743***
		(0.379)
Origin-Destination FE	YES	YES
Origin-Skill FE	YES	YES
Observations	152,684	126,280

Notes: Column 1 shows the results when the independent variable is calculated from the Census. Column 2 shows the results when the independent variable is calculated from the yearbook. ***p<0.01, **p<0.05, and *p<0.1.

[25] The true parameter is very likely to be somewhere between the two estimators. Also, as robustness checks, we solved several models under a variety of parameter choices from 1.5 as in Tombe and Zhu (2019) to 2.0 which is slightly higher than our estimation. In all cases, all the results hold as in the paper, though the magnitudes changes slightly. The results are available upon request.

B.3 Supplementary Results on Model Unobservables

A. Universal Reduction in Migration Costs

Table B4: **Average Migration Costs**

	Share of Emp.		Migration Costs			
	2005	2010	2005	2010	Relative	Changes
Overall	11%	22%	11.0	7.2	65%	-3.8
Low-skill	11%	23%	11.2	7.3	65%	-3.9
High-skill	9%	17%	8.9	7.0	79%	-1.9

Notes: This table displays migration-weighted harmonic means of migration costs in 2005 and 2010. Share of Employment among high-skill is high-skill migrants over high-skill population. Because τ_{ij}^{s} is proportional in the model, we show % changes.

Table B4 provides detailed summary statistics of the migration cost estimates. Using our model, we find that there is a universal reduction in migration costs from 2005 to 2010. In 2010, overall migration costs dropped dramatically by 35% relative to 2005. For low-skill workers, the changes were similar to the national average, while for high-skill workers, the drop on average was smaller (21%). With these huge drops in migration costs, we observe the share of migrants relative to the total working population doubling to 22%. More importantly, high-skill workers started to move more. These results indicate that the decreasing migration costs contribute a lot to the increasing migration flows.

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

B. Uneven Productivities and Uneven Growth in Productivities

Table B5 presents the standard deviation of the productivities A_j^s for both high-skill and low-skill workers, for all cities j grouped by net stock of migrant workers. On average, the overall standard deviation of productivity across all cities grows by 129% for high-skill and by 36% for low-skill workers. To show the results in a more compact way, we group cities by their net stock of migrant workers. (6,13) refers to cities having a net stock of migrant workers between 6 million and 13 million. Similarly, (-4,-1) refers to cities having a net stock of migrant workers between -4 million and -1 million. We find the changes in standard deviations follow a similar pattern as the changes

Table B5: **Standard Deviation of Productivity Growth**

Net Migrants (2010)	No. of Cities	High-skill 2005	2010	Relative	Changes	Low-skill 2005	2010	Relative	Changes
Average	233	0.34	0.78	229%	+0.44	2.93	3.99	136%	+1.06
(6,13)	5	1.54	3.79	246%	+2.25	3.97	7.13	179%	+3.16
(1,6)	19	0.36	0.80	222%	+0.44	2.85	4.70	165%	+1.85
(0, 1)	45	0.25	0.61	244%	+0.36	3.24	3.97	123%	+0.73
(-1,0)	134	0.11	0.19	173%	+0.08	2.07	3.63	175%	+1.56
(-4,-1)	30	0.02	0.07	350%	+0.05	2.12	2.87	135%	+0.75

Notes: This table displays standard deviations in both 2005 and 2010 and their changes. The level of high-skill and low-skill productivity are not directly comparable. For readability, we normalize both numbers. The unit of both is 1e3. The net stock of migrant worker range groups are classified by net stock of migrant workers in 2010 (unit: millions). Each Net Migrant Range Group consists of the same cities in 2005 and 2010. There are 233 cities in the model.

in average productivities.

B.4 Supplementary Results of Inequality in the Model

A. Share of Contribution to National Theil Index

Table B6: **Share of Contribution to National Theil Index**

Net Migrants (2010)	No. of Cities	Share of Wage Theil 2005	2010	Relative	Share of Income Theil 2005	2010	Relative
National Theil	233	0.0985	0.0622	64%	0.1156	0.0921	80%
(6,13)	5	+1.49	+1.41	97%	+1.43	+1.27	89%
(1,6)	19	+0.58	+0.83	143%	+0.53	+0.70	132%
(0, 1)	45	+0.22	+0.26	118%	+0.19	+0.20	105%
(-1,0)	134	-0.92	-1.00	108%	-0.81	-0.78	96%
(-4,-1)	30	-0.37	-0.49	132%	-0.35	-0.39	111%

