Floating population: migration with(out) family and the spatial distribution of economic activity

Online Appendix

A Data description

This section provides complements to Section 1 of the paper: (i) a brief description of our data; and (ii) a lengthy discussion of the allocation of migrants, barriers to migration, and split families across space and over time.

A.1 Living conditions in cities

We collect data on living conditions in cities: pollution data from satellite images; commuting data from the "2015 Mini-Census"; and additional wage data for years other than 2005. We leave the description of additional data used for identification purposes to Appendix D.

Pollution Pollution data come from TEMIS satellite images and cover the period 1997–2015 with a 20-25 km resolution. We map raster data on NO_2 concentration, which captures industrial and exhaust gas pollution, to Chinese prefectures to create pollution concentration measures at the prefecture × year level. These measures can be interpreted as a proxy for air quality.

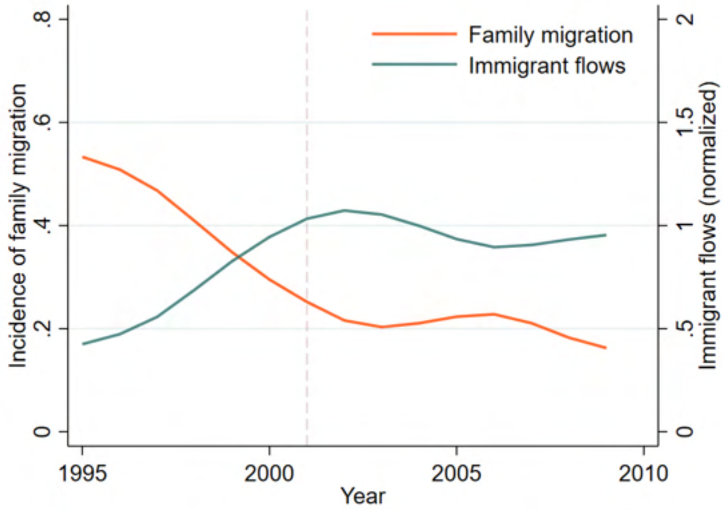
Commuting We also compute average commuting times at the prefecture level from a random 20% micro extract of the 2015 1% Population Survey. These data allow us to proxy for congestion.

Statistical Yearbooks We use aggregate data compiled by the National Bureau of Statistics based on the Reporting Form System on Labor Wage Statistics, the National Monthly Sample Survey System on Labor Force, and the System of Rural Social and Economic Surveys (http://www.stats.gov.cn/tjsj/ndsj/2018/indexeh.htm) to extract measures of wages at baseline, in 2000.

A.2 Descriptive statistics

In this section, we provide complements to the main descriptive statistics discussed in Section 1.3.

Figure A.1. Immigrant inflows and family migration over time.

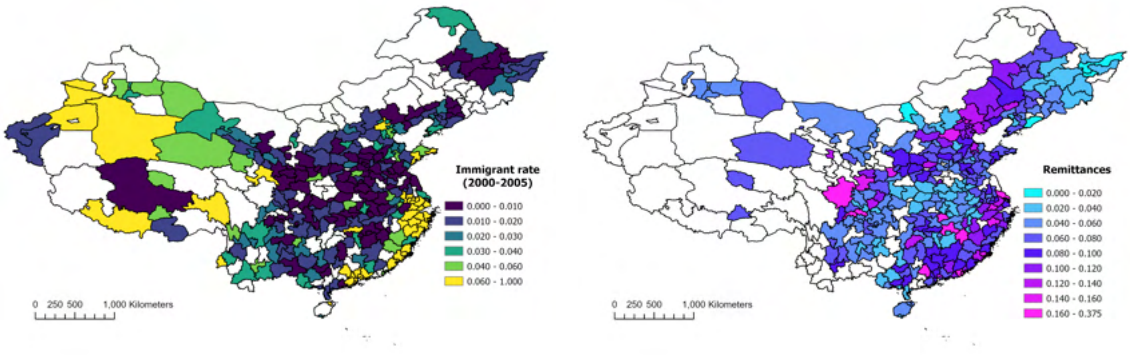


Notes: This figure shows the composition and magnitude of immigrant inflows to urban areas between 1995 and 2010 using Population Censuses (2000, and 2010) and the "2005 Mini-Census." A migrant is defined as an individual whose prefecture of residence is different from her prefecture of household registration. The definition of family migration follows that of our baseline specification (a migrant living at destination with at least a parent or a child). The dashed line indicates the WTO accession of China in 2001. Note that there are two differences with Figure 1 of the paper: Migration incidence is captured here by yearly flows; migrant flows are normalized by contemporary population in cities and set equal to 1 in 2000.

Immigrant inflows and family migration over time Figure A.1 shows the composition and magnitude of immigrant inflows to urban areas between 1995 and 2010. Immigrant inflows accelerate around the time of WTO accession, coinciding with other reforms contributing to pushing migrants from rural hinterlands into growing metropolitan areas. After 2000–2001, urban areas experience a steady increase of population, and, more importantly for our purpose, the composition of immigrant inflows appears to be stable over time: about 20% of new immigrants to cities are moving with their family.

Immigrant inflows and remittances across space Figure A.2 displays the geography of migration to cities in China: the allocation of immigrants across space in 2005 in panel (a), and the remittance share across destinations in panel (b). Ignoring the Western, less populated areas, we see that migrants tend to go to large cities (Beijing, Shanghai) and to the new exporting centers: Tianjin, Fuzhou, and Shenzhen/Guangzhou in the South. From these favored destinations, migrants appear to remit larger fractions of their income (panel b of Figure A.2).

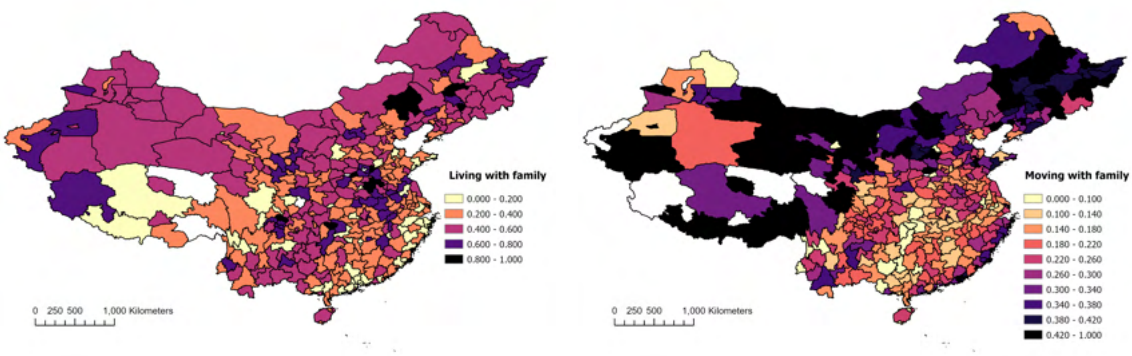
Figure A.2. Immigrant inflows and remittances across prefectures in 2005.



(a) Immigration rate (b) Remittance share

Notes: Panel (a) displays the share of rural-urban immigrants in the 2005 1% Population Survey or "2005 Mini-Census" across urban prefectures. We restrict the sample to urban locations and define rural-urban immigrants as rural-*Hukou* holders at those urban locations. Note that the Western regions appear to have large immigrant shares, mostly because those are less populated areas. Panel (b) displays the share of income devoted to remittances across destinations (from CMDS, 2011–2012).

Figure A.3. Migration patterns across destinations and origins in 2005.

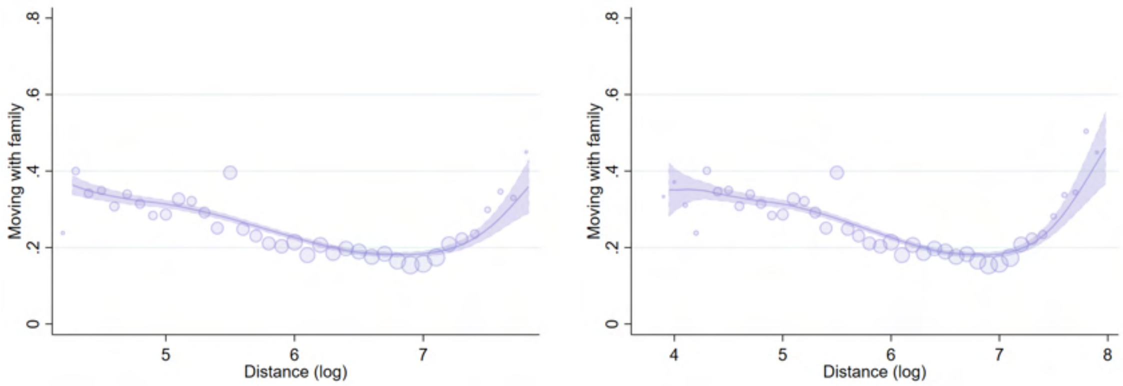


(a) Living with family (destination) (b) Moving with family (origin)

Notes: Panel (a) shows the variation in migration arrangements across destinations (share of immigrants living at destination with family). Panel (b) shows the variation in migration arrangements across origins (share of emigrants moving with family).

Migration patterns Figure A.3 shows that migration patterns strongly vary across space. First, the spatial distribution of migrants living with family across destinations (negatively) correlates with immigrant incidence and with the propensity to remit back to origins: In large cities and new exporting centers, migrants are also less likely to live with family—see panel (a). Second, the previous observation, coupled with the gravity of migration flows, induces spatial disparities in the share of migrants having moved with family from different origins and thus with the incidence of family members left behind by the main breadwinners—see panel (b). These geographic differences are very marked and illustrate a strong spatial heterogeneity in migration patterns across Chinese cities.

Figure A.4. Migration patterns and distance in 2005.



(a) Distance

(b) Travel time

Notes: Panel (a) shows the variation in migration arrangements (share of immigrants living at destination with family) across migration spells implying different geodetic distances between origins and destinations (as the crow flies). Panel (b) uses instead an indicator of distance based on travel time through the transportation network.

The gravity of migration flows has two distinct implications for the decisions of families to move jointly or remain split between two locations: (i) the proximity to congested locations with strong barriers to family migration induces a higher incidence of split families, for a given distance, as shown in panel (b) of Figure A.3; and (ii) the distance between origins and destinations does predict some of the incidence of the different migration patterns (see Figure A.4). In fact, the former effect is most predictive of family migration: Most population lives in Central China and along the coast, not so far from typical migration destinations, such that the higher incidence of family migration from very distant prefectures (see the right tails in Figure A.4) does not represent more than 1% of all migration spells.[1]

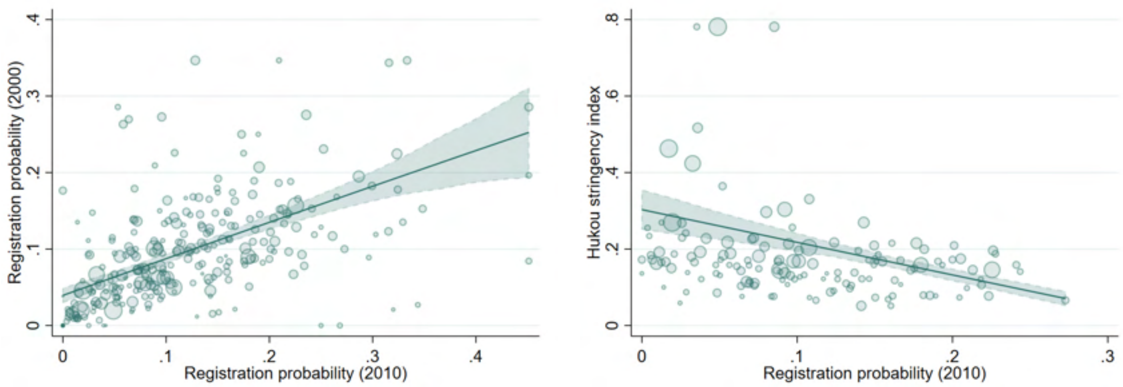
Migration barriers One crucial factor underlying the allocation of migrants and their families across space is the stringency of local barriers to migration (see Section 1.1 of the paper). In this section, we first describe and compare the measures we use to capture such barriers. We then show how they reflect migrants' experiences at destination. Fi-

[1]Western and northern families might also be more likely to move jointly with their family, because nearby cities are cheaper and with less stringent *Hukou* restrictions.

nally, we discuss the spatial distribution of *Hukou* stringency across cities and how this distribution was affected by the 2014 reform.

In the paper, we use two measures of the local regulatory environment affecting immigration. First, we follow Wu and You (2021) and use census data to compute the share of migrants between 15 and 64 years old, having moved for work-related reasons, and born in another county, who were registered locally with a non-agricultural *Hukou*. This gives us a city-level measure of the probability for immigrants to convert their household registration at destination; we denote it by r_u.[2] Second, we use the composite indices from Zhang et al. (2018), who collated local regulations and policy documents to quantify how easily migrants can obtain local household registration at destination. These indices are available for two periods: before (2000–2013) and after (2014–2016) the landmark 2014 *Hukou* reform, and for 124 cities; we denote those indices by $h_{u,a}$ and $h_{u,b}$ for the pre- and post-2014 periods, respectively. In Section 4, we rely on the registration probability measure from the 2010 Census,[3] and in Section 5, we leverage legislation-based indices to estimate the effect of the 2014 *Hukou* reform in a counterfactual exercise.

Figure A.5. Measures of the *Hukou* environment.



(a) Registration probability, r_u (b) *Hukou* index, $h_{u,a}$

Notes: Panel (a) shows the correlation between the census-based measures of local household registration probability for 2000 and 2010, following Wu and You (2021). Panel (b) shows the correlation between the pre-2014 *Hukou* stringency index developed by Zhang et al. (2018) and the household registration probability for 2010. A bubble is a prefecture of destination and is weighted by its initial urban population in 2000. The lines are local polynomial fits, where each observation is weighted by population.

We show the correlations between measures of the *Hukou* environment in Figure A.5.

[2]Census data do not record past *Hukou* types. This measure thus assumes away urban-urban migration.

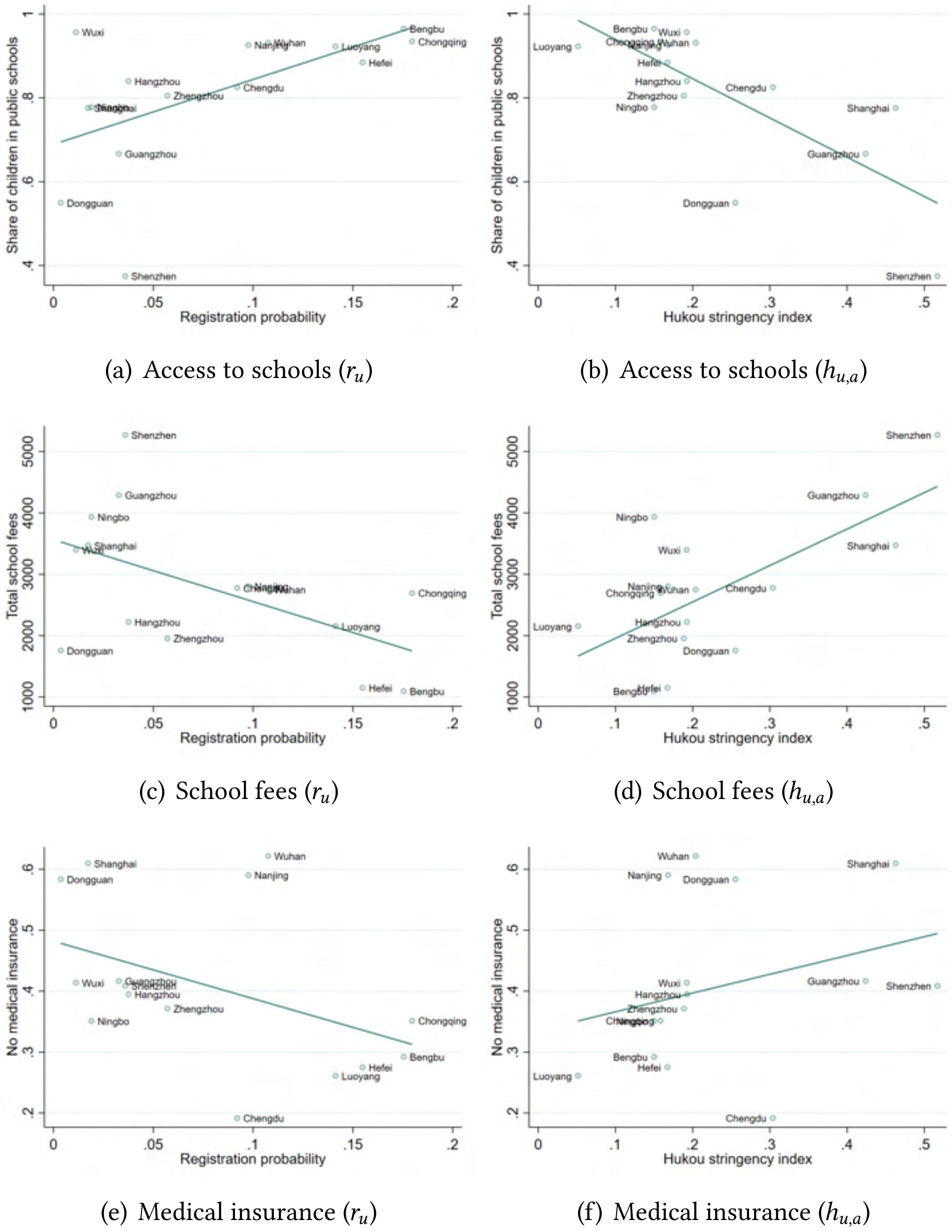
[3]The “2005 Mini-Census” does not contain information on the place of birth. Results are unchanged if we measure the registration probability in 2010 instead.

Panel (a) plots the registration probability in 2000 against that in 2010 (our main measure of the *Hukou* environment), using census data. We see that the two measures are strongly, positively correlated, which illustrates the presence of inertia in local legislation, despite the fast growth in immigration in that period (see Figure 1). Nonetheless, the majority of prefectures lie below the 45-degree line, which implies that many prefectures eased restrictions on *Hukou* conversion between 2000 and 2010. This measure of the *Hukou* environment is however a complex equilibrium object, as it is based on observed, and therefore selected, immigration. In panel (b), we correlate our measure of registration probability in 2010 with the composite index from Zhang et al. (2018), which instead relies on a coding of legislation rather than on observed migration and conversion probability. As expected, the two measures are strongly negatively correlated, which suggests that they do capture the leniency and stringency, respectively, of the local *Hukou* environment.

An important caveat of both census- and legislation-based measures is that they rely on *Hukou* conversion, which remains a rare event for rural migrants, in particular for the average—low-income, low-education—migrant. Cities typically condition local registration on migrants' meeting a set of stringent criteria, e.g., investing more than one million RMB in an enterprise or having a college degree. In Figure A.6, we leverage an additional dataset, the 2007 China Household Income Project (CHIP) rural-urban migrant survey, which constitutes a representative survey of migrant workers and their households in 15 cities in nine provinces,[4] to investigate whether our *Hukou* conversion measures are good proxies for the experiences of rural migrants at destination, i.e., for their access to public goods. We display in Figure A.6 correlations using the census-based registration probability in left panels and the legislation-based *Hukou* index in right panels. The top two panels show the correlation of the probability for migrants' children (conditional on living at destination) to attend public schools with the *Hukou* environment at destination. We see that cities that are characterized by a tougher stance on migrant *Hukou* conversion are indeed more likely to restrict migrants' access to public goods. The middle panels show that, conditional on going to school at destination, migrants' children

[4]Given the absence of a sampling frame, CHIP selected migrant respondents in the following way: (i) they randomly sampled enumeration areas within each city, (ii) they listed all workplaces within each enumeration area, (iii) they collected information on the number of staff and the number of migrant workers from each workplace, and (iv) they randomly selected migrant workers to participate in the survey (Meng and Manning 2010).

Figure A.6. Access to public goods and the *Hukou* environment.



(a) Access to schools (r_u)

(b) Access to schools ($h_{u,a}$)

(c) School fees (r_u)

(d) School fees ($h_{u,a}$)

(e) Medical insurance (r_u)

(f) Medical insurance ($h_{u,a}$)

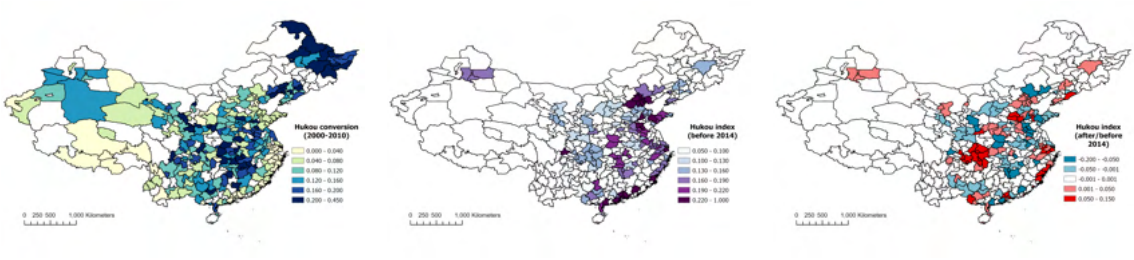
Notes: This figure shows the correlation between measures of access to public goods from the 2007 CHIP rural migrant survey and measures of the leniency or stringency of the *Hukou* environment. The latter is captured by the census-based measure of local household registration probability for 2010, following Wu and You (2021), and by the pre-2014 *Hukou* stringency index developed by Zhang et al. (2018), in left (r_u) and right panels ($h_{u,a}$), respectively. A dot is a prefecture of destination. The lines are local polynomial fits. "Share of children in public schools" is the share of migrant households' children who attend public schools, conditional on living at destination. "Total school fees" includes tuition fees, the cost of food, the cost of remedial classes taken at schools, and other fees (e.g., school uniform); it excludes sponsorship, boarding, and selection fees. "No medical insurance" is the share of immigrant household heads who do not have any medical insurance.

pay higher school fees in more restrictive *Hukou* environments.[5] Turning to healthcare

[5]Similar patterns obtain if we focus on tuition fees, i.e., excluding the cost of food, remedial classes, and other fees included in total fees.

as another major public good that migrants are known to have limited access to in urban China, the bottom panels show that immigrants in more stringent *Hukou* environments are much less likely to have a medical insurance.

