

Floating population: consumption and location choices of rural migrants in China*

Clement Imbert

University of Warwick, BREAD, CEPR, EUDN and JPAL

Joan Monras

UPF, BSE, CREI, and CEPR

Marlon Seror

Université du Québec à Montréal

Yanos Zylberberg

University of Bristol, CEPR

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Abstract

This paper provides new theory and evidence on how the consumption patterns of the “floating population” of rural migrants affect the distribution of activity across Chinese cities. We first show (i) that rural migrants sort into cities where wages are high, but rents are also high, (ii) that in these cities they live in poorer housing conditions and without their children, (iii) especially so in cities with tighter registration (*Hukou*) requirements that make it harder for them to settle. We then develop a quantitative spatial model in which migrants partly consume in their origin location. We estimate the model and compute counterfactual migration flows when rural migrants consume all of their income in cities: we predict that they would move away from large, high wage and high rent cities.

KEYWORDS: migration, remittances, geography.

JEL CLASSIFICATION: R12, J61, O15.

*Imbert: c.imbert@warwick.ac.uk; Monras: jm3364@gmail.com; Seror: seror.marlon@uqam.ca; Zylberberg: yanos.zylberberg@bristol.ac.uk. We are grateful to UPF-CREI, Princeton University, the University of Warwick, UQAM, and the University of Bristol for research support. We would like to thank Juan Manuel Castro and Steve Redding for useful comments, and conference and seminar participants at Princeton and Warwick. We are also grateful to Yifan for excellent research assistance. Monras is thankful to Princeton University’s IES Section for hospitality and support. The usual disclaimer applies.

1 Introduction

The World Bank estimates that immigrant remittances now amount to about USD 500-600 billions in a given year, which is almost as large as the flow of foreign direct investment (Yang 2011). Dustmann and Mestres (2010) document that remittances amount to at least 10% of immigrants' disposable income in Germany. These numbers suggest that remittances are an integral part of the migration process. One reason why remittances are so important may be related to the institutions that govern migration. Migrating is not an easy process. Legal restrictions to migration are usually difficult to overcome, leading many to migrate illegally, often leaving close family behind. This process naturally leads to a prominent role for remittances, as household members who migrate remit (an important) part of their income to the members left behind.

Previous literature has mostly focused on how institutional restrictions to labor mobility limit the number of potential migrants that can migrate (Clemens 2011, Borjas 2015). In this paper, we explore instead how the limits faced by migrants to fully settle with their families at destination shapes the destinations that they choose, and how these choices, in turn, affect the economy.

A particularly interesting setting to study these questions is China. Unlike other countries, internal migration in China is restricted in ways that often resemble the restrictions faced by international migrants. The *Hukou* system, which we describe in more detail below, assigns a residence and a status to each individual. Individuals born in a rural location have a rural *Hukou*, entitling them to land, and public services such as education and health care in that same location. If they are born in a city, then the *Hukou* is also urban, entitling the person to urban public services and activities in that city. Until the 2014 reform, of the *Hukou* system, changing one's place of registration, especially from a rural to an urban *Hukou*, was very difficult: in 2010 only 10% of migrants born with a rural *Hukou* were registered in the city they lived in.¹

We argue that this system means, effectively, that it is hard for rural workers to migrate to cities—the main winners of China's integration to the world economy—, especially if they want to migrate with their entire family. The only option for rural workers to migrate to a city with their family is to substitute publicly provided services by private ones, which, in China, are both expensive and usually of lower quality. As a result, most migrants leave their families behind, particularly young children who are then raised by their grandparents. This phenomenon started in the 1990s but really took off in the 2000s after China entered the World Trade Organization (Facchini et al. 2015, Tombe and Zhu 2019). In 2010, this “floating population” counted 200 million people.²

Registration regulations frictions mean that remittances are a substantial aspect of the internal migration experience in China. Migrants send a large fraction of their income to family members left behind and, hence, an important part of their consumption does not take place at destination, but rather, via remittances, at origin. We argue, in line with Albert and Monras (2018), that this shapes the destinations that migrants choose. If a substantial fraction of the income is remitted, migrants

¹Authors' calculations based on 2010 population census data.

²Authors' calculations based on 2010 population census data.

have strong incentives to locate in high wage cities, where they are not as deterred by the high housing costs (and poor living conditions) that usually act as an important congestion force. This, in turn, has consequences for the aggregate economy. We build this argument in three parts.

In the first part of the paper, we document a number of empirical facts that are difficult to rationalize with models of migration that do not take into account the role of remittances and displaced consumption – as we make explicit later. First, we show that rural migrants disproportionately concentrate in high wage, high rent destinations relative to urban residents. Second, we find that rural migrants are more likely to live in poorer housing conditions, and less likely to live with their children than urban residents. Third, we document that these patterns are even stronger when strict registration rules make their settlement at destination more precarious. Consistent with the previous observation, we show that migrants transfer part of their consumption to their origin locations through generous remittances, and even more so when they live in cities with stringent *Hukou* regulations.

In the second part of the paper, we develop a quantitative model of location choice that tries to capture the essential forces behind the migration experience in China during the 2000s. In the theory, workers who are exogenously born in different locations can locate in their birthplace or across a set of urban locations characterized by different productivity fundamentals. As in standard spatial models, higher productivity cities, can sustain in equilibrium more population, higher wages, and higher housing costs. If consumption took place only at destination, high nominal wages in a location would not necessarily make the location more attractive, since high housing prices (associated to large populations) would compensate against these high nominal wages. However, when a smaller fraction of consumption takes place at destination, as implied by the restrictions that the *Hukou* system imposes, rural migrants have stronger incentives to locate in high wage, high rent locations, than urban residents, in line with our motivating facts.

In the third part of the paper, we estimate the main parameters of the model and use it for counterfactual simulations. We first compute the shares of income that natives and migrants spend on local goods; and the share of income that immigrants remit to their family at origin. We find that natives spend 27% of their income on housing against 20% for migrants, who remit 7.6% of their income. We then regress migration flows between 2000 and 2005 on real wages at origin and destination, instrumented by labor demand and housing supply shocks, to compute migration elasticities. Next, we estimate the local labor demand and housing supply elasticities at destination, using a shift-share instrumental variable strategy similar to [Imbert et al. \(2020\)](#). Based on these estimates, we then recover rural and urban location amenities. Finally, we perform a counterfactual exercise in which we assume that migrants do not send remittances and spend all their income at destination and compute the resulting change in migration flows, in urban wages and rents.

From this counterfactual exercise, we find that internal rural to urban migration, paradoxically, decreases. This is so because of an increased sensitivity of migrants to high rents in cities of destination. Moreover, we find that the counterfactual decline in immigration is particularly pronounced in larger cities, which are high wage-high rent destinations. As a result, in this counterfactual world, the

largest cities experience stronger wage growth but slower rent growth. Finally, we show that the model predictions match the recent changes in migration policy in China: counterfactual migration rates are higher in destinations which made the *Hukou* system less stringent in the 2014 reforms—presumably because these cities could not attract as many migrants as they wanted, and, hence, lowered *Hukou* restrictions.

Overall, we think that our empirical exercises and counterfactual lead to a different view of the effect of migration frictions on the migration experience that was not explored in previous literature: allowing family migration reduces migrant flows and redirects migration towards lower income, lower rent destinations.

More specifically, our paper makes three main contributions. There is a large literature that studies the role of migration frictions in limiting migrant opportunities within countries. In part, this literature is motivated by the observation that productivity and wage gaps between urban and rural sectors are large (Young 2013, Gollin et al. 2014). One way to rationalize these large wage gaps is through mobility costs, especially given the evidence that other natural candidates, such as worker sorting or amenity differences between rural and urban locations seem to have small empirical bite (Gollin et al. 2021). As a result, a number of papers tries to understand the potential sources of these mobility costs. A set of papers studies the role of information frictions and argues that reducing disinformation may be a very positive investment that increases overall migration (e.g., Bryan et al. 2014). Another set of papers studies natural barriers to mobility which include things such as poor transport networks, prevalent in many developing countries (e.g., Bryan and Morten 2019). These papers study how reductions in these mobility costs would lead to a better allocation of labor across locations of a same country and overall aggregate productivity gains. In the specific context of China, mobility costs, which take various forms Adamopoulos et al. (2022), seem to reduce overall migration in significant ways (Brandt et al. 2013, Gai et al. 2021). Our paper differs from those contributions in two main dimensions: (i) we investigate how migration frictions affect preferences for consumption across locations. (ii) we show that migration frictions shape not only overall migration levels but also migrant allocation across destinations. In line with our paper, Pan and Sun (2022) also study the role of remittances sent by Chinese internal migrants to rural locations. Their focus is, however, on how remittances affected structural transformation in China, both in sending and receiving communities, rather than on tying remittances to migration frictions and how these, in turn, affect the distribution of workers across locations.

Our work also contributes to the literature on international migration that studies how migration policies affect the labor market outcomes of migrants, return migration, family migration, and remittances.³ For example, there are numerous, recent contributions discussing temporary migration (see Dustmann and Görlach 2016, for a review), and Adda et al. (2021). These research is related to this paper because, at least in part, temporary migration may be motivated by restrictive migration policies that give only limited access to local labor markets and local public goods (see Hanson 2006, Hoen 2020,

³The research closely relates to the contributions discussing the role of remittances (Yang 2008, 2011), especially those discussing their role in the allocation of migrants across space (Albert and Monras 2018)—as previously discussed.

Fasani et al. 2021, looking at: policies affecting illegal migrants; language policies; and restrictions on labor supply from refugees). In contrast with these contributions, we study how migration policies directly affect consumption rather than labor supply—a dimension which is generally overlooked (with the notable exception of Dustmann et al. 2017)—and how this, in turn, creates links between origin and destination locations and how it affects migration decisions—dimensions omitted in the previous work on temporary migration.

Finally this paper investigates how consumption patterns of migrants affect their sensitivity to living standards and how this affects the distribution of activity across cities. We thus relate to the large urban literature discussing the role of agglomeration and dispersion forces in disciplining city size (Tabuchi 1998). More specifically, we relate to previous work by Au and Henderson (2006a,b) discussing city size in China and the role of migration barriers: (productive) cities are too small, with an implication on aggregate productivity. One unexpected consequence of the peculiar form of relocation frictions induced by *Hukou* policies is that some cities may actually grow too large. This is a new insight in the literature on *Hukou* policies, which generally emphasizes its role in limiting the overall reallocation of workers across space (Tombe and Zhu 2019, Gai et al. 2021).

2 Data and institutional framework

In this section, we describe important contextual elements and the data used to establish our main stylized facts, identify the model, and perform counterfactual experiments.

2.1 Rural-urban migration

China has urbanized very rapidly in the past decades; this urbanization has been fueled by large emigration flows from rural hinterlands.

Institutional background

The *Hukou* system is a key feature of Chinese society established in 1958 to prevent spatial mobility. Between 1958 and the late 1970s, migration was effectively illegal in China unless mandated by the government. In the Reform era, labor mobility remains subject to legal requirements, e.g., being lawfully employed at destination. The large flows of internal migrants that have characterized China’s recent development (from 1990 onward) show that barriers are not prohibitive in practice: by 2010, there were over 200 million rural-urban migrants in cities (Chan 2012).

Migrants, however, do not enjoy the same rights as the locally registered population, which has shaped the nature of migration flows. Agricultural *Hukou* holders have access to land, while non-agricultural *Hukou* holders enjoy public services in their cities of registration. Access to welfare benefits and public services (e.g., enrollment in local schools, access to healthcare, urban pension plans, and subsidized housing) is conditional on being officially recorded as a local urban dweller. Migrants thus need to return to their places of registration for basic services such as education and healthcare or they are charged higher fees (Song 2014), which typically implies that they have to leave their dependent

relatives behind. These broad characteristics of the *Hukou* system have experienced major changes, both over time and across cities, in the last couple of decades; we review this evolution in Section 2.2.

This peculiar registration system allows us to unambiguously observe migrants in the census data. During our period of interest, all Chinese citizens are classified along two dimensions: their household registration type (agricultural versus non-agricultural) and location. One can infer the status of an individual by comparing their location of residence with their registration details. Note however that *Hukou* conversions are possible, even though they remained rare during our period of interest.⁴

Data

The main source of data for this paper is the 2005 1% Population Survey (hereafter, “2005 Mini-Census”), which allows us to measure migrant flows. The sampling frame of the Mini-Census is the Public Security Bureau’s 2004 population registry and covers the entire Chinese population, regardless of migration status. We use a random 20% extract of the micro-data to characterize each individual’s migration situation, based on her current place of residence (the destination), her place of household registration or *Hukou* (the origin), and her *Hukou* type (agricultural or non-agricultural). Further information on the date of arrival at destination allows us to create a bilateral prefecture-level matrix of migration flows covering the period 2000–2005.

In the empirical part of the paper, we define a migrant as an individual residing in a different prefecture from her prefecture of registration.⁵ According to this definition, 5.6% of the Chinese population in 2005 were internal migrants, most of which (80%) originating from rural areas. Figure 1 puts these rates in perspective using similar data from the 1982, 1990, 2000, and 2010 Population Censuses. The migration rate series shows a structural break around 2000, corresponding to China’s accession to the WTO (Facchini et al. 2015, Tombe and Zhu 2019), with low and slow-growing migration rates before 2000 and a rapid increase afterwards.

