Migration Restrictions and the Migrant-Native Wage Gap: The Role of Wage Setting and Sorting*

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Abstract

This study examines the factors contributing to the wage gap between migrants and natives, as well as the influence of internal mobility constraints on this gap. Using matched employer-employee panel data from a Chinese metropolis, I estimate a two-way fixed effect wage model and decompose the wage gap into group differences in skills, wage setting, and sorting. Decomposition analysis reveals that migrants tend to earn lower wages within the same employer and are less likely to be employed by companies offering high wage premiums. These two factors account for a 10 percentage-point wage penalty for migrants with comparative skills. Additionally, I investigate the impact of a policy change that restricted the "hukou" (household registration) quota to understand the mechanisms underlying the migrant-native wage gap. Following a one-third reduction in hukou quotas, wages of migrants increased relative to those of native workers, particularly in the private sector where significant quota reductions occurred, and among young migrants who have a higher demand for hukou. This effect is mainly driven by an increase in the wage premium paid by employers due to the unavailability of hukou. However, the tightening of hukou quota exacerbates the misallocation of workers, making high-ability migrants more likely to work in low-productivity public sectors.

Keyword: Migrant-Native Wage Gap, Hukou Quota, Wage Premium, Sorting

JEL codes: J31, J32, J42, J61, O15

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1 Introduction

Massive migration is a salient feature of both developed and developing economies. According to UN data, about one in every seven individuals is either an immigrant or an internal migrant (Bell and Charles-Edwards, 2013). Associated with this substantial migration, there exists a notable disparity in the wage incomes between migrants and native workers across different countries. On the one hand, immigrants often earn lower wage income than natives in many developed countries (Åslund et al., 2014; Clarke et al., 2019; Dostie et al., 2023). On the other hand, while a large rural-urban wage gap induces a large flow of rural-to-urban migration in developing countries (Gollin et al., 2014; Lagakos et al., 2020; Young, 2013), rural-to-urban migrants often earn less wage income than local urban residents (Ma, 2018; Zhang et al., 2016; Zhu, 2016). Understanding the causes of the disparity in labor market conditions between migrants and native workers is crucial for mitigating income inequality, promoting social equity, and improving labor market efficiency.

Previous research on the wage gap between rural-urban migrants and native workers in urban China predominantly used traditional regression-based decomposition methods to detect potential driving factors of the wage gap (see, e.g., Chen and Zhang, 2018; Lee, 2012; Ma, 2018; Song, 2016; Zhang et al., 2016). These studies find that differences in observable characteristics, as well as differences in the returns to these characteristics, contribute to the lower wage income of migrants. However, the migrant-native wage gap may also arise from selection on unobserved characteristics. Investigating this issue is challenging without access to panel data sets. Moreover, employers may pay different wage premiums to migrants and native workers, and there may be differences in the sorting patterns exhibited by migrants and native workers. Notably, internal migration restrictions can influence these two factors. To comprehensively understand the role of employers' pay policies and sorting patterns in shaping the migrant-native wage gap, it is generally necessary to have access to a matched employer-employee data set. However, in many developing countries, including China, such kind of data is hardly accessible. Therefore, there remains a lack of sufficient empirical exploration regarding the causes of the migrant-native wage gap.

This study utilizes a unique matched employer-employee data set from the formal sector in a major city in China to examine the factors influencing the wage gap between migrants and natives. The analysis builds upon the estimations of the two-way fixed effect model for wages, commonly referred to as the "AKM model" (named after Abowd et al., 1999). Additionally, this study explores the impact of a significant internal migration restriction, the household registration ("hukou") system, on the migrant-native wage gap. To investigate this, the study leverages an exogenous policy shock in 2011 that reduced one-third of the hukou quotas granted to employers.

Specifically, I first estimate the AKM model separately for migrants and native workers. Then, I conduct a decomposition analysis of the migrant-native wage gap based on the estimated person effects and employer effects. The results reveal that migrants earn 19 percentage points (pp) higher observed income than native workers. This gap is driven primarily by migrants' higher skills that account for a 21 pp higher average wage. In contrast, migrants have *lower* wage-negotiating power than native workers, which explains a -4.8 pp of the migrant-native wage gap. While positive sorting into high-premium employers of migrants explains a 7 pp wage gap, when controlling for employers' varying demand for skills, migrants with equivalent skills are *less* likely than native workers to be employed by high-premium employers. This discrepancy explains a -4.8 pp of the migrant-native wage gap. Together, unfavorable treatment against migrants contributes to a roughly 10 pp lower wage for migrants.