Figure A.7. Migration barriers across prefectures.



(a) *Hukou* conversion (2010) (b) *Hukou* index (before 2014) (c) *Hukou* change (pre-post 2014)

Notes: Panel (a) shows the variation in *Hukou* conversion between 2000 and 2010, r_u—a measure constructed following the procedure developed in Wu and You (2021). Panel (b) uses the composite index capturing the ease with which migrants could obtain a local urban *Hukou* before 2014, $h_{u,a}$ (Zhang et al. 2018). Panel (c) uses the differences in such composite indices after 2014 compared to the pre-reform period, $h_{u,b} - h_{u,a}$.

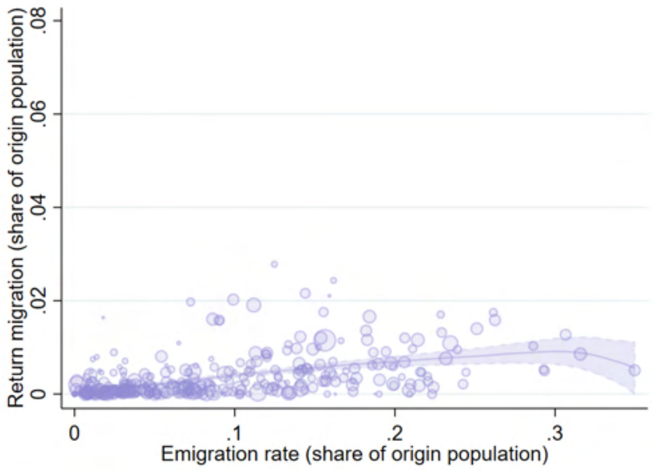
We finally shed some light on the spatial distribution of barriers to internal migration in Figure A.7 with: (i) the measure of *Hukou* conversion from the 2010 Census in panel (a); (ii) the composite index capturing the ease with which migrants could obtain a local urban *Hukou* before 2014 (Zhang et al. 2018) in panel (b); and (iii) the differences in the composite indices after 2014 compared to the pre-reform period in panel (c).

Migration barriers coincide more or less with the allocation of economic growth during the Reform period. Indeed, the extent to which prefectures constrain access to public services depends on the expected fiscal deficits and (historically) on possible food shortages if they were to allow for migration. Such deficits are thus tied to expected migration (very correlated with local growth prospects) and to fiscal balance and food reserves. In Section 4, we exploit the latter to isolate exogenous variation in the allocation of migration barriers across space.

In 2014, the government implemented a *Hukou* reform (exploited in Gao et al. 2022, in order to uncover its effect on left-behind children) with the aim of displacing rural migrants from congested cities to smaller agglomerations. Panel (c) of Figure A.7 shows that large metropolitan areas (e.g., Beijing, Shanghai, Shengzhen/Guangzhou, Fuzhou, etc.) experienced a tightening of restrictions when satellite cities experienced a loosening of barriers. We discuss the subtle effect of such a reform on the allocation of migrants in

Section 5.

Figure A.8. The incidence of return migration.



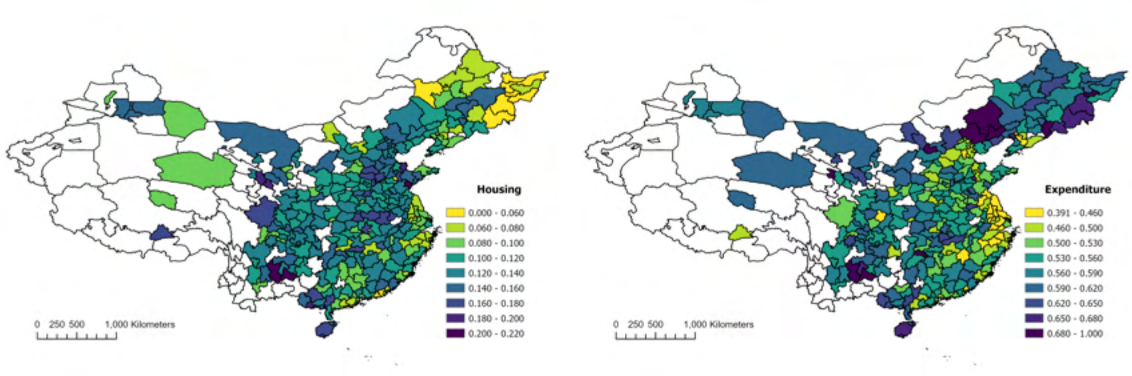
Notes: This Figure compares the number of migrants having departed from their origins after 2000 (x-axis) to the number of those having returned between 2004 and 2005 (y-axis) across prefectures.

Return migration An intriguing feature of rural-urban migration in China, given the institutional constraints to settling in cities, is the low incidence of return migration. One factor could be the lack of non-agricultural employment opportunities in rural hinterlands (in spite of the effect of remittances documented in Pan and Sun 2022). We quantify the incidence of return migration in Figure A.8, where we compare the number of migrants having departed from their origins after 2000 to the number of those having returned between 2004 and 2005. In rural areas where about 10% of the rural population left during this period, only about 0.3% returned.[6] We further discuss return migration and the prospects of movers in Appendix B.8, where we show that most of them would prefer to stay at destination even when currently leaving the family behind.

Robustness and alternative definitions We now discuss a few robustness checks. We first provide a sensitivity analysis of Figure A.2 by displaying alternative measures of (displaced) consumption in Figure A.9. We first extract the share of income devoted

[6] Imbert et al. (2022) further studies the patterns of return migration in the "2005 Mini-Census," e.g., allowing them to infer the extent of return migration between 2000 and 2005 rather than between 2004 and 2005 only. The conclusion remains that return migration is one order of magnitude lower than migration flows.

Figure A.9. Consumption of non-tradables and expenditure shares of migrants across space.



(a) Housing share

(b) Expenditure share (excl. remittances)

Notes: Panel (a) displays the share of income devoted to housing expenditures across destinations (from CMDS, 2011–2012; the measure includes the employer contribution if housing is provided by the employer). Panel (b) displays the ratio of expenditures (from CMDS, 2011–2012; excluding remittances) to income.

to housing in panel (a) and find that favored destinations, where migrants appear to remit larger fractions of their income, are also places where they spend less on housing. They do not only spend less on housing: They consume less as a whole. We indeed show in panel (b) of Figure A.9 that the ratio of consumption to income is lower in the most-favored destinations.

In the paper, we use a baseline dichotomy to characterize migration spells and we distinguish migrants living with family (i.e., with at least one parent or child) from migrants living without family at their destination. In practice, there are many different arrangements, some involving the migration of one spouse only, others involving both parents—thus leaving children with their grandparents. In Table 1, we replicate Table 1 and report four other splits of the data: one that distinguishes migrants living with children from those living without children; one that distinguishes female migrants living with children at destination from having left their children at origin (thereby focusing on females with children only, using the fertility module of the "2005 Mini-Census"); one that distinguishes migrants living with any relative from those living without relatives; and one that distinguishes migrants living with a spouse from those living without a spouse. The findings are quite consistent with our baseline dichotomy. Interestingly, we find that migrants who move *alone* are the ones with the largest number of co-residents: They indeed tend to live in dorms or in shared, low-quality accommodation.

Table A.1. Descriptive statistics—living arrangements.

	Children		Children (f)		Spouse		Relatives	
	With	Without	With	Without	With	Without	With	Without
Panel A: Demographic characteristics								
Age	36.08	30.12	35.61	35.40	35.20	29.86	35.13	28.97
Female (head)	0.220	0.397	1.000	1.000	0.095	0.467	0.188	0.471
Married	0.987	0.609	0.992	0.988	0.999	0.566	0.961	0.515
Number of children	1.691	1.428	1.687	1.605	1.433	1.499	1.592	1.437
Number of children (OCP*)	1.643	1.354	1.643	1.530	1.333	1.436	1.508	1.379
Panel B: Education								
High school (at least)	0.133	0.188	0.129	0.105	0.151	0.186	0.146	0.196
College (at least)	0.011	0.022	0.010	0.007	0.014	0.022	0.014	0.024
Panel C: Economic characteristics								
Income (head, RMB)	1,196	1,024	1,186	969	1,175	1,012	1,154	1,000
Hours worked per week	55.32	55.53	55.31	56.11	55.83	55.34	55.61	55.41
Housing share	0.232	0.213	0.226	0.234	0.162	0.230	0.199	0.224
Panel D: Living arrangements								
Co-residents	3.106	2.779	3.281	2.203	2.747	2.893	2.673	2.967
No kitchen	0.388	0.594	0.385	0.541	0.465	0.583	0.444	0.618
No toilets	0.545	0.573	0.544	0.613	0.593	0.556	0.576	0.561
House ownership	0.174	0.047	0.172	0.071	0.115	0.059	0.130	0.039
Panel E: Location characteristics								
City income (RMB)	711	862	715	822	762	857	754	879
Observations	12,952	46,231	9,999	15,388	17,234	41,949	23,525	35,658
	0.218	*0.782*	*0.393*	*0.607*	*0.291*	*0.709*	*0.397*	*0.603*

Notes: The sample is restricted to household heads aged 15–64 and living in urban areas (2005 1% Population Survey). In columns 1 and 2, we distinguish those having moved with children or not (for women with children in columns 3 and 4); in columns 5 and 6, we distinguish those having moved with a spouse or not; and in columns 7 and 8, we distinguish those having moved with some relatives or not. Descriptive statistics for *Monthly income (RMB)* and *Hours worked per week* are restricted to individuals who reported positive working hours in the past week. *Number of children alive* is available for female respondents (OCP* excludes females who were above 25 when the One-Child-Policy was adopted). *Housing share* is based on the predicted outcome from a regression of monthly rent (in log) for respondents renting in commercial housing on prefecture fixed effects interacted with various characteristics of the dwelling.

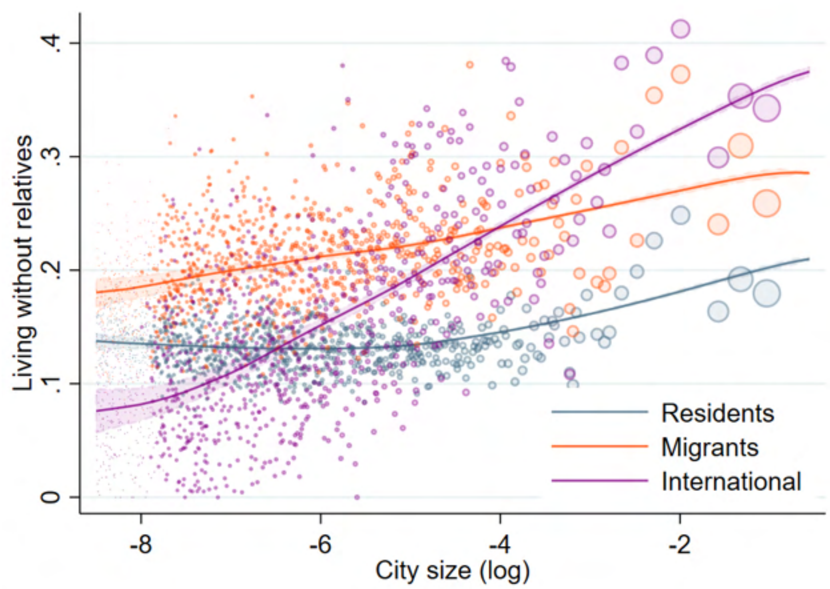
B Complements to the empirical analysis

This section provides some motivational evidence discussed in the introduction and complements to Section 2.

B.1 Motivational evidence

We argue that the patterns observed in China have some similarities with the patterns observed across multiple countries. Figure B.1 uses data on 149 Census extracted from IPUMS to show that indeed migrants concentrate more into larger cities than residents. The patterns are even stronger for international migrants.

Figure B.1. Living without relatives in urban settings (residents, rural-urban migrants and international migrants).

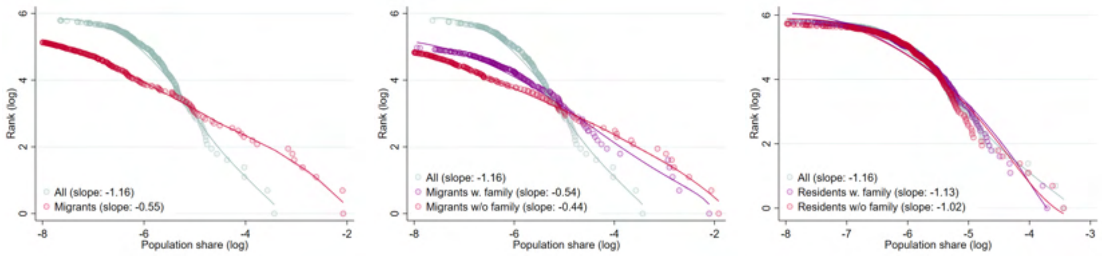


Notes: This Figure relies on 149 censuses extracted from IPUMS, for which we observe administrative units at the second level, the location of respondents (rural or urban settings), their migration status (inferred from their location at birth or 10 years prior to the interview), and their living conditions at destination. The y-axis is the propensity to live without relatives at destination (i.e., alone or in a couple, but without children). The lines are local polynomial fits, where each observation is weighted by population. The dots represent the average across 1,000 bins of (log) relative city size. The relative city size is calculated as the city size divided by the total population across urban areas within a given census wave. The covered countries are: Argentina, Benin, Bolivia, Brazil, Cambodia, Cameroon, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, Egypt, El Salvador, Fiji, Ghana, Greece, Guatemala, Guinea, Haiti, Honduras, India, Indonesia, Iran, Iraq, Israel, Kyrgyz Republic, Lesotho, Malawi, Malaysia, Mali, Mauritius, Mexico, Mongolia, Mozambique, Myanmar, Nepal, Nicaragua, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Rwanda, Senegal, Sierra Leone, South Africa, Thailand, Togo, Uganda, United States, Uruguay, Venezuela, Vietnam, Zimbabwe.

B.2 The concentration of migrants across cities

In this section, we document the extent to which migrants, especially when they move without family, concentrate in a few cities. To do so, we rely on the so-called Zipf law of city size, which conjectures that (log) population should be linearly related to the associated (log) rank and that the coefficient of such a linear relationship should be -1.

Figure B.2. The concentration of migrants across cities.



(a) Migrants and residents (b) Migrants with children (c) Residents with children

Notes: The x-axis reports (log) population by type (all, migrants, etc.) across prefectures using the "2005 Mini-Census"—note that we normalize the population by type to sum to 1 across all prefectures. The y-axis reports the associated (log) rank of these prefectures. The Zipf law of city size conjectures that (log) population should be linearly related to the associated (log) rank and that the coefficient of such linear relationship should be -1.

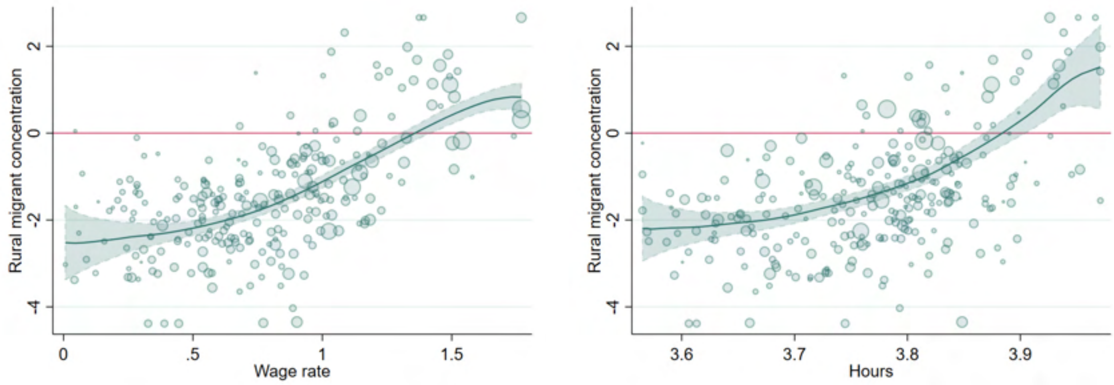
Panel (a) of Figure B.2 shows this relationship for all urban dwellers (green dots and line) and computed with rural migrants only (red dots and line). While the Zipf law of city size appears to hold for all urban dwellers, rural migrants are (much) more concentrated than the average urban dweller: The (relative) size of the migrant population is thrice as large in the most populated city relative to the average urban dweller (panel a). Panel (b) of Figure B.2 shows that migrants without family are even more concentrated—a gradient that is far less obvious when looking at urban dwellers with a local, urban *Hukou* (panel c).

B.3 The sorting of migrants across cities

Our motivating evidence in Section 2 documents that migrants sort into cities where monthly wages are high.

In Figure B.3, we decompose this finding into two distinct effects: (i) migrants sort into cities where wage rates are high (i.e., the wage adjusted by the number of hours worked during a normal week); and (ii) migrants sort into cities where workers work

Figure B.3. Rural migrant concentration, hourly wage, and hours worked.



(a) Hourly wage

(b) Hours

Notes: The y-axis reports the migrant concentration in city c, m_c, as defined in Section 2. In panel (a), the x-axis reports the (log) hourly wage rate; in panel (b), the x-axis reports a measure of (log) number of hours worked during a normal week. Hours and wages are constructed by aggregating individual responses from the 2005 1% Population Survey. A bubble is a prefecture of destination and is weighted by its initial urban population in 2000. The lines are local polynomial fits, where each observation is weighted by population.

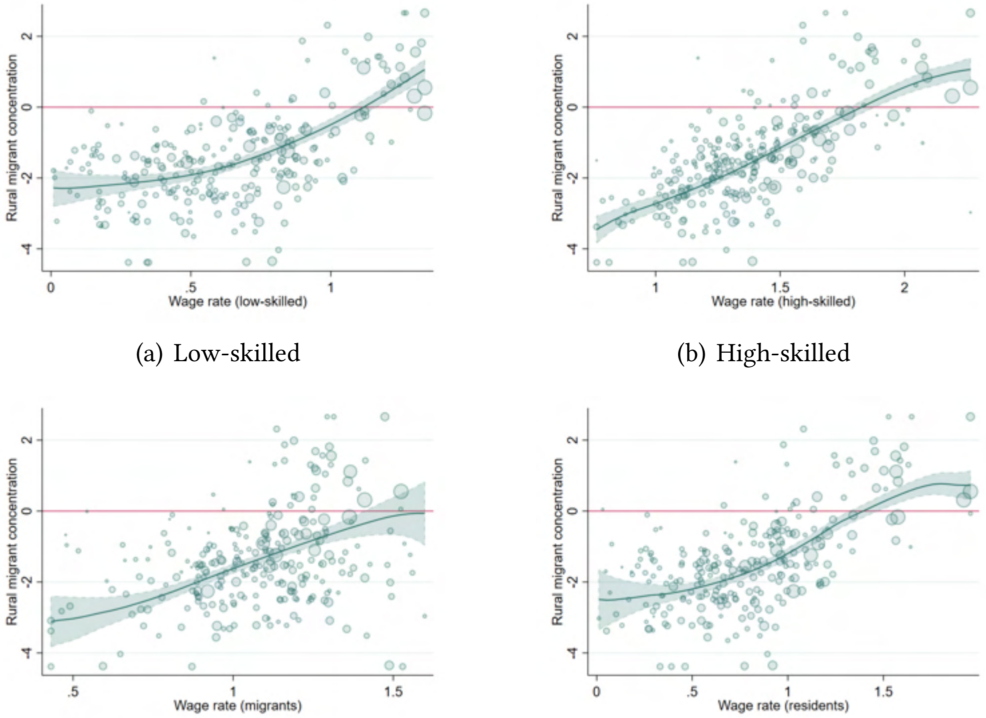
longer hours. The latter effect is not negligible as workers in "highest-wage" locations appear to work between 25-30% more than in the "lowest-wage" locations.[7]

In Figure B.4, we further probe the relationship between migrant concentration and returns to labor by extracting four different measures of wages from the "2005 Mini-Census": a measure of low-skilled wage in panel (a); a measure of high-skilled wage in panel (b); a measure of the average wage earned by rural migrants in panel (c); and a measure of the average wage earned by residents in panel (d). These measures are strongly correlated between each other and thus deliver a very similar message: Rural migrant concentration is higher where wages are higher (across the board).

We have shown in Section 2 that rural migrants may face lower mobility costs than urban residents when they relocate *across cities*: The latter are already settled and benefit from access to services that would be lost if they were to move to other urban settings (e.g., with higher returns to labor). One corollary of this observation is that urban migrants should be less numerous and their location choices should differ quite markedly from that of rural migrants. To document this fact, we construct a measure of relative

[7]One explanation could be that the substitution effect dominates the income effect for the relatively low-income workers present in Chinese cities between 2000 and 2005. Another likely explanation is a compositional effect, both in terms of available occupations and in terms of worker characteristics. For instance, migrants typically work longer hours and tend to be over-represented in these high-wage locations.

Figure B.4. Rural migrant concentration and various measures of wages.