Important for our analysis is the share of consumption that occurs at origin rather than at destination. We capture remittances using the China Migrants Dynamic Survey (CMDS), a nationally representative repeated cross-section conducted by the National Health Commission of the People’s Republic of China every year since 2011 (Wang et al. 2021). We use the 2011 and 2012 data on the amount remitted during the past year and divide it by yearly income to obtain an estimate of the share of income remitted by migrants to their households of origin. Although the periods covered by CMDS and the 2005 Mini-Census do not overlap, we find a remittance share of 7.6% in CMDS, which is almost equal to the percentage point difference between rural migrants’ and urban non-migrants’ housing shares (from Mini-Census data on rents), which is most likely a lower bound for the difference in income share that is spent locally.

⁴We are able to observe *Hukou* conversions in the data, by combining information on the birthplace of individuals with their current place of *Hukou* registration.

⁵Prefectures are the administrative level between provinces (which are immediately below the central government in the Chinese administrative hierarchy) and counties. There were 345 prefectures in China in 2005. Note that prefecture boundaries are subject to change; all the data used in this paper are mapped to consistent 1991 administrative boundaries.

Exogenous variation in local conditions

Identification of some parts of the model requires exogenous variation in (i) local conditions to predict migration flows and in (ii) migrant inflows to estimate their effect at destination. We briefly describe our approach below and leave the relevant details to Appendix A.

One important equation of our theory relates the location choice of migrants to conditions in cities *and* to conditions at origin. This raises endogeneity concerns. First, wages and local prices (e.g., rents) partly reflect the unobserved attractiveness of the different locations (omitted variation, e.g., in local amenities or in local policies). Second, wages and local prices are directly affected by the large migration flows from rural hinterlands to cities (reverse causality). To isolate exogenous variation in real wages at *origin*, we leverage agricultural shocks as predicted by international commodity prices and cropping patterns. Letting α_{co} denote the revenue share of crop c at origin o and p_c the crop-specific excess price in 2000, we construct an agricultural income shock, ω_o , as follows:⁶

$$\omega_o = \sum_c \alpha_{co} \times p_c$$

where p_c is constructed by filtering international commodity prices from their long-term trend (Imbert et al. 2020). To isolate exogenous variation in real wages at *destination*, we construct two instruments: a shift-share nominal wage based on industrial composition; and a land supply shifter affecting the price of local non-tradable goods (i.e., housing services). The first instrument, ω_d , is obtained by combining industrial employment shares, α_{id} , with industry-specific wages in 2005, w_i ,

$$\omega_d = \left(\sum_i \alpha_{id} \times w_i \right)$$

The second instrument is a land supply shifter exploiting the shape of cities before mass migration and the topography in their immediate hinterlands. More specifically, we isolate impervious areas to identify the urban extent of each city in 2000,⁷ we draw a buffer around each urban area within their prefecture—proportional to city size and calibrated on their actual growth between 2000–2005 (Harari 2020), and we calculate the “non-developable” area share, s_d , within the buffer.⁸

The exogenous variation in local conditions at origin further allows us to predict emigration from a certain location into a particular destination. We leverage agricultural revenue shocks (ω_o) to isolate exogenous variation in immigrant flows across the destinations following the shift-share procedure developed by Imbert et al. (2020). We combine exogenous shocks to rural incomes in each prefecture of origin (shifts) with a gravity matrix based on distance between each origin and each potential prefecture of destinations (shares).⁹

⁶We measure the revenue share of a given crop in a given prefecture by overlaying rasters of harvested area in 2000 and predicted yield (World Census of Agriculture 2000, and Global Agro-Ecological Zones, GAEZ) with prefectures boundaries. The international commodity prices are calculated by constructing the producer price at the farm gate in all countries but China and by averaging these producer prices across countries.

⁷Shapefiles of impervious areas were obtained from the Beijing City Lab—see <https://www.beijingscitylab.com/>.

⁸In our baseline analysis, we define a “non-developable” pixel as a 30m × 30m pixel with an average slope above 5 degrees.

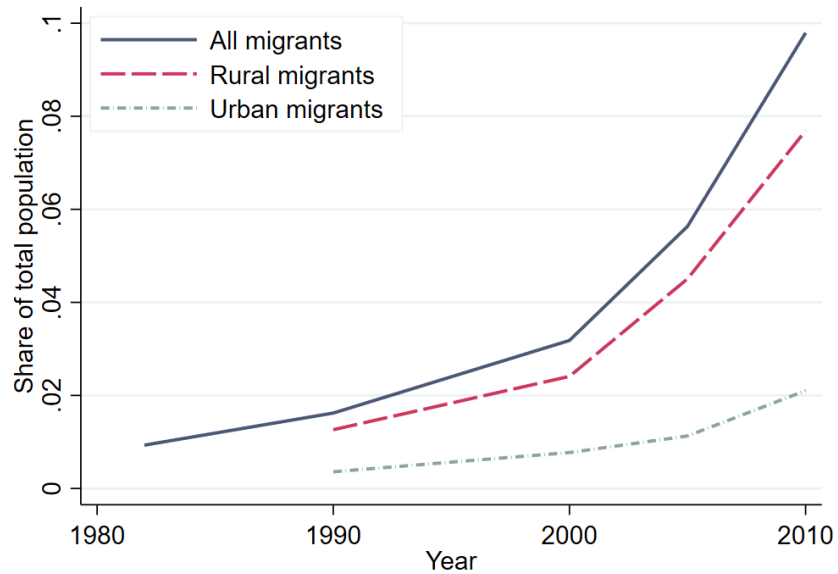
⁹More specifically, we convert a shock at origin on emigration flows, ω_o , into a shock at destination on migrant inflows,

2.2 Migration policies

Recent developments in Chinese internal migration policy induce a wide variation of such policies across prefectures.

We can distinguish three major phases in the development of the *Hukou* system since the beginning of the Reform era. Before 2000, the rules restricting internal migration were fixed by the central government, and essential services such as food provision were still attached to the place of household registration, which severely curtailed individuals’ ability to work outside of their places of origin for long periods of time. From 2000 onward, as we see from Figure 1, migration between prefectures was limited and progressed at the pace of the liberalization of the urban economy. Between 2000 and 2013, food provision and place of registration were separate, and the central government increasingly devolved to local governments (provinces and prefectures) the power to devise their own migration policies (Song 2014). This period thus coincides with large variation between cities in terms of *Hukou* stringency. Since 2014, the central government has been promoting a relaxation of migration restrictions to foster urbanization and domestic demand growth, in particular through the development of small and medium-sized towns.

Figure 1: Evolution of the migration rate by *Hukou* type.



Notes: This figure represents the internal migration rate in China between 1982 and 2010, using Population Census (1982, 1990, 2000, and 2010) and 2005 Mini-Census data. A migrant is defined as an individual whose prefecture of residence is different from her prefecture of household registration. “Rural” and “urban” refer to agricultural and non-agricultural *Hukou* holders, respectively.

One of our objectives is to investigate the effect of migration restrictions—their level but also their

ρ_d , by using a simple market access matrix:

$$\rho = M\omega,$$

where $M = \left(\frac{1}{d_{od}} / \sum_o \frac{1}{d_{od}} \right)_{o,d}$.

heterogeneity—on mobility between rural and urban areas and on migrant allocation across destinations. To measure *Hukou* stringency, we follow [Wu and You \(2021\)](#) and use census data from 2000 and 2010, which record whether people were born in a different county, whether they were registered locally, and what their type of registration was (agricultural or not). We compute the registration probability as the share of 15-64 year-old work migrants born in another county who were registered locally with a non-agricultural *Hukou*. The proportion is 9% in 2000 and 10% in 2010. To measure *Hukou* restrictions in the 2010s, and especially their large-scale reform in 2014, we rely on [Zhang et al. \(2018\)](#), who collected policy documents to create various indices of the ease with which migrants can obtain a local urban *Hukou* in 124 Chinese cities. We use the composite index, which summarizes different channels through which migrants can obtain local registration.¹⁰ The index is available for two periods: pre and post 2014 reform.

2.3 Living conditions in cities

Living conditions (e.g., return to labor and price of non-tradables) markedly differ across Chinese cities. We rely on two main data sources to capture these differences: (i) census data for rents and (ii) census data and Statistical Yearbooks for wages. We also measure non-monetary dimensions of living conditions, using (iii) census data to characterize housing quality and household living arrangements, and (iv) pollution and census data on commuting to capture amenities.

Rents

We use the 2000 Population Census and the 2005 1% Population Survey to measure the cost of housing in 2000 and in 2005. The data contain a rich housing module, which includes the monthly rent paid, as well as a wide array of housing characteristics. With these data, we create a measure of rental price at the prefecture level by averaging monthly rent by square meter across all tenants living in private accommodation.¹¹

Wages

Similarly, we need to measure wages at baseline in 2000 and in 2005. Information on wages is not available from the 2000 Census. We therefore use average wages from the Statistical Yearbooks as a baseline.¹² The yearbooks distinguish between the wage in the “city” proper, i.e., the urban core

¹⁰The “employment” component of this index is most relevant to rural migrants (e.g., having a high-school degree, legal and stable residence and employment for a certain number of years, no criminal record, etc.). The other components pertain to other channels of *Hukou* conversion, e.g., the purchase of a residential unit, investment, and eligibility for “talent” programs, which are less likely avenues for unskilled rural migrants.

¹¹We also create a residualized measure of rents, based on individual and housing characteristics available from the Mini-Census. More specifically, we regress monthly rent (in logarithm) on the dwelling’s quality and size, the number of floors, building material, building year, access to tap water, kitchen type, fuel type, toilet type, bathroom type, and square-footage (flexibly introduced as decile bins) as well as the rental type (public or commercial housing), the individual’s migration status, and we average the residuals by prefecture.

¹²These data are 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>).

of the prefecture, and the prefecture as a whole, i.e., including the rural hinterland. We leverage this distinction to measure destination and origin wages differently, using “city” and prefecture wages, respectively. One must bear in mind that origin wages reflect both the indirect utility of staying at origin and of moving within the prefecture, which we do not consider as migration in the empirical analysis.

We complement the aggregate data from Statistical Yearbooks with individual data on wages in 2005 as reported from the 2005 1% Population Survey. This source further allows us to observe hours worked and occupations/industries, which enables us to characterize working conditions and better isolate exogenous variation in real wages at destination (see Section 2.1).

Housing conditions and living arrangements

The 2000 Population Census and the 2005 1% Population Survey allow us to characterize housing conditions for both migrants and non-migrants. We create indices of poor housing conditions based on the rich housing module available and in particular on the description of housing materials and the types of kitchen, bathroom, and toilet in the dwelling, characteristics that display a wide variation across Chinese prefectures as well as across migrant statuses within a city.

Expenditure on non-tradables crucially depends on whether migrants live with their children at destination or leave them behind in their rural homes. We use the same data sources to compute the prefecture-level probability that migrants live with their children at destination, which we can compare with a similar measure for non-migrants. We compute these probabilities by combining the household roster module of the census with information on marital status.¹³

Another dimension of living conditions in cities is amenities. Since amenities are largely unobservable, we estimate them based on the model (see Section 5), and assess the validity of our model-based amenity estimates using data on pollution and commuting—see Appendix A for details about these additional data sources.

3 Motivating facts

This section establishes the following motivating facts: rural migrants sort into cities with high nominal wages and high cost of living; they are also more likely to live in poor housing conditions and without their children. This is especially the case in cities where *Hukou* restrictions make it more difficult for them to settle, and where they remit a higher share of their income.

3.1 Migrant concentration and living conditions in cities

To characterize the allocation of migrants across cities, we construct a measure of migrant concentration relative to urban residents based on census data. Let R_c denote population in city c and R total urban

¹³This measure relies on the assumption that married individuals have children, and that the children are living at origin if not present in the household roster module. Another option is to use the fertility module. This module is presented to every female respondent aged 15-64; while this module allows us to unambiguously determine coresidence with children, it is only available for women. The two measures, however, are highly positively correlated and yield similar results.

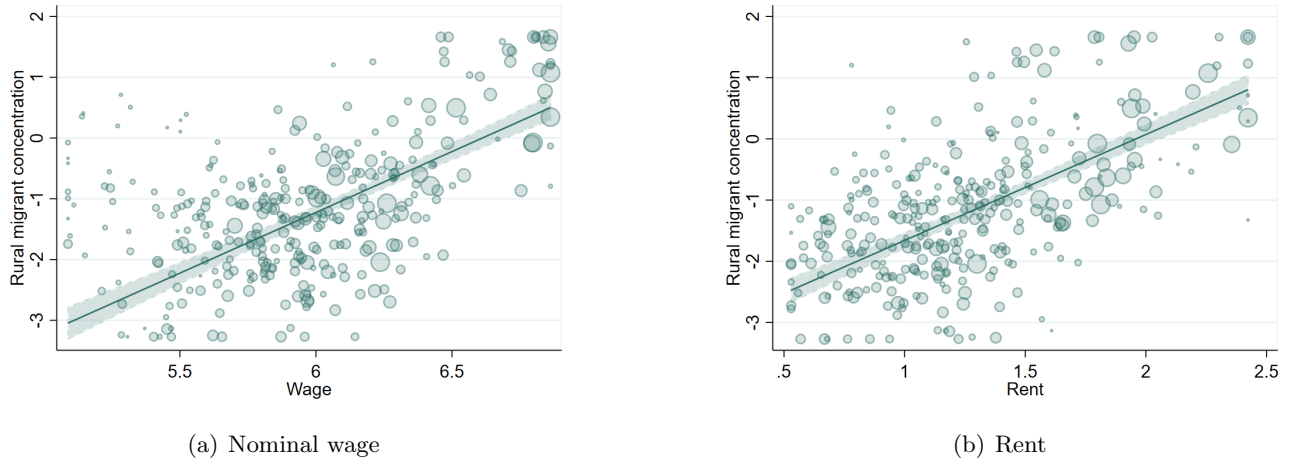
population in China, both measured in 2000. Let M_c denote the number of rural migrants in city c who arrived between 2000 and 2005 and M the total number of rural migrants across the country. Migrant concentration in city c , writes:

$$m_c = \log \left(\frac{M_c / R_c}{M / R} \right).$$

This measure would be equal to 0 if the allocation of rural migrants was proportional to the resident population, or equivalently, if the immigrant rate was constant across cities.