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

Table B6 shows contribution shares to national Theil Indexes. The first row shows the national Wage Theil Index and Income Theil Index for both 2005 and 2010. At the national level, income inequality is still higher than wage inequality. Both measures dropped as more workers migrated from lower productivity areas to higher productivity areas.[26] Moreover, if we examine by city

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

groups, we observe that larger cities with positive net migration contribute massively to both national Theil Index measures. For instance, for the Wage Theil of Tier 1 cities in 2005, +1.49 means that if we do not account for all workers in Tier 1 cities, the national Wage Theil would decrease by 149%. This pattern holds for both inequality measures and does not change much from 2005 to 2010.

B. Skill Premium and Housing Premium

Table B7: **Skill Premium and Housing Premium**

Net Migrants (2010)	No. of Cities	Skill Premium 2005	Skill Premium 2010	Skill Premium Relative	Housing Premium 2005	Housing Premium 2010	Housing Premium Relative
Average	233	1.47	1.40	95%	0.36	0.49	136%
(6,13)	5	1.35	1.39	103%	0.93	1.89	203%
(1,6)	19	1.40	1.40	100%	0.39	0.56	144%
(0, 1)	45	1.42	1.39	97%	0.31	0.35	113%
(-1,0)	134	1.50	1.40	93%	0.27	0.25	93%
(-4,-1)	30	1.58	1.45	92%	0.24	0.31	129%

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

To further indicate how housing constraints play an essential role, we show the skill premium and the housing premium (measured as average annual housing return over the average annual wage) and their changes in Table B7. The national average skill premium and the city groups' skill premiums are very similar and do not change much over time. However, the average housing premium increased from 0.36 in 2005 to 0.49 in 2010, resulting in a 36% jump. For an "average" worker, housing asset income is almost 50% of their wage income. Furthermore, if we break down by city groups, we observe that in Tier 1 cities, the housing premium increased from 0.93 to 1.89, which is substantially above the average rate of growth. Given that houses in these large cities are almost all owned by locals and many more migrants are moving into these cities, it is not hard to understand the astonishing income inequality in Table 4.

C Counterfactual Analysis Appendix

C.1 Algorithm for Counterfactual Analysis

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

We first specify the exogenous variables and the model equation system. The exogenous variables are $\{H_i^s, A_j^s, \tau_{ij}^s, L_j, \phi_j\}$ where i indexes origination cities, j indexes destination cities, and s indexes skill. The equation system consists of three blocks. The migration block consists of worker income equation (8), and gravity equation (14), the production block consists of production equation (15) and wage equations (16, 17), and the housing block consists of construction equation (20) and market clearing equation (21).

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

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

$$\{\hat{S}_j\}^1 = \hat{\phi}_j L_j \text{ from eq.(20)} \tag{29}$$

$$\{\hat{Q}_j\}^1 = \frac{1-\beta}{\beta} \frac{w_j^l H_j^l + w_j^h H_j^h}{\{\hat{S}_j\}^1} \text{ from eq.(21)} \tag{30}$$

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

$$\{\hat{v_{ij}^s}\}^1 = w_j^s + \frac{\{\hat{Q}_i\}^1 \{\hat{S}_i\}^1}{H_i^R} \text{ from eq.(8)} \tag{31}$$

$$\{\hat{\pi_{ij}^s}\}^1 = \frac{(\tau_{ij}^s {\{\hat{Q}_j\}^1}^{1-\beta})^{-\epsilon} (\{\hat{v_{ij}^s}\}^1)^{\epsilon}}{\sum_{k=1}^{K} (\tau_{ik}^s {\{\hat{Q}_k\}^1}^{1-\beta})^{-\epsilon} (\{\hat{v_{ik}^s}\}^1)^{\epsilon}} \text{ from eq.(14)} \tag{32}$$