(a) Low-skilled (b) High-skilled

(c) Migrants (d) Residents

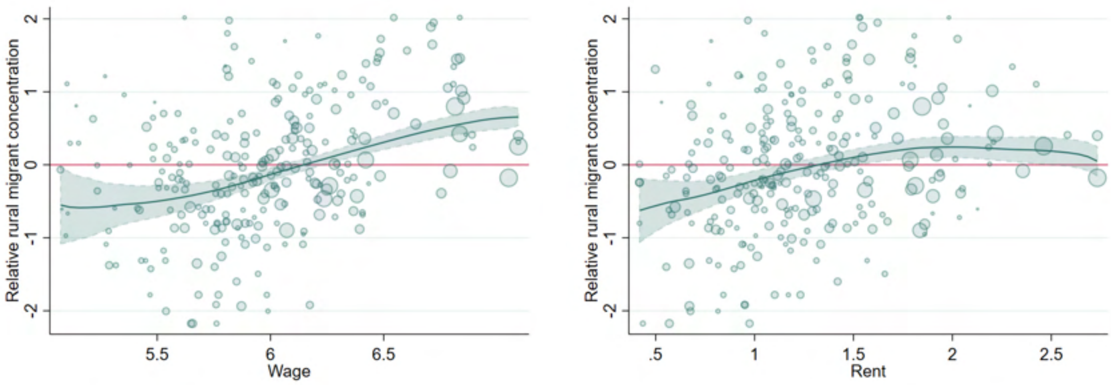
Notes: The y-axis reports the migrant concentration in city c, m_c, as defined in Section 2. The x-axis reports different measures of (log) monthly wages constructed using the "2005 Mini-Census": (i) low-skilled average wages in panel (a) based on all workers without a high-school degree; (ii) high-skilled average wages in panel (b) based on all workers with a high-school degree; (iii) migrant wages in panel (c); and (iii) resident wages in panel (d).

migrant concentration in city c, rm_c, as follows,

$$rm_c = m_c - \log\left(\frac{U_c/\left(\sum_c U_c\right)}{R_c/\left(\sum_c R_c\right)}\right) = \log\left(\frac{M_c/\left(\sum_c M_c\right)}{U_c/\left(\sum_c U_c\right)}\right),$$

where U_c denotes the number of urban migrants in city c having arrived between 2000 and 2005. This measure would be equal to 0 if migrants were allocated in the same fashion, independently of their registration type (rural or urban). In panel (a) of Figure B.5, we display the relationship between this relative concentration and nominal wages, and we find that rural migrants seem to sort into high returns to labor, and even more so than urban migrants. A percent increase in the nominal wage is associated with a 0.5 percent increase in the relative share of rural migrants. Panel (b) shows the same relationship with our measure of rents.

Figure B.5. Relative migrant concentration and living conditions in cities.



(a) Nominal wage (b) Rent

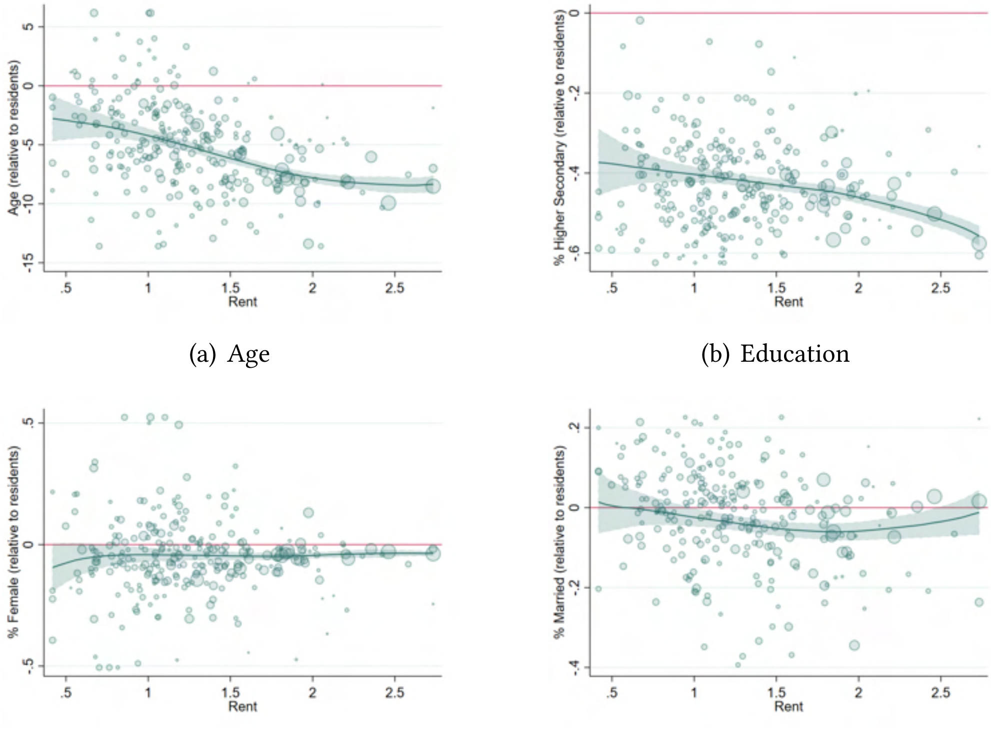
Notes: The y-axis reports the relative migrant concentration in city c, rm_c. In panel (a), the x-axis reports the (log) monthly wage; in panel (b), the x-axis reports a measure of (log) rents. Rents and wages are constructed by aggregating individual responses from the 2005 1% Population Survey. A bubble is a prefecture of destination and is weighted by its initial urban population in 2000. The lines are local polynomial fits, where each observation is weighted by population.

B.4 The selection of migrants across cities

We have shown in Section 2 that the selection of rural migrants differs from that of residents across cities subject to different living conditions. For instance, migrants are much less likely to live in decent housing conditions and with children in high-wage/rent locations. In Figure B.6, we further document the selective sorting of migrants across destinations, compared to urban residents. We find that: migrants are younger, and even more so in expensive locations (panel a); migrants are much less likely to have completed high school (panel b); migrants are (relatively) more likely to be males in expensive locations (panel c); and migrants are less likely to be married than residents in locations that are more expensive (panel d).

Migrants with different characteristics sort into different cities. In our main discussion (see, e.g., Section 2.2), we mostly focus on the *choice* of moving with or without family and how it interacts with location choices. We now provide a sensitivity analysis in Figure B.7. We first replace living with/without family by living with/without children in panel (a). Second, the evidence presented in Figure B.6 may threaten our main interpretation: Is the lower probability of living with family entirely explained by the fact that migrants in expensive locations are more often male and single? To test this, we focus on women who have children and consider the probability that they bring them

Figure B.6. The selection of migrants relative to residents in expensive cities.



(a) Age

(b) Education

(c) Gender

(d) Marriage

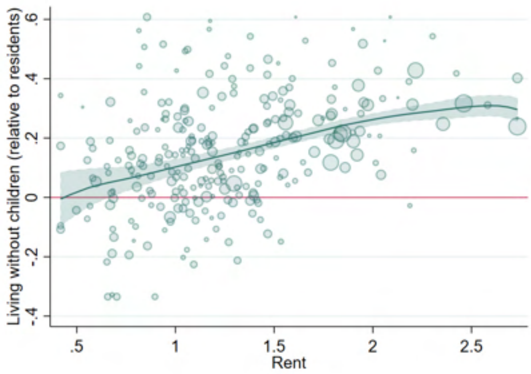
Notes: The x-axis reports a measure of (log) monthly rents constructed using the "2005 Mini-Census." In panel (a), the y-axis reports the difference between the average age of rural migrants relative to that of urban residents. In panel (b), the y-axis reports the difference between the proportion of migrants and the proportion of urban residents who have at least higher secondary education. In panel (c), the y-axis reports the difference between the fraction of migrants and the fraction of urban residents who are female. In panel (d) the y-axis reports the difference between the fraction of migrants and the fraction of urban residents who are married.

to expensive destinations. Panel (b) of Figure B.7 shows that rural migrant mothers are as likely to live with their children as urban resident mothers in the least expensive locations, but that they are 20 percentage points less likely to bring their children in the most expensive destinations. Panel (c) shows the relative probability to live without a spouse across destinations. Panel (d) broadens the definition of family to living with any relative and shows similar patterns: Rural migrants are more likely to live without any relatives in the most expensive locations, while they are as likely as residents to live with relatives in the least expensive cities.

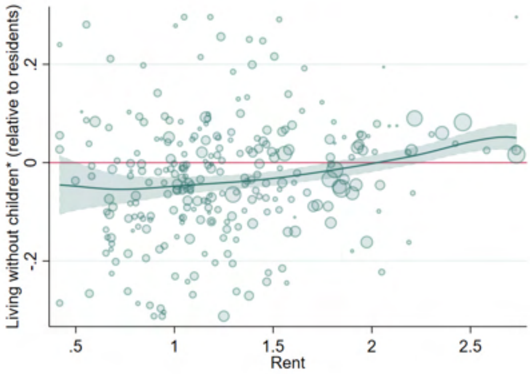
B.5 Remittances and housing expenditures

In Section 2, we document the income share spent by migrants on remittances, distinguishing migrants living with family and migrants living without. The former are found

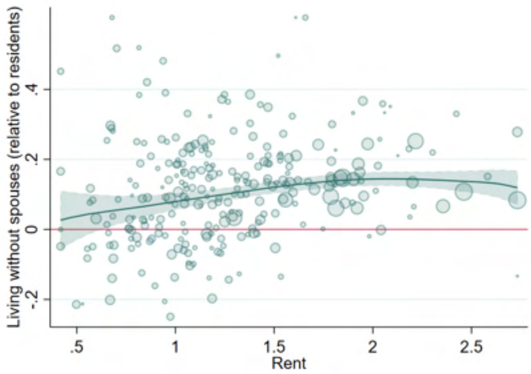
Figure B.7. Migrants and family—sensitivity analysis.



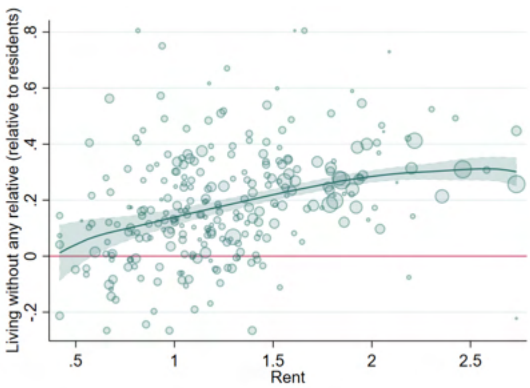
(a) Children



(b) Children (female with children)



(c) Spouse



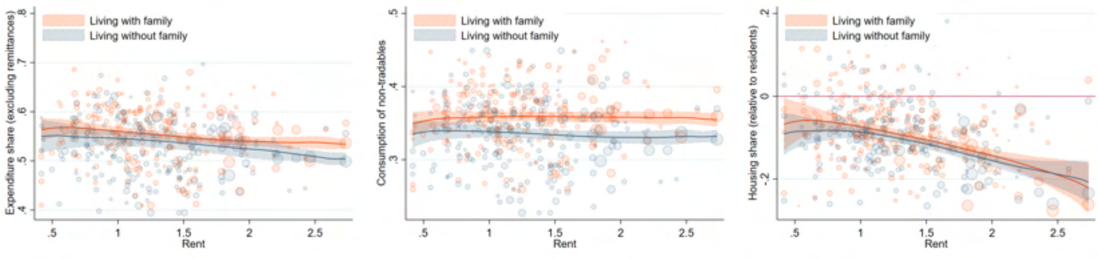
(d) Relatives

Notes: The x-axis reports a measure of (log) monthly rents constructed using the "2005 Mini-Census." In panel (a), the y-axis reports the difference between the fraction of rural migrant mothers and the fraction of urban resident mothers who live without their children; in panel (b), we restrict the sample to females declaring having children. In panel (c), the y-axis reports the difference between the fraction of rural migrants and urban residents who live without spouses. In panel (d), the y-axis reports the difference between the fraction of rural migrants and urban residents who live without any relatives. A bubble is a prefecture of destination and is weighted by its initial urban population in 2000. The lines are local polynomial fits, where each observation is weighted by population.

to remit less. We now provide a sensitivity analysis for this motivating fact. In Figure B.8, we display a measure of expenditures at destination for migrants living with or without family and across cheap or expensive destinations. We find that the ratio of monthly expenditures—excluding remittances—to monthly income is higher for migrants living with family and lower in more expensive locations. In fact, migrants living with family spend more on non-tradable goods at destination (see panel b).

In Figure B.9, we replicate the main Figure 3 (panel c) illustrating the heterogeneity in the share of income spent on remittances at destination. While Figure 3 uses a dichotomy based on the presence of family at destination, Figure B.9 replaces this dichotomy with:

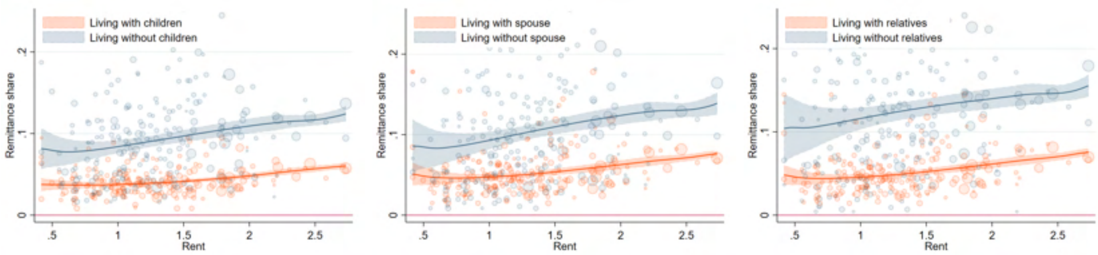
Figure B.8. Total expenditures, expenditures on non-tradable goods and housing expenditures.



(a) Expenditure share (b) Non-tradable share (c) Housing share

Notes: The x-axis reports a measure of (log) monthly rents constructed using the "2005 Mini-Census." In panel (a), the y-axis reports the average ratio of monthly expenditures—excluding remittances—to monthly income for migrants who live with their family (orange) and migrants living without family (blue). In panel (b), the y-axis reports the ratio of consumption on food and rents to monthly income for migrants who live with their family (orange) and migrants living without family (blue). In panel (c), the y-axis reports housing expenditures as a share of income for migrants who live with their family (orange) and migrants living without family (blue). A bubble is a prefecture of destination and is weighted by its initial urban population in 2000. The lines are local polynomial fits, where each observation is weighted by population.

Figure B.9. Migrants living with (orange) and without children/spouse/relatives (blue) and remittances.



(a) Remittances (children) (b) Remittances (spouse) (c) Remittances (relatives)

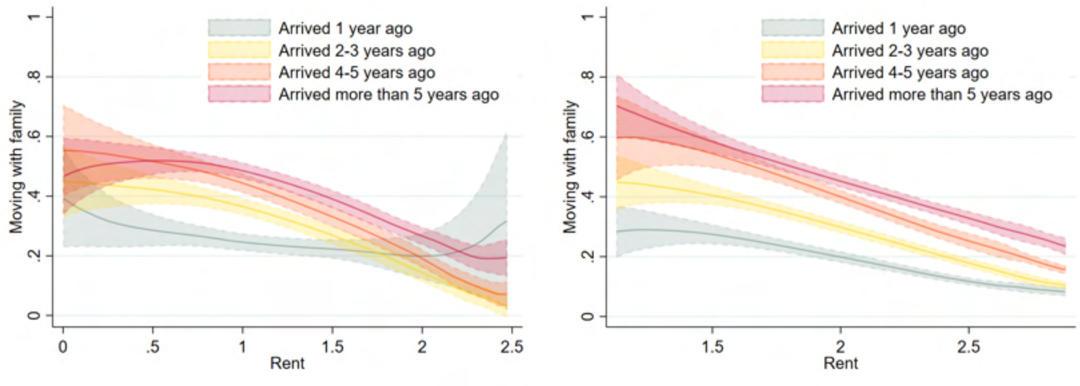
Notes: The x-axis reports a measure of (log) monthly rents constructed using the "2005 Mini-Census." The y-axis reports a measure of remittances as a share of income, r_c, as extracted from CMDS (2011). The orange (resp. blue) lines and bubbles are computed from: the subsample of migrants living with (resp. without) children at destination in panel (a); the subsample of migrants living with (resp. without) relatives at destination in panel (b); and the subsample of migrants living with (resp. without) a spouse at destination in panel (c). A bubble is a prefecture of destination and is weighted by its initial urban population in 2000. The lines are local polynomial fits, where each observation is weighted by population.

the subsample of migrants living with (resp. without) children at destination in panel (a); the subsample of migrants living with (resp. without) relatives at destination in panel (b); and the subsample of migrants living with (resp. without) a spouse at destination in panel (c).

B.6 The dynamics of migration arrangements across cities

Our main evidence presented in Section 2 ignores any possible dynamic adjustment of migration arrangements over the life cycle of migrants and over time. We provided

Figure B.10. Living with children throughout the migration spell.

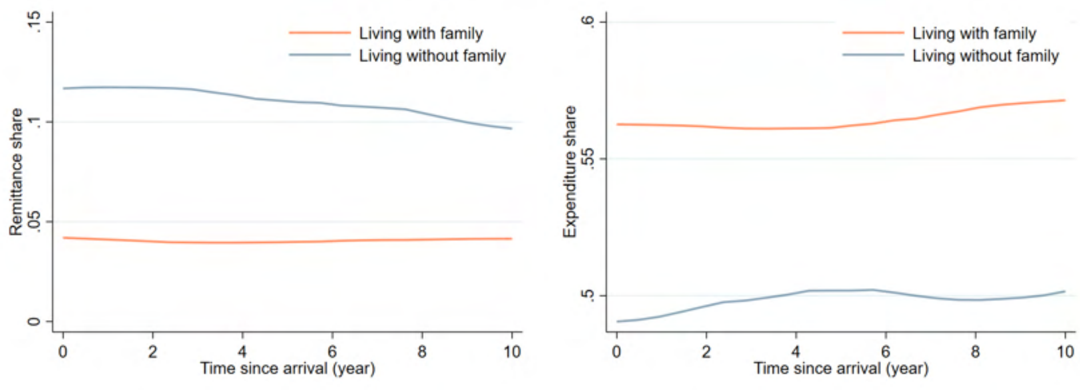


(a) Living with children (2005) (b) Living with children (2010)

Notes: The x-axis reports a measure of (log) monthly rents constructed using the "2005 Mini-Census." The y-axis reports the share of migrants living with family at destination (in 2005 for panel a, in 2010 for panel b). The lines are local polynomial fits, where each observation is weighted by population: The green line is computed for migrants having arrived one year prior to the census (after 2004 in panel a, after 2009 in panel b); the yellow line is computed for migrants having arrived between 2 and 3 years prior to the census; the orange line is computed for migrants having arrived between 4 and 5 years prior to the census; and the red line is computed for migrants having arrived more than 5 years prior to the census.

some insight about the (stable) composition of migrant inflows in Appendix A.2 and Figure A.1 between 2000 and 2010. We now shed light on dynamic adjustment of migration arrangements throughout the migration spell.

Figure B.11. Remittances throughout the migration spell.



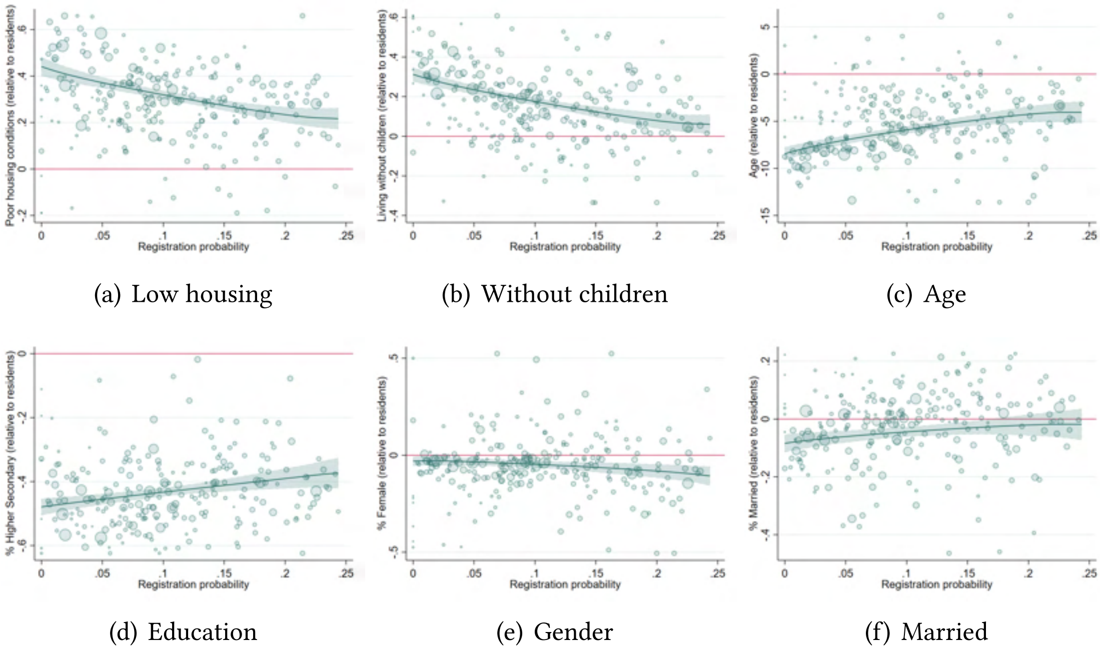
(a) Remittances (b) Expenditures

Notes: The x-axis reports the time since arrival for migrants interviewed in CMDS (2011). In panel (a), the y-axis reports the remittance share for migrants living with family at destination (orange line) and migrants living without family (blue line). In panel (b), the y-axis reports the ratio of expenditures (excluding remittances) to income for migrants living with family at destination (orange line) and migrants living without family (blue line).

Figure B.10 displays the incidence of family migration as a function of the time since arrival (at destination) in 2005 (panel a) and in 2010 (panel b). One concern could be that split migration, e.g., leaving children behind, is a temporary arrangement that does not outlive the time for migrants to accumulate resources and knowledge at destination. In short, migrants might just take longer to bring their family to expensive cities. We do not find evidence for such adjustments: If anything, time appears to matter in the least expensive cities, and the gradient of migration arrangements with prices at destination tilts even further after 4-5 years.

Figure B.11 displays the consumption patterns of migrants with and without family as a function of the time since arrival. While there is some adjustment throughout the migration spell, the gap between migrants with and without family remains large and stable (or converging very slowly), whether we capture it through remittance behaviors (panel a) or through consumption at destination (panel b).

Figure B.12. The selection of migrants relative to residents across cities with different local restrictions.