Figure 2 shows that this is not the case. In panel (a), we display the relationship between the migrant concentration, m_c , and a measure of nominal monthly wages, w_c in 2005. The relationship is clearly positive: a doubling of the wage is associated with receiving four times more migrants. In panel (b), we display the relationship between the same migrant concentration and a measure of (log) monthly rents, r_c in 2005. Again, the relationship is positive: a city with rents twice as high would receive 3.4 times more rural immigrants.

Figure 2: Rural Migrant Concentration, Wages and Rents.



Notes: The y-axis reports the migrant concentration in city c , m_c . In panel (a), the x-axis reports a measure of (log) monthly wage; in panel (b), the x-axis reports a measure of (log) of the monthly rent per square meter. Hours and Wages are constructed using the 2005 census.

The positive relationship between migrants and the monthly wage may be due to the fact that migrants work in destinations and sectors that require longer working hours. Appendix Figure A2 shows that indeed migrants are concentrated in cities where workers work more hours per month. However, even when we consider hourly wage rates, the stylized fact that migrants concentrate in high wage locations still holds.

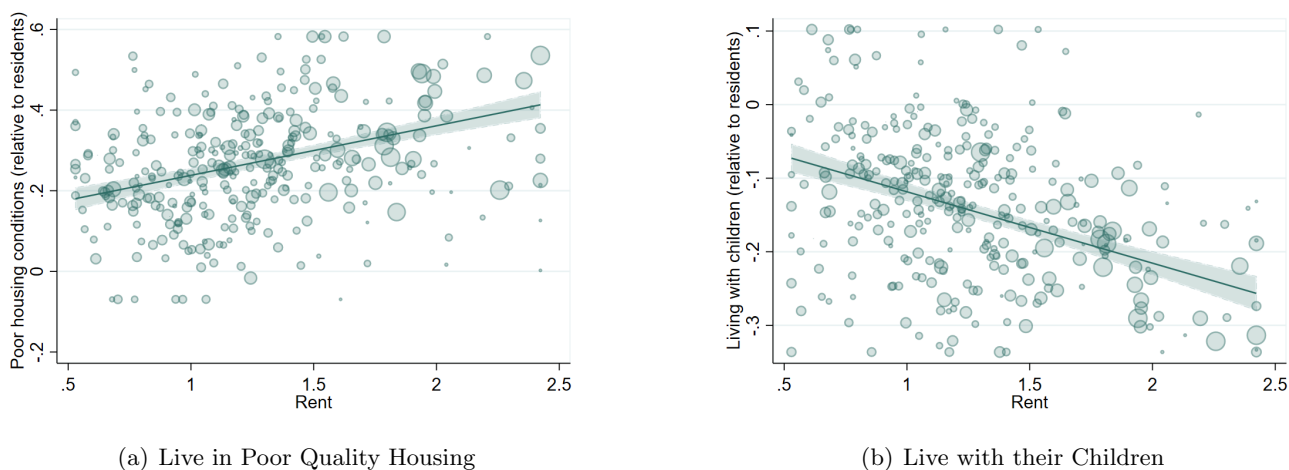
Rural migrants may face lower mobility costs than urban residents when they move between cities, since urban residents are already settled and benefit from access to services which would be lost if they were to move to other urban settings. This could explain why there are more rural migrants relative to urban residents in high wage locations. To test this, we use an alternative comparison group and

compute the concentration of rural migrants relative to urban migrants. Appendix Figure A3 confirms that rural migrants are disproportionately concentrated in high wage - high rent cities.

3.2 Migrants living conditions

Our first finding that rural migrants locate in cities with high living costs is puzzling, since they are poorer than urban residents. We next investigate their living conditions. Specifically, we compare the proportion of rural migrants with the proportion of urban residents who live in poor quality housing, based on the characteristics of their dwelling (building material, kitchen, bathroom and toilet type). We also compare the proportion of rural migrants with the proportion of urban residents who live with their children among those who have a family.

Figure 3: Stylized fact 2—Migrants live in precarious conditions



Notes: The x-axis reports a measure of (log) monthly rents constructed using the 2005 census. In panel (a), 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 census. In panel (b), the y-axis reports the difference between the proportion of rural migrants and the proportion of urban residents who live with their children (among those who do have children).

Figure 3 shows that on average migrants are about 30pp. more likely to live in poor quality housing and 15pp. less likely to live with their children when they have a family. Strikingly, these proportions increase in cities with higher rents. This suggests that the reason why migrants can disproportionately locate in expensive cities despite being poorer than urban residents is because they consume less locally and remit part of their income to their family who live in their origin location.

In Appendix Figures A4 we provide further evidence on how the selection of rural migrants relative to urban residents differ between high- and low-rent cities. Rural migrants are on average younger and less educated than urban residents; these differences are even larger in high rent cities. On average, rural migrants and urban residents have similar gender compositions and marriage rates. However, in high rent cities, rural migrants are more likely to be male and single. These selection patterns are consistent with the idea of rural migrants as a “floating population”, which does not plan to settle in

these expensive cities but maximizes income at destination to remit money back home.

3.3 Hukou restrictions and the consumption of migrants

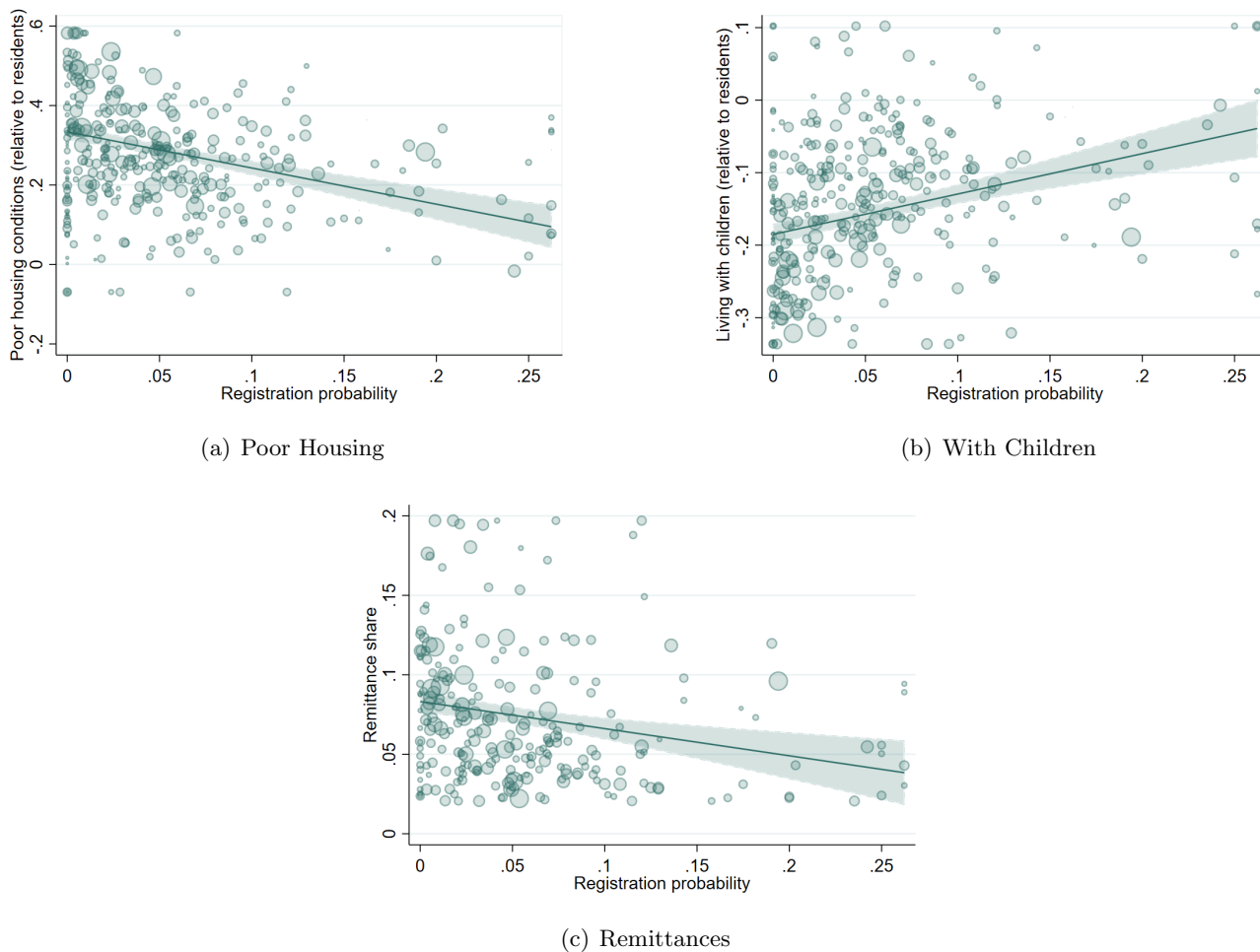
Rural migrants' ability to settle at destination is regulated by the local *Hukou* policy. We now link migrants' living conditions to the probability that they can obtain the local *Hukou*. We measure this probability as the fraction of migrants born in rural areas who are registered locally in the census 2010 data. On average this probability is 10% and stable between 2000 and 2010, so that it is likely that migrants would use it to form their expectations and make migration and consumption decisions.

In Figure 4, we show that migrants are more likely to live in poor housing conditions, and less likely to live with their children in cities where it is difficult for them to settle. Interestingly, when the probability of being registered is high (about 25%), rural migrants' living conditions become much more similar to those of urban residents. This suggests that the decision to locate in expensive cities in poor living conditions may be the migrants' response to their inability to settle.

We also consider the relationship between the share of income that migrants spend on remittances based on the nationally representative CMDS survey in 2011-2012. Figure 4 shows that migrants remit a higher share of their income when they live in cities where it is unlikely they will be allowed to settle. In cities where the registration probability is the highest, the remittance share of income is much lower and tends towards zero. This stylized fact suggests that the *Hukou* policy is a reason for migrants to transfer consumption from urban to rural areas.

In the next section, we will develop a spatial equilibrium model of migration decisions that takes into account the fact that migrants consume part of their income at origin, to rationalize the fact that they tend to concentrate in high-wage high-rents locations. In the last section of the paper we will consider how different the allocation of migrants across cities would be if they had the same consumption behavior as urban residents.

Figure 4: Stylized fact 3—Hukou restrictions and the consumption of migrants.



Notes: The x-axis reports the share of rural migrant workers born in another county who held a local urban registration (*Hukou*), from the 2010 Census. In panel (a), the y-axis reports the fraction of migrants living in poor housing conditions relative to the fraction of urban residents living in poor housing conditions. In panel (b), the y-axis reports the fraction of migrants living with their children relative to the fraction of urban residents living with their children. In panel (c), the y-axis reports a measure of remittances as a share of income, r_c , from CMDS 2011-12 data;

4 Model

In this section, we introduce the model that guides our empirical investigation. The model tries to capture the specific context experienced in China before and after the liberalization of migration that took place after the 2000s. Before the 2000s, migration was (severely) limited in China, as we document in Figure 1, so much so that for simplicity we assume that population in each location, both rural and urban, is fixed pre-2000s. After the liberalization, migrants are allowed to relocate. However, the *Hukou* system still imposes that an important fraction of immigrant income is spent at origin. This reflects the fact that the *Hukou* system effectively means that migrants are forced to leave their children and other family members in the rural origins and remit part of their income. Throughout, we denote with a subscript 0 the variables from before the 2000s (essentially the initial population distribution) and without subscripts the variables after the 2000s. For simplicity, we assume that urban migrants do not move, although this can be relaxed. We explore how to relax this assumption in the Appendix C.1. In Appendix C.2, we explore how the model changes when we have multiple, instead of just one, labor type.

4.1 Preferences

We assume that the utility of an individual i , who is potentially a rural migrant from r and considers urban destination u , is given by the following expression:

$$\ln U_{iru} = \ln Z_u + (1 - \alpha) \ln C_T + \alpha_D \ln C_H + \alpha_O \ln C_R + \ln \varepsilon_{iru},$$

subject to standard budget constraint:

$$C_T + p_r C_R + p_u C_H \leq w_u.$$

We denote by Z_j the amenity levels in each location $j \in J = R \cup U$ — R denotes the set of rural locations and U the set of urban ones. We denote by $\alpha = \alpha_D + \alpha_O$ the share of expenditures on non-tradables. Among those, there is a fraction α_D of expenditures that takes place at destination and a fraction α_O that takes place at origin, possibly via remittances. C_T denotes the consumption of tradable goods, C_H denotes the consumption of housing (at destination), and C_R denotes the goods that can be bought with remittances. ε_{iru} is an idiosyncratic taste shock for each individual i for each origin-destination pair.

Utility maximization results in the following indirect utility for each individual i with origin $r \in R$ and destination $u \in U$:

$$\ln V_{ru} + \varepsilon_{iru} = \ln Z_u + \ln w_u - \alpha_D \ln p_u - \alpha_O \ln p_r + \varepsilon_{iru}$$

This indirect utility means that indirect utility for rural to urban migrants is given by wages at destination discounted by migrants price index, which is a combination of destination and origin prices.