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

$$\{\hat{X}_j\}^1 = [(A_j^h\{\hat{H}_j^h\}^1)^{\frac{\sigma-1}{\sigma}} + (A_j^l\{\hat{H}_j^l\}^1)^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \text{ from eq.(15)} \tag{33}$$

$$\{\hat{w}_j^l\}^1 = A_j^{l\,\frac{\sigma-1}{\sigma}}\{\hat{X}_j\}^{1\,\frac{1}{\sigma}}\{\hat{H}_j^l\}^{1^{-\frac{1}{\sigma}}} \text{ from eq.(16)} \tag{34}$$

$$\{\hat{w}_j^h\}^1 = A_j^{h\,\frac{\sigma-1}{\sigma}}\{\hat{X}_j\}^{1\,\frac{1}{\sigma}}\{\hat{H}_j^h\}^{1^{-\frac{1}{\sigma}}} \text{ from eq.(17)} \tag{35}$$

So far we have updated all the endogenous variables once. We calculate how far $\{\hat{x}_j\}^1$ is from $\{\hat{x}_j\}^0$, where x means any specific variable. If the distance is large, we go back to eq.(29) and eq.(30) to iterate until the distance is small enough. For other counterfactuals, the starting block of iteration may differ, but the general algorithm is identical. The key is to update all the endogenous variables in a loop. We terminate the iteration loop when all the aggregate variables reach an updating error smaller than 1e-7.

C.2 Supplementary Results on Migration-based Land Supply Reform

A. Additional Results on Income Inequality

Table C1: **Share of National Theil Index: Land Supply Reform**

Net Migrants (2010)	No. of Cities	Share of Wage Theil 2010	$\widehat{2010}$	Relative	Share of Income Theil 2010	$\widehat{2010}$	Relative
National Theil	233	0.062	0.062	100%	0.092	0.074	80%
(6,13)	5	+1.41	+1.46	104%	+1.27	+1.28	101%
(1,6)	19	+0.83	+0.84	101%	+0.70	+0.66	94%
(0, 1)	45	+0.26	+0.23	88%	+0.20	+0.30	150%
(-1,0)	134	-1.00	-0.95	95%	-0.78	-0.73	94%
(-4,-1)	30	-0.49	-0.58	118%	-0.39	-0.50	128%

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

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

Table C2: **Skill Premium and Housing Premium: Land Supply Reform**

Net Migrants (2010)	No. of Cities	Skill Premium 2010	Skill Premium $\widehat{2010}$	Skill Premium Relative	Housing Premium 2010	Housing Premium $\widehat{2010}$	Housing Premium Relative
Average	233	1.40	1.40	100%	0.49	0.45	92%
(6,13)	5	1.39	1.39	100%	1.89	1.12	59%
(1,6)	19	1.40	1.43	102%	0.56	0.41	73%
(0, 1)	45	1.39	1.38	99%	0.35	0.40	114%
(-1,0)	134	1.40	1.39	99%	0.25	0.33	132%
(-4,-1)	30	1.45	1.43	98%	0.31	0.26	84%

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

We also additionally show the skill premium and the housing premium in Table C2. The skill premium is the high-skill wage over the low-skill wage, and the housing premium is the average housing return over the average wage return. The underlying reason why wage inequality does not change much is that the skill premium does not move at all. The only changes come from the location choices of high-skill workers relative to low-skill, which changes the composition of workers in each city. However, for the housing premium, it is another story. Since the government increases land supply in cities with insufficient land quotas, housing costs drop massively, which dilutes the asset return from property ownership. As a result, housing premia fall by 41% and 27% in Tier 1 and Tier 2 cities. These results help us to better understand the changes in the Theil Indexes.

B. Decomposition of Housing Asset Income Changes in Theil Index

Table C3 shows a further decomposition of the effect of housing asset income changes on the Income Theil Index. Besides the benchmark, we construct two decompositions: Out-Fixed assumes that cities which are losing workers did not suffer housing price decreases, so migrants' housing asset income from their hometown is unchanged, but they did push up housing prices in city that they moved to. In-Fixed assumes that cities which are gaining workers did experience higher housing prices, so migrants' housing asset income from their hometown does change, but they did not push up housing prices in the city that they moved to. The results show that the Out-Fixed case is closer to the benchmark, which means that inflow migrants pushing up housing prices in more developed cities is the main channel of observed counterfactual changes in income inequality.