(a) Low housing (b) Without children (c) Age

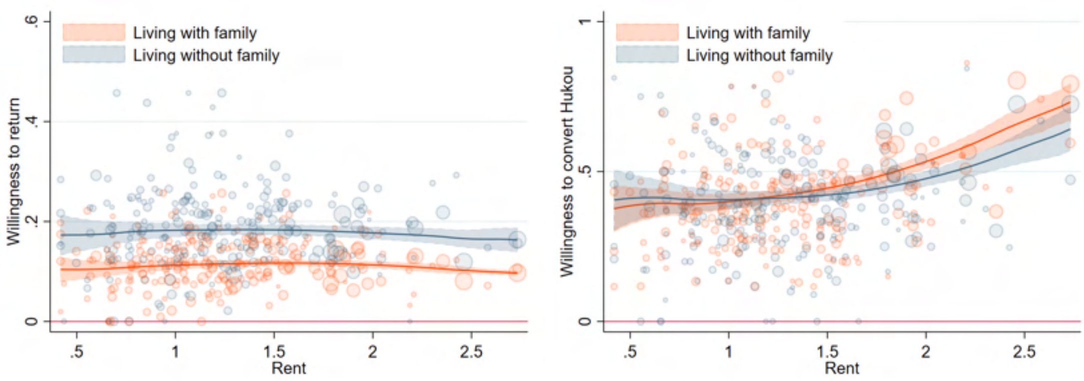
(d) Education (e) Gender (f) Married

Notes: The x-axis reports the probability for rural migrants to convert their *Hukou* registration, as computed from the 2010 Census. In panel (a), the y-axis reports the difference between the share of rural migrants and the share of urban residents who live without children. In panel (b), the y-axis reports the difference between the fraction of rural migrants and the fraction of urban residents who live in poor housing conditions, based on their dwelling characteristics measured in the "2005 Mini-Census." In panel (c), the y-axis reports the difference between the average age of rural migrants relative to that of urban residents. In panel (d), the y-axis reports the difference between the proportion of migrants and the proportion of urban residents who have at least higher secondary education. In panel (e), the y-axis reports the difference between the fraction of migrants and the fraction of urban residents who are female. In panel (f) the y-axis reports the difference between the fraction of migrants and the fraction of urban residents who are married. A bubble is a prefecture of destination and is weighted by its initial urban population in 2000. The lines are local polynomial fits, where each observation is weighted by population.

B.7 Migration patterns and *Hukou* restrictions

We provide some evidence about the selection of migrants and migration patterns across cities with different registration restrictions. To do so, we rely on our main measure of *Hukou* stringency from the 2010 Census: the share of migrants between 15 and 64 years old, who moved for work-related reasons and were born in another county, and who were registered locally with a non-agricultural *Hukou* (in the manner of Wu and You 2021). We then replicate Figure 1 and Figure B.6, but replacing the x-axis with the *Hukou* stringency measure. As apparent in panels (a) and (b) of Figure B.12, living arrangements between migrants and residents are much closer in locations where *Hukou* restrictions are milder (and the probability for rural migrants to convert their *Hukou* registration is higher). The gap in education remains however very large, irrespective of migration restrictions at destination (panel d).

Figure B.13. Future prospects across migration spells.



(a) Return migration

(b) *Hukou* conversion

Notes: The x-axis reports a measure of (log) monthly rents constructed using the "2005 Mini-Census." In panel (a), the y-axis reports the average willingness to return (from CMDS) for migrants who live with their children (orange) and migrants living without children (blue). In panel (b), the y-axis reports the average willingness to convert *Hukou* to the destination location (from CMDS) for migrants who live with their children (orange) and migrants living without children (blue). A bubble is a prefecture of destination and is weighted by its initial urban population in 2000. The lines are local polynomial fits, where each observation is weighted by population.

B.8 Prospects, return migration, and *Hukou* conversion

In Figure B.13, we document the heterogeneity in prospects for migrants living across different destinations and with or without family. More specifically, we exploit questions about the willingness to return for migrants interviewed in the China Migrants Dynamic

Survey (CMDS) and questions about the willingness to convert *Hukou* to the destination location (irrespective of the requirements for doing so).

We find that the share of migrants willing to go back to their origin locations is small (see panel a): About 16% of migrants living without family are willing to return versus 11% of migrants living with family at destination. About 40% of migrants are willing to have their *Hukou* converted to their destination locations, a prospect that is quite unlikely around 2000 but becomes more realistic with the gradual changes in registration policies (culminating in the 2014 reforms). This evidence rationalizes that we do not consider a dynamic model allowing, among other mechanisms, for return migration.

B.9 *Hukou* conversion and robustness to the definition of migration

Our measure of migration relies on the discrepancy between the place of household registration and the place of residence. The possibility for (some) migrants to change their *Hukou* and register at destination thus means that we mis-measure some rural-urban migrants as urban residents in the census. This measurement issue may affect the interpretation of our stylized facts. For instance, the large under-representation of migrants in inexpensive cities visible in Figure 2 (b) may be due to a higher *Hukou* conversion probability; in the notation of Section 2.1, identifying *Hukou* converts correctly would increase m_c (through a decline in R_c and an increase in M_c) at low levels of housing rents.

In this section, we use additional information from the 2005 and 2000 censuses to create alternative measures of migration and check the robustness of our stylized facts. Our baseline measure of migration relies on the following ingredients: (i) the discrepancy between the current place of residence and the place of household registration; (ii) information on the *Hukou* type; and (iii) information on the year of migration (within the past 5 years). *Hukou* conversion poses a challenge for this measure, as it breaks the link between migration and the first two ingredients. Conversely, (iii) is recorded for every respondent. In what follows, we leverage (iii) and complement it with data on the place of birth (in 2000) or on the place of residence 5 years before the census (as a proxy for the place of birth, which is not available in 2005).[8] Since these alternative measures

[8]The latter is an acceptable proxy of birthplace or the place of *Hukou* registration before conversion if step migration is limited. Imbert et al. (2022) show that this was indeed the case in 2000–2005 in China.

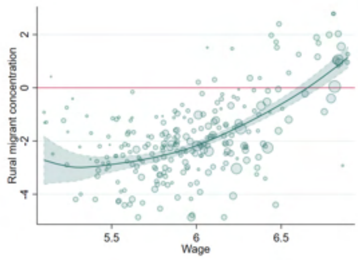
of migrants' origins are recorded at the province rather than at the prefecture level, we also reproduce our main stylized facts considering only (*Hukou*-defined) migration spells across provincial boundaries.

Figure B.14 reproduces Figure 2 (a) and (b), using alternative migration definitions. The alternative migration definitions vary the date at which migration flows are constructed (2005 as in the baseline, or 2000 using the 2000 census), the level at which they are constructed (prefecture-level as in the baseline, or province-level) and the way migrants are identified (*Hukou*-based definition as in the baseline, versus a birthplace-based definition of migration). Across all cases, we observe gradients nearly identical to our first stylized fact.

Similarly, Figure B.15 reproduces Figure 3 (a) and (b), respectively, using alternative migration definitions. We observe that the level and steepness of the fitted polynomials may change slightly, but our second stylized fact remains robust to the change of migration definitions.[9]

[9]Our third and fourth stylized facts rely on remittance data; such information are not available in the censuses.

Figure B.14. Rural migrant concentration—alternative migration definitions.



(a) Wage and migrant concentration (prefecture, *Hukou*, 2005)

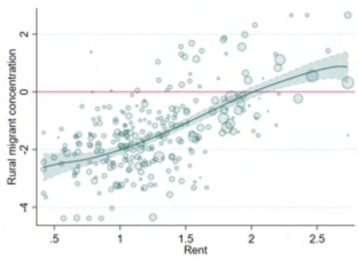
(b) Wage and migrant concentration (province, *Hukou*, 2005)

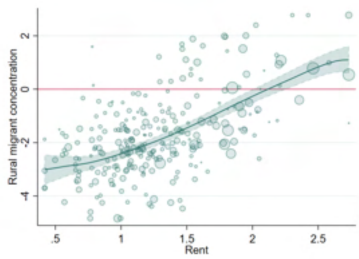
(c) Wage and migrant concentration (province, birthplace, 2005)

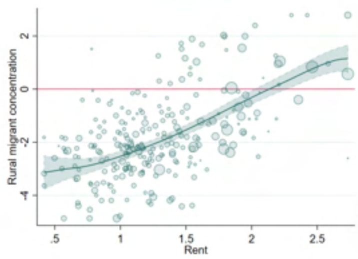
(d) Wage and migrant concentration (prefecture, *Hukou*, 2000)

(e) Wage and migrant concentration (province, *Hukou*, 2000)

(f) Wage and migrant concentration (province, birthplace, 2000)



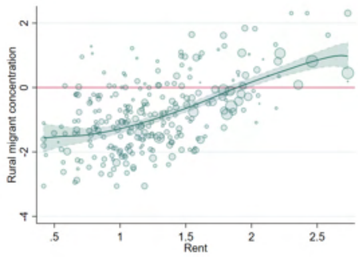


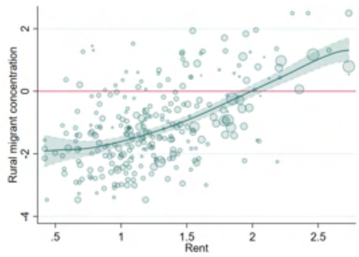


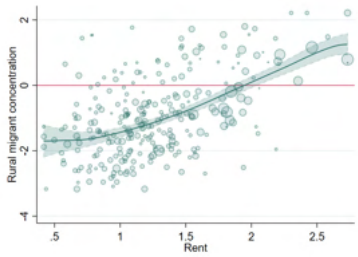
(g) Rent and migrant concentration (prefecture, *Hukou*, 2005)

(h) Rent and migrant concentration (province, *Hukou*, 2005)

(i) Rent and migrant concentration (province, birthplace, 2005)







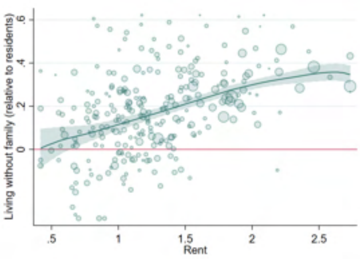
(j) Rent and migrant concentration (prefecture, *Hukou*, 2000)

(k) Rent and migrant concentration (province, *Hukou*, 2000)

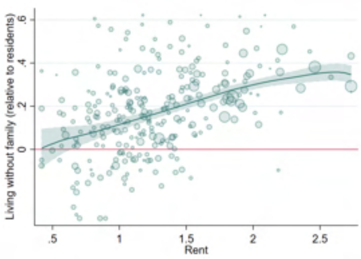
(l) Rent and migrant concentration (province, birthplace, 2000)

Notes: The y-axis reports the migrant concentration in city c, m_c—see Section 2.1. In panels (a) to (f), the x-axis reports a measure of (log) monthly wage. Wages are constructed using the "2005 Mini-Census" in 2005 or the City Statistical Yearbooks in 2000. In panels (g) to (l), the x-axis reports a measure of (log) monthly rent per square meter. Rents are constructed using the "2005 Mini-Census" in 2005 or the 2000 Census in 2000. A bubble is a prefecture of destination and is weighted by its urban population in 2000. The lines are local polynomial fits, where each observation is weighted by population.

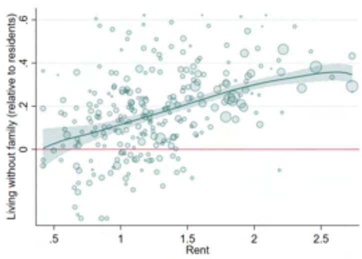
Figure B.15. Migrants, family, and housing conditions—alternative migration definitions.



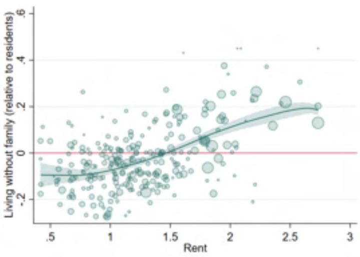
(a) Live without family (prefecture, *Hukou*, 2005)



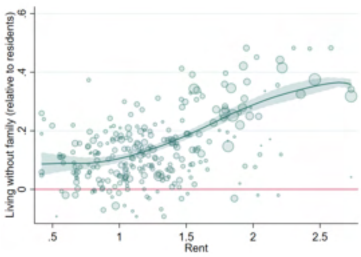
(b) Live without family (province, *Hukou*, 2005)



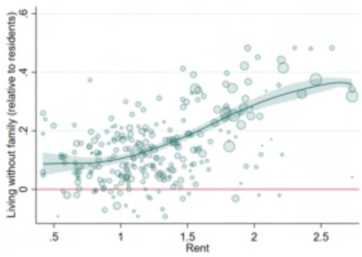
(c) Live without family (province, birthplace, 2005)



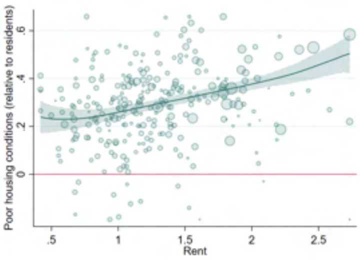
(d) Live without family (prefecture, *Hukou*, 2000)



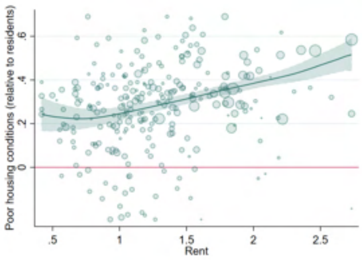
(e) Live without family (province, *Hukou*, 2000)



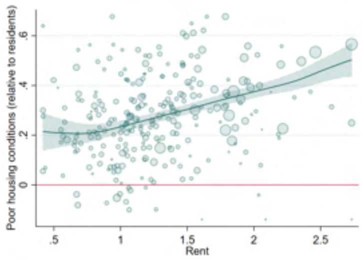
(f) Live without family (province, birthplace, 2000)



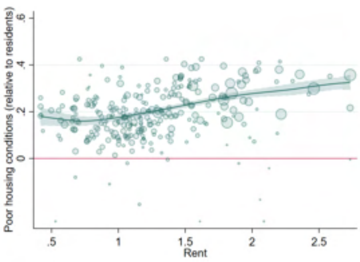
(g) Low-quality housing (prefecture, *Hukou*, 2005)



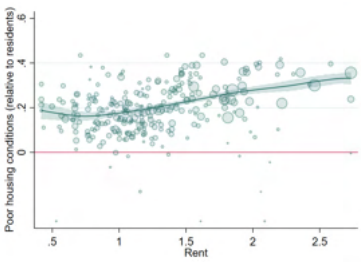
(h) Low-quality housing (prov., *Hukou*, 2005)



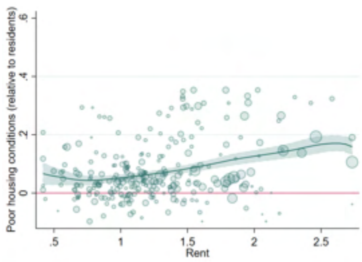
(i) Low-quality housing (province, birthplace, 2005)



(j) Low-quality housing (prefecture, *Hukou*, 2000)



(k) Low-quality housing (prov., *Hukou*, 2000)



(l) Low-quality housing (province, birthplace, 2000)

Notes: The x-axis reports a measure of (log) monthly rents constructed using the "2005 Mini-Census" (2000 Census) for the top (bottom) three panels. The y-axis reports the difference between the share of rural migrants and the share of urban residents who live without family in panels (a) to (f) and the difference between the fraction of rural migrants and the fraction of urban residents who live in poor housing conditions in panels (g) to (l). A bubble is a prefecture of destination and is weighted by its initial urban population in 2000. The lines are local polynomial fits, where each observation is weighted by population.

C Complements to the model

C.1 Model with urban to urban migration

In our baseline model, we assumed for simplicity that urban residents were immobile. In practice, there is some urban-urban migration in China, even if, as Figure 1 makes clear, it is much less important than rural-urban migration. In this section, we expand our model so that urban residents are mobile across locations, which allows us to determine the initial allocation of urban residents as a function of location fundamentals and model parameters.

The fact that there is not much urban to urban mobility around the year 2000 in China, as documented in Figure 1, probably reflects the fact that the gain from moving is much lower for urban residents than for rural ones, rather than limits to mobility. In fact, the rate of conversion to local *Hukou* is much higher among urban movers than among rural ones.

Urban to urban mobility Urban *Hukou* holders decide where to live based on the following utility function:

$$\ln U_{iu} = (1-\alpha)\ln C_T + \alpha \ln C_{NT} + \ln \varepsilon_{iu},$$

subject to standard budget constraint:

$$C_T + p_u C_{NT} \leq w_u,$$

where we use the same notation as the main text, and where we assume that $\alpha_O = 0$. In this context, utility maximization results in the following indirect utility for each individual i with origin u and destination $u' \in U$:

$$\ln V_{juu'} - \tau_{juu'} + \varepsilon_{ijuu'} = \ln w_{u'} - \alpha \ln p_{u'} - \tau_{juu'} + \varepsilon_{ijuu'}$$

This maximization problem results in the following share of workers across locations:

$$\frac{N_{juu'}}{N_{jU}} = \left(\exp(-\tau_{juu'})\frac{V_{juu'}}{V_{jU,u}}\right)^{1/\lambda_U},$$

where $\frac{N_{juu'}}{N_{jU}}$ is the probability for inhabitants of u to j-migrate to u', conditional on j-migrating to any other city in U. In this case, the marginal mover between any two urban locations is indifferent across locations, as is normal in spatial equilibrium models.

We can use this labor supply equation together with the Cobb-Douglas version of the labor demand equation to solve for the initial distribution of urban residents across locations, which, in the baseline model, we took as exogenous:

$$w_u = Z_u \beta N_u^{-(1-\beta)} K_u^{1-\beta} = \tilde{A}_u N_u^{-(1-\beta)}$$

and:

$$p_u = \left(\alpha \frac{w_u}{T_u^H} N_u\right)^{\frac{1}{1+\eta}} = \left(\frac{\alpha}{T_u^H}\right)^{\frac{1}{1+\eta}} N_u^{\frac{\beta}{1+\eta}} = \left(\tilde{T}_u^H\right)^{-1/\alpha} N_u^{\frac{\beta}{1+\eta}}$$

Hence, we can substitute these two equations into V_u to obtain that:

$$V_u = Z_u \tilde{A}_u \tilde{T}_u^H N_u^{-(1-\beta)-\frac{\alpha\beta}{1+\eta}}$$

Hence,

$$V_U = \left[\sum_u \left[Z_u \tilde{A}_u \tilde{T}_u^H N_u^{-(1-\beta)-\frac{\alpha\beta}{1+\eta}}\right]^{1/\lambda_U}\right]^{\lambda_U}$$

These equations define a system of U equations and U unknowns ($N_u, \forall u \in U$) that uniquely determines the distribution of urban residents N_u as a function of fundamentals $\left\{A_u, T_u^H\right\}$ and the main elasticities of the model $\{\lambda_U, \beta, \alpha, \eta_u\}$, as formally shown in Allen and Arkolakis (2014).

Note that we can even get closed-form solutions for the distribution of urban residents as a function of fundamentals.

C.2 Model with multiple skills

In our baseline model, we assumed, for simplicity, that there is only one labor type. In practice, labor may be heterogeneous, and hence captured better with multiple factor types. We discuss here how the model changes when we think about multiple skill types.

Considering multiple skills is probably more important from the perspective of recipient locations than from sending rural communities. It is quite natural to think that, in urban locations, there are many highly qualified jobs that are different in nature than jobs that require fewer/other types of skills.

To address this simplification of our baseline model, we present here an extension with multiple types of labor that follows Amior and Manning (2021), and we investigate how this affects the local labor and housing markets.

Local production As in the main text, we assume that tradable output in location u is produced with the following production function:

$$Y_u = Z_u \left[(1-\beta) K_u^{\frac{\sigma-1}{\sigma}} + \beta L_u^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}};$$

however, in this case, L_u is a labor composite of different types of workers that can be expressed as:

$$L_u = \left[\sum_e \beta_e (L_{ue})^{\frac{\sigma_e-1}{\sigma_e}} \right]^{\frac{\sigma_e}{\sigma_e-1}}.$$

As in the main text, Z_u is the local (exogenous) productivity, K_u denotes capital or land, and the parameter σ denotes the elasticity of substitution between labor and the other factor.

This production function allows us to apply the results in Amior and Manning (2021). For this, we need to assume that each factor can be decomposed between urban residents and (rural) migrants as $L_{ue} = N_{ue} + M_{ue}$. We can denote the fraction of urban residents and migrants in each (e, u) cell as $\nu_{ue} = N_{ue}/N_u$ and $\mu_{ue} = M_{ue}/M_u$. Then, we can rewrite the labor aggregate as:

$$L_u = F(N_{ue} + M_{ue}, \forall e) = \left[\sum_e \beta_e (\nu_{ue} N_u + \mu_{ue} M_u)^{\frac{\sigma_e-1}{\sigma_e}} \right]^{\frac{\sigma_e}{\sigma_e-1}} = F(\nu_{ue} N_u + \mu_{ue} M_u) = Z(N_u, M_u)$$

In this setting, an inflow of migrants, holding the immigrant distribution across factor types fixed, results in the following:

$$\frac{\partial Z(M_u, N_u)}{\partial M_u} = \sum_e \mu_{ue} \frac{\partial F_e(N_{ue} + M_{ue}, \forall e)}{\partial M_{eu}}$$

The effect of a migrant shock will be the weighted average of the effect of migrants to each factor type. Under perfect competition in the labor market, this can be interpreted as the average effect on wages in the location.

Hence, the counterfactuals that we performed should be interpreted as holding the distribution of migrants across skill types fixed in each location.