Similarly, we can obtain the indirect utility of staying in the rural location as:

$$\ln V_{rr} + \varepsilon_{irr} = \ln Z_r + \ln(w_r + (1 - \pi_{rr})\alpha_O \bar{w}_{rU}) - \alpha \ln p_r + \varepsilon_{irr}$$

where π_{rr} is the fraction of stayers (which we determine later), and $\bar{w}_{rU} = \sum_u \pi_{ru} w_u$ is the average wage of rural migrants in urban locations. This last expression can be re-written as follows:

$$\ln V_{rr} + \varepsilon_{irr} = \ln Z_r + \ln w_r - \alpha \ln p_r + (1 - \pi_{rr}) \frac{\alpha_O \bar{w}_{rU}}{w_r} + \varepsilon_{irr}$$

This expression is intuitive. It says that the value of staying in a rural location is equal to the (standard) adjusted real wage plus the value of remittances. In turn, the value of remittances at origin is given by the fraction of remitters in the rural location times the fraction of income remitted relative to location of origin income.

4.2 Location choice

The indirect utility function allows us to formulate a discrete choice model on how migrants decide on whether to move or not, and, if they do, where to move. This problem is given by:

$$\max_j \{ \ln V_{rj} + \varepsilon_{iru} \}$$

We assume that ε_{iru} is drawn from a nested logit. The probability that one individual i moves from r to u , which, by the law of large numbers, is going to be the same as the fraction of individuals in r that move to u is given by:

$$\pi_{ru} = \frac{M_{ru}}{N_{r,0}} = \chi \left(\frac{V_U}{V_r} \right)^{1/\gamma} \left(\frac{V_{ru}}{V_U} \right)^{1/\lambda} \quad (1)$$

We define by $1 - \chi$, the weight that migrants attach to home locations, or, alternatively, by χ the propensity for individuals to migrate. This parameter captures a home bias and plays an important role in shaping how many emigrants are observed.

Equation (1) shows that the flow of migrants from r to u can be decomposed in two terms. The first term, $\chi \left(\frac{V_U}{V_r} \right)^{1/\gamma}$, captures the fraction of population initially in r that moves somewhere else. The second term, $\left(\frac{V_{ru}}{V_U} \right)^{1/\lambda}$, captures the fraction of movers that choose destination u . The parameters γ and λ govern the elasticity of substitution between moving or staying in the original location, and between choosing alternative destinations.¹⁴

We denote the expected value of being born in r by V_r , which is given by:

$$V_r = [(1 - \chi)V_{rr}^{1/\gamma} + \chi V_U^{1/\gamma}]^\gamma,$$

We denote the expected value of migration away from r by V_U , which is given by:

¹⁴We also obtain a simple expression for the fraction of stayers among the initial population, which is given by:

$$\pi_{rr} = \frac{M_{rr}}{N_{r,0}} = (1 - \chi) \left(\frac{V_{rr}}{V_r} \right)^{1/\gamma}.$$

$$V_U = \left[\sum_{u \in U} V_{ru}^{1/\lambda} \right]^\lambda.$$

4.3 Local labor markets

We assume that tradable output in location u is produced with the following production function:

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

where A_u is the local (exogenous) productivity, K_u denotes capital or land, and L_u denotes the amount of workers in u . The parameter σ denotes the elasticity of substitution between labor and the other factor. The parameter β is the weight of labor in production.

Profit maximization leads to the following (inverse) labor demand equation:

$$\ln w_u = \ln A_u + \ln \beta - \frac{1}{\sigma} \ln L_u + \frac{1}{\sigma} \ln Y_u \quad (2)$$

4.4 Local housing markets

Non-tradable output, or, in short, housing services, is produced by combining tradable good and land, a fixed factor, according to the following production function:

$$Y_u^H = \tau_u^{-\tau_u} (Y)^{\tau_u} (T_u^H)^{1-\tau_u}$$

where $1 - \tau_u$ is the importance of land as an input in location u . In places where land is an important input, the supply of housing is more costly to adjust.

Profit maximization leads to the following housing supply equation:

$$Y_u^H = T_u^H (p_u)^{\eta_u}$$

where $\eta_u = \frac{\tau_u}{1-\tau_u}$ is the housing supply elasticity. Lower values of η_u indicate that housing supply is less responsive to the housing price, p_u .

4.5 Goods market clearing and equilibrium

Tradable goods market clearing occurs in the aggregate economy, and is given by:

$$(1 - \tilde{\beta})Y = (1 - \tilde{\beta}) \sum_u Y_u = \sum_r w_u L_u + \sum_r w_r L_r. \quad (3)$$

where $\tilde{\beta}$ is the share of income that goes to labor, which, in principle, is endogenous and depends on the elasticity of substitution between labor and the other factors. In practice, this share is close to β , the weight of labor in production. When the production function for the tradable good is Cobb-Douglas, then $\tilde{\beta} = \beta$.

Housing clears at the local level. Local market clearing is given by:

$$T_u^H(p_u)^{\eta_u} = \alpha \frac{w_u}{p_u} N_u + \sum_r \alpha_D \frac{w_u}{p_u} M_{r,u} \Rightarrow T_u^H(p_u)^{\eta_u} = \frac{w_u}{p_u} [\alpha N_u + \alpha_D M_u],$$

This expression equates housing supply and demand. It is worth noting that the demand for housing in a location depends on the demand for housing of urban residents (N_u) and on the demand for housing of migrants ($\sum_r M_{r,u} = M_u$), who spend a smaller fraction of their income on housing.

From the market clearing condition, we obtain the equation:

$$\ln p_u = \frac{1}{1 + \eta_u} \ln w_u + \frac{1}{1 + \eta_u} \ln \alpha N_u + \frac{1}{1 + \eta_u} \frac{\alpha_D}{\alpha} \frac{M_u}{N_u} - \frac{1}{1 + \eta_u} \ln T_u^H$$

We can combine the market clearing condition with the (inverse) labor demand equation to obtain:

$$\ln p_u = \frac{1}{1 + \eta_u} (\ln A_u + \beta \ln Y_u) + \frac{1 - \frac{1}{\sigma}}{1 + \eta_u} \ln \alpha N_u + \frac{1}{1 + \eta_u} \left(\frac{\alpha_D}{\alpha} - \frac{1}{\sigma} \right) \frac{M_u}{N_u} - \frac{1}{1 + \eta_u} \ln T_u^H \quad (4)$$

This equation shows that local housing prices depend on local productivity, the size of the location, the availability of land, and the relative size of the migrant population—measured as the ratio of migrants to urban residents. Whether migrants have a large, positive or negative effect on housing prices depends on three parameters. First, whether immigrants exert pressure or relax pressure on housing markets depends on whether the fraction of income spent locally ($\frac{\alpha_D}{\alpha}$) is larger or smaller than the pressure immigrants exert on labor markets (governed by the inverse elasticity of substitution between labor and the other factors).

To give some intuition, if the local production function is Cobb-Douglas, then the market clearing for housing implies that:

$$\ln p_u = \frac{1}{1 + \eta_u} \ln A_u + \frac{1 - \beta}{1 + \eta_u} \ln K_u + \frac{1}{1 + \eta_u} \left(\frac{\alpha_D}{\alpha} - \beta \right) \frac{M_u}{N_u} - \frac{1}{1 + \eta_u} \ln T_u^H$$

In this case, whether immigrants have a positive or negative effect on housing prices depends on whether the share of income that immigrants devote to housing is higher than the share of income in production that goes to labor.

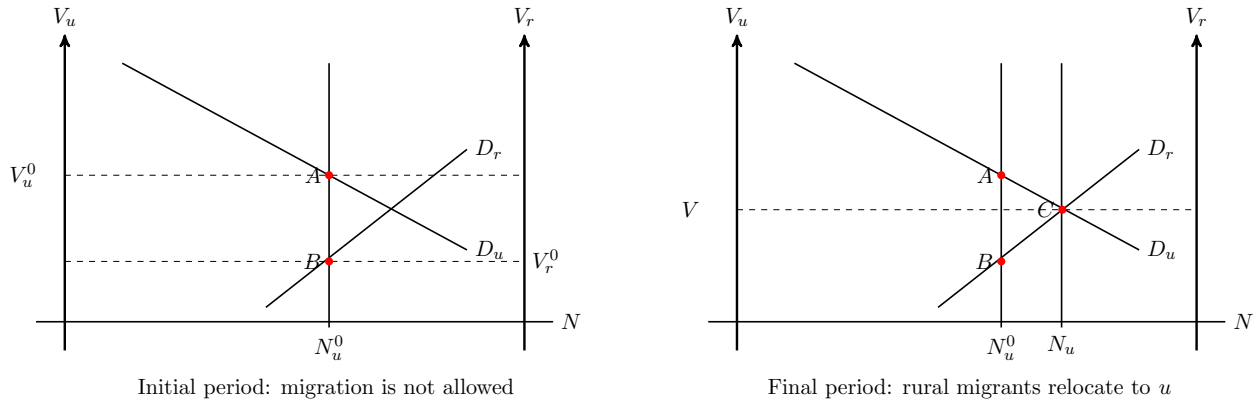
Irrespective of whether immigrants lead to an increase or a decline in house prices, the effect of migration on housing markets is attenuated by the housing supply elasticity. Intuitively, if it is easy to expand the supply of housing, then η_u is larger, and, hence, tends to mitigate any effect that immigrants may have on local housing prices.

4.6 Graphical representation of the model

To provide some intuition on the model, we now discuss its graphical representation. We start by discussing a model where migrants do not remit income to their family members. This is the standard two-period [Rosen \(1974\)](#)-[Roback \(1982\)](#) model in which mobility is forbidden in the first period and mobility barriers are removed in the second period. After gaining some intuition using this standard model, we explain how remittances modify the framework, and we discuss the same thought experiment, with an initial period when free mobility is restricted and a second period when it is not.

Figure 5 represents the standard model to think about migration (both internally and internationally). The graph on the left panel represents the initial period in which migration is not allowed. On the left hand side of the y-axis, we plot the value of living in the urban location u . In the right hand side of the y-axis, we represent the value of living in the rural location r . We assume that, for historical reasons, the amount of workers in the urban location is N_u^0 , which is represented as a vertical line. The demand for living in both the urban and rural location is declining in the amount of residents in the location. We assume that, initially and also for historical reasons, the demand for urban locations is higher. Because migration is forbidden, the supply of labor is fixed in each location. As a result, the equilibrium welfare of leaving in the urban location, denoted by V_u^0 is higher than the welfare of living in the rural location, denoted by V_r^0 . This is an economy where there are strong incentives for workers to move from r to u , but this is forbidden, as was effectively the case in China 30 years ago or so, and as is also the case—at least to a large extent—with international migration.

Figure 5: A model without remittances



Once migration is allowed, workers have incentives to move from r to u . We depict this in the right panel of Figure 5. With free mobility, workers are going to move towards u up to the point where indirect utility is equalized between r and u , i.e., up to the point where the two demand curves cross, which we denote with point C in the graph. Note that this model predicts the same (proportional amount) of migrants to two urban locations that, before migration is allowed, are at similar levels of indirect utility. That is, if there are two potential destinations u and u' such that initially were such that $V_u = V_{u'}$, then the fraction of migrants to u relative to u' will be the same as the fraction of urban residents in u relative to u' .

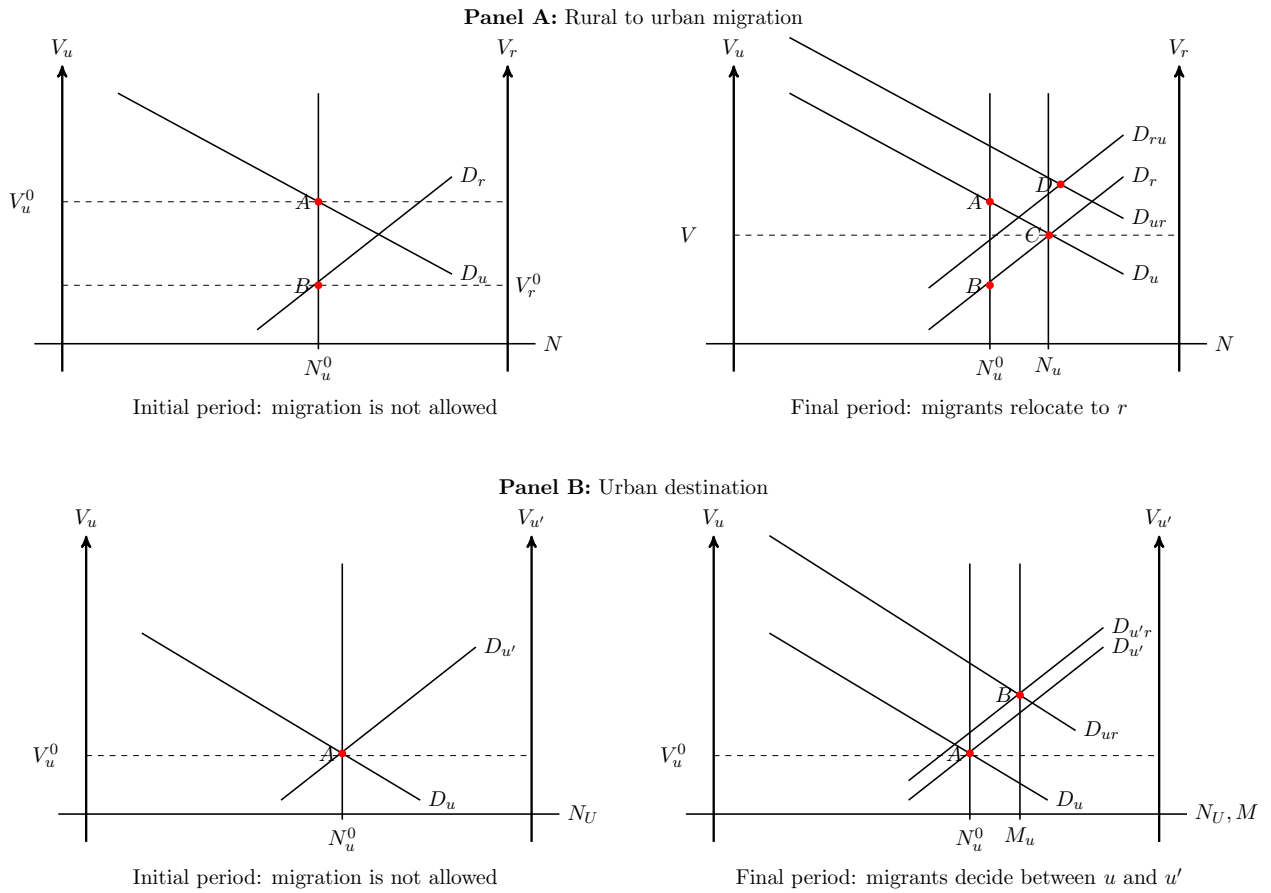
As we have seen analytically, the main thing that remittances do is to alter the supply of labor to a location, which is obviously the same as the demand for living in a location. With remittances, the demand for living in a location depend also on your origin location, before migration takes place. The starting point in this model is the same as before: an economy with imbalances in the demand for living across locations and population fixed at an exogenous point determined by historical circumstances. This is showed in the first panel of Figure 6, which is the same than in the standard model depicted

in Figure 5. Remittances affect the demand for living in each location of both rural migrants and stayers. On the one hand, the fact that migrants can remit income increases the attractiveness of urban locations, hence the demand for living in u for migrants coming from r is the line D_{ur} rather than D_r . On the other hand, the income received from remittances also increases the demand for staying in the rural location, hence moving it from D_r to D_{ru} for the rural residents who receive remittances. These two forces affect the overall level of migration in opposite ways. Hence, it is an empirical question to know which one of these two will dominate.