C. Changes in Population-Weighted Productivities

Table C3: **Decomposition of Housing Asset Income Changes on Theil Index**

Net Migrants (2010)	No. of Cities	Reality 2010	Benchmark $\widehat{2010}$	Benchmark Relative	Out-Fixed $\widehat{2010}$	Out-Fixed Relative	In-Fixed $\widehat{2010}$	In-Fixed Relative
Average	233	0.0184	0.0121	66%	0.0127	69%	0.0181	98%
(6,13)	5	0.0908	0.0428	47%	0.0450	50%	0.0802	88%
(1,6)	19	0.0223	0.0139	62%	0.0152	68%	0.0213	96%
(0, 1)	45	0.0092	0.0098	106%	0.0104	113%	0.0087	95%
(-1,0)	134	0.0052	0.0045	86%	0.0047	90%	0.0046	88%
(-4,-1)	30	0.0062	0.0051	82%	0.0053	85%	0.0056	90%

Notes: This table displays population-weighted means of inequality measures of the benchmark economy and two decomposition. The original equilibrium is 2010 and the counterfactual equilibrium is $\widehat{2010}$. Relative is calculated via dividing $\widehat{2010}$ by 2010. Out-Fixed assumes that cities which are losing workers did suffer a decline in housing prices, so migrants' housing asset income from their hometown is unchanged, but assumes they did push up housing prices in the city they moved to. In-Fixed assumes that cities which are gaining workers did experience housing price increases, so migrants' housing asset income from their hometown does change, but that they did not push up housing prices in the city that they moved to.

Table C4 shows that the land supply reform does increase measured producitivities in cities with migration inflows as well as the national average producitivities, however, not for the high-skill workers. For low-skill productivity, since many more low-skill workers are moving from less developed cities to more developed cities, the gain in measured productivity is much higher in developed cities. For high-skill productivity, this is not exactly the case. Land supply reform actually increases high-skill workers' comparative advantage in less developed cities. As a result, measured high-skill productivity in more developed cities actually decreases.

C.3 Supplementary Results on Property Taxes and Redistribution

Table C5 shows how this counterfactual policy changes net migration and housing costs. First, the policy motivates 1% more workers to move from low productivity cities to high productivity cities, and the increases are the highest in the most productive cities (Tier 1: 2% = Tier 2: 2% > Tier 3: 0%). Meanwhile, because there is no land supply redistribution, no additional land is distributed to cities with more incoming migrants, and housing costs in these cities do not change.

We then show how within-city inequality changes in Table C6. The first thing to notice is that the Wage Theil Index effectively does not change. The only noticeable change is that the Theil Index in Tier 1 cities increases by 3%. This is mainly because more high-skill workers move to Tier 1 and Tier 2 cities due to additional transfer from the property tax system. Nevertheless, for any other city group, the Wage Theil Index is almost identical. However, the population-weighted

Table C4: **Changes in Population-Weighted Productivities**

Net Migrants (2010)	No. of Cities	High-skill 2010	High-skill $\widehat{2010}$	High-skill Relative	Low-skill 2010	Low-skill $\widehat{2010}$	Low-skill Relative
Overall	233	14.0	14.2	101%	17.1	17.4	102%
(6,13)	5	45.7	44.0	96%	21.2	22.0	104%
(1,6)	19	12.0	11.4	95%	19.5	20.0	103%
(0, 1)	45	10.5	11.1	106%	16.3	16.4	101%
(-1,0)	134	2.3	2.6	113%	16.3	16.2	99%
(-4,-1)	30	1.6	1.5	94%	15.2	15.3	101%

Notes: This table displays population-weighted means in both 2005 and 2010 and their changes. The levels of high-skill and low-skill productivity are not directly comparable. For readability, we normalize both numbers. The unit of high-skill productivity is 1e2 and the unit of low-skill productivity is 1e3. The net stock of migrant worker groups are classified by net stock of migrant workers in 2010 (unit: millions). Each Net Migrants group consists of the same cities in 2005 and 2010. There are 233 cities in the model.

Table C5: **Migration Flows and Housing Costs: Property Tax**

Net Migrants (2010)	No. of Cities	Net Migrants 2010	Net Migrants $\widehat{2010}$	Net Migrants Relative	Housing Cost 2010	Housing Cost $\widehat{2010}$	Housing Cost Relative
Overall	233	96m	97m	101%	114	115	101%
(6,13)	5	+45m	+46m	102%	226	230	102%
(1,6)	19	+38m	+39m	102%	136	137	101%
(0, 1)	45	+13m	+13m	100%	118	118	100%
(-1,0)	134	-48m	-47m	102%	87	87	100%
(-4,-1)	30	-48m	-50m	104%	80	80	100%

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

mean Income Theil Index drops significantly from 0.0184 to 0.0145 (21% drop). Moreover, if we divide by city groups, the drops are much larger for Tier 1 and Tier 2 cities. Since almost 30% of all workers live in these cities, it significantly lowers the average within-city Income Theil Index even though the Income Theil Index rises in cities losing workers. Therefore, the property tax reform helps to reduce within-city income inequality.