Building on these findings, this study further investigates the role of hukou in contributing to the wage gap between migrants and native workers. Hukou serves as an amenity provided by employers that is crucial for access to a bundle of public services (Meng, 2012; Song, 2014). In the studied city, the local government allocates hukou quotas to employers, with varying quotas assigned to employers in different sectors. It is worth noting that hukou is only valuable for migrants but not for natives who already possess it. In this case, employers can conduct group-based price discrimination when offering hukou, thereby compensating migrant and native workers differently. Additionally, migrants will sort into different employers not only depending on the wage premium but also on the accessibility to hukou.

To investigate the impacts of hukou on the wage gap, this study leverages a policy shock in 2011 that reduced the overall hukou quota by one-third in the studied city. Importantly, the reduction in hukou quota was not evenly distributed among employers, allowing for variations in identification. Employers in the public sector had priority in acquiring hukou quotas. Therefore, the policy shock induced a more significant reduction in hukou quotas in the private sector, generating heterogeneous impacts on migrants across different employers. Noting that once a worker obtains a hukou, they retain it thereafter, it is expected that younger migrants have a greater demand for hukou than older migrants. Consequently, the policy shock also affects migrants of different ages differently.

Based on the exogenous variation created by the policy shock, I first estimate difference-in-differences (DID) models to estimate the change in relative earnings between migrants and native workers following the policy shock. Additionally, I consider the variations of policy shock across different sectors and age groups to conduct a triple-difference (DDD) analysis. I establish several novel findings. First, the relative wage of migrants (vs. natives) increased by 3.0 log points (lp) following the policy shock. On the one hand, employers need to provide higher pecuniary compensation to migrants because of the decline in the aggregate value of hukou. On the other hand, employers that no longer provide hukou quotas witnessed a reduction in their monopsony power, resulting in higher wages for workers.[1] This wage-increasing effect predominates a potentially negative sorting effect. Controlling for observed employer characteristics, the treatment effect becomes 5.4 lp. Second, I found that the relative wage of migrants increased by an additional 11.1 lp in the private sector when compared with the public sector, which is consistent with the fact that the private sector witnessed a more significant reduction in hukou quotas. Third, I found that the relative income of young migrants, compared to young native workers, increased by an extra 6.7 lp compared with older workers. This result is in line with hukou being a "portable" amenity. Event study results further verify that the policy effects are not driven by pre-trends.

I also conduct decompositions of the migrant-native wage gap in both pre-shock and post-shock periods. Results reveal that the wage-setting effect increased after the policy shock, leading to a 3.2 pp higher income for migrants, which is consistent with the case where the reduced hukou quotas increased the wage-negotiating power of migrants. Nevertheless, migrants are less likely to work for high-premium employers following the policy shock, resulting in a 1.6 pp lower income for migrants. This latter result suggests that the policy leads to a worse allocation of workers across employers.

[1] Workers will find it easier to search for an alternative job in substitution with the one without a hukou quota, compared with searching for another job with a hukou quota. Therefore, losing access to hukou reduces employers' monopsony power.

Another way to investigate the policy effect on worker allocation is through the sector choice of workers. I first document that migrants have higher skills than their native coworkers, especially in the public sector. This finding suggests that public sector employers are more selective in hiring migrants, or high-skilled migrants prefer employers with hukou quotas to a greater extent when compared with other migrants. Either way, because public sector employers have lower productivity, the hukou policy leads to a misallocation of workers. Following the policy shock, because the reduction in hukou quota mainly occurs in the private sector, high-productivity private sector firms face a greater loss in their ability to attract high-skilled migrants. Specifically, high-skilled migrants witnessed a 3.9 pp decrease in the probability of working in the private sector after the policy shock. This finding supports that the reduction in hukou quotas leads to a worse worker allocation across employers. Therefore, although the reduction in hukou quotas increases migrants' wage-negotiating power, it hurts the migrants by exacerbating worker misallocation.

To ensure the validity of the empirical findings, a set of robustness checks is conducted. First, an alternative AKM model specification is considered by incorporating employer-period effects, aligning with recent developments in the literature on employer effect dynamics (Engbom et al., 2023; Lachowska et al., 2023). Second, various alternative sample selections and specifications are explored in estimating the AKM model. This includes using alternative normalization of estimated fixed effects, altering the estimation sample, and focusing on commercial firms but not other types of employers (e.g., government agencies, schools, and hospitals). These robustness checks confirm the consistency of the qualitative conclusions. Finally, I conduct supplemental analysis on a subsample of workers with hukou location information. Migrants who had obtained local hukou before the policy shock experienced significantly smaller wage growth than other migrants, highlighting the role of the hukou system in determining the migrant-native wage gap. Additionally, the sectoral choice patterns of migrants with local hukou attest to the case where the public sector offers more hukou quotas but a lower utility net of hukou.