This discussion highlights two results. First, remittances are good for migrants. Both migrants and stayers benefit from the fact that the income is generated in the urban locations and is consumed in the rural ones (particularly when migrants are altruistic and care about the family members left behind). Second, remittances are unlikely to lead to major increases in overall migration levels, since both the demand for moving and for staying increase with remittances, and the latter one increases with the overall level of migration.

The bottom part of Figure 6 shows how migrants decide on particular destinations. To illustrate this part of the model, it is convenient to assume that initially the differences in the value of living across urban destinations u and u' is not very different – and assumption that we endogenize in Appendix C.1. This is depicted in the left hand side graph of panel B in Figure 6. The fact that migrants send remittances, means that the demand for location u is going to be higher than over u' if nominal wages (and housing prices) are higher in u than in u' . This is depicted in the right hand side of panel B. This figure shows how the fact that immigrants spend a fraction of their income on remittances alters their location choices, relative to urban residents, as can be seen from comparing points A and B.

Figure 6: A model with remittances: rural to urban migration



5 Estimation

In this section, we estimate the main parameters of the model: the share of income spent on non-tradable goods, the migration elasticities with respect to conditions at origin and destination, and the two elasticities that govern the response of wages and rents at destination to migrant inflows, i.e. the labor demand and the housing supply elasticities.

Consumption shares

First, we compute the share of income spent on local non-tradables by urban residents (parameter α in the model) and rural migrants in cities (α_D in the model). For this we use the 2005 census and divide monthly housing rents by household income. Table 1 reports the results. Urban residents spend a higher share of their income (27%) than rural migrants (20%). In our model, the difference is explained by the fact that migrants spend part of their income on housing at origin in the form of remittances. We use CMDS survey data from 2011 to compute the share of migrants' income that is spent on remittances (α_O in our model). As Column 3 in Table 1 shows, it is equal to 7.6%, which is approximately the difference between the housing share of urban residents and that of migrants, which is consistent with the model.¹⁵

Table 1: Share of income spent on local public goods at origin and destination

	Census 2005		CMDS 2011
	(1) Urban Residents	(2) Rural Migrants	(3) Rural Migrants
Housing Share	0.272	0.196	
Remittance Share			0.076
Observations	13686	33430	98623

Note: Columns 1 and 2 report the average share of household income spent on rents every month for urban residents and migrants with an Agricultural *Hukou* respectively, as computed in the Census 2005. Column 3 reports the share of household income spent on remittances by rural migrants in the 2011 CMDS survey.

Estimation of the location choice model

The internal migration part of the model depends on γ and λ , which jointly govern the flows of migrants from each origin to each destination.

From equation (1) we obtain:

$$\ln \pi_{ru} = \ln \frac{M_{ru}}{N_{r,0}} = \ln \chi + \frac{1}{\gamma} (\ln V_U - \ln V_r) + \frac{1}{\lambda} (\ln V_{ru} - \ln V_U)$$

We can approximate this expression by:

¹⁵In results not reported here, we compute the remittance share from the Chinese Health and Income Panel (CHIP) survey for 2002, and find a very similar number: a remittance share of 7.8%

$$\ln \frac{M_{ru}}{N_{r,0}} = \underbrace{\ln \chi}_{\text{Migration costs}} + \underbrace{\frac{1}{\lambda} [\ln w_u - \alpha_D \ln p_u]}_{\text{Real wages at destination}} - \underbrace{\frac{1}{\gamma} [\ln w_r - \alpha \ln p_r]}_{\text{Real wages at origin}} + \varepsilon_{ru}$$

This expression shows that this model delivers a migration equation that has three parts. The first part, captures migration costs. Multiple factors make migrating difficult, and many of these factors do not depend on economic variables. All these costs are captured in χ . Note that χ captures in a reduced form way much of what prior literature has investigated, such as land (in)security at origin, distance, information barriers, and limits to migration of various kinds (Young 2013, Gollin et al. 2014, Bryan and Morten 2019, Brandt et al. 2013, Tombe and Zhu 2019, Gai et al. 2021, Adamopoulos et al. 2022). The second is real wages at destination to which migration responds with an elasticity $\frac{1}{\lambda}$. The third is real wages at origin, with the associated migration elasticity $\frac{1}{\gamma}$. There is an important difference in the way we compute real wages at origin and destination. For the destination, the real wage is the nominal wage minus rents weighted by the share of income that migrants spend on destination housing α_D , whereas the corresponding weight for origins is the share of income that residents spend on housing α .

There are two main identification concerns for this migration model: (i) that wages and rents are themselves affected by migration, and (ii) that they are correlated with other unobserved destination characteristics, such as amenities. We alleviate these concerns in two ways. First, we include baseline population at origin and destination as controls which should alleviate concerns on some unobservables. For example, high amenity locations, which is not observed, should have, everything else equal, more inhabitants, something we control for. Second, we instrument real wages at origin and destination using three instrumental variables. The first is a shift-share instrument where the shift is the national average of the wage in each industry and the share is the employment share of each industry in the prefecture of destination. The second instrument exploits the topography surrounding each city to measure constraints to housing supply in the prefecture of destination. The third instrument measures changes in the value of the agricultural portfolio of the prefecture of origin due to international price shocks as in (Imbert et al. 2020).

The estimating equation for the migration model is the following:

$$\ln EMR_{ru} = \chi \ln d_{ru} + \frac{1}{\lambda} [\ln w_u - \widehat{\alpha}_D \ln p_u] - \frac{1}{\gamma} [\ln w_r - \widehat{\alpha} \ln p_r] + \delta \mathbf{X}_{\mathbf{ru}} + \varepsilon_{ru} \quad (5)$$

where EMR_{ru} is the emigration rate between prefecture of origin r and prefecture of destination u between 2000 and 2005, d_{ru} is the geographical distance between r and u , w_u and w_r are wages at destination and origin in 2005, p_u and p_r are rents at destination and origin in 2005, and $\mathbf{X}_{\mathbf{ru}}$ is a vector of controls, which includes log population at origin in 2000, and log population at destination in 2000.¹⁶ We use the estimates from the previous section, $\widehat{\alpha} = 0.27$ and $\widehat{\alpha}_D = 0.2$ as weights on rents.

¹⁶To simplify notation, we write migration costs as $\chi \ln d_{ru}$ although this contains a constant as well, i.e. $\chi \ln d_{ru} = \chi_1 + \chi_2 \ln d_{ru}$.

The estimation is done with Poisson regressions, and with standard errors clustered at the origin level.

We present the estimates in Table 2. The coefficients have the expected sign: migrants are less likely to go to more remote destinations, more likely to go to destinations that offer high real wages, and less likely to leave when their place of origin offers high real wages. The estimates are robust to the inclusion of population controls – column (2) – and to instrumenting real wages at origin and destination, in column (3).¹⁷ Our estimates imply an elasticity of migration with respect to real wages at destination of $\frac{1}{\lambda} = 3$ and an elasticity of migration with respect to real wages at origin of $-\frac{1}{\gamma} = -2.6$.

Table 2: Estimates of location choice model

	ln Emigration Rate 2000-2005		
	(1)	(2)	(3)
D.ln_real_wages_2005	4.103 (0.087)	3.451 (0.092)	3.014 (0.113)
O.ln_real_wages_2005	-1.475 (0.143)	-1.324 (0.158)	-2.577 (0.568)
Observations	78314	78314	78314
Controls	No	Yes	Yes
Instruments	No	No	Yes

Note: The outcome is the log emigration rate between 2000 and 2005. The estimation is done with Poisson regressions, with standard errors clustered at the origin level. “Log Distance” is the log of the geographical distance between the centroids of the prefectures of origin and destination. “Log Destination Real Wages 2000” is the log of nominal wages minus $0.2 \times$ rents at destination in 2000. “Log Origin Real Wages 2000” is the log of nominal wages minus $0.27 \times$ rents at destination in 2000. In Column 3, real wages at origin and destination in 2000 are instrumented by nominal wages at origin and destination in 1995. Controls include log population at origin in 2000, log population at destination in 2000, and log migrant population from the origin living at destination in 2000.

Estimation of parameters at destination

There are two more important elasticities in the model: the production function depends on the (inverse) labor demand elasticity and the production of housing depends on the housing supply elasticity. To estimate the elasticities at destination we can use the labor and housing market equations introduced before. The demand for labor takes the following form:

$$\ln w_u = \ln A_u - \frac{1}{\sigma} \ln L_u + \frac{1}{\sigma} \ln Y_u$$

¹⁷We report the first-stage estimates in appendix table A1. As expected, the wage shift-share has a positive effect and the land supply shock a negative effect on real wages at destination, while the agricultural price shocks have a positive effect on real wages at origin.

This equation relates wages in each urban destination to (working-age) population in each location. To estimate this equation we need exogenous changes in the supply of labor.

To identify the wage elasticity, we regress changes in wages on changes in log population at destination:

$$\Delta \ln w_u = \beta \Delta \ln L_u + \delta \mathbf{X}_u + \varepsilon_u \quad (6)$$

where $\Delta \ln w_u$ is the change in log wages at destination between 2000 and 2005, $\Delta \ln L_u$ is the change in log population rate between 2000 and 2005, and \mathbf{X}_u is a vector of controls which include the land supply shock and the wages shift-share instruments used in the estimation of migration elasticities, as well as the log of the stock of migrants in 2000 divided by population. These controls are meant to capture potentially differential trends across locations. To further address issues of endogeneity, we instrument changes in population with a shift-share instrument as in [Imbert et al. \(2020\)](#). The identification relies on the exogeneity of changes in international prices for agricultural commodities, which affect rural incomes, and hence emigration decisions across China. We construct shifts as the weighted sum of shocks to crop prices between 2000 and 2005, weighted by local cropping patterns in each prefecture of origin, and construct shares as the probabilities that migrants from a given origin chose a particular prefecture of destination pre-2000.

The second equation that we obtain from the model comes from the housing market:

$$\ln p_u = \frac{1}{1 + \eta_u} (\ln A_u + \beta \ln Y_u) + \frac{1 - \frac{1}{\sigma}}{1 + \eta_u} \ln \alpha N_u + \frac{1}{1 + \eta_u} \left(\frac{\alpha_D}{\alpha} - \frac{1}{\sigma} \right) \frac{M_u}{N_u} - \frac{1}{1 + \eta_u} \ln T_u^H$$

This equation relates housing prices to migration ‘shocks’ measured as the ratio between migrants and urban residents. We can also estimate this equation using the pre-migration housing prices as a baseline and relate changes in housing prices to migrant shocks.

To estimate the housing supply elasticity, the estimating equation is

$$\Delta \ln p_u = \beta \ln(1 + IMR_u) + \delta \mathbf{X}_u + \varepsilon_u \quad (7)$$

where $\Delta \ln p_u$ is the change in log rents at destination between 2000 and 2005, IMR is the immigration rate between 2000 and 2005, and \mathbf{X}_u is a vector of controls which include log destination population in 2000 and log migration population in 2000. IMR is instrumented with the same shift-share instrument as in the wage equation.