We also want to show how the policy changes national inequality and each city's contribution to national inequality in Table C7. Similar to the pattern of within-city inequality, the counterfactual policy does not have much effect on national wage inequality or cities' contributions to

Table C6: **Within-city Theil Index: Property Tax**

Net Migrants (2010)	No. of Cities	Wage Theil Index 2010	$\widehat{2010}$	Relative	Income Theil Index 2010	$\widehat{2010}$	Relative
Average	233	0.0070	0.0071	101%	0.0184	0.0145	79%
(6,13)	5	0.0097	0.0100	103%	0.0908	0.0670	74%
(1,6)	19	0.0079	0.0080	101%	0.0223	0.0171	77%
(0, 1)	45	0.0083	0.0084	101%	0.0092	0.0081	88%
(-1,0)	134	0.0058	0.0058	100%	0.0052	0.0047	90%
(-4,-1)	30	0.0058	0.0058	100%	0.0062	0.0053	85%

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

Table C7: **Share of National Theil Index: Property Tax**

Net Migrants (2010)	No. of Cities	Share of Wage Theil 2010	$\widehat{2010}$	Relative	Share of Income Theil 2010	$\widehat{2010}$	Relative
National Theil	233	0.062	0.062	100%	0.092	0.074	80%
(6,13)	5	+1.41	+1.42	104%	+1.27	+1.31	103%
(1,6)	19	+0.83	+0.83	101%	+0.70	+0.73	104%
(0, 1)	45	+0.26	+0.26	88%	+0.20	+0.21	105%
(-1,0)	134	-1.00	-0.98	95%	-0.78	-0.82	111%
(-4,-1)	30	-0.49	-0.52	118%	-0.39	-0.44	116%

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

national wage inequality. The national Wage Theil Index is unchanged. However, the counterfactual policy significantly lowers national income inequality by 20% measured by the Income Theil Index. By city groups, the positive contributions of Tier 1, 2 and 3 cities and the negative contributions of Tier 4 and Tier 5 cities increase in magnitude. All these results indicate that the property tax reform lowers national income inequality but not cross-city income inequality since we redistribute housing asset income from local house owners to migrants.

Table C8: **Skill Premium and Housing Premium: Property Tax**

Net Migrants (2010)	No. of Cities	Skill Premium 2010	Skill Premium $\widehat{2010}$	Skill Premium Relative	Housing Premium 2010	Housing Premium $\widehat{2010}$	Housing Premium Relative
Average	233	1.40	1.40	100%	0.49	0.46	94%
(6,13)	5	1.39	1.39	100%	1.89	1.60	85%
(1,6)	19	1.40	1.43	102%	0.56	0.51	91%
(0, 1)	45	1.39	1.38	99%	0.35	0.34	97%
(-1,0)	134	1.40	1.39	99%	0.25	0.26	104%
(-4,-1)	30	1.45	1.43	98%	0.31	0.21	68%

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

Finally, we show the skill premium and the housing premium in Table C8. The skill premium is the high-skill wage over the low-skill wage, and the housing premium is the average housing return over the average wage return. The underlying reason why any measures of wage inequality do not change much is that the skill premium does not move at all. The only changes come from the location choices of high-skill workers relative to low-skill, which changes the composition of workers in each city. However, for the housing premium, it is another story. Since the government taxes house owners in cities with insufficient land quotas, after-tax housing premium drop massively, which dilutes the asset return from property ownership. As a result, housing premia fall by 15% and 9% in Tier 1 and Tier 2 cities. These results help us to better understand the changes in the Theil Indexes.

C.4 Directly Increasing Land Supply Proportionally to Migration Inflows

In Table C9, we consider an alternative counterfactual which directly increases land supply in larger cities proportional to migration inflows but without the trade of land quotas across cities. Since most Chinese cities (except Shenzhen and Dongguan) retain a large portion of farmland, this counterfactual is generally feasible. This counterfactual is to increase the total land supply increment from 2005 to 2010 proportional to positive migration inflows. As a result, cities with positive net inflows keep the same worker-land ratio as in 2005, while cities losing workers do not lose the land quotas.