Local housing markets Having multiple factor types also affects the housing market. With multiple skills, there are multiple wage levels. These different wage levels enter the demand for housing, which is reflected in the market clearing condition of the housing sector:

$$T_u^H (p_u)^\eta = \sum_e \frac{w_{ue}}{p_u} \left[\alpha N_{ue} + \alpha_D M_{ue} \right],$$

We can rewrite this expression as:

$$\ln p_u = \frac{1}{1+\eta} \ln \left[\alpha N_u \left(\sum_e w_{ue} \nu_{ue} \right) + \alpha_D M_u \left(\sum_e w_{ue} \mu_{ue} \right) \right] - \frac{1}{1+\eta} \ln T_u^H.$$

In turn, this expression can be re-written as:

$$\ln p_u = \frac{1}{1+\eta} \ln \left[\alpha N_u \bar{w}_u^N + \alpha_D M_u \bar{w}_u^M \right] - \frac{1}{1+\eta} \ln T_u^H.$$

This expression is very similar to the one in our baseline model, except that we now need to take into account that the average wage of urban residents and immigrants may be different because natives and immigrants may be differently distributed over factor types. However, the main intuition still applies. An immigrant inflow will increase the demand for housing, thereby putting upward pressure on housing prices. At the same time, however, the immigrant shock may affect wages in the city, which in turn, affects the demand for housing. Which of these two forces dominates is, in general, ambiguous.

In this case, the counterfactuals that we perform would need to take into account the potentially heterogeneous effect of migration on average wages of natives and immigrants separately.

D Complements to the model estimation

This section provides complements to Section 4: (a) we first describe the identification of the elasticity of substitution between consuming at origin and at destination, ρ; (b) we identify the shape parameters of the location choice model and we describe how we extract exogenous variation in the relative value of emigrating with family; and (c) we estimate the labor demand and housing supply elasticities.

D.1 A composite price index

Section 4.1 relies on the estimation of the elasticity of substitution between consuming the non-tradable good across locations. The average (log) expenditure share on remittances in city u, $\ln(\mathcal{E}_u)$, is related to local housing prices, p_u, as follows:

$$\ln(\mathcal{E}_u) = \ln\alpha + \ln\alpha_O + (\rho - 1)\ln p_u + e_u.$$

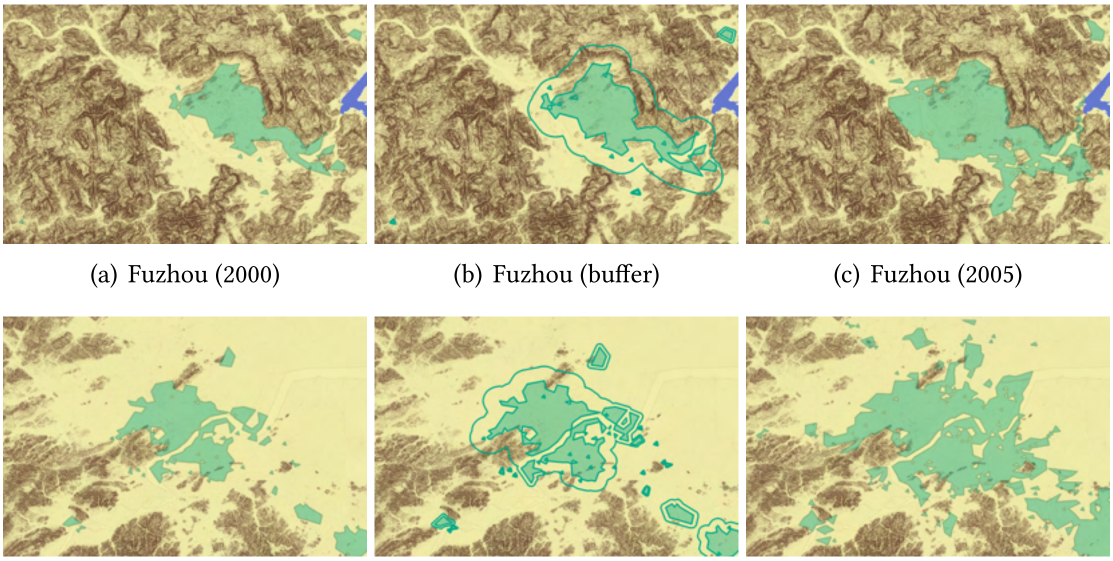
We now describe how we construct a housing-price shifter.

Exogenous variation in housing supply We exploit exogenous variation in housing supply across destinations to predict variation in the price of non-tradables (i.e., housing services). To do so, we identify the shape of cities before our episode of mass migration, and we precisely characterize topography in their immediate hinterlands.

We proceed in three steps. In a first step, we draw on the identification of impervious areas by the Beijing City Lab in 2000 to identify the urban extent of each city within a given prefecture. In a second step, we construct a city-specific buffer, the extent of which is calibrated to ensure that all cities grow proportionally, and homogeneously in all directions (Harari 2020). In a third step, we identify water coverage and the local ruggedness within this buffer of potential urban sprawl. In our baseline strategy, we calculate the share of non-developable land within this land stretch for city u, s_u, by classifying a pixel of 30m × 30m as "non-developable" if the average slope is above 5 degrees.

Figure D.1 provides insight about the construction of the instrument and the variation that it induces across urban areas. Fuzhou and Hangzhou are two historical cities. As shown in panels (a) and (d) of Figure D.1, they markedly differ in constraints to their

Figure D.1. An example of our procedure with Fuzhou and Hangzhou.



(a) Fuzhou (2000) (b) Fuzhou (buffer) (c) Fuzhou (2005)

(d) Hangzhou (2000) (e) Hangzhou (buffer) (f) Hangzhou (2005)

Notes: Shapefiles of impervious areas, as identified from Landsat satellite imagery, are provided by the Beijing City Lab—see https://www.beijingcitylab.com/—and are indicated as plain green areas (2000 in panels a-b and d-e, 2005 in panels c and f). The green line in panels b and e corresponds to urban sprawl, as predicted by a uniform growth across cities and within cities across all directions.

expansion before mass migration: Fuzhou is in a valley along the Min River and is surrounded by steep hills (especially in the north), while Hangzhou is located in a plain with a few scattered hills. Fuzhou would need to build on a very large share of "non-developable" land if it were to expand in all directions and as much as the average Chinese city (panel b). Hangzhou, on the other hand, would face very limited constraints (panel e). In 2005, we find indeed that Fuzhou experienced an unbalanced urban sprawl concentrated toward the south, while Hangzhou sprawled massively in every direction.

Elasticity of substitution between consuming at origin and destination We use the previous instrument, i.e., the share of developable land at the fringe of cities, to identify the elasticity of substitution between consuming at origin and destination. We rely on the following specification,

$$\ln\left(\mathcal{E}_u\right) = a + (\rho - 1)\ln p_u + \mathbf{X}_u \beta + e_u,$$

where u is a city, $\ln\left(\mathcal{E}_u\right)$ is the average (log) expenditure share on remittances, and p_u is the average rent, both inferred from the "2005 Mini-Census." We use our previous geo-

Table D.1. Estimates of ρ—first-stage.

	Rent (log)
Share of non-developable land	1.857
	(0.458)
Share of non-developable land × TFP	0.905
	(0.522)
Observations	199

Notes: A unit of observation is a prefecture. Robust standard errors are reported between parentheses. The specification uses population weights in 2000. The dependent variable is the (log) rent, computed using the housing module of the "2005 Mini-Census." The (log) rent is instrumented by (i) the share of developable land as induced by local geography around city borders in the baseline period (an instrument based on the work by Saiz 2010, Harari 2020) (2000-2005) and (ii) its interaction with manufacturing Total Factor Productivity in 2000 (Imbert et al. 2022). The set of controls consists of: manufacturing Total Factor Productivity in 2000, the share of developable land as induced by local geography around city borders before the baseline period (1995-2000), and (log) population in 2000.

graphical variation to construct two instruments: (i) s_u, the share of developable land as induced by local geography around city borders in the baseline period, and (ii) its interaction with (log) manufacturing Total Factor Productivity in 2000 (Imbert et al. 2022). The specifications reported in Table 3 thus include (log) manufacturing Total Factor Productivity in 2000 and (log) population at destination as separate controls. Table D.1 shows the first-stage estimates.

The identification assumption is that local geography at the fringe of cities only affects expenditures on housing through local housing prices, and that it does so more acutely in highly productive cities. One concern is that local geography could affect the type of housing arrangements (dorms, informal housing, etc.) and that local housing prices might be contaminated by such variation. In unreported robustness checks, we further correct for housing arrangements in the construction of local housing prices without finding any significant differences in our final estimates.

D.2 Estimation of the location choice model

The location choice model of Section 4.2 is characterized by three nests and three associated specifications.

The lower nest (λ_1, λ_2) and its gravity structure In Section 4.2, we estimate a simple model of location choice across destinations for workers migrating with and without family (see Table 4). The identification of the lower nest relies on a productivity shifter that impacts real wages at destination. This productivity shifter is constructed as follows. The National Bureau of Statistics (NBS) provides a longitudinal census of all state-owned manufacturing enterprises (SOEs) and all non-SOEs manufacturing establishments, as long as their annual sales exceed RMB 5 million. We use the NBS data to estimate total factor productivity in 2000 following Imbert et al. (2022). The productivity shifter is constructed as the residual of the following equation:

$$y_i = Z_i f(k_i, l_i),$$

where i is a manufacturing firm and the function f is a CES production function (consistent with our present modeling of the tradable sector). We then construct a measure z_u of the average (log) productivity, $\ln Z_i$, across the various manufacturing firms within a given prefecture u. In principle, this industrial shifter to labor productivity at destination is driven by persistent patterns in industrial activity across space and more likely to be orthogonal to local (unobserved) amenities.

Table D.2. The lower nest (λ_1, λ_2)—first-stage.

Value at destination	(1)	(2)
Total Factor Productivity	0.118	0.126
	(0.064)	(0.058)
Trade shock	2.122	1.864
	(0.414)	(0.385)
Migration type	$j = 1$	$j = 2$
Observations	48,438	48,438

Notes: A unit of observation is a pair of origin/destination prefectures in 2005. The specification uses population weights at origin in 2000. Standard errors are reported between parentheses and clustered at the level of origins. The dependent variable is the value at destination calculated for migrants leaving their family at origin ($j = 1$, column 1) and for migrants bringing their family at destination in columns (2) ($j = 2$). The set of controls consists of: (log) population at destination in 2000 and (log) geodesic distance between the origin and destination prefectures. The explanatory variables are manufacturing Total Factor Productivity at destination in 2000 (Imbert et al. 2022) and a trade shock computed following Facchini et al. (2019).

We provide the first-stage specification underlying the estimations of the lower nest in Table D.2. Both the productivity shifter z_u and the trade shock (Facchini et al. 2019) are strong predictors of real wages across destinations—irrespective of the manner in which real wages are computed (using a family-based composite price index, $\mathcal{P}$, or not). We obtain similar results irrespective of using either one or the other instrument, or both.

The middle nest (μ) The middle nest of our nested structure can be identified through the decision of moving with or without family, given the relative value of migrating with and without the family from each origin r, $\ln\left(V_{2U,r}/V_{1U,r}\right)$. More specifically, the relative incidence of family emigration verifies:

$$\ln\left(\frac{\pi_{2r}^{c}}{\pi_{1r}^{c}}\right) = \frac{1}{\mu}\ln\left(\frac{V_{2U,r}}{V_{1U,r}}\right),$$

where $\pi_{jr}^{c} = \sum_u \pi_{jru}^{c}$ is the emigration rate of migrants of mode j from origin r, conditional on emigrating from r. The relative value of family migration across origins r can be written as follows:

$$\ln\left(\frac{V_{2U,r}}{V_{1U,r}}\right) = \ln\left(\frac{\left[\sum_{u\in U}\left(\exp\left(-\tau_{2ru}\right)V_{2ru}\right)^{1/\lambda_2}\right]^{\lambda_2}}{\left[\sum_{u\in U}\left(\exp\left(-\tau_{1ru}\right)V_{1ru}\right)^{1/\lambda_1}\right]^{\lambda_1}}\right).$$

We use the parameters $(\rho, \alpha, \alpha_{1O}, \alpha_{2O}, \lambda_1, \lambda_2, A_u)$ and the residual migration costs (τ_{jru}) from the lower nest estimation to compute the relative value of migrating with and without the family from each origin r, $\ln\left(V_{2U,r}/V_{1U,r}\right)$. More precisely, the residual migration costs are defined in relative terms. For each rural origin r, we take one reference destination $\bar{u}$ and compute $\pi_{jru}^{c}/\pi_{jr\bar{u}}^{c} = \left[\exp(-\tau_{jru})V_{jru}/\exp(-\tau_{jr\bar{u}})V_{jr\bar{u}}\right]^{\frac{1}{\lambda_j}}$. Re-arranging yields the relative τ: $\exp(-\tau_{jru})/\exp(-\tau_{jr\bar{u}}) = \left[\pi_{jru}^{c}/\pi_{jr\bar{u}}^{c}\right]^{\lambda_j} V_{jr\bar{u}}V_{jru}$. In what follows, we simplify the notation and write $V_{2U,r}/V_{1U,r}$, although at this step of the estimation we can only reconstruct $V_{2U,r}/V_{1U,r} \times \exp(-\tau_{1r\bar{u}})/\exp(-\tau_{2r\bar{u}})$. The estimation of γ—see below—will allow us to recover the absolute τ's and V's.

We can see from the structure of these values that they interact a gravity-driven component (τ_{jru}) with a composite attractiveness of destinations for migrants with or without family (V_{jru}). Both objects are black boxes combining many different, unobservable factors. Our main strategy thus consists in keeping a gravity structure, but leveraging exogenous variation in the relative attractiveness of destinations.

The relative value of residing at destination u with or without the family might be contaminated by measurement error or by omitted variation. For instance, this value should be strongly predicted by *hukou* stringency or prices at destination. These *hukou* restrictions and prices are, however, endogenous to migration flows: Many cities implemented severe restrictions in expectation of large immigration from their rural hinterlands; and prices typically respond to migration inflows or to omitted variation affecting immigrant flows.

In a first step, we rely on exogenous variation in prices at destination that differentially affect migrants with family and without. More specifically, we create a measure of predicted wages in cities by regressing observed wages on manufacturing Total Factor Productivity at destination in 2000 (Imbert et al. 2022) and a trade shock computed following Facchini et al. (2019); we create a measure of predicted rents in cities based on the share of developable land as induced by local geography around city borders; and we combine these two prices to extract a measure of real wages, $\hat{\omega}_{ju}$, per migration mode j, accounting for differential consumption of non-tradables at destination. This first instrument is then:

$$z_r^1 = \ln \frac{\sum_{u \in U} \xi_{ru} \hat{\omega}_{2u}}{\sum_{u \in U} \xi_{ru} \hat{\omega}_{1u}},$$

which is a gravity-weighted—ξ_{ru} captures the baseline emigration incidence from an origin r to destination u—combination of relative real wages, as induced by exogenous variation in prices across destinations.

The second step of our approach consists in extracting a backward-looking, exogenous predictor of restrictions: the relative level of grain reserves before 2000, as in Zhang et al. (2020). The rationale goes back to Mao Zedong's conception of development, a major tenet of which was local self-sufficiency in grain. This tenet can be seen from the Great Leap Forward (1958–1960) to the Cultural Revolution (1966–1976) and partly owes to the severe constraints on the non-market allocation of resources in a poor country with limited communications and state capability (see, e.g., Riskin 1981). China, as many Communist countries, had a rigid system to allocate resources, but its low level of development put limits on how centralized this system could be, and reallocation of resources across sub-regional administrative units was kept to a minimum. The opening of the Chinese economy in the 1990s and the 2000s was expected to generate significant migration flows, which could further strain the allocation of resources. For this reason, the initial disparity in *hukou* stringency reflected the capacity of a prefecture to sustain its population without external intervention. As food provision became completely separated from household registration only in 2000, cities indeed had to maintain the agricultural capacity to nourish their population, including migrants (Cai et al. 2001).[10] We leverage this variation by considering the level of grain reserves before 2000, g_u, as a predictor of *hukou* stringency.[11] We combine this variation g_u with the (baseline) migration incidence from an origin r to possible destinations u, ξ_{ru}, in a gravity structure mimicking the previous equation to construct an instrument z_r^2 for the relative value of family migration:

$$z_r^2 = \ln \sum_{u \in U} \xi_{ru} g_u,$$

following the same gravity structure exhibited by the relative value of migrating with and without the family.

Table D.3. The middle nest (μ)—first-stage.

Value of family migration	(1)	(2)	(3)
Exposure to high relative real wages (z_r^1)	0.152		0.139
	(0.036)		(0.035)
Exposure to grain reserves (z_r^2)		0.127	0.094
		(0.043)	(0.039)
Observations	180	180	180

Notes: A unit of observation is a prefecture. Robust standard errors are reported between parentheses. The specification uses population weights in 2000. The dependent variable is the relative value of family migration. The explanatory variables are gravity-based measures combining predicted real wages from TFP and from trade and land supply shocks, $\hat{\omega}_{ju}$ (per mode j), and based on the relative level of grain reserves before 2000, g_u. In column (1), the instrument is z_r^1; in column (2), the instrument is $z_r^2 = \sum_{u \in U} g_u \xi_{ru}$; and we include both instruments, z_r^1 and z_r^2, in column (3). The set of controls consists of: dummies for each decile in the level of grain reserves within the prefecture before 2000, the manufacturing Total Factor Productivity at origin in 2000 (Imbert et al. 2022), a trade shock computed following Facchini et al. (2019), a local price shock as induced by international crop prices (Imbert et al. 2022), and the share of developable land as induced by local geography around city borders before the baseline period (1995-2000).

We provide the first-stage specification underlying the estimations of the middle nest in Table D.3. As shown in columns (1) and (3), prices at the typical destination do predict the relative value of family migration. Local grain sufficiency in the 1990s is also a strong

[10] This policy implied huge costs from misalignment with local comparative advantage. The mark left by the Great Famine and its handling by the Central Government (Meng et al. 2015) may however have made this policy palatable to local decision makers, because of the risks of relying on outside supplies of grain.

[11] We proxy g_u with per capita grain output in 1990 from the Statistical Yearbooks.

predictor of the relative value of family migration (see columns 2 and 3).

The upper nest (γ) The identification of the upper nest (γ) of the location model relies on the following equation:

$$\ln\left(\frac{1-\pi_{rr}}{\pi_{rr}}\right) = \frac{1}{\gamma}\ln\left(\frac{V_{U,r}}{V_{rr}}\right).$$

We consider the following empirical counterpart:

$$\ln\left(\frac{1-\pi_{rr}}{\pi_{rr}}\right) = a + b\ln\left(\frac{V_{U,r}}{V_{rr}}\right) + \varepsilon_r,$$

where $V_{U,r}$ is the value of migrating from location r:

$$\ln V_{U,r} = \ln\left[\sum_{j\in\{1,2\}}\left(V_{jU,r}\right)^{1/\mu}\right]^{\mu},$$

and V_{rr} is the real wage in origin location r:

$$\ln V_{rr} = \ln w_r - \alpha \ln p_r.$$

Constructing V_{rr} is straightforward, but the construction of the value $V_{U,r}$ is more involved and relies on the estimates of μ, $V_{1U,r}$ and $V_{2U,r}$ from the estimation of the middle nest. Recall that we were only able to recover $V_{jU,r}/\exp(-\tau_{jr\bar{u}})$ from this earlier step. We now consider migration without family as a reference and note that:

$$\frac{\pi^c_{2rU}}{\pi^c_{1rU}} = \left(\frac{V_{2U,r}}{V_{1U,r}}\right)^{\frac{1}{\mu}}.$$

Using this equation, we can recover:

$$\frac{V_{2U,r}}{\exp(-\tau_{1r\bar{u}})} = \left(\frac{\pi^c_{2rU}}{\pi^c_{1rU}}\right)^{\mu} \times \frac{V_{1U,r}}{\exp(-\tau_{1r\bar{u}})},$$

which we use to compute:

$$\frac{V_{U,r}}{\exp(-\tau_{1r\bar{u}})} = \left[\sum_{j\in\{1,2\}}\left(\frac{V_{jU,r}}{\exp(-\tau_{1r\bar{u}})}\right)^{1/\mu}\right]^{\mu}.$$

We will denote the previous quantity as $V_{U,r}$ for the time being, noting once again that only the estimation of γ will allow us to recover all the τ's and the V's—see below.

We instrument the relative value, $V_{U,r}/V_{rr}$, with exogenous shocks to agricultural productivity across possible origins by combining international commodity prices with local cropping patterns (in the manner of Imbert et al. 2022). We first collect Agricultural Producer Prices data (APP, 1991–2016) from the FAO: The data report producer prices at the farm gate in each producing country. For any given crop, we aggregate these country-specific prices into a yearly, international producer price as a weighted average across countries using the baseline share in crop-specific exports as the country/crop weight.[12] We then clean these (log) international producer prices from long-run trends by applying a HP filter (see Imbert et al. 2022) and isolating the residual, d_{ct}, for any given year t and commodity c.

Table D.4. The upper nest (γ)—first-stage.

Relative value of emigration	(1)	(2)
Agricultural revenue shock	-9.815	-10.656
	(1.780)	(2.344)
Observations	258	187
Controls	No	Yes

Notes: A unit of observation is a prefecture. Robust standard errors are reported between parentheses. The specification uses population weights at origin in 2000. The dependent variable is the relative value of emigration. The set of additional controls consists of: dummies for each decile in the level of grain reserves within the prefecture before 2000, the manufacturing Total Factor Productivity at destination in 2000 (Imbert et al. 2022), a trade shock computed following Facchini et al. (2019), and the share of developable land as induced by local geography around city borders. The instrument interacts cropping patterns in 2000 with the HP-filtered prices of agricultural commodities in 2000 (as in Imbert et al. 2022).