This study is related to several strands of literature. First, this paper contributes to the literature on the migrant-native wage gap. Previous research on the wage gap between rural-urban migrants and native workers in urban China typically uses regression-based Oaxaca-Blinder decomposition and finds that migrants suffer discrimination in the labor market (Lee, 2012; Zhang et al., 2016; Zhu, 2016). Ma (2018) uses the Brown model to study labor market segmentation by industry sectors and its impact on the migrant-native wage gap. She finds that individual characteristic differentials in the same industry sector are the main cause of the wage gap. Recently, there has been a growing body of literature that utilizes matched employer-employee data to estimate worker and employer two-way fixed effect models to examine group wage gaps, building on the work of Abowd et al. (1999).[2] Card et al. (2016) find that differential bargaining power is an important driving factor of the gender wage gap in Portugal. Gerard et al. (2021) find that differential sorting of workers into high-premium employers is an important explanatory factor to racial wage gaps in Brazil. Dostie et al. (2023) find that firm-specific wage premiums contribute to the wage gap between immigrants and natives. Unlike previous research, studies based on the AKM model can measure the contribution of employers to the wage gap. To my best knowledge, this is the first paper to utilize the estimations from the AKM model to investigate group wage differences in China. Also, this study contributes to the literature by including two-side heterogeneity and employer-worker interactions relating to amenities into account.

Second, this study contributes to a growing literature on the wage-setting power of employers and its sources (Azar et al., 2022a; Berger et al., 2022; Card, 2022; Hall and Mueller, 2018; Lamadon et al., 2022; Sorkin, 2018). As highlighted by Ashenfelter et al. (2022) and Card (2022), recent research on firms' role in determining wage dispersion has shown that firm has wage-setting power. Two sources of such wage-setting power are particularly related to this study. The first one is monopsony power, reflecting the labor supply elasticity of workers governed by search friction and the taste heterogeneity for employer differentiations (Manning, 2021). Card et al. (2018) propose a simple job differentiation model to illustrate the monopsony power of firms. Azar et al. (2022a) take an IO approach to estimate the labor supply elasticity in the presence of job differentiations, with a particular focus on the geographic distance to jobs. Azar et al. (2022b) use online job posting data to study the labor market power from concentration. Jarosch et al. (2019) use Austrian data and find that size-based market power leads to substantially reduced wages. Berger et al. (2022) study firms' strategical behavior in wage settings faced with different labor market concentrations. The second source is compensating dif-

[2] Åslund et al. (2014) also utilizes a matched employer-employee data of the Swedish labor market to study the hiring patterns of migrants and native workers in driving wage differences, although they do not estimate an AKM model

ferential arises from differences in amenities. Hall and Mueller (2018), Lamadon et al. (2022), and Sorkin (2018) find that the non-wage value of jobs is important in shaping the worker-firm match and wages. Haanwinckel and Soares (2021) study the compensating differential of informality using Brazil data. Le Barbanchon et al. (2020) find that differential preference for shorter commuting distances contributes to the gender wage gap. This study contributes to the literature by studying the impact of government-granted hukou quota on the migrant-native wage gap where the hukou quota serves as both a source of monopsony power to firms and an important amenity that is partially priced in wages for migrants.

Third, this study is related to a large literature on sorting and misallocation of workers (see the review by Eeckhout, 2018). Lopes De Melo (2018) documents coworker segregation and finds that a model of worker-coworker sorting captures the job market characteristics better than that of worker-firm sorting. The role of search friction in driving talent misallocation is studied by Fredriksson et al. (2018), Gautier and Teulings (2015), Lise and Robin (2017) and Rabinovich and Wolthoff (2022), among others. How limited information on both the firm side and the worker side leads to inefficient job matches has also been studied by many research (see Carranza et al., 2022 for a recent example). This study adds to the literature by considering the hukou system as an explicit institutional barrier that distorts the sorting pattern.

Fourth, this study contributes to a large literature on the hukou system and its reform in China (Fan, 2019; Gai et al., 2021; Meng, 2012; Sieg et al., 2023; Song, 2014). This study works on a policy shock on hukou quotas in a major city, which is less studied in previous literature. Specifically, some previous research also studied the impacts of internal migration restrictions on the allocation of talents (An et al., 2022; Brzezinska, 2021; Gai et al., 2021; Whalley and Zhang, 2007). An et al. (2022) and Whalley and Zhang (2007) work on city- and province-level data to study the aggregate impact of hukou reform. Brzezinska (2021) works on firm-level data and establishes micro evidence on the impact of reducing concentration on wage-setting power. Gai et al. (2021) leverage hukou policy reform to study the rural-to-urban migration pattern, based on individual-level data. Compared with this literature, this study takes a perspective that focuses on the wage-setting power of employers and the sorting between workers and employers, with both worker-side and employer-side individual information taken into account.