Table C9: **Counterfactual Construction Land Supply: Direct Land Supply Increment**

Net Migrants (2010)	No. of Cities	Land Supply (Data)				Counterfactual		
		2005	2010	Relative	Changes	$\widehat{2010}$	$\widehat{Relative}$	$\widehat{Changes}$
National	233	24,277	31,705	131%	+7,428	39,133	161%	+14,856
(6,13)	5	5,135	5,648	110%	+513	10,389	202%	+5,254
(1,6)	19	3,801	5,912	155%	+2,111	10,461	275%	+6,660
(0, 1)	45	5,555	7,250	131%	+1,695	8,103	145%	+2,548
(-1,0)	134	7,950	10,363	130%	+2,413	8,026	101%	+76
(-4,-1)	30	1,836	2,532	138%	+696	1,836	100%	+0

Notes: This table displays the total land supply data by migration groups in 2005 and 2010, as well as the counterfactual land supply in 2010 (unit: km^2). Net Migrants is classified by the net stock of migrant workers in 2010 as in the data (unit: millions). Each net migrant group consists of the same cities in 2005 and 2010.

Table C10: **Migration Flows and Housing Cost: Direct Land Supply Increment**

Net Migrants (2010)	No. of Cities	Net Migrants			Housing Cost		
		2010	$\widehat{2010}$	Relative	2010	$\widehat{2010}$	Relative
Overall	233	96m	111m	116%	114	93	82%
(6,13)	5	+45m	+54m	120%	226	145	64%
(1,6)	19	+38m	+46m	121%	136	84	62%
(0, 1)	45	+13m	+12m	108%	118	98	83%
(-1,0)	134	-48m	-48m	100%	87	87	100%
(-4,-1)	30	-48m	-63m	131%	80	72	90%

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

Table C11: **Within-city Theil Index: Direct Land Supply Increment**

Net Migrants (2010)	No. of Cities	Wage Theil Index			Income Theil Index		
		2010	$\widehat{2010}$	Relative	2010	$\widehat{2010}$	Relative
Average	233	0.0070	0.0072	103%	0.0184	0.0245	133%
(6,13)	5	0.0097	0.0092	95%	0.0908	0.1189	131%
(1,6)	19	0.0079	0.0088	111%	0.0223	0.0275	123%
(0, 1)	45	0.0083	0.0083	100%	0.0092	0.0097	105%
(-1,0)	134	0.0058	0.0059	101%	0.0052	0.0051	98%
(-4,-1)	30	0.0058	0.0056	97%	0.0062	0.0066	106%

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

Table C12: **Share of National Theil Index: Direct Land Supply Increment**

Net Migrants (2010)	No. of Cities	Share of Wage Theil			Share of Income Theil		
		2010	$\widehat{2010}$	Relative	2010	$\widehat{2010}$	Relative
National Theil	233	0.062	0.067	108%	0.092	0.104	113%
(6,13)	5	+1.41	+1.44	102%	+1.27	+1.25	98%
(1,6)	19	+0.83	+0.85	102%	+0.70	+0.68	97%
(0, 1)	45	+0.26	+0.25	96%	+0.20	+0.17	85%
(-1,0)	134	-1.00	-0.95	95%	-0.78	-0.68	87%
(-4,-1)	30	-0.49	-0.58	118%	-0.39	-0.42	108%

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

Table C13: **Skill Premium and Housing Premium: Direct Land Supply Increment**

Net Migrants (2010)	No. of Cities	Skill Premium			Housing Premium		
		2010	$\widehat{2010}$	Relative	2010	$\widehat{2010}$	Relative
Average	233	1.40	1.40	100%	0.49	0.64	131%
(6,13)	5	1.39	1.39	100%	1.89	2.78	147%
(1,6)	19	1.40	1.43	102%	0.56	0.63	112%
(0, 1)	45	1.39	1.38	99%	0.35	0.35	100%
(-1,0)	134	1.40	1.39	101%	0.25	0.25	100%
(-4,-1)	30	1.45	1.43	102%	0.31	0.18	58%