We present the results of this estimation in [Table 3](#), with and without instrumenting the immigration rate by the shift-share instrument. The OLS estimates have the expected sign: destinations that received more migrants experienced declines in wages. Since migrants choose high wage destinations, one might expect the first estimate to be biased upward. Indeed, once we include controls, the coefficient becomes more negative. The IV estimate is even more negative, but imprecisely estimated. Turning to the effects of migration on rents, we see that the raw correlation between migration and rents is positive but small. Since migrants prefer low rent destinations, one might expect the estimated effect on rents to be biased downward. However, in our model, we argue that migrants are relatively insensitive to

Table 3: Estimates of the labor demand and housing supply elasticities

	$\Delta \ln \text{ Wage}$			$\Delta \ln \text{ Rents}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln \text{ Population}$	-0.063 (0.042)	-0.088 (0.045)	-0.195 (0.151)			
$\ln(1+\text{Immigration Rate})$				0.074 (0.111)	0.332 (0.158)	0.301 (0.392)
Observations	253	253	253	321	321	321
Controls	No	Yes	Yes	No	Yes	Yes
fstat	.	.	23.136	.	.	50.604

Note: In Columns 1 to 3 the outcome is the change in log wages between 2000 and 2005, in columns 4 to 6 it is the change in log rents between 2000 and 2005. Immigration rate is the number of rural migrants arrived between 2000 and 2005 divided by population in 2000. In Columns 3 and 6, immigration is instrumented using a shift-share instrument as in [Imbert et al. \(2020\)](#). Controls include log population in 2000 and log migrant population in 2000.

rents at destination, so that this bias may not be strong. Indeed once we include controls the estimate becomes positive, 0.332. The IV estimates are close to the OLS, but are once again much more noisy. To compute the model parameter, we rely on the IV point estimates which are close to [Imbert et al. \(2020\)](#) estimates using firm wage data. The (average) housing supply elasticity can be computed using the model equation $\frac{1}{1+\eta_u} \left(\frac{\alpha_D}{\alpha} - \frac{1}{\sigma} \right) = 0.30$, which implies $\bar{\eta}_u = 0.75$, which is in the lower range of [Saiz \(2010\)](#) estimates for US cities with high geographic constraints.

Estimation of the value of amenities

To obtain estimates of the value of unobservable amenities across locations we can use the structure of the model, adapting to our context the methods summarized in [Redding and Rossi-Hansberg \(2018\)](#). Note that using this procedure we can obtain an estimate of the value of amenities ($Z_j, \forall j \in U, R$) relative to a reference location.

In our context, and to ease exposition, it is convenient to proceed in two steps. First, we can use one urban destination as our reference location, \bar{u} . From our model we have that:

$$\ln \frac{\pi_{ru}}{\pi_{r\bar{u}}} = \hat{\chi}(\ln d_{ru} - \ln d_{r\bar{u}}) + \frac{1}{\hat{\lambda}} [(\ln Z_u + \ln w_u - \widehat{\alpha}_D \ln p_u) - (\ln Z_{\bar{u}} + \ln w_{\bar{u}} - \widehat{\alpha}_D \ln p_{\bar{u}})]$$

This expression implies that we can express the level of amenities Z_u as a function of the level of amenities in our reference location given our estimates of the parameters of the model and the data at our disposal:

$$\ln Z_u = \ln Z_{\bar{u}} + \hat{\lambda} \ln \frac{\pi_{ru}}{\pi_{r\bar{u}}} - \hat{\chi} \hat{\chi}(\ln d_{ru} - \ln d_{r\bar{u}}) - (\ln w_u - \widehat{\alpha}_D \ln p_u) + (\ln w_{\bar{u}} - \widehat{\alpha}_D \ln p_{\bar{u}})$$

Note that this gives an estimate for Z_u for each $r \in R$, hence, we can estimate Z_u as an average across r .

In a second step, we do a similar procedure to recover the amenities in the rural locations relative to a reference rural location, \bar{r} , by comparing migrant flows to the different urban destinations:

$$\ln Z_r = \ln Z_{\bar{r}} - \hat{\gamma} \ln \frac{\pi_{ru}}{\pi_{\bar{r}u}} + \hat{\gamma} \hat{\chi} (\ln d_{ru} - \ln d_{\bar{r}u}) + (\ln w_r - \hat{\alpha} \ln p_r) - (\ln w_{\bar{r}} - \hat{\alpha} \ln p_{\bar{r}})$$

As before, this gives us an estimate for Z_r for each $u \in U$, which we can average out.

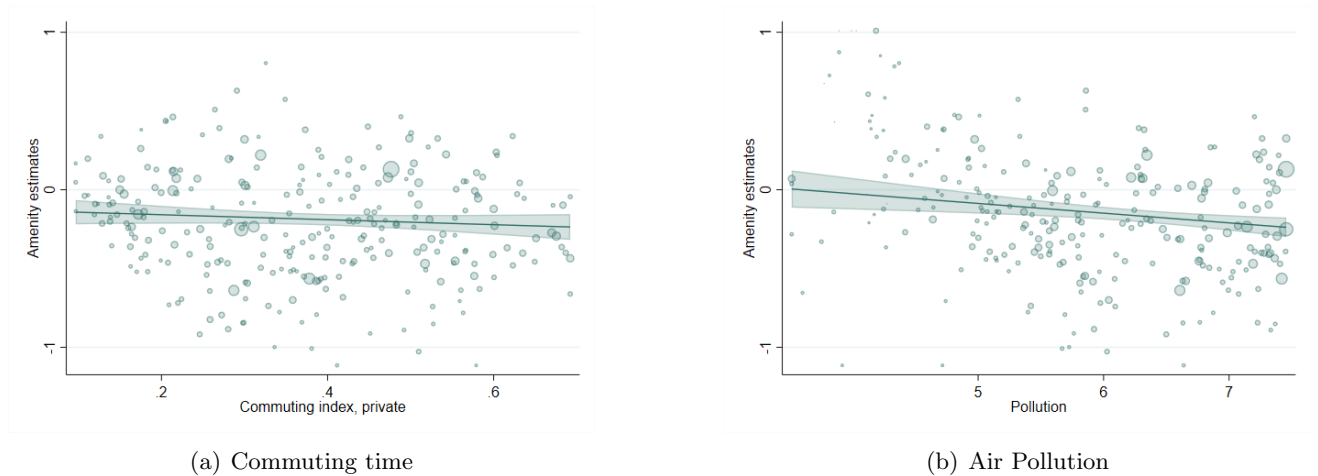
Finally we can use the flows from \bar{r} to \bar{u} to recover the relative value between our two reference locations:

$$\ln Z_{\bar{r}} = \hat{\gamma} [\hat{\chi} \ln d_{\bar{r}\bar{u}} + \frac{1}{\hat{\lambda}} [(\ln Z_{\bar{u}} + \ln w_{\bar{u}} - \hat{\alpha}_D \ln p_{\bar{u}})] - \frac{1}{\hat{\gamma}} [(\ln w_{\bar{r}} - \hat{\alpha} \ln p_{\bar{r}})] - \ln \pi_{\bar{r}\bar{u}}]$$

Hence, we can recover estimates for amenity levels in each location relative to our reference location \bar{u} , which we can normalize to one without loss of generality (i.e. we can assume $Z_{\bar{u}} = 1$). While in theory we can use any base location, in practice it is convenient to use locations that receive or send large number of immigrants, which avoid having many zeros in our bilateral flows.

To test the validity of our model-based amenity estimates, we plot them against two independent measures of urban disamenities: traffic congestion and air pollution. In Figure 7, we show that our estimate of urban amenities is negatively correlated with the average commuting time in the city from the 2015 census (only measure available), and also negatively correlated with air pollution from 2000 to 2005.

Figure 7: Model-based urban amenities, congestion and pollution



Notes: The y-axis reports the value of amenities in each urban location computed based on the model and the mobility elasticity estimates. In panel a) the x-axis is the average of the log of time spent commuting according to the 2015 census. In panel (b), the x-axis is the log of air pollution between 2000 and 2005.

It is worth noting that, as explained above, we can use these estimates on amenity levels to re-

estimate our migration model specified in equation 5 including the amenity level both at origin and at destination. When we do so, we obtain almost identical estimates for the migration elasticities, something that is consistent with the assumptions needed to estimate the model, while getting the right sign and tight estimates for how amenities are shaping migration.

Estimation of bilateral costs

For the estimation of the migration model we have parameterized χ , the migration costs, as $\chi \ln d_{ur}$. However, if we want the model to match the data we can be more precise than this parameterization, something that may be useful when doing counterfactuals. In particular we can obtain an estimate of all the bilateral costs between any origin and any destination that are not captured in our model by χ_{ur} :

$$\chi_{ru} = \left(\frac{V_U}{V_r}\right)^{1/\gamma} \left(\frac{V_{ru}}{V_U}\right)^{1/\lambda} - \pi_{ru}$$

Since χ_{ru} is a measure of migration costs, we can check that it correlates well with our parameterization of migration costs: distance. Not surprisingly, when regressing χ_{ur} on distance between u and r we get a negative intercept and slope equal to negative one and very significant (see Appendix Figure A5).¹⁸

Estimation of the value of each location

In the previous sections we have explained how to estimate all the parameters of the model. The main reason why we estimate all these parameters is to recover the value of migrating to each location from each possible origin (V_{ru}).

First, we compute the (indirect) utility of migrating from r to u as a function of the urban amenity Z_u , the wage and rents at destination, the rents at origin, and the share of income consumed locally α_D and remitted at origin α_O :

$$\ln V_{ru} = \ln Z_u + \ln w_u - \alpha_D \ln p_u - \alpha_O \ln p_r$$

Second, we turn to the indirect utility from staying in the rural location based on rural amenities Z_r , the wage and rents at origin, as well as the average wage across destinations \bar{w}_{rU} :

$$\ln V_{rr} = \ln Z_r + \ln(w_r + (1 - \pi_{rr})\alpha_O \bar{w}_{rU}) - \alpha \ln p_r$$

With these estimates we can compute all the other aggregate V s that determine the flow of people from any origin and any destination.

It is worth noting that with these estimates we can perform counterfactuals. For instance we can recompute the share of migrants from u to r that the model predicts if α_D took a different value. We turn to these counterfactuals in the following section.

¹⁸These estimates correspond to the χ_1 and χ_2 mentioned above. These results also match well with the estimation of the migration model.

6 Counterfactual

In this final section, we explore how much the fact that the *Hukou* system encourages migrants to remit a large fraction of their income affects the distribution of economic activity. To be precise, we estimate how migration patterns would change if migrants consumed as much non-tradable goods at destination as urban residents, i.e. if migration restrictions did not make them less sensitive to rents at destination. We then compute how wages and rents would have changed across cities in this counterfactual world. Finally, we correlate the changes in *Hukou* policies in 2014 aimed at attracting more migrants, which happened after the period we study, with the counterfactual change in immigration by city. We view this as a test to see whether cities where we predict relatively lower migration indeed were the ones who find it easier to relax migration restrictions.

6.1 Reallocation of Migrants

To predict how migration patterns would look like if rural migrants consumed as much housing as urban residents, we use our location model estimates, but reweight rents in the expression of real wages at destination using the income share of urban residents instead of that of migrants. Formally we use $[\ln w_u - \alpha \ln p_u]$ instead of $[\ln w_u - \alpha_D \ln p_u]$. We then use this to recompute the value of migrating from each location V_{ur} and the value of staying in each location V_{rr} . This gives us the counterfactual migration rate from any origin to any destination.

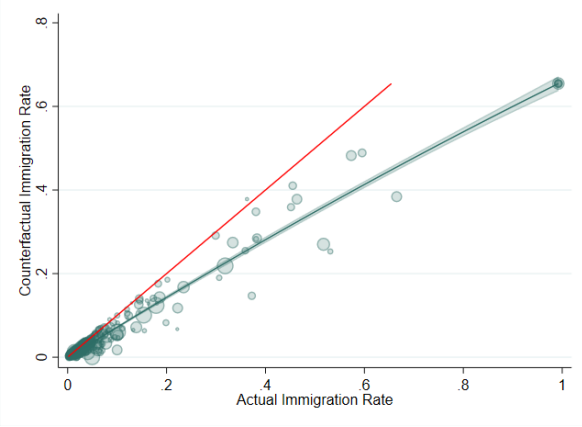
Figure 8 illustrates the change in migration patterns in this counterfactual and compares it to actual migration rates, see graph (a). On average migration declines slightly, since migrants become more sensitive to high rents in urban destinations. The decline is driven by destinations which have in the actual data high migration rates, i.e. by destinations which are initially more populated, have higher wages, and higher rents. We show this explicitly in graphs (b), (c) and (d).

The implications of this exercise are provocative: they suggest that easing migration restrictions that encourage immigrants to not bring the family and send large fractions of income back to origin, would actually reduce migratory pressures on the largest urban centers, rather than accentuate them. Moreover, such policies are a strong force toward concentrating the distribution of migrants to a particular set of destinations. Removing these incentives, hence, makes the distribution of immigrants much more even across destinations. In this sense, it can be argued that if the goal of a policy that restricts settlement of family migrants to all potential destinations is to lower migration, then it can backfire. This is, it can end up encouraging migration and particularly so in high wage, high price cities, which are typically also the more congested destination and plausibly the ones that may push for these type of policies.