These international commodity prices affect agricultural hinterlands differently, depending on local cropping patterns. We exploit this intuition and combine international prices with the revenue share of crop c at origin r in a shift-share design. More specifically, we need the following ingredients to construct a revenue share for each crop: (i) a measure of output (e.g., as measured in tonnes) across locations; and (ii) a price per

[12] We focus on the following 21 crops (commodities): banana, cassava, coffee, cotton, fodder crops (barley), groundnut, maize, millet, other cereals (oats), potato, pulses (lentil), rapeseed, rice, sorghum, soybean, sugar beet, sugar cane, sunflower, vegetables (cabbage), tea, and wheat. The international price of these commodities is disciplined by World demand and World supply, and China is a large World supplier for a few crops. The most obvious one is tobacco, where China is the leading producer and one company enjoys a local monopoly; we thus exclude tobacco from our agricultural productivity measures.

tonne. We construct a measure of output by multiplying local harvested areas in 2000 (a measure "in acres") with a local predicted yield (a measure "in quantity per acre"). The harvested areas are provided by the World Census of Agriculture 2000 and the predicted yield is constructed within the Global Agro-Ecological Zones project. Nesting these measures within Chinese prefectures requires some geographic approximation that is best described in Imbert et al. (2022). We weight this predicted output in 2000 by the baseline commodity price in 1980 to construct a revenue share for each crop, α_{cr}, which is orthogonal to later deviations in international prices. Letting d_c denote the previous price residual at a period of interest, our agricultural productivity shock, ω_r, will be defined as:

$$\omega_r = \sum_c \alpha_{cr} \times d_c.$$

The estimates reported in Table 6 rely on a two-stage specification where we instrument the real wage w_r with ω_r. We provide the first-stage specification underlying the estimations of the upper nest in Table D.4. The agricultural revenue shock from Imbert et al. (2022) is a strong predictor of the relative value of migrating across origins ($\frac{V_{U,r}}{V_{rr}}$).

Finally, using the estimated parameter γ, we can compute,

$$\exp(-\tau_{1r\bar{u}}) = [(1 - \pi_{rr})/\pi_{rr}]^{\gamma} \times \exp(-\tau_{1r\bar{u}})/V_{U,r} \times V_{rr},$$

and reconstruct the (absolute) migration frictions, τ_{jru}, which we use in our mapping of Section 4.3 and our counterfactual exercises of Section 5. Based on these τ's, we can also recalculate the "true" value functions, and re-estimate the middle and the upper nests. The estimates of μ and γ are virtually unchanged.

D.3 Labor demand and housing supply at destination

The identification of the production block of the model requires exogenous variation in migrant inflows to estimate their effect at destination. The previously-described, exogenous variation in local conditions at origin ω_r allows us to predict emigration from a certain location into a particular destination. We leverage these agricultural revenue shocks (ω_r) to isolate exogenous variation in immigrant flows across the destinations following the shift-share procedure developed in Imbert et al. (2022). More specifically, we combine exogenous shocks to rural incomes in each prefecture of origin (shifts) with

Table D.5. Labor demand and housing supply elasticities—first-stage.

Immigration rate	(1)	(2)
Shocks at the typical origin	-1.324	-0.864
	(0.267)	(0.170)
Observations	216	252

Notes: A unit of observation is a prefecture. Robust standard errors are reported between parentheses. The specification uses population weights at origin in 2000. The dependent variable is the immigration rate between 2000 and 2005, computed using the migration module of the "2005 Mini-Census." The set of baseline controls consists of: (log) population in 2000 and the agricultural shocks at the typical origin associated with the prefecture before the period of interest (1995-2000). We add the following controls in column (1): the manufacturing Total Factor Productivity at destination in 2000 (Imbert et al. 2022), and a trade shock computed following Facchini et al. (2019). We add the following controls in column (2): the (log) migrant population in 2000, the share of developable land as induced by local geography around city borders before the baseline period (an instrument based on the work by Saiz 2010, Harari 2020, see Appendix D.1), and their interaction. The instrument exploits agricultural shocks between 2000–2005 at the typical origin associated with the prefecture (as in Imbert et al. 2022).

a gravity matrix based on distance between each origin and each potential prefecture of destinations (shares):

$$z_u = \sum_{r \in R} \left(\frac{1}{d_{ru}} \right) \omega_r,$$

relying on the same gravity structure exploited in Appendix D.2 but nested across destinations (rather than origins).

To estimate the (inverse) labor demand elasticity, we use Equation (2) in the paper and derive an empirical counterpart as follows. We consider the equation in difference between 2000 and 2005 in order to clean for unobserved, fixed heterogeneity across destinations indexed by u:

$$\Delta \ln w_u = -\frac{1}{\sigma} m_u + \mathbf{X_u} \delta + \varepsilon_u, \tag{1}$$

where $\Delta \ln w_u$ is the change in (log) wages between 2000 and 2005, $m_u = \ln(1 + M_u/N_u)$ is the immigrant-driven population change during the period, and $\mathbf{X_u}$ is a vector of controls. To identify the elasticity of substitution between labor and other factors, we exploit an agriculture-based shock that pushes migrants at the typical origin of destination u (in a shift-share design, closely following Imbert et al. 2022, see also Appendix D.2). As the nature of the push shock relates to rural cropping patterns and the price of agricultural commodities, the identification relies on the assumption that crop production only affects urban production through rural-urban migration. A similar approach can be used

Table D.6. Labor demand and housing supply elasticities.

	Wage			Rent		
	(1)	(2)	(3)	(4)	(5)	(6)
Immigration rate	-0.131	-0.128	-0.198	0.084	0.454	0.163
	(0.055)	(0.061)	(0.164)	(0.078)	(0.123)	(0.564)
Observations	216	216	216	252	252	252
Controls	No	Yes	Yes	No	Yes	Yes
Instrument	No	No	Yes	No	No	Yes
F-stat	-	-	27.31	-	-	24.88

Notes: A unit of observation is a prefecture. Robust standard errors are reported between parentheses. The specification uses population weights at origin in 2000. The explanatory variable is the relative immigration rate between 2000 and 2005, computed using the migration module of the "2005 Mini-Census." The set of baseline controls consists of: (log) population in 2000 and agricultural shocks at the typical origin associated with the prefecture before the period of interest (1995-2000). We add the following controls in columns (1) to (3): the manufacturing Total Factor Productivity at destination in 2000 (Imbert et al. 2022), and a trade shock computed following Facchini et al. (2019). We add the following controls in columns (4) to (6): the (log) migrant population in 2000, the share of developable land as induced by local geography around city borders before the baseline period (an instrument based on the work by Saiz 2010, Harari 2020, see Appendix D.1), and their interaction. The instrument exploits agricultural shocks between 2000–2005 at the typical origin associated with the prefecture (as in Imbert et al. 2022, see also Appendix D.2).

to estimate the elasticity of housing supply. We difference out Equation (4) of the paper between 2000 and 2005 to obtain:

$$\Delta \ln p_u = \frac{1}{1+\eta}\left(\Lambda - \frac{1}{\sigma}\right) m_u + \mathbf{X_u}\delta + \varepsilon_u, \tag{2}$$

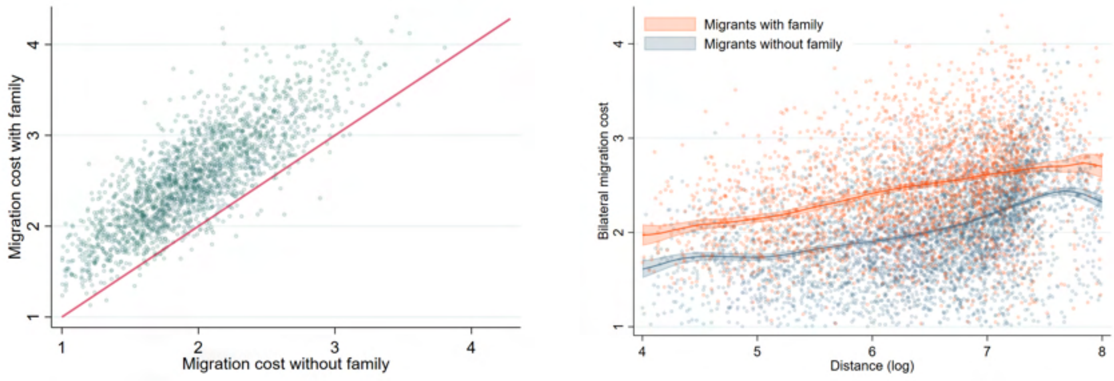
where $\Delta \ln p_u$ is the change in (log) rents between 2000 and 2005 and m_u is instrumented with the previous shift-share instrument.

We report the first-stage estimates in Table D.5. We report our preferred estimates for the labor demand and housing supply elasticities in in Table D.6 (columns 3 and 6). The labor demand elasticity is close to the one reported in Imbert et al. (2022), $1/\sigma \approx 0.2$. The housing supply elasticity can be computed from $\left(\Lambda - \frac{1}{\sigma}\right) / (1 + \eta_u) = 0.163$, which implies that $\eta = 2.4$.

D.4 A decomposition of migration costs

This section provides complements to Section 4.3. More specifically, we shed light on the variation underlying our inferred migration frictions, $\left\{\tau_{jru}\right\}_{j,r,u}$, most notably their relationship with observable characteristics, e.g., distance between origins and destinations or disamenities at destination such as pollution or urban sprawl/commuting costs.

Figure D.2. Bilateral migration costs and distance.



(a) Overall distribution (b) Geographic distance

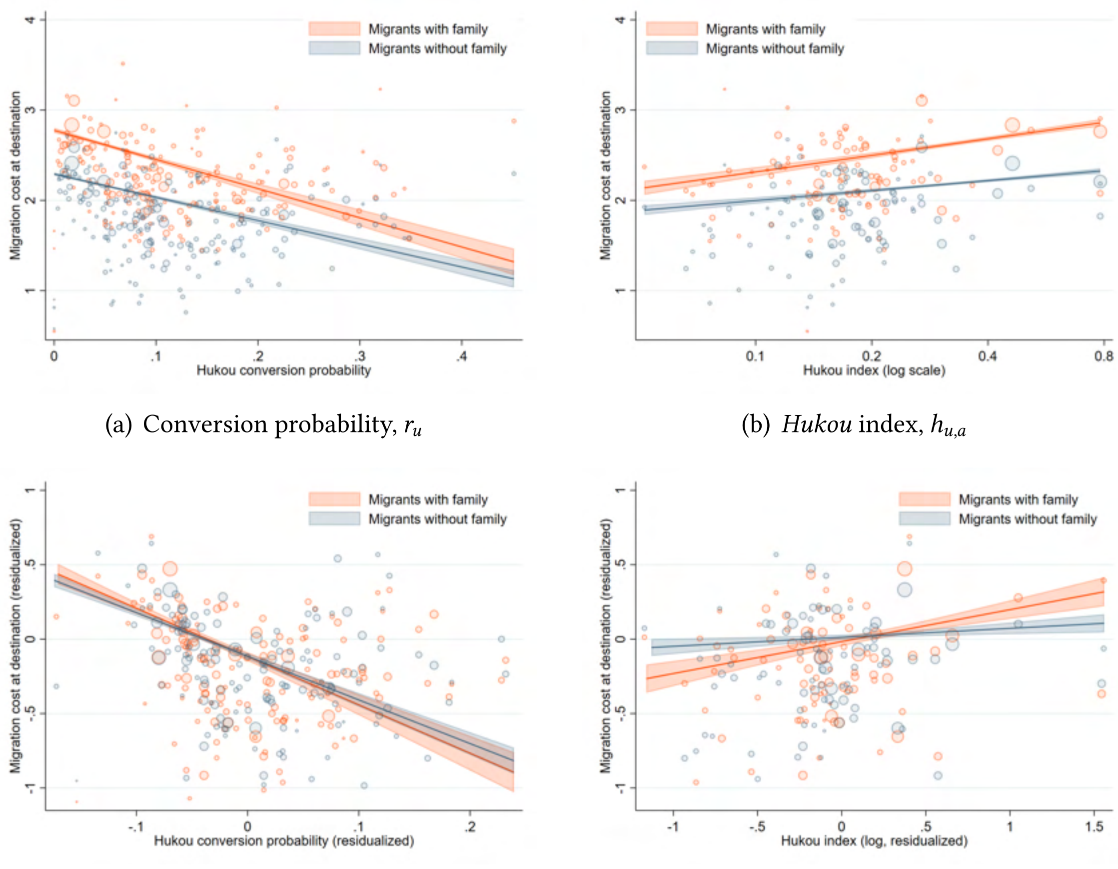
Notes: Panel (a) plots the bilateral migration costs for family migration (y-axis, τ_{2ru}) against the bilateral migration costs for non-family migration (x-axis, τ_{1ru}). Panel (b) plots these bilateral migration costs against the (log) distance between origin r and destination u. The lines are local polynomial fits.

We first shed light on the distribution of bilateral migration costs for family migration (τ_{2ru}) and non-family migration (τ_{1ru}) in panel (a) of Figure D.2 and their relationship with (log) distance between origins and destinations in panel (b). We find that migration systematically induces higher costs for family spells than for non-family ones, and such costs are markedly higher when destinations are distant from origins (panel b). These findings reflect the relatively low incidence of family migration and the observed geographic gravity in movements across Chinese prefectures.[13]

We then illustrate the relationship between migration policies and migration barriers in Figure D.3, where we plot the average disamenity, τ_{ju}, for family ($j = 2$) versus non-family migrants ($j = 1$) against two alternative measures of *hukou* stringency or leniency: the share of migrants who had converted their *hukou* registration place to the local prefecture in 2010, and the composite *hukou* stringency index developed by Zhang

[13]Our estimates of migration costs are comparable to those of Bryan and Morten (2019) and Tombe and Zhu (2019). It is worth noting two things. First, Tombe and Zhu (2019) do not take into account the 0s in the migration matrix when estimating the elasticity of substitution across destinations. This attenuates the estimates of $1/\lambda$ which mechanically leads to higher estimates of migration costs. Second, when reporting average migration costs (as these two papers do), it is also important to think about the role of 0s. The model interprets zero migration flows between an origin and a destination as infinite migration costs (or as costs that equal to 100 percent of the wage at destination). Hence, whether the data set has more or less 0s, which may be related to data collection rather than true migration costs, has a strong influence on reported average migration costs. This explains why we do not emphasize the level of our estimates as much as its heterogeneity.

Figure D.3. Relative cost of family migration and *hukou* stringency.



(a) Conversion probability, r_u

(b) *Hukou* index, $h_{u,a}$

(c) Conversion probability, r_u (res.)

(d) *Hukou* index, $h_{u,a}$ (res.)

Notes: This Figure plots the correlation between the average disamenity estimates, τ_{ju}, for family ($j = 2$) versus non-family migrants ($j = 1$) across destinations against two alternative measures of *hukou* stringency: the share of migrants having converted their *hukou* in 2010 in panel (a); the composite *hukou* stringency index developed by Zhang et al. (2018) in panel (b); the residualized share of migrants having converted their *hukou* registration place to the local prefecture in 2010, r_u (panel c); and the residualized *hukou* stringency index developed by Zhang et al. (2018), $h_{u,a}$ (panel d). The residualized measures are obtained by regressing them on local population in 2000, local pollution, and commuting time.

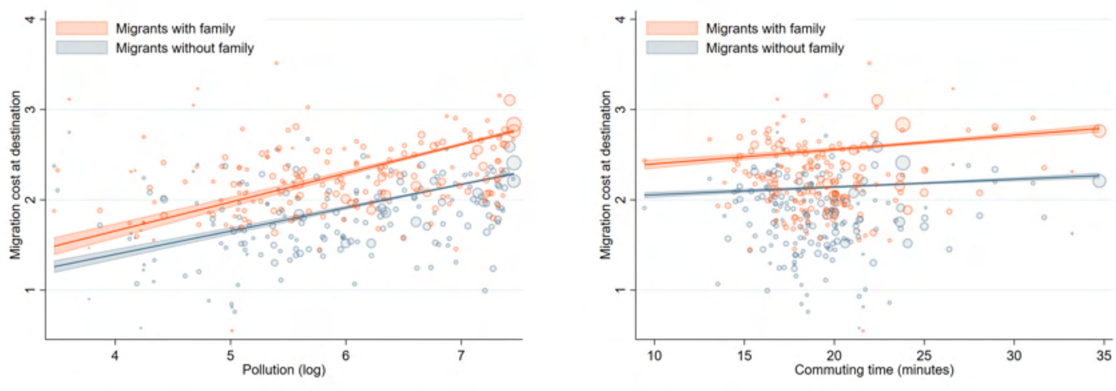
et al. (2018).[14] Figure D.3 shows that our estimated migration frictions negatively correlate with the likelihood of converting *hukou* registration at destination (panel a), and such a negative correlation is observed both for family (τ_{2u}) and for single-specific migration frictions (τ_{1u}). The gradient is however more pronounced for the former: While the average disamenity is much higher for family migrants in destinations where *hukou* conversion is unlikely, the average disamenity for family migrants gets closer to that of

[14]In this exercise, we consider the following projection of bilateral migration costs onto an origin-destination component (τ_{ru}), a destination-mode component (τ_{ju}), and an origin-mode component (τ_{jr}):

$$\tau_{jru} = \tau_{ru} + \tau_{jr} + \tau_{ju} + \varepsilon_{jru}.$$

non-family migrants in destinations where *hukou* conversion is likely, as we documented with causal estimates in Table 7. The same gradients can be observed for another measure of *hukou* leniency (or stringency in this case, see panel b), and also when the share of migrants having converted their *hukou* registration place to the local prefecture in 2010 or the *hukou* stringency index developed by Zhang et al. (2018) are residualized for observable amenities at destination, e.g., pollution and commuting (panels c and d).

Figure D.4. Relative cost of family migration and observable amenities.



(a) Pollution

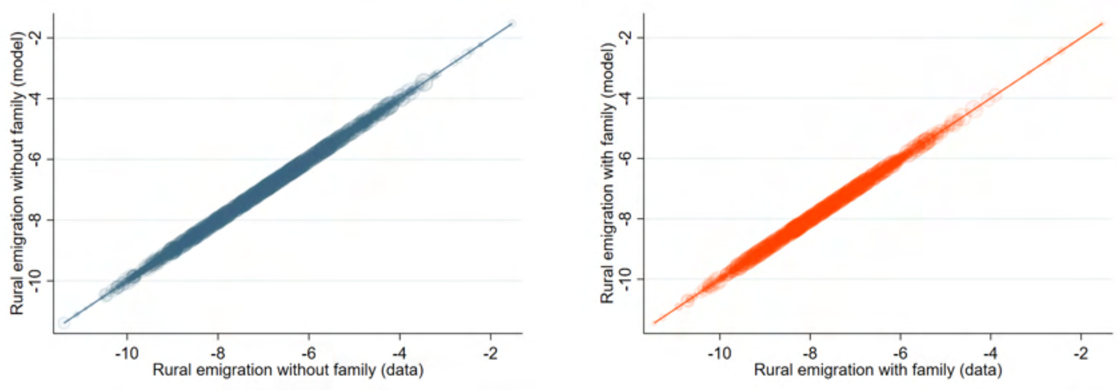
(b) Commuting time

Notes: This Figure plots the correlation between the average disamenity estimates, τ_{ju}, for family ($j = 2$) versus non-family migrants ($j = 1$) across destinations against: (log) pollution (2001–2005), commuting time (from the "2015 Mini-Census").

In Figure D.4, we complement the previous evidence by plotting the relationship between the average disamenities and measures of pollution (panel a) and commuting time (panel b). We find that higher levels of pollution and longer commutes are both associated with higher perceived barriers at destination for both migration modes, but even more markedly so for family migrants.

Finally, we display in Figure D.5 a validation of our bilateral migration estimates. By construction, these estimates—combined with the other estimates of the nested location model—should allow us to match migration flows between all origins and destinations of the largest connected set (Abowd et al. 1999, Card et al. 2013, Buggle et al. 2023). Figure D.5 shows that our inferred migration barriers indeed allow us to match exactly migration incidences from all origins to all destinations. We perform the same sanity checks for all alternative models described in Section 5.3 and Appendix E.3.

Figure D.5. Bilateral migration costs—matching migration flows.



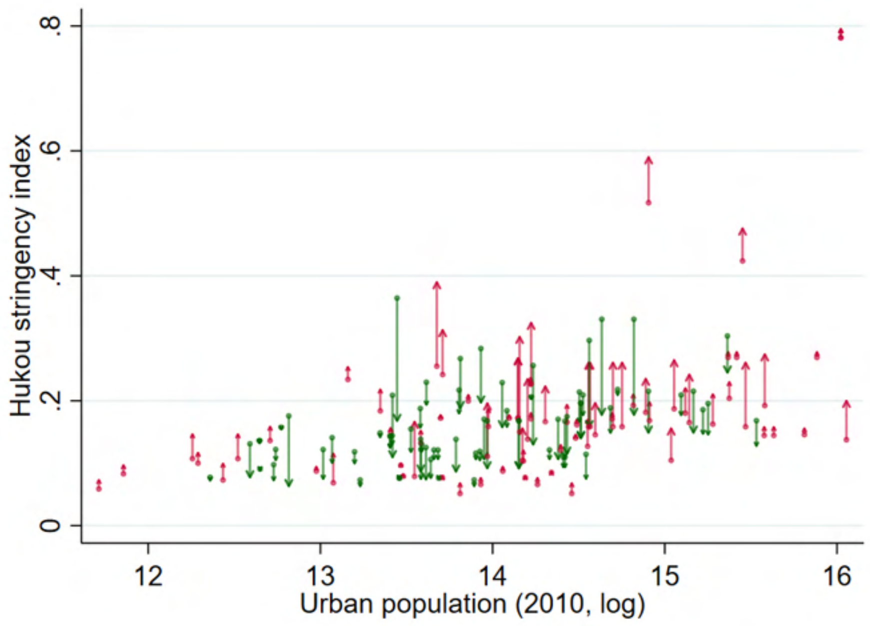
(a) Without family (τ_{1ru}) (b) With family (τ_{2ru})

Notes: Panel (a) plots the predicted non-family migration induced by bilateral migration costs (τ_{1ru}) against the actual migration rates. Panel (b) plots the predicted family migration induced by bilateral migration costs (τ_{2ru}) against the actual migration rates.