Finally, the findings of this paper may have broader implications for other settings and institutional contexts. For example, our results shed light on the migrant labor market in other economies with household registration systems or other institutional constraints on migration (Deshingkar, 2006; Nguyen, 2018; Nguyen et al., 2015; Vo, 2020). Broadly speaking, our results also provide implications for the understanding of the role of visa policies and other institutional obstacles in shaping labor market outcomes for immigrants (Dorn and Zweimüller, 2021; Kerr et al., 2015; Naidu et al., 2016; Peri et al., 2015; Peri, 2016).

This paper is organized as follows. Section 2 introduces the data used in this study and conducts descriptive analysis on the observed migrant-native wage gap in our data. Section 3 shows the decomposition framework and results of the migrant-native wage gap. Section 4 introduces the policy shock and the corresponding empirical analysis of this study. Section 5 discusses the robustness checks of the results. Finally, Section 6 concludes.

2 Data

The main data source of this study is the administrative records of the Housing Provident Fund in the studied city, spanning the period from 2006 to 2014. The Housing Provident Fund is a part of China's employment-based social insurance system, known as the "five insurances and one fund" system, where the "one fund" refers to the housing provident fund. Employers must provide this fund for all formal employees. Thus, our data mainly covers the formal sector of the city. In total, there are 6,101,370 unique workers and 116,091 unique employers in the data set. To concentrate on individuals with a more consistent labor participation rate, this study restricts the sample to workers aged between 25 and 50 years old. Also, I excluded labor dispatch companies from the sample. As a result, the final sample consists of 114,511 employers and 4,890,448 employees.

The formal sector has been expanding as more employers are included in the social security network. Therefore, our sample reflects an increasing coverage of the formal sector in the city. In 2006, it covered 11.4% employers and 25.8% employees of the aggregate numbers reported in the statistical yearbook, respectively. By 2014, the coverage had increased to 13.6% and 34.8% of the aggregate numbers, respectively. The expansion of formal sector should not affect the results of our analysis as long as new-coming employers behave the same way as existing employers regarding the wage-setting policies for migrants and native workers. However, we cannot test this assumption with our data. Therefore, to ensure the validity of my results, especially in the precent of a policy shock in 2011 that may potentially change the behavior of employers, I focus on employers that presented at least once in both the pre-shock (2006 – 2010) and post-shock (2011–2014) periods throughout the baseline analysis. I also consider other sample selection criteria in robustness checks.

Employee information – In the data set, each employee is identified by a unique identifier. The first 6-digit code of this identifier indicates the hukou registration location of each individual when they first acquired their national ID, which usually occurred before 16 years old. I define migrants as those whose 6-digit code indicates cities other than the studied one. Additionally, the gender and year of birth of each individual are available. The contribution to an employee's housing provident fund is influenced by their contractual wage levels and a fixed timing factor set by the government. Hence, by examining the original housing provident fund contribution records in the data, I can infer the wages of each individual. It is worth noting that bonuses, overtime pay, and in-kind compensations, etc., are not included in the wage. Furthermore, for a subset of workers (403,343 workers, constituting 7.6% of the sample) who utilize the housing provident fund to apply for a house mortgage, I also have information of their hukou location, education levels, and marriage status.

Employer information – This data set covers different types of employers including commercial firms and other non-firm employers like government departments, schools, and hospitals. Each employer is also assigned a unique identifier. Employers report contribution records for each of their employees, allowing for the identification of a matched employer-employee network. For workers who utilize the housing provident fund to apply for a house mortgage, additional information such as the employer's sector, location, and industry are collected. There are 37,766 employers (33.0%) with supplementary information available. Notably, these employers hire a total of 4,289,966 employees (87.7% of the sample), covering 85.4% of the employee-year observations.

Data representativeness – Compared to the aggregate data, the workers in our data set exhibit a similar sex ratio and average age. However, there is a higher proportion of native workers and a higher proportion of individuals with a college degree (see Table A1). While our data could be selective, it covers a substantial labor market within one of China's largest cities. Consequently, the empirical findings derived from this data set not only shed light on the experiences of millions of workers in the covered labor market but also have implications for dozens of millions of migrants affected by hukou restrictions in China, as well as for an even larger global labor force that faces various forms of residential restrictions.