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

C.5 Counterfactual Analysis of the Model with Agglomeration Effect

C.5.1 Introducing Agglomeration Forces

We now introduce endogenous agglomeration forces as in Ahlfeldt et al. (2015) with slight modifications. We allow urban labor productivities for both skills to depend on production fundamentals (a^h_{ju} and a^l_{ju}) and production externalities (Υ_j). Production externalities impose structure on how the productivity of a given region is affected by the density of workers with the region,[27]

$$A^s_j = a^s_j \times (\Upsilon_j)^\gamma, \quad \Upsilon_j = \frac{H^h_j + H^l_j}{\bar{L}_j} \tag{36}$$

where $(H^h_j + H^l_j)/\bar{L}_j$ is the working population density per unit of administrative land area; and γ controls its relative importance in determining the overall productivity. Since we have no feasible data or method to estimate γ, we calibrate the agglomeration parameters using Combes, Duranton, and Gobillon (2008). The value ranges from 0.01 to 0.02. That is, productivity increases by 1 to 2 percent if the total population is increased by 1 percent. In this section, we choose $\gamma = 0.02$.

C.5.2 Land Supply Policy Reform Results with Agglomeration Forces

The results of the land supply policy reform with agglomeration forces are summarized in the tables below. There are no significant changes.

Table C14: **Migration Flow and Housing Cost: Land Supply Reform with Agglomeration Forces**

Net Migrants	No. of	Net Migrants			Housing Cost		
(2010)	Cities	2010	$\widehat{2010}$	Relative	2010	$\widehat{2010}$	Relative
Overall	233	96m	113m	118%	114	119	104%
(6,13)	5	+45m	+56m	124%	226	158	70%
(1,6)	19	+38m	+44m	116%	136	102	75%
(0, 1)	45	+13m	+13m	100%	118	132	112%
(-1,0)	134	-48m	-48m	100%	87	115	132%
(-4,-1)	30	-48m	-65m	135%	80	105	131%

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

[27] Considering administrative zones are fixed, the changes in density are identical to changes in population.

Table C15: **Within-city Theil Index: Land Supply Reform with Agglomeration Forces**

Net Migrants (2010)	No. of Cities	Wage Theil Index 2010	$\widehat{2010}$	Relative	Income Theil Index 2010	$\widehat{2010}$	Relative
National Theil	233	0.062	0.062	100%	0.092	0.074	80%
Average	233	0.0070	0.0072	103%	0.0184	0.0121	66%
(6,13)	5	0.0097	0.0092	97%	0.0908	0.0428	47%
(1,6)	19	0.0079	0.0090	114%	0.0223	0.0140	63%
(0, 1)	45	0.0083	0.0082	99%	0.0092	0.0098	107%
(-1,0)	134	0.0058	0.0059	101%	0.0052	0.0046	88%
(-4,-1)	30	0.0058	0.0056	97%	0.0062	0.0052	84%

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

Table C16: **Share of National Theil Index: Land Supply Reform with Agglomeration Forces**

Net Migrants (2010)	No. of Cities	Share of Wage Theil 2010	$\widehat{2010}$	Relative	Share of Income Theil 2010	$\widehat{2010}$	Relative
National Theil	233	0.062	0.062	100%	0.092	0.074	80%
(6,13)	5	+1.41	+1.47	104%	+1.27	+1.28	101%
(1,6)	19	+0.83	+0.84	101%	+0.70	+0.66	94%
(0, 1)	45	+0.26	+0.23	88%	+0.20	+0.29	145%
(-1,0)	134	-1.00	-0.95	95%	-0.78	-0.73	94%
(-4,-1)	30	-0.49	-0.58	118%	-0.39	-0.50	128%

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

Table C17: **Skill Premium and Housing Premium: Land Supply Reform with Agglomeration Forces**

Net Migrants (2010)	No. of Cities	Skill Premium 2010	Skill Premium $\widehat{2010}$	Skill Premium Relative	Housing Premium 2010	Housing Premium $\widehat{2010}$	Housing Premium Relative
Average	233	1.40	1.40	100%	0.49	0.45	92%
(6,13)	5	1.39	1.39	100%	1.89	1.12	59%
(1,6)	19	1.40	1.44	103%	0.56	0.41	73%
(0, 1)	45	1.39	1.38	99%	0.35	0.40	114%
(-1,0)	134	1.40	1.39	99%	0.25	0.33	132%
(-4,-1)	30	1.45	1.43	98%	0.31	0.26	84%

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