E The role of displaced consumption and frictions in shaping migration

This Appendix provides complements to our counterfactual exercises discussed in Section 5. The analysis is summarized in Section 5.3 and proceeds in three steps. In a first step, we explore the normative implications of displaced consumption and migration frictions with a focus on their redistributive effects. In a second step, we consider simple extensions of our baseline quantitative model to allow for agglomeration and congestion externalities. In a third step, we illustrate the quantitative and qualitative insights induced by our precise modeling of migration and consumption choices. In settings with large differences in living standards across space, the incentives for households to migrate with or without family and split their consumption between origin and destination are instrumental in explaining migration flows. Ignoring them leads to a misspecification of bilateral migration frictions.

Figure E.1. The 2014 *hukou* reform.



Note: This Figure shows the distribution of the *hukou* reform, as captured by $h_{u,a} - h_{u,b}$, across cities of different size (see Zhang et al. 2018, for a description of indices, $h_{u,a}, h_{u,b}$). Positive changes in restrictions are indicated in green; negative changes in restrictions are displayed in red.

Before discussing these issues, we illustrate the distribution of $h_{u,a} - h_{u,b}$ across cities of different size in Figure E.1—a variation that is underlying our counterfactual experiment (3) (see Section 5.2).

E.1 Normative implications and redistributive effects

We highlight the redistributive effects of displaced consumption and migration frictions by discussing: (i) additional evidence about the impact of our counterfactual exercises on wages, rents, and remittances; (ii) distributional effects across cities and across space; (iii) redistributive welfare effects between urban-born and rural-born households; and (iv) an analysis of welfare effects in general versus partial equilibrium for urban-born and rural-born households.

Table E.1. The role of consumption patterns and migration frictions—complements.

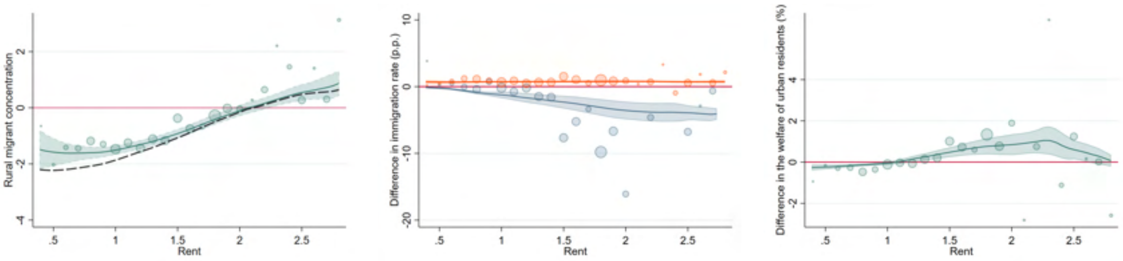
	Urban wage (% rel. base.)	Urban rent (% rel. base.)	Remittances (% rel. base.)
		1. Shutting down remittances	
Counterfactual (1)	0.302	-0.248	-100.00
		2. Consumption patterns and migration frictions	
Counterfactual (2a)	-0.681	0.560	71.11
Counterfactual (2b)	-1.326	1.090	29.87
		3. Evaluating the 2014 reform	
Counterfactual (3)	-0.124	0.102	-8.77

Notes: This Table reports additional statistics on the consequences of migration flows in counterfactual experiments (1), (2a), (2b), and (3). Across all experiments, we report the differences implied by the experiment—relatively to the baseline, and in percentage points—on: urban wage in column 1, the urban rent in column 2, and the level of remittances by migrants of all types from all urban destinations to all origins (column 3).

Wages, rents, and remittances In Sections 5.1 and 5.2, we present the effects of our counterfactual experiments on migration patterns in China and on the aggregate welfare of rural-born and urban-born households. In Table E.1, we further report their effect on wages and rents at destination and on the amount that is remitted from urban locations to rural origins. One can see that wages and rents respond to immigration flows in similar (yet opposite!) fashion. However, the wage effect is the one explaining most of the welfare response of urban-born households to migration for a straightforward reason: Rents only represent a small fraction of expenditures (about 0.28) such that a decrease of 1.3% of nominal wage has a much larger impact on real wage than an increase of

1.1% in rents. Table E.1 also sheds light on the compositional effect of migration flows on remittances. For instance, counterfactual experiment (2b) induces a 60% increase in migration flows but a significant, yet smaller, increase in remittances: (i) the migration increase is disproportionately explained by family migration, which typically generates smaller shares of remittances from each migrant household; and (ii) migration lowers wages at destination.[15]

Figure E.2. The role of consumption patterns and migration frictions—shutting down remittances.



(a) Migrant concentration (1) (b) Moving with(out) family (1) (c) Welfare of natives (1)

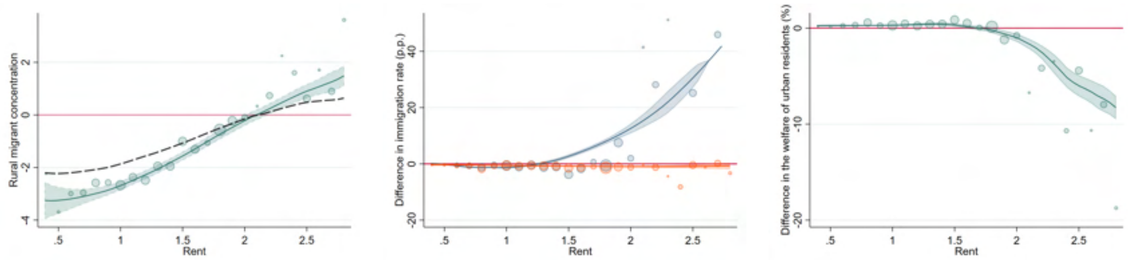
Notes: This Figure reports statistics on the extent, nature, and consequences of migration flows in counterfactual experiment (1). More specifically, we display: the concentration of migrants across cities (counterfactual in green, baseline as the dashed line) in panel (a); the incidence of migration in percentage points of the baseline city population (with family in orange, without family in blue) in panel (b); and the differences in the welfare of urban-born households relative to the baseline in panel (c). We group cities by bins of similar rents to limit the number of points; and their size is weighted by the total population at baseline in those cities.

Distributional effects across space We provide additional evidence on the distributional effects of our counterfactual experiments in Figures E.2 (counterfactual 1), E.3 (counterfactuals 2a and 2b), and E.5 (counterfactual 3). More specifically, we display the concentration of migrants across cities (as in Figure 2), the incidence of migration as a function of baseline city population, and the differences in the welfare of urban-born households relative to the baseline across cities. In all figures, as in our main stylized facts, we differentiate cities using the actual level of rents in 2005. Figure E.2 illustrates that shutting down remittances reduces migrant concentration toward larger, expensive agglomerations (panel a). In other words, removing the possibility for migrants to displace their consumption leads to fewer of them moving to expensive cities without their family and more of them moving with family across all cities. This experiment thus leads to moderate welfare gains for urban-born households in the most attractive (and

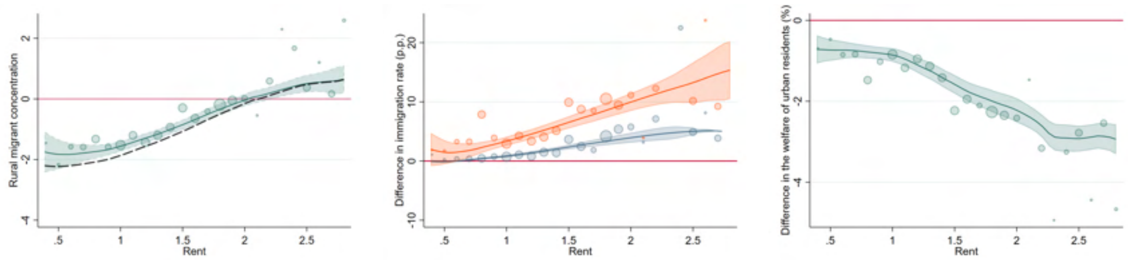
[15] Migration also increases rents at destination, thus inducing more substitution from the consumption of non-tradable goods in cities to consumption in rural origins.

expensive) cities and welfare losses for urban-born households in the least attractive (and expensive) cities.

Figure E.3. The role of consumption patterns and migration frictions.



(a) Migrant concentration (2a) (b) Moving with(out) family (2a) (c) Welfare of natives (2a)



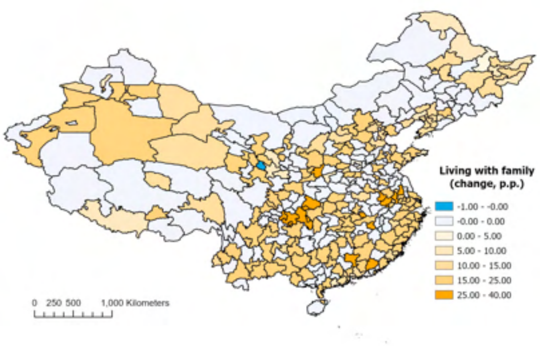
(d) Migrant concentration (2b) (e) Moving with(out) family (2b) (f) Welfare of natives (2b)

Notes: This Figure reports statistics on the extent, nature, and consequences of migration flows in counterfactual experiments (2a) and (2b). More specifically, we display: the concentration of migrants across cities (counterfactual in green, baseline as the dashed line) in panels (a) and (d); the incidence of migration in percentage points of the baseline city population (with family in orange, without family in blue) in panels (b) and (e); and the differences in the welfare of urban-born households relative to the baseline in panels (c) and (f). We group cities by bins of similar rents to limit the number of points; and their size is weighted by the total population at baseline in those cities.

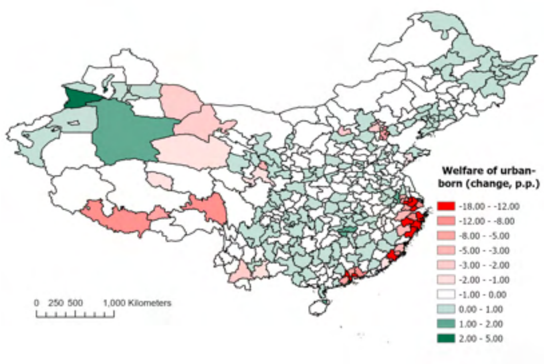
Figure E.3 illustrates the distributional effects of (a) tilting consumption patterns and (b) the removal of migration barriers across cities. We see that counterfactual experiment (2a) further concentrates migrant flows toward the very expensive mega-cities, in parallel with a downward shift of family migration across *all* cities. In other words, many more migrants move to those attractive, expensive locations that were protected by tough restrictions, but only by leaving relatives behind. The main losers are urban-born households in attractive cities, with welfare losses of up to 8%. The distributional effect of counterfactual experiment (2b), which lowers migrant restrictions, is very different: Migration concentration across cities does not vary much relative to the baseline, but migrants are (much) more likely to move with their family. Welfare losses for urban-born households are more widespread and not confined to attractive locations.

We shed further light on the impact of counterfactual experiment (2b) and its redis-

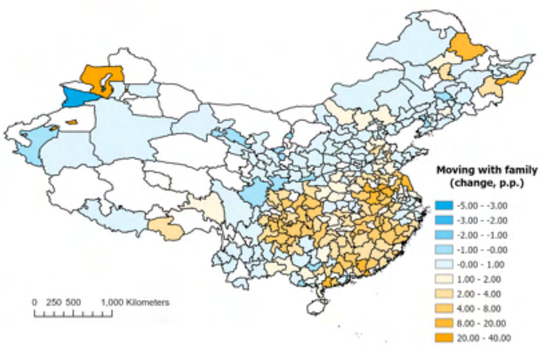
Figure E.4. Removing barriers to migration (2b)—variation across destinations and origins.



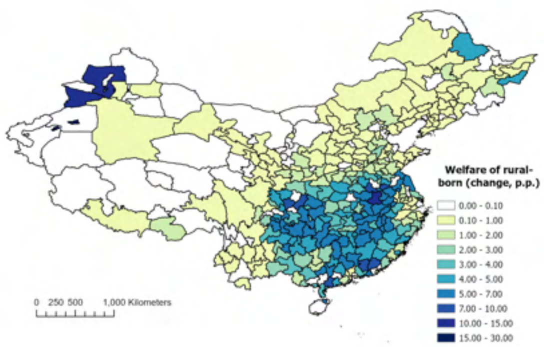
(a) Living with family



(b) Welfare of urban-born



(c) Moving with family

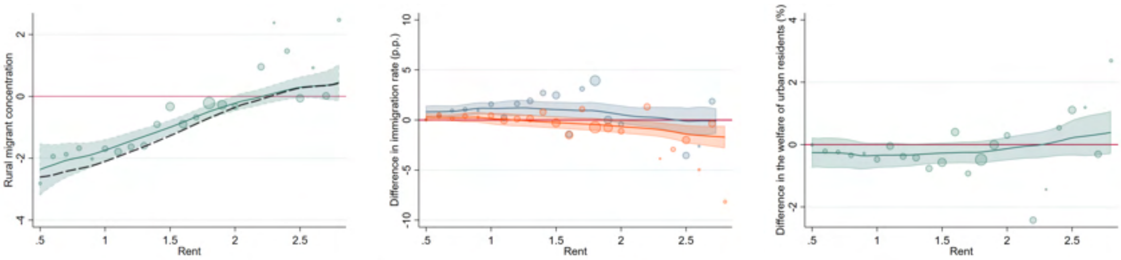


(d) Welfare of rural-born

Notes: Panel (a) displays the change in the incidence of family migration at destination as induced by the counterfactual that removes barriers to migration (in percentage points, relative to the initial urban population in 2000). Panel (b) displays the change in the welfare of urban-born households (in percentage points). Panel (c) displays the change in the incidence of family emigration across origins. Panel (d) displays the change in the welfare of rural-born households (in percentage points) across origins.

tributive welfare effects in Figure E.4. In panels (a) and (b), we nest those effects across destinations and report the change in the number of migrants living with family and the welfare effect of the experiment on urban-born households. We find that many more migrants would live with their family at destination and across many such destinations (as already observed in panel b of Figure E.3). The negative welfare effect of the experiment would however be concentrated toward a few urban centers: the large cities (Beijing, Shanghai); and the new exporting regions (Shenzhen/Guangzhou, Fujian, Zhejiang). Indeed, prefectures of the Northeast and of interior provinces, where *hukou* policies are the most lenient and where productivity is lower, would not experience additional migration, contrary to the productive coastal prefectures with the toughest stance on (family) immigration. In panels (c) and (d), we nest those effects across origins and report the change in the number of migrants leaving family behind and the welfare effect of the experiment on rural-born households. We find that fewer rural migrants of the “hinterlands” of the highly productive coastal prefectures would leave family behind (panel c), and there would be very significant average welfare effects for rural households in those locations (panel d).

Figure E.5. The role of consumption patterns and migration frictions—the 2014 reform.



(a) Migrant concentration (3) (b) Moving with(out) family (3) (c) Welfare of natives (3)

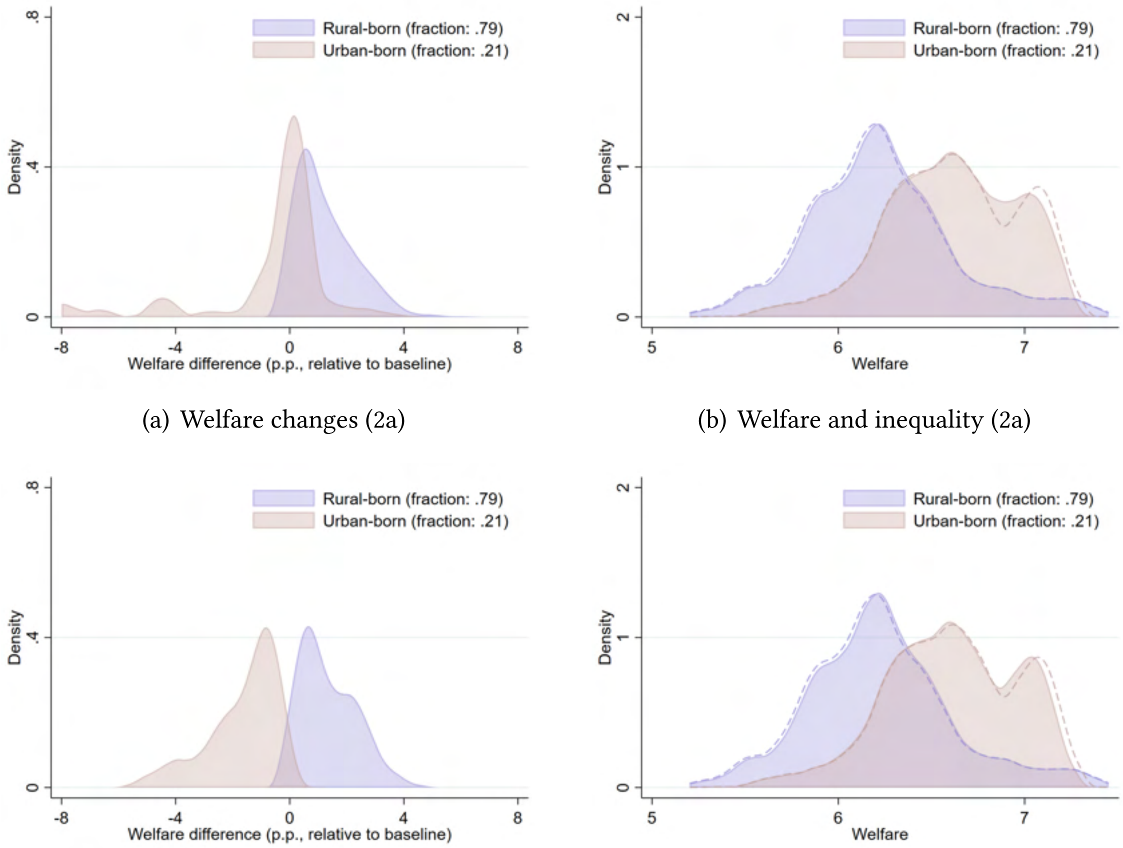
Notes: This Figure reports statistics on the extent, nature, and consequences of migration flows in counterfactual experiment (3). More specifically, we display: the incidence of migration in percentage points of the baseline city population (with family in orange, without family in blue) in panel (b); and the differences in the welfare of urban-born households relative to the baseline in panel (c). We group cities by bins of similar rents to limit the number of points; and their size is weighted by the total population at baseline in those cities.

Finally, Figure E.5 provides the same evidence for counterfactual experiment (3) mimicking the 2014 reform. Panels (b) and (c) of Figure E.5, in particular, illustrate the distributional effects of the reform, leading to a migration outflow from large cities toward smaller cities—thus inducing mirroring welfare gains/losses for urban residents.

Welfare and inequalities The previous section sheds some light onto the distributional effects of migration restrictions across space. We now discuss the redistributive effects of such policies between rural- and urban-born households, and within these two categories. Migration restrictions in China may indeed protect an urban middle class at the expense of poorer households living in rural regions, thereby limiting social mobility and consolidating income inequalities.

We provide some evidence about the normative implications of our main policies—counterfactual (2a) tilting consumption patterns and counterfactual (2b) removing migration restrictions as discussed in Section 5.2—in Figure E.6. Panel (a) shows that the incentives for potential migrants to remit favors rural-born households: a counterfactual economy where consumption would be more closely tied to origins would induce wel-

Figure E.6. Consumption patterns and migration frictions—welfare and inequality.



(a) Welfare changes (2a)

(b) Welfare and inequality (2a)

(c) Welfare changes (2b)

(d) Welfare and inequality (2b)

Notes: This Figure displays the welfare effects of our main policies: counterfactual (2a) tilting consumption patterns, in panels (a) and (b); and counterfactual (2b) removing migration restrictions, in panels (c) and (d). The left panels report the differences in the welfare of urban-born and rural born households in percentage points relative to the baseline. Given our assumptions, those differences can be interpreted as (log) units of equivalent real wage. In other words, a one percentage point difference is equivalent to a change in real wage of 1%. The right panels show instead the levels of welfare in the counterfactual experiments versus the baseline (as a dashed line). Finally, we report the fraction of rural-born versus urban-born households in the legend of these different sub-figures.

fare losses for urban-born households and would benefit rural-born households. We see that the welfare losses for urban dwellers are dispersed, reflecting the wide heterogeneity in attractiveness across possible destinations: The main losers would be urban-born households in booming, expensive cities. By contrast, the welfare gains for rural households are less dispersed—reflecting the possibility for those households to choose among many destinations and the gravity structure of migration flows. More specifically, households living in the proximity of expensive cities are most affected by such an experiment, while households living far from any attractive cities are far less impacted. However, even the most affected households might still be able to mitigate the effect of the policy through a swap across migration modes and/or destinations. Panel (b) displays the levels of indirect utility for rural-born and urban-born households in the baseline (dashed lines) and in counterfactual (2a). We see that counterfactual (2a): reduces inequalities between urban-born and rural-born households; reduces the welfare differences within urban-born households; and slightly increases the welfare differences across rural-born households. Indeed, the lucky urban households born in attractive cities are worse off than before, when the relatively lucky rural households born in the hinterlands of such cities are better off.

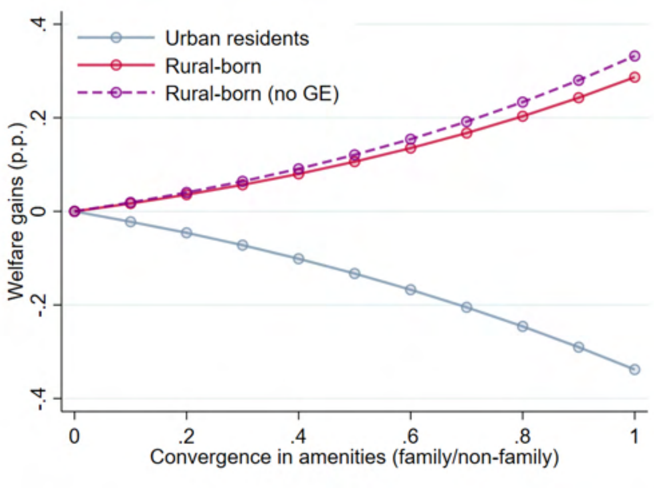
Removing migration restrictions also induces very significant redistributive effects, as illustrated in panels (c) and (d) of Figure E.6. Many destinations would receive more migrants, thus markedly affecting the welfare of their registered inhabitants. The removal of migration barriers would however generate moderate gains for a very large number of rural-born households, the extent of which would depend on the location of rural areas compared to the most attractive destinations. The large mass of rural households in China's interior provinces would gain between 2 and 4% in equivalent real wage from this relaxation of *hukou* restrictions—see Figure E.4, panel (d). In conclusion, this relaxation would be a progressive policy, in the sense that it would reduce the gap between rural- and urban-born households and partly bridge welfare differences among the latter group.