Table 1 shows the summary statistic of the data used in this study. It is evident that migrants have higher average wages than native workers in the sample. The presence of a positive wage gap between migrants and natives, in contrast to most previous findings (Chen and Zhang, 2018; Lee, 2012; Ma, 2018; Song et al., 2019; Zhang et al., 2016), can be attributed to two primary reasons. First, migrants employed in the formal sector are more likely to have received tertiary education or higher within the city. As a result, they are likely to possess higher observed and unobserved skills compared to native workers in the data set. Second, previous literature often defined migrants as individuals holding agricultural hukou in a different city. However, in our study, the definition of migrants includes individuals who were not born in their current city of residence. Following this definition, individuals born in another city but have obtained local hukou and those holding non-agriculture hukou are categorized as migrants. These two types of migrants are more likely to have higher incomes compared to rural-to-urban migrants who have not yet obtained local hukou.

In Appendix B, I provide further descriptive analysis on the observed wage gap between migrants and native workers, with observed worker and employer characteristics taken into account. The migrant-native wage gap is positive and statistically significant. Using national-representative data sets including the 2005 1% population survey, Urban Household Survey (UHS), and China Household Finance Survey (CHFS), I also document positive migrant-native wage gaps following the definition of migrants in this study.

3 Decomposition of the Migrant-Native Wage Gap

The preceding section provides statistics on the observed wage gap between migrants and native workers. However, this gap does not offer a thorough understanding of the "true" wage gap between a migrant worker and an otherwise identical native worker. Therefore, it is crucial to dig deeper into the migrant-native wage gap and examine its underlying causes. This section adopts a decomposition framework, as proposed in pre-

Table 1: Summary Statistics

	Migrants		Natives	
	Male	Female	Male	Female
Number of individuals	1,352,620	1,074,748	1,314,307	1,148,773
Proportion of females (%)		43.8		46.8
Age	32.3	31.8	37.9	36.9
	(5.9)	(5.8)	(7.9)	(7.6)
Wage (CNY)	86,177.8	70,728.8	68,230.9	64,871.4
	(74,012.5)	(59,679.7)	(61,632.7)	(54,815.9)
Percent of public sector (%)	35.5	41.5	69.1	71.9
	(47.9)	(49.3)	(46.2)	(44.9)
Percent of job switches in the past year (%)	9.7	8.3	6.1	5.3
	(29.7)	(27.6)	(23.9)	(22.4)
Average employer size	46.6	46.3	49.4	48.9
	(189.8)	(182.4)	(176.3)	(177.4)
Median employer size	11	11	14	13
Average employer-average wage (CNY)	79,653.3	74,387.8	65,356.4	66,431.4
	(51,813.1)	(50,315.0)	(41,918.0)	(44,543.5)

Notes: Each cell shows the average of a specific worker group defined by migration status and gender. Standard deviations are shown in parentheses.

vious studies (Card et al., 2016; Dostie et al., 2023; Gerard et al., 2021), to decompose the migrant-native wage gap into three components: selection, sorting, and wage setting.

3.1 The AKM model

Utilizing the longitudinal matched employer-employee data, I first estimate the two-way fixed effect model of wage determination proposed by Abowd et al. (1999) and solved by Abowd et al. (2002). The model is specified as follows.

$$\ln y_{git} = \alpha_{gi} + X'_{git}\beta_g + \psi^g_{j(g,i,t)} + \varepsilon_{git} \tag{1}$$

where $\ln y_{git}$ is the log-transformed wage of worker i in group g in year t. I use $g = M, N$ to indicate migrants and natives, respectively. α_{gi} captures individual fixed effect representing the fully portable component of earnings capacity of individual i, $\psi^g_{j(g,i,t)}$ is a wage premium paid by employer j to workers in group g, $j(g,i,t)$ is an index function indicating the employer for worker i in group g in year t. X_{git} is a vector of observed characteristics of employees, including the polynomial of age and their interactions with gender. ε_{it} is the error term.

I estimate the AKM model separately for migrants and native workers. Considering the studied policy shock (details below) that occurred in 2011 may lead to substantial changes to the labor market, at this stage, I focus on the sample from 2006 to 2010, i.e., the pre-shock period.

The identification of the AKM model is based on the assumptions of exogenous mobility and additive separability of worker and employer effects (Card et al., 2018). First, there is no sorting based on unobserved match components between individuals and employers. To test this assumption, I follow Card et al. (2013, 2018) and show that wage changes are symmetric when moving from high-paying employers to low-paying employers or vice versa (see Figure C1). Also, I show that even without accounting for the match component of individuals and employers, the AKM model captures most of the wage variations in the data, suggesting that the match effect may not be important in our context. Second, there is no drift in the expected wage that predicts employer-to-employer transitions. As shown in Figure C1, the wage remains relatively stable before different types of job switch, supporting the absence of such a drift component. Finally, I divide the worker and employer effect into deciles and calculate the residuals of the AKM model within each of the 100 cells based on these deciles (see Figure C2). I find no systematic patterns in the mean residuals across cells, and the magnitude of the mean residuals is generally close to zero.