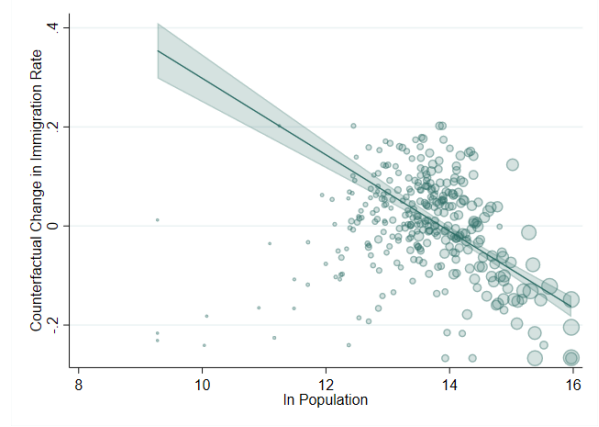
6.2 Changes in wages and rents at destination

To see more explicitly how counterfactual migration would have changed living conditions in cities of destination, we compute the changes in wages and rents implied by the counterfactual immigration,

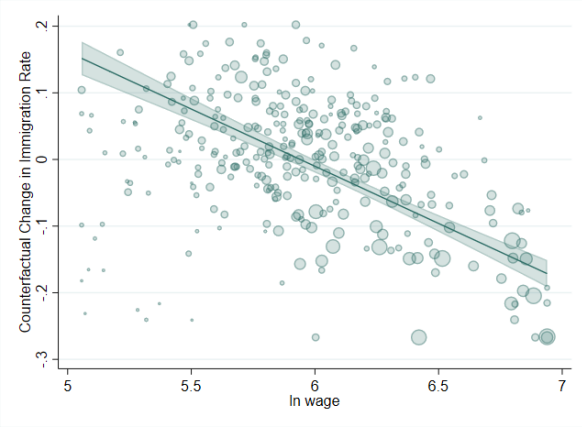
Figure 8: Counterfactual changes in migration patterns



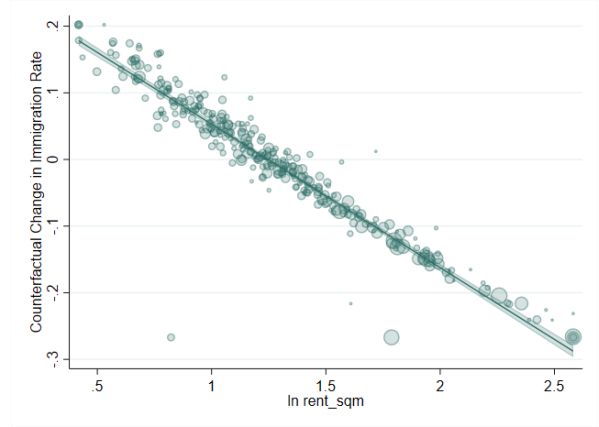
(a) Counterfactual vs Actual Migration



(b) Counterfactual Change in Migration and Population



(c) Counterfactual Change in Migration and Wages



(d) Counterfactual Change in Migration and Rents

Notes: In figure (a) the y-axis reports counterfactual immigration rate in each destination, against the actual immigration rate in the x-axis. In Figures (b) to (d) the y-axis is the percentage change between the counterfactual and the actual immigration rate. In Figure (b) the x-axis is the log Population in 2000, in Figure (c) it is the log wage in 2000 and in Figure (d) the log Rents in 2000.

as compared to the trends predicted based on actual immigration. For that, we first multiply the counterfactual emigration rates with origin population, aggregate these counterfactual flows at the level of the destination, and compute a counterfactual immigration rate for each destination IMR_u^C . We then use the estimates from equation 7 in the previous section to predict changes in wages and rents implied by the counterfactual immigration rate, which we compare to predictions based on our baseline model. In practice, we compute the following two differences:

$$\Delta^C w_u - \widehat{\Delta w_u} = \widehat{\beta}_w (\Delta \ln L_u^C - \Delta \ln L_u)$$

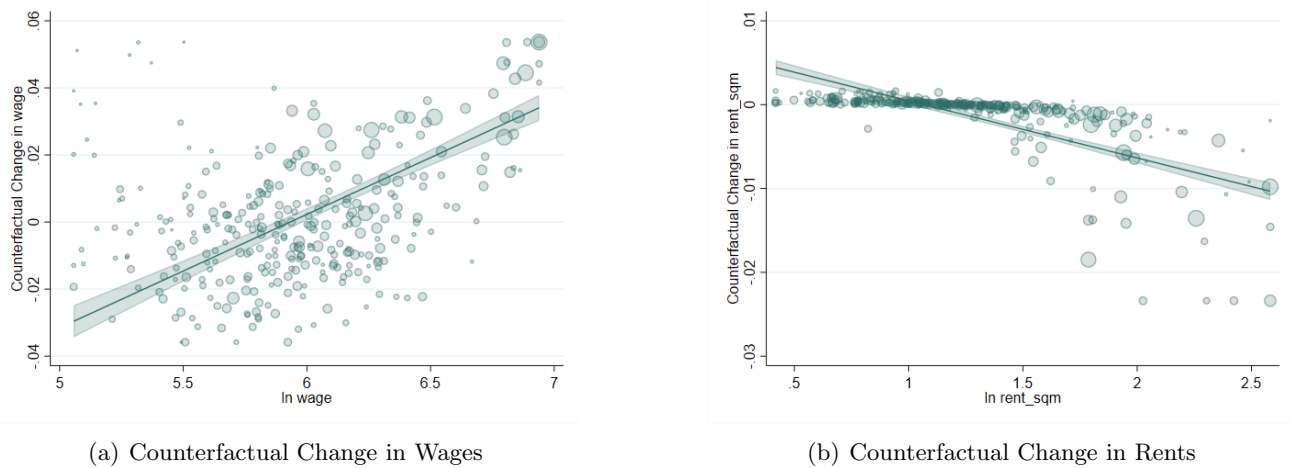
for wages, and

$$\Delta^C p_u - \widehat{\Delta p_u} = \widehat{\beta}_p (\ln(1 + IMR_u^C) - \ln(1 + IMR_u))$$

for rents.

Figure 7 presents the results. Since in the counterfactual migrants are moving away from high wage locations, wage growth in these locations is higher than predicted. Since they are also moving away from high rent locations, rent growth in these locations is lower than predicted. This result is again surprising, it implies that relaxing *Hukou* restrictions and allowing rural migrants to settle may reduce rent growth and increase labor costs in the largest urban centers.

Figure 9: Counterfactual changes in wages and rents



Notes: In figure (a) the y-axis reports counterfactual changes in wages compared to predicted changes in wages between 2000 and 2005, against log wages in 2000 on the x-axis. In Figure (b) the y-axis is the difference between counterfactual and predicted rent trends and the x-axis is log rents in 2000.

6.3 Migrant policy reform

In this last part, we investigate whether the predictions of the model can help us understand subsequent reforms in migration policy. In 2014, the central government implemented a reform of the *Hukou* system, which facilitated the registration of rural migrants, with the explicit objective to develop small and medium size cities. We use the composite policy index constructed by Zhang et al. (2018), who coded *Hukou* restrictions before and after 2014, and compute the easing of migration restrictions as one minus the ratio of the index post 2014 and the index pre 2014. We then correlate the change in *Hukou* restrictions with the counterfactual change in immigration based on our model, i.e. we test whether cities that we predict would have attracted more migrants in 2000-2005 if migration restrictions had been eased were the ones who actually eased these restrictions ten years later.

The results presented in 10 are suggestive, there is a clear positive correlation between the easing in *Hukou* restrictions and counterfactual changes in migration if migrants consumed as much housing as urban residents. We view this as evidence that either small and medium size cities experienced difficulties in attracting migrants or that they realized that removing restrictions to convert urban *Hukou* were probably not very costly since they did not attract many migrants in the first place. We view this evidence also, as a way to validate our model to further think about what migration restrictions

Figure 10: Easing of *Hukou* restrictions post 2014 and counterfactual change in immigration



Notes: The y-axis reports the easing of migration restrictions by city, based on the index by Zhang et al. (2018). The x-axis presents counterfactual changes in immigration rates if migrants consumed the same share of their income on housing as urban residents.

are doing to the spatial distribution of economic activity.

7 Conclusion

Overall, this paper offers a new perspective on migration frictions. While most of the literature has studied how migration frictions deter migration, in this paper we argue that migration institutions that limit the extent to which migrants move with their families has important implications for the distribution of economic activity. We make this argument in the context of China. Chinese internal migration policies limit the extent to which rural families can fully migrate to urban settings. We use this setting to argue that the *Hukou* system resulted in a concentration of rural migrants into the highest wage, highest rent, and potentially more congested urban destinations.

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A Data description

This section provides complements to Section 2: we describe how we generate exogenous shocks to living conditions across possible origins and destinations; we provide additional contextual elements to understand the various dimensions of migration policies and their evolution over time; and we describe a few data sources capturing amenities in cities.

A.1 Exogenous variation in local conditions

Return to labor across origins

We generate exogenous shocks to agricultural productivity across possible origins by combining international commodity prices with local cropping patterns (in the manner of [Imbert et al. 2020](#)). We first collect Agricultural Producer Prices data (APP, 1991–2016) from the FAO: the data reports 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.¹⁹ We then clean these (log) international producer prices from long-run trends by applying a HP filter (see [Imbert et al. 2020](#)) and isolating the residual, p_{ct} , for any given year t and commodity c .

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 o 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 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. \(2020\)](#). We weight this predicted output in 2000 by the baseline commodity price in 1980 to construct a revenue share for each crop, α_{co} , which is orthogonal to later deviations in international prices. Letting p_c denote the previous price residual at a period of interest, our agricultural productivity shock, p_c , will be defined as,

$$\omega_o = \sum_c \alpha_{co} \times p_c$$

¹⁹We 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.

Return to labor across destinations

We generate an industrial shifter to labor productivity across possible destinations by exploiting the individual wage data available in the 2005 1% Population Survey. Respondents of the 2005 Mini-Census document their monthly income, the number of hours worked during a normal week and a 2-digit industrial classification of their current job. We construct a wage prediction at a given location that is uniquely based on the local industrial composition. To do so, we compute the industry-specific average monthly wage in 2005 (w_i where i denotes a 2-digit sector) and we derive industrial employment shares, α_{id} , from the representative sample of respondents. The industrial shifter to labor productivity, ω_d , is then defined as follows,

$$\omega_d = \left(\sum_i \alpha_{id} \times w_i \right)$$

In principle, the 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. We describe below a second instrument for real wages at destination, which rather exploits constraints in land supply (thereby affecting mostly the “denominator” in the real wage).

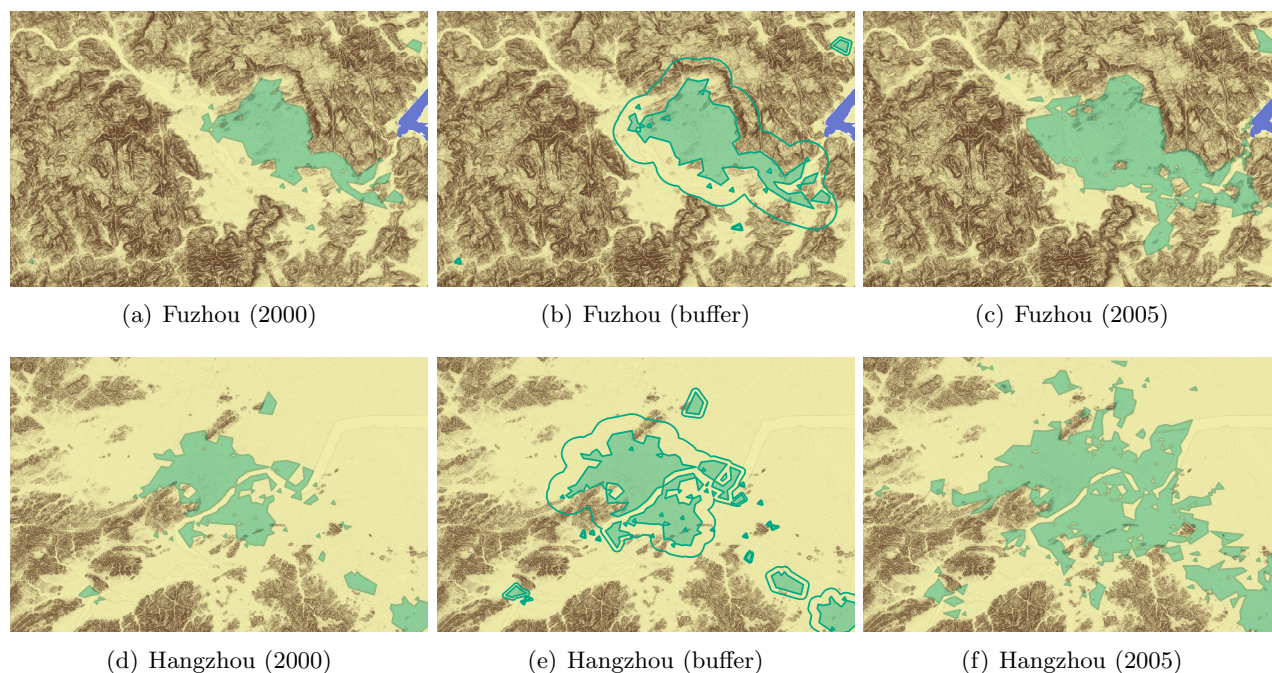
Housing supply across destinations

We exploit exogenous variation in housing supply across destinations to predict variation in the price of non-tradables (i.e., housing services) and thus in the real wage. 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, whose extent is calibrated to ensure that all cities grow proportionally, and with similar width 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 by classifying a pixel of 30m \times 30m as “non-developable” if the average slope is above 5 degrees (and we thus ignore “water” pixels).

Figure A1 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 A1, they markedly differ in constraints to their expansion before mass migration: Fuzhou is in a valley along the Min River and is surrounded by steep hills (especially so 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 (panels b and e). Hangzhou, on the other hand, would face very limited constraints. In 2005, we find indeed that Fuzhou experienced an unbalanced urban sprawl concentrated towards the South when Hangzhou sprawled massively and in every direction.

Figure A1: An example of our procedure with Fuzhou and Hangzhou.



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

A.2 Migration policies

A.3 Living conditions in cities

We collect data on amenities in cities: pollution data from satellite images; and commuting data from the 2015 Mini-Census.

Pollution

Pollution data come from TEMIS satellite images and cover the period 1997–2015 with a 20-25km 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 \times 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. The data further contain information on commuting mode: walking, cycling, driving a private vehicle, or using public transportation. These data allow us to proxy for congestion.