Welfare effects of relaxing family restrictions and general equilibrium Our quantitative model of location choice is in general equilibrium, allowing economic conditions to adjust across locations and feeding them back into the complicated problem of possible migrants. To shed light on the implications of general equilibrium effects on urban- versus rural-born households, we consider the following experiment. We model the effect of a family-friendly policy that gradually bridges the gap between perceived restrictions across migration modes:

$$\tau'_{2ru} = (1-x)\,(\tau_{2ru} - \tau_{1ru}) + x\tau_{1ru}.$$

for $x \in \{0, 0.1, \ldots, 1\}$. When $x = 0$, we are in the baseline and family migration induces additional barriers. When $x = 1$, the average migrant faces similar barriers (the ones without family), irrespective of the migration mode. For each x, we simulate the new

Figure E.7. Illustrating the welfare effects of relaxing family restrictions.



Notes: This Figure illustrates the welfare effects of the following experiment. We model the effect of a family-friendly policy that only removes the family-specific restrictions at destination, i.e., we consider:

$$\tau'_{2ru} = (1 - x)(\tau_{2ru} - \tau_{1ru}) + x\tau_{1ru}.$$

for $x \in \{0, 0.1, \ldots, 1\}$. The red curve shows the welfare gains for rural-born households. The blue curve displays the welfare losses for urban-born households. The purple, dashed line shows the welfare gains for rural-born households, absent general equilibrium effects through the adjustments of labor and housing markets at destination.

allocation of migrants across space, the welfare gains of rural-born households, and the welfare losses of urban-born households. We do so for two scenarios: one in which economic conditions adjust, and one in which they do not.[16]

Figure E.7 shows the welfare changes induced by the previous experiment when x goes gradually from 0 to 1. For instance, when half of the gap between perceived restrictions across migration modes is bridged, the welfare of rural-born households increases by 8% and the welfare of urban-born households decreases by about 10%, an effect entirely driven by the adjustments of labor and housing markets at destination. The purple, dashed line shows instead the welfare gains for rural-born households, absent general equilibrium effects. The difference with the actual welfare gains is then an order of magnitude smaller than that felt by urban-born households. In other words, absent general equilibrium effects, rural-born households would be better off, but by not much. The reason lies in the high substitutability across migration destinations (see Table 4) and across migration modes (see Table 5): Potential migrants are always able to trade off various

[16]Note that urban-born households can only be affected by the experiment through an adjustment of economic conditions. Accordingly, the partial equilibrium welfare effects for them are nil, irrespective of the parameter x.

options and mitigate the endogenous deterioration of living standards across targeted locations. Allowing urban-born resident mobility (see Appendix C.1) would enable such trading off and thus reduce the welfare deterioration they experience when *hukou* restrictions are lifted; in this sense, the estimated counterfactual decline in urban-born household welfare constitutes an upper bound.

E.2 Introducing externalities

Our quantitative model does not feature any agglomeration externalities or other congestion forces than the ones operating through the adjustment of labor and housing markets across locations. In this section, we show how agglomeration spillovers and congestion externalities at destination would affect (i) the allocation of rural-urban migrants across space and (ii) the normative implications of a relaxation of migration policies.

We consider our baseline model, as estimated in Section 4, and add the following features across four alternative models and three sources of externalities: (i) constant and size-varying production externalities in cities, e.g., the total factor productivity is $\mathcal{A}_u L_u^{0.05}$, where L_u is labor and $\mathcal{A}_u$ is an exogenous productivity shifter in urban location u, as standard in quantitative models of urban economics (see, e.g., Ahlfeldt et al. 2015); (ii) negative congestion externalities arising from urban sprawl or pollution (see, e.g., Khanna et al. 2021), i.e., $Z_u = \mathcal{Z}_u L_u^{-0.025}$, where $\mathcal{Z}_u$ is an exogenous amenity shifter; and (iii) positive externalities from remittances at origin, i.e., the total factor productivity is $\mathcal{A}_r R_r^{0.05}$, where R_r are the level of remittances received in rural location r (conveying the idea that remittances can be used as productive investment, see Pan and Sun 2022, Khanna et al. 2022).

Table E.2 shows that the addition of productive spillovers (sometimes called agglomeration economies) further boosts the effect of relaxing migration restrictions with a larger number of migrants moving to cities with or without family than in the baseline model. The effect remains, however, limited: The first panel of Table E.2 predicts an additional inflow of about 400,000 rural-born households. Adding positive agglomeration externalities implies that rural-born households are left better off from the relaxation of restrictions than estimated through our externality-free model and urban-born households are less worse off—both effects being driven by a muted response of wages to migration flows. Negative congestion externalities have the exact opposite effect: The migration response to the policy is lower, and its normative implications are less positive. More specifically, urban-born households lose more from the relaxation of restrictions when rural-born households gain slightly less. Finally, assuming that remittances boost production at origin changes our predictions in the most significant manner: While this spillover increases the social returns to migration, these returns are not internalized by migrants such that the increase in local wages mitigates the desire to move toward urban destinations. In such a model, migrants would respond *less* positively to a relaxation policy, even though the policy would have much larger welfare effects. Their muted response implies that the level of remittances would be lower than that predicted by the externality-free model. In the presence of such externalities, a social planner would be tempted to subsidize migration rather than penalize it.

Table E.2. The role of consumption patterns and migration frictions—counterfactual experiments.

	Migrant households (millions)				Welfare, wages, price and remittances (% rel. baseline)				
	All	No fam.	Fam.	Fam. sh.	Rural	Urban	Wage	Rent	Remit.
Baseline	27,29	22,27	5,02	0.184	-	-	-	-	-
Baseline experiment (2b)	42,54	26,98	15,56	0.366	1.350	-1.641	-1.326	1.090	29.87
1. Agglomeration spillovers									
With productive spillovers (cons.)	42,92	27,25	15,67	0.365	1.380	-1.393	-1.073	1.106	31.96
With productive spillovers (var.)	42,94	27,26	15,68	0.365	1.380	-1.393	-1.074	1.104	31.89
2. Negative spillovers on amenities									
With negative externalities	42,49	26,94	15,55	0.366	1.340	-1.668	-1.324	1.088	29.66
3. Spillovers from remittances at origin									
With remittance spillovers	39,53	25,10	14,43	0.365	4.540	-1.349	-1.090	0.896	22.31

Notes: This Table reports statistics on the extent, nature, and consequences of migration flows in the baseline and in counterfactual experiment (2b) across five alternative models: the baseline model, a model with agglomeration spillovers, a model with size-dependent agglomeration spillovers, a model with negative externalities on amenities at destination, and a model with positive productive spillovers at origin as induced by the level of remittances. Across all experiments, we report: the number of migrant households (overall in column 1, without family in column 2, with family in column 3, all reported in millions of migrant households between 2000 and 2005); the share of migrants living with family in column 4; the welfare of rural-born households in column 5 (in % relative to the baseline); the welfare of urban-born households in column 6 (in % relative to the baseline); urban wage in column 7 (in % relative to the baseline); urban rent in column 8 (in % relative to the baseline); and the level of remittances by migrants of all types from all urban destinations to all origins (column 9, in % relative to the baseline).

E.3 Sensitivity analysis and alternative migration models

Our quantitative model of location choice is designed to best capture the choice of rural residents in transforming economies with large productivity and price differentials across urban areas and an even wider rural-urban gap. In those settings, rural migrants often consume at origin to mitigate the living costs at destination, and an important adjustment margin is whether to leave relatives behind or not (as we document in Section 2). For these reasons, we add the following ingredients to the standard migration models (see, for instance, Bryan and Morten 2019, Tombe and Zhu 2019, Monras 2020): (i) a three-nest structure for the location choice model allowing potential migrants to trade off whether to migrate or not, how to do so (with or without family), and where to go; and (ii) a technology to displace part of the consumption of non-tradable goods to origins, depending on the migration mode (with or without family).

In this section, we illustrate the quantitative and qualitative insights gained through the adoption of those two novel features. To do so, we estimate four alternative models: (1) a simple model of location choice among numerous alternatives, and where the birth location is one of those alternatives (Bryan and Morten 2019, Tombe and Zhu 2019); (2) a two-nest structure with the upper nest capturing the decision to migrate or not, and the lower nest modeling the choice of destinations (Monras 2020); (3) a two-nest structure adding the possibility for migrants to displace part of their consumption (Albert and Monras 2022); and (4) a three-nest structure akin to our baseline model (i.e., with two migration modes and two associated technologies for the consumption of non-tradable goods), but where there is limited substitutability between migration modes.[17]

We estimate these models using a similar approach as in Section 4. We thus estimate Model 1 by assuming a standard formulation for real wages, i.e., $\ln(w_u/p_u^{\alpha})$, and estimating the parameter λ in a similar manner as in Table 4 (but with a slightly different explanatory variable). We estimate Model 2 by assuming the same standard formulation for real wages, i.e., $\ln(w_u/p_u^{\alpha})$, estimating the parameter λ in a similar manner as in Table 4, and estimating the parameter γ in a similar manner as in Table 6. Model 3 follows the same estimation as Model 2, except for the computation of real wages. We then account for remittances as in the baseline model, but we use an average remittance

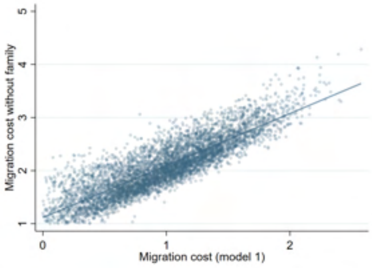
[17] We impose that $1/\mu$ is one order of magnitude smaller than in our baseline estimation (see Table 5): We set $1/\mu = 0.4$.

share irrespective of the migration mode. The estimation of Model 4 follows the exact steps of our baseline model, except that we impose $1/\mu = 0.4$.

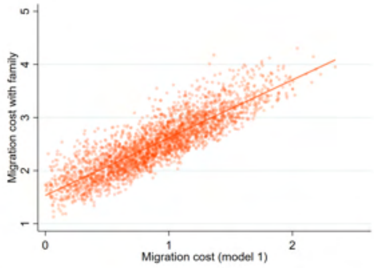
In Figure E.8, we show the correlation between our baseline bilateral costs against the estimated costs in alternative models. Overall, we find that our estimated bilateral costs for family migration are never closely matched by any of these alternative models, even Model 4. In fact, Model 4 displays wide departures from our baseline model for both types of bilateral costs because it partly loads positive variation in one mode onto a negative variation in the other mode. The bilateral costs for migration without family are more closely matched by other models. In particular, the average migration costs of Model 3 are very close to our bilateral costs for migration without family, in part because this is the dominant migration mode in the baseline.

One crucial element of such migration models—including our baseline model—is to nest all residual, unexplained variation in migration flows onto bilateral migration costs. This set of inferred parameters, labeled $\left\{\tau_{jru}\right\}_{j,r,u}$ in our framework, are capturing actual pull or push factors, gravity or network effects, but also residual errors or biases when the model is misspecified. We look at the variation underlying these residual terms in Table E.3. Panel A regresses the bilateral migration costs obtained across the different models onto a set of observable predictors for these migration frictions: (i) the rent at destination as a placebo variable that should not be predictive outside of its indirect effect through real wages, (ii) the wage of migrants at destination, (iii) distance between origins and destinations to capture the iceberg costs of migration, (iv) pollution at destination (Chen et al. 2017, Khanna et al. 2021), and (v) population at destination in 2000 to capture fixed amenities (e.g., other environmental or cultural factors). Models 1 and 2 fail to restrict the effect of housing prices to its impact through real wages (see columns 1 and 2)—a feature that we attribute to their failure to account for displaced consumption and the fact that migrants only allocate about 20% of their income to housing (versus 28% for residents). Model 3 indeed neutralizes the correlation between bilateral migration costs and rents at destination, and displays expected correlations with all the other variables. Model 4 introduces heterogeneity across migration modes (column 4 for migrants leaving family behind and column 5 for migrants with family at destination). However, because it ignores substitutability across migration modes, any factor favoring one migration mode will appear in both bilateral costs, positively in one and negatively in the

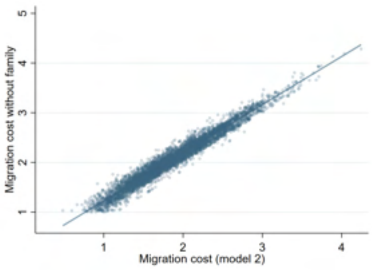
Figure E.8. Correlation between migration frictions across models.



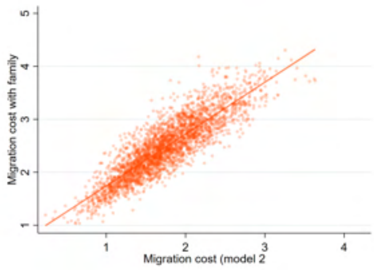
(a) Migration without family (M1)



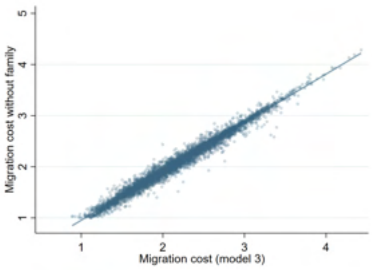
(b) Migration with family (M1)



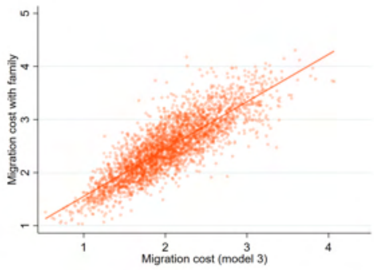
(c) Migration without family (M2)



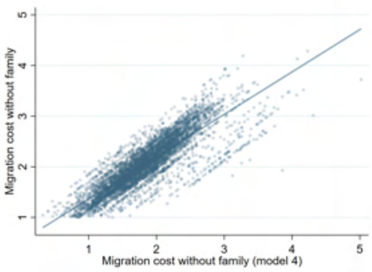
(d) Migration with family (M2)



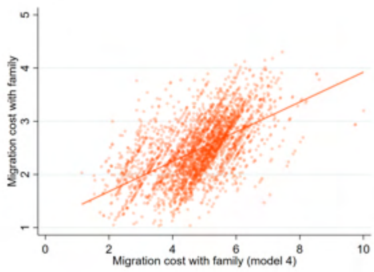
(e) Migration without family (M3)



(f) Migration with family (M3)



(g) Migration without family (M4)



(h) Migration with family (M4)

Notes: Model 1 has only one nest and one elasticity λ. Model 2 has two nests: the upper nest between migrating or staying and the lower nest across destinations for households who decide to emigrate. The previous models assume away heterogeneity in family migration (or not), and construct real wages across destinations without allowing for displaced consumption. Model 3 is similar to Model 2, except that real wages are calculated using the average remittance share. Model 4 is designed and estimated like our baseline model (three nests allowing for two migration modes and different remittance behaviors), except for one component: we shut down the substitution across migration modes by imposing that $1/\mu = 0.4$.

Table E.3. Identifying migration frictions—alternative models.

	Model 1	Model 2	Model 3	Model 4		Baseline	
Bilateral migration costs	τ^1_{ru}	τ^2_{ru}	τ^3_{ru}	τ^4_{1ru}	τ^4_{2ru}	τ_{1ru}	τ_{2ru}
Panel A: explaining migration frictions							
Rent (log)	-0.234	-0.237	-0.421	-0.423	-0.042	-0.381	-0.220
	(0.073)	(0.121)	(0.149)	(0.137)	(0.106)	(0.148)	(0.155)
Migrant wage (log)	0.729	0.524	0.899	0.496	1.621	0.761	0.719
	(0.208)	(0.308)	(0.381)	(0.379)	(0.499)	(0.372)	(0.319)
Distance (log)	0.189	0.109	0.118	0.208	0.233	0.134	0.208
	(0.032)	(0.069)	(0.071)	(0.042)	(0.050)	(0.065)	(0.066)
Pollution (log)	0.129	0.150	0.153	0.098	0.286	0.146	0.222
	(0.033)	(0.045)	(0.055)	(0.057)	(0.069)	(0.055)	(0.052)
Population (log, 2000)	0.060	0.158	0.156	0.169	-0.184	0.160	0.073
	(0.034)	(0.052)	(0.064)	(0.060)	(0.068)	(0.063)	(0.065)
Observations	1,864	1,864	1,864	1,864	1,864	1,864	1,864
Migration mode	-	-	-	$j = 1$	$j = 2$	$j = 1$	$j = 2$

	Model 1	Model 2	Model 3	Model 4		Baseline	
Bilateral migration costs	τ^1_{ru}	τ^2_{ru}	τ^3_{ru}	τ^4_{1ru}	τ^4_{2ru}	τ_{1ru}	τ_{2ru}
Panel B: the causal effect of migration policies							
Hukou conversion	-2.686	-4.266	-3.566	-3.443	-8.882	-4.094	-8.316
	(1.871)	(2.198)	(2.616)	(2.592)	(2.890)	(2.738)	(3.105)
Observations	3,586	3,586	3,586	3,113	1,613	3,113	1,613
Migration mode	-	-	-	$j = 1$	$j = 2$	$j = 1$	$j = 2$
F-stat	9.62	9.62	9.62	9.83	9.90	9.83	9.90

Notes: A unit of observation is a destination/origin pair within the connected set. Standard errors are clustered at the level of destinations and are reported between parentheses. The specification uses population weights in 2000 in both panels. The dependent variables are the model-computed bilateral costs of migration computed in the baseline (last two columns) and four alternative models of location choice. Model 1 has only one nest and one elasticity λ. Model 2 has two nests: the upper nest between migrating or staying and the lower nest across destinations for households who decide to emigrate. The previous models assume away heterogeneity in family migration (or not), and construct real wages across destinations without allowing for displaced consumption. Model 3 is similar to Model 2, except for real wages that are calculated using the average remittance share. Model 4 is designed and estimated like our baseline model (three nests allowing for two migration modes and different remittance behaviors), except for one component: we shut down the substitution across migration modes by imposing that $1/\mu = 0.4$. Panel A regresses the model-computed bilateral costs of migration on (log) rent in 2005, (log) migrant wage in 2005, (log) distance between origins and destinations, (log) pollution (2001–2005), and (log) population in 2000. Panel B replicates the causal analysis of Table 7 (columns 1 and 2).

other. The impact of such misspecification is made salient through the observed gaps across migration modes in the estimates for rents, wages, or population—a gap that we do not observe in our baseline model (columns 6 and 7). We interpret these findings as supportive evidence for Model 3 and our baseline model. Model 3 nonetheless cannot shed light on the importance of family migration (or the absence of family migration) in explaining the impact of restrictions in China, as we will see next.

Table E.4. The role of migration frictions in shaping migration—alternative models.

	Migrant households (millions)		
	All	No family	Family
Baseline	27,29	22,27	5,02
Counterfactual (2b)—Model 1	46,48		
Counterfactual (2b)—Model 2	39,60		
Counterfactual (2b)—Model 3	33,64		
Counterfactual (2b)—Model 4	71,79	55,00	16,79
Counterfactual (2b)—Baseline model	42,54	26,98	15,56

Notes: This Table reports statistics on the extent, nature, and consequences of migration flows in the baseline and in counterfactual experiment (2b). Across all experiments, we report the number of migrant households (overall in column 1, without family in column 2, with family in column 3, all reported in millions of migrant households between 2000 and 2005). The counterfactual experiment is simulated across four alternative models of location choice (as well as our baseline model). Model 1 has only one nest and one elasticity λ. Model 2 has two nests: the upper nest between migrating or staying and the lower nest across destinations for households who decided to emigrate. The previous models assume away heterogeneity in family migration (or not), and construct real wages across destinations without allowing for displaced consumption. Model 3 is similar to Model 2, except for real wages that are calculated using the average remittance share. Model 4 is designed and estimated like our baseline model (three nests allowing for two migration modes and different remittance behaviors), except for one component: we shut down the substitution across migration modes by imposing that $1/\mu$ is small.

We then evaluate the role of migration policies in shaping the extent of migration in China through the lens of these alternative models. We first isolate the causal effect of migration policies on the various inferred bilateral costs, in the manner of Table 7 (columns 1 and 2), and report the estimates in Panel B of Table E.3. We then simulate the counterfactual experiment (2b) in all these alternative models and report their effect on migration numbers in Table E.4. All models naturally predict a very significant uptick in migration with an increase in migrant concentration toward more expensive, restrictive cities. For instance, 33 million migrant households would leave their origins in Model 3 against 42 million in our preferred model, with a similar concentration across cities. What Model 3 misses is that family migration becomes much more attractive following the reform, leading to a disproportionate increase in this migration mode. This explains the missing 9 million migrant households, but also the composition of such missing households. Model 4 does account for the two types of migration and does allow for a differential effect of policies on bilateral costs (see Panel B of Table E.3), but it ignores substitutability between these modes implying that the expansion of family migration does not hinder the emigration of migrants without family. Model 4 thus predicts too large an adjustment following the relaxation of policies, with about 29 million additional migrant households, most of them leaving without their family.

In summary, our quantitative model of location choice does not only provide qualitative insights about the nature of migration in transforming economies; it also has quantitative implications for the effect of various migration frictions (including the endogenous frictions related to migration policies) on the spatial allocation of population across space.

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