The separate identification of person and employer effects in the AKM model is only obtained in a "connected set" of workers and employers that are linked with worker mobility (Abowd et al., 1999, 2002). Following previous literature, I consider the identification of person and employer effects within the largest connected set (Card et al., 2013, 2016, 2018; Dostie et al., 2023; Gerard et al., 2021). The largest connected set accounts for 83.5% (80.6%) of employers, 96.1% (96.3%) of movers, and 97.0% (96.7%) of observations in the pre-shock (post-shock) period sample.

It is worth noting that I only focus on job movers (i.e., who have switched jobs at least once) in our baseline specification. The reasons are twofold. First, employer fixed effects are identified through the analysis of job movers rather than job stayers. Since our primary interest lies in examining the cross-group disparity in employer fixed effects, which are influenced by employers' pay policies in the presence of the hukou system, focusing on movers would not introduce biases into our estimations but would largely reduce the computation burdens. Second, and more importantly, the first two identification assumptions mentioned above are made on movers. Accordingly, the empirical tests on these two assumptions are valid for job movers but may not apply to job stayers. Nevertheless, for robustness, I include job stayers to conduct empirical analysis as an additional check (see Section 5).

Recent research on the AKM model documented the existence of sampling errors when estimating second-order moments of person and employer effects in situations where there is limited worker mobility across employers (Bonhomme et al., 2023; Kline et al., 2020). This limited mobility bias leads to overestimated variation in employer effects and underestimated correlation between person and employer effects.

To solve the limited mobility bias, I follow previous literature (Gerard et al., 2021) to employ the method proposed by Kline et al. (2020) (henceforth referred to as "KSS"). The KSS method utilizes a leave-one-out procedure. The first step is to determine a leave-one-out connected set, i.e., a set of employers that remains connected with any single employees dropped from the set. Bias-corrected estimations are then performed based on this leave-one-out connected set.[3] Implementing the leave-one-out procedure, approximately 25.2% (23.7%) of employers, 61.3% (67.7%) of movers, and 51.2% (62.3%) observations from the largest connected set are dropped in the pre-shock (post-shock) periods. In Table C1, I present the summary statistics of key variables for both the largest connected set and the leave-one-out connected set. We can see that the levels and variances of wage, age, proportion of females, proportion of native workers, and other variables are comparable between these two connected sets in both periods.

The estimation results of equation 1 for both migrants and native workers, using both the traditional method and the KSS method, are shown in Table 2. Focusing on the first two columns, two findings are worth noting. First, the two-way fixed effect model has high explanatory power to wage variance, with R^2 values of 89.8% and 88.3%. The inclusion of the employer-employee match effect only marginally increases the R^2 to 91.2% to 90.1%. This suggests that idiosyncratic match effects in wage determination are not significant in our data set, which aligns with findings from the previous literature (Card

[3]It was proven in Kline et al. (2020) that an estimator with bias-correction term is equivalent to a leave-one-out estimator that depends on leave-one-out estimations of parameters. Leaving out any single person-year observation at a time would not change our qualitative conclusions.

et al., 2013, 2016, 2018; Gerard et al., 2021). Second, the total impact of employers on wage dispersion, encompassing both direct employer fixed effects and the correlation between person and employer effects, accounts for about 33% and 46% of the overall wage variance for natives and migrants. This range largely aligns with findings in previous literature ([26.7, 40.2] in Card et al., 2013, 2016, 2018; Gerard et al., 2021). In line with theoretical prediction and previous literature, I find a smaller variance of employer effects but a larger correlation between person and employer effects after addressing the limited mobility bias through the KSS method (columns (3) – (4)). However, the total impact of employers on wage variance remains largely the same.

In this study, I mainly focus on the migrant-native gaps between first-order moments of the fixed effects estimations. Therefore, the limited mobility bias should be less of a concern regarding these parameters of interest. Moreover, as shown here, the KSS method leads to a substantially smaller sample size. Thus, in the following analysis, I will use the traditional AKM estimations on the largest connected set as the baseline results to include more employers and employees. Using the sample in the leave-one-out connected set and fixed effect estimations with the KSS method, with a loss of statistical power, would not change our qualitative conclusions.