B Complements to the empirical analysis and estimation

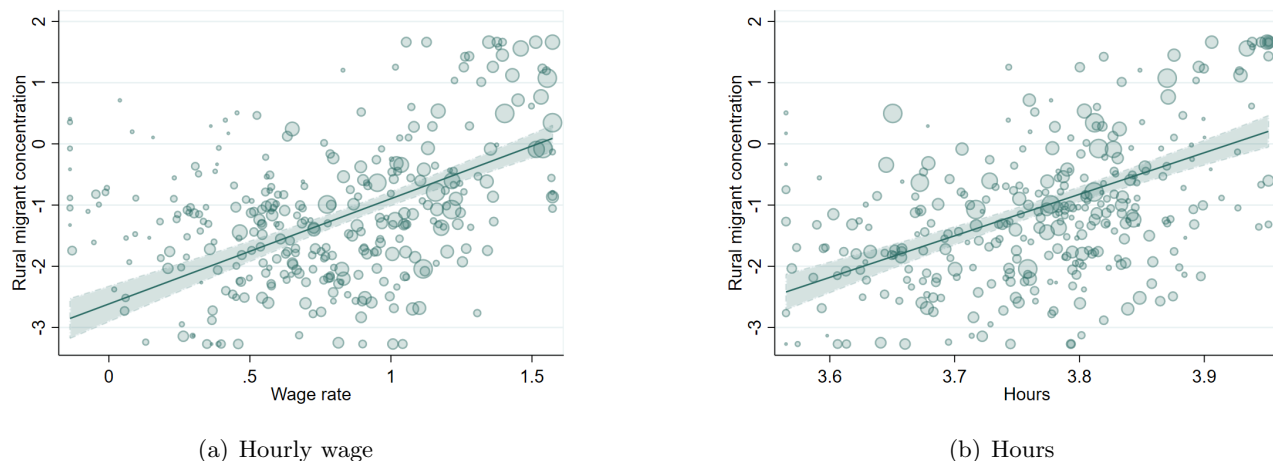
This section provides complements to the empirical analysis (Section 3) and to the estimation (Section 5).

B.1 Motivating facts

The sorting of migrants across cities

Our motivating evidence in Section 3 documents that migrants sort into cities where monthly wages are high.

Figure A2: Rural migrant concentration, hourly wage, and hours worked.



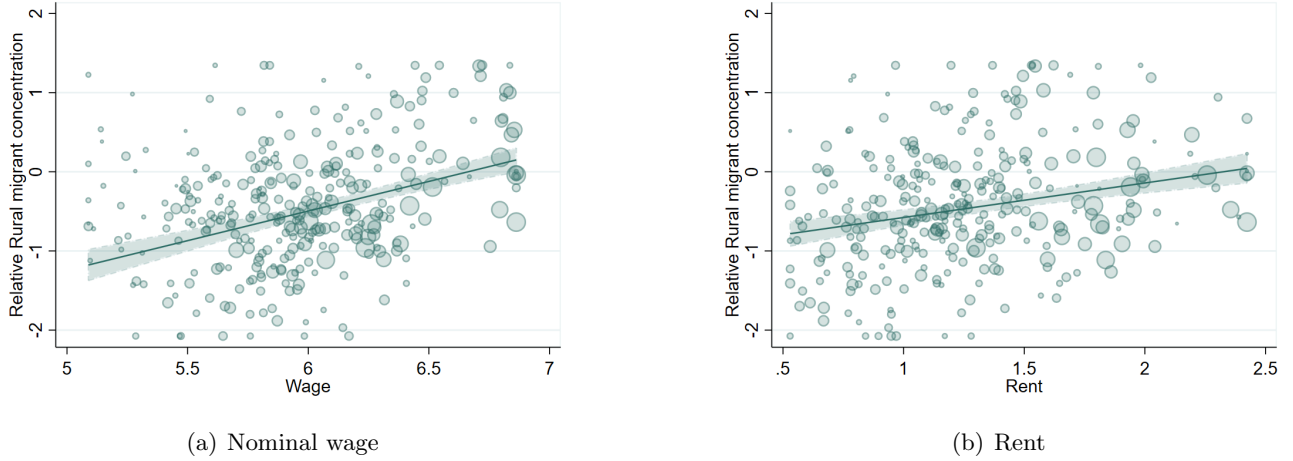
Notes: The y-axis reports the migrant concentration in city c , m_c , as defined in Section 3. In panel (a), the x-axis reports the (log) hourly wage rate; in panel (b), the x-axis reports a measure of (log) number of hours worked during a normal week. Hours and wages are constructed by aggregating individual responses from the 2005 1% Population Survey.

In Figure A2, 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 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.²⁰

We have shown in Section 3 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 which 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

²⁰One explanation could be that the substitution effect dominates the income effect for the relatively low-income workers present in Chinese cities between 2000–2005. 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 A3: Relative migrant concentration and living conditions in cities.



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.

of relative migrant concentration in city c , rm_c , as follows,

$$rm_c = m_c - \log\left(\frac{U_c/R_c}{U/R}\right) = \log\left(\frac{M_c/U_c}{M/U}\right).$$

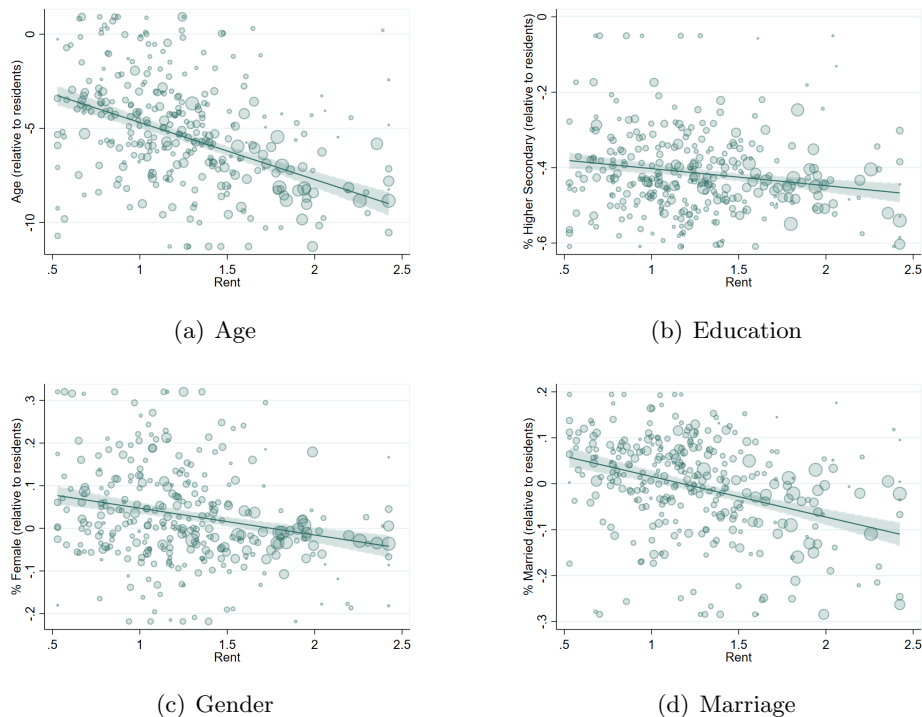
where U_c denotes the number of urban migrants in city c having arrived between 2000–2005 and U represents its aggregate across all cities. This measure would be equal to 0 if migrants were allocated in the same fashion, independently of their initial registration status (rural or urban). In panel (a) of Figure A3, 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.

The selection of migrants across cities

We have shown in Section 3 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 their children in high-wage/rent locations.

In Figure A4, 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 much less likely to be married than residents in locations that are most expensive (panel d).

Figure A4: The selection of migrants relative to residents in expensive cities.



Notes: The x-axis reports a measure of (log) monthly rents constructed using the 2005 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.

B.2 Estimation

Migration choices across origins and destinations

In Section 5, we estimate a simple model of location choice across destinations for workers registered in different locations. The model relates migration incidence with the real wage in possible destinations and at origin.

The estimation presented in Table 2 relies on three instruments (described in Section 2.1 of the paper and Appendix A). In Appendix Table A1, we report the first-stage estimates relating real wages at destination and origin to the origin-specific instrument and the two destination-specific instruments. As shown in column (1), the shift-share prediction for nominal wages at destination has a very strong effect on the real wage, while the share of non-developable land also affects the real wage through a strong, positive effect on rents at destination. Importantly, the instrument for living conditions at origin is unrelated to conditions at destination.

Appendix Table A1 also shows that the agricultural shock across origins strongly predicts the real wage at origin. Again, the instruments at destination are orthogonal to conditions at origin: while the actual first stage has two endogenous variables and three instruments, it is very similar to two separate equations with two and one instruments respectively.

Table A1: First stage of the location choice model.

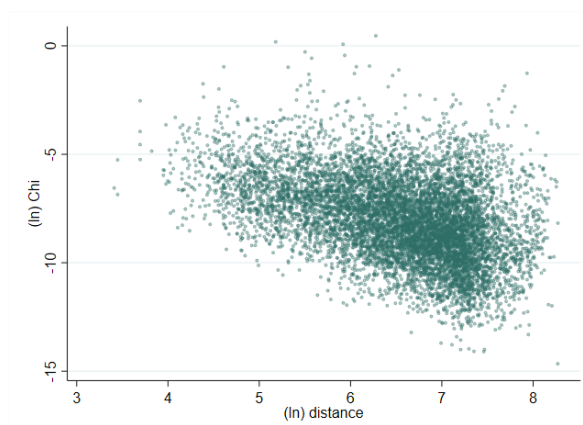
	ln Destination Real Wage	ln Origin Real Wage
	(1)	(2)
Destination Wages Shift-Share	1.404 (0.002)	-0.010 (0.005)
Destination Land Supply Shock	-0.291 (0.002)	0.003 (0.003)
Origin Agricultural Price Shock	0.005 (0.024)	5.676 (1.124)
Observations	78830	79044
Controls	Yes	Yes

Note: In Column 1 the outcome is the log of the real wage at destination, computed as the average log monthly wage minus 0.20 times the average log monthly rent in the prefecture of destination. In column 2 the outcome is the log of the real wage at origin, computed as the average log monthly wage minus 0.27 times the average log monthly rent in the prefecture of origin. “Destination Wages Shift-Share” is a shift-share instrument in which the shift is the average log monthly wage in each industry at the national level and the share is the employment share of each industry in the prefecture of destination. “Destination Land Supply Shock” is a measure of topographical constraints on city expansion due to ruggedness and water bodies at the periphery of the city. “Origin Agricultural Price Shock” measures changes in the value of the agricultural portfolio of the prefecture of origin due to shocks to international commodity prices. See Section 5 for more details. Standard Errors are clustered at the origin level.

Bilateral migration costs

In Section 5, we show how bilateral migration costs can be retrieved as residuals from the location model. These bilateral migration costs may capture various dimensions affecting the preferences of workers from a given origin to a certain location. One obvious factor in such preferences is gravity.

Figure A5: Model-based estimate of migration costs and bilateral distance.



Notes: The y-axis reports the log of the model-based estimate of migration costs and the x-axis reports the log of the bilateral euclidean distance between each origin-destination pair.

In Figure A5, we show that gravity is indeed a major explanatory factor in the observed cross-sectional variation in bilateral migration costs χ_{ru} . A percentage increase in distance leads to a percentage decrease in migration flows, all else equal.

C Appendix: 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 to urban migration in China, even if, as Figure 1 makes clear, it is much less important than rural to urban migration. In this section, we expand our model so that urban residents are, themselves, mobile across locations, something that 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 more that the gain from moving is much lower among urban residents than among rural ones, than limits to mobility. In fact, the 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:

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

subject to standard budget constraint:

$$C_T + p_r C_R + p_u C_H \leq w_u.$$

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 $u \in U$:

$$\ln V_u + \varepsilon_{iu} = \ln Z_u + \ln w_u - \alpha \ln p_u + \varepsilon_{iu}$$

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

$$\frac{N_u}{N} = \left(\frac{V_u}{V_U} \right)^{1/\lambda_U}$$

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:

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

and:

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

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

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

Hence,

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

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 fundamental $\{A_u, T_u^H\}$ 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 get close form solutions for the distribution of urban residents as a function of fundamentals when we do not have heterogeneity in the elasticity parameters. Alternatively, we can get closed form solutions but also as a function of the prices which depend on the heterogeneous elasticities.

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 the 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 type 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:

$$Y_u = A_u [(1 - \beta) K_u^{\frac{\sigma-1}{\sigma}} + \beta L_u^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}},$$

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

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

As in the main text, A_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 use 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 $L_{eu} = N_{ue} + M_{eu}$. We can denote the fraction of urban residents and migrants in each e, u cell as $\eta_{eu} = \frac{N_{ue}}{N_u}$ and $\mu_{eu} = \frac{M_{eu}}{M_u}$. Then, we can rewrite the labor aggregate as:

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

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

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

This is, 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 affect the housing market. With multiple skills, there are multiple wage levels. These different wage levels enter the demand for housing, something that gets reflected in the market clearing condition of the housing sector:

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

We can re-write this expression as:

$$\ln p_u = \frac{1}{1 + \eta_u} \ln [\alpha N_u (\sum_e w_{ue} \eta_{ue}) + \alpha_D M_u (\sum_e w_{eu} \mu_{eu})] - \frac{1}{1 + \eta_u} \ln T_u^H$$

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

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

This expression is very similar to the one in our baseline model, except that we need now to take into account that the average wage of urban residents and immigrants may be different because natives and

immigrants may be distributed over factor types differently. However, the main intuition still applies. An immigrant inflow will increase the demand for housing, hence, 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 heterogenous effect of migration on average wages of natives and immigrants separately.