3.2 Normalization of fixed effects

To enable cross-group comparisons of person and employer effects in equation 1, a normalization procedure is necessary, as outlined by Gerard et al. (2021). This normalization involves identifying a group of employers that offer zero wage premiums to their employees, thereby allowing all unexplained wage variation to be captured by the person effect. By doing so, the normalized employer effects provide a measure of the true wage premium for employees, making them comparable across different worker groups. Following previous literature, low-paying employers in a competitive labor market are more likely to have zero wage premiums. Therefore, I define a set of benchmark employers with zero wage premiums as follows: private sector employers with average wage ranks falling within the bottom 5 to 10 percentiles of the overall sample. I exclude the bottom 5 percentiles to exclude extremely small and low-productivity employers. I also exclude the public sector since it is generally less competitive than the private sector, and public sector employers may hold certain rents that could serve as a source of wage premiums for their employees. As shown later in Section 5, the results are also robust to

Table 2: The AKM Model Estimation Results, 2006 – 2010

Sample	Native	Migrant	Native	Migrant
Method	AKM	AKM	KSS	KSS
	(1)	(2)	(3)	(4)
Standard deviation of log wages	0.715	0.742	0.700	0.712
Mean log wages	10.765	10.994	10.775	11.262
Variance decomposition				
SD of person effects	0.541	0.481	0.446	0.357
SD of employer effects	0.395	0.474	0.346	0.441
SD of covariates	0.145	0.21	–	–
Correlation of person/employer effects	0.035	0.058	0.155	0.189
Adjusted R^2 of model	0.898	0.883	0.748	0.752
Adjusted R^2 with match effect	0.912	0.901	–	–
Percentage of variance of log wages due to:				
Person effect	57.2	42	40.6	25.1
Employer effect	30.4	40.8	24.4	38.4
Covariance of person and employer effects	2.9	4.8	9.7	11.7
Emp. effects + covariance person and emp. effects	33.3	45.6	34.1	50.1
Number of employers	28251	26101	20504	18237
Number of movers	447700	399160	184199	143461
Number of person-year observations	1513611	1115698	760746	523598

Notes: Models include dummies for individual workers and individual employers, year dummies, and quadratic terms in age interacted with gender dummies. Samples in columns (1) and (2) include only observations in the largest connected set. Samples in columns (3) and (4) include only observations in the leave-one-out connected set. In columns (3) and (4), I partial out covariates before KSS estimations. Therefore, the standard deviation of log wages and mean log wages represent the standard deviation of *residualized* log wage and the mean of *residualized* log wages, respectively.

an alternative definition of benchmark firms that further restricts observed average wage difference between groups to in the bottom 10 percentiles.

With a set of benchmark employers, I first compute the average estimated employer effect of the benchmark employers. Then, I subtract this average employer effect from all estimated employer effects of employers in the sample. That is, I shift the distribution of employer effects such that the normalized employer effects of benchmark employers have a mean zero. Accordingly, I add the average employer effect of benchmark employers to all estimated person effects to get normalized person effects.

3.3 Decomposition of the migrant-native wage gap

Based on equation 1, the wage difference between migrants and native workers can be expressed by the following equation:

$$\begin{aligned} E\left[\ln y_{Mit}\right] - E\left[\ln y_{Nit}\right] = & \underbrace{\alpha_M - \alpha_N}_{\text{gap in Person Effect}} + \underbrace{\bar{X}'_M \beta_M - \bar{X}'_N \beta_N}_{\text{gap in covariates}} \\ & + \underbrace{\sum_j \psi_j^N \left(\pi_{Mj} - \pi_{Nj}\right)}_{\text{sorting}} + \underbrace{\sum_j \left(\psi_j^M - \psi_j^N\right) \pi_{Mj}}_{\text{wage-setting}} \end{aligned} \tag{2}$$

where $g = M$ stands for migrants while $g = N$ stands for native workers.

The wage difference consists of four components. The first component is the mean difference in person effects. The second component is the difference attributed to employee's observed characteristics. This component can be further decomposed as the difference in the level of employee characteristics and the difference in the returns to these characteristics. However, In this study, I do not focus on this particular component for three reasons. First, it has already been the focus of most previous literature (Chen and Zhang, 2018; Lee, 2012). Second, and more importantly, this is unrelated to the role of employers in driving the wage gap between migrants and native workers, as it remains consistent across employers. Lastly, important time-invariant characteristics including gender and education are already taken into account in the person effect.

The third component is a weighted average of the difference in employment shares of migrants and native workers across different employers. The weights assigned to each employer are the wage premiums for native workers. This component provides an estimate of the impact of differential sorting of the two groups across employers, assuming that migrants receive the same wage premiums as native workers.[4]

[4]We can conduct an alternative way of decomposition following the equation below:

$$\begin{aligned} E\left[\ln y_{Mit}\right] - E\left[\ln y_{Nit}\right] = & \underbrace{\alpha_M - \alpha_N}_{\text{gap in Person Effect}} + \underbrace{\bar{X}'_M \beta_M - \bar{X}'_N \beta_N}_{\text{gap in covariates}} \\ & + \underbrace{\sum_j \psi_j^M \left(\pi_{Mj} - \pi_{Nj}\right)}_{\text{sorting}} + \underbrace{\sum_j \left(\psi_j^M - \psi_j^N\right) \pi_{Nj}}_{\text{wage-setting}} \end{aligned} \tag{3}$$

where

$$\sum_j \psi_j^M \left(\pi_{Mj} - \pi_{Nj}\right) = \underbrace{\sum_j \psi_j^M \left(\pi^*_{Mj} - \pi^*_{Nj}\right)}_{\text{skill-based sorting}} + \underbrace{\sum_j \psi_j^M \left[\left(\pi_{Mj} - \pi^*_{Mj}\right) - \left(\pi_{Nj} - \pi^*_{Nj}\right)\right]}_{\text{residual sorting}}$$

In this way of decomposition, the employer effect for migrants is used as a measure of the employer's wage

The fourth component is a weighted average of the difference in wage premiums between migrants and native workers across employers. The weights used in this calculation are the employment shares of migrants. This component focuses on the effect of differential wage setting between the two groups, based on the actual distribution of migrants across employers.

Due to the selectivity of migrants in our sample, there exist substantial skill differences between migrants and native workers. Therefore, the estimated sorting effect may be influenced by the differential demand for employees with different skill levels. Moreover, considering the endogenous location choice of migrants, they are more likely to live in high-paying regions. In this case, even if employers adopt a hiring policy that is neutral towards migration status, they will still hire a higher proportion of migrants. To account for these impacts, I follow Gerard et al. (2021) to decompose the sorting effect into skill-based sorting and residual sorting:

$$\sum_j \psi_j^N \left(\pi_{Mj} - \pi_{Nj}\right) = \underbrace{\sum_j \psi_j^N \left(\pi^*_{Mj} - \pi^*_{Nj}\right)}_{\text{skill-based sorting}} + \underbrace{\sum_j \psi_j^N \left[\left(\pi_{Mj} - \pi^*_{Mj}\right) - \left(\pi_{Nj} - \pi^*_{Nj}\right)\right]}_{\text{residual sorting}}$$

Where π^*_{Mj} captures the counterfactual proportion of migrants in employer j, assuming that j holds a fixed skill composition but randomly hire employees with different skill levels from the local labor market. Skills are defined by their age groups and estimated person effects.[5] Subtracting the skill-based sorting, the residual sorting captures the disparity in the probability of migrants and native workers entering high-paying employers, holding skill level fixed and controlling for the spatial distribution of workers.

Among the factors listed above, I primarily focus on the wage-setting effect, skill-based sorting effect, and residual sorting effect in determining the migrant-native wage gap because they shed light on the restrictions faced by migrants in the labor market in pursuing a high payment.

Decomposition results are shown in Table 3. Following the discussions above, I take column (1) as the benchmark. While the wage gap is positive (the first row), suggesting higher income of migrant workers, we can see that the gap will reverse once we eliminate the positive gap in person effects between migrants and natives (row 1). Migrants being

premium. However, this approach may not be as appropriate for this study when compared to our baseline specification. This is because the employer effect for migrants could be influenced by the hukou policy.

[5]Specifically, age is divided into $[25, 29]$, $[30, 34]$, $[35, 39]$, $[40, 44]$, $[45, 50]$, and estimated person effects are divided into four quartiles.

substantially younger than native workers in our sample has a notable negative impact on relative wages (row 2).

Furthermore, the analysis reveals a negative employer effect gap, suggesting that employers treat migrants unfavorably (row 3). The negative employer effect gap is mainly driven by two parts: a negative wage-setting effect that explains about -4.8% of the migrant-native wage gap (row 3.1), and a negative residual sorting effect that explains an additional -4.8% of the wage gap (row 3.2.2). Notably, the positive sorting effect (row 3.2) is completely driven by the fact that high-premium firms have a higher demand for high-skilled workers, who are more likely to be migrants in our sample. Together, I find that negative treatment against migrants leads to a -9.6% wage gap, despite migrants earning higher average wages than native workers.

As shown in Appendix B, the positive migrant-native wage gap narrows when we include more observable characteristics, but it is never reversed. On the contrary, the results here highlight the fact that a *negative* migrant-native wage gap is masked by the observed positive difference in average wages. The results highlight the importance of unobserved skills in explaining the migrant-native wage gap, even in data sets with rich demographic characteristics. They also suggest the importance of incorporating the AKM model into the investigation of group wage differences. Without estimations of person effects and employer effects, we will not be able to reveal the existence of a true *negative* migrant-native wage gap from an observed *positive* one.

4 Hukou Quota Reduction and Migrant-Native Wage Gap

In this section, I first introduce the institutional background related to the hukou system in the studied city and the policy shock that I focus on. Then, I present three sets of analyses: (1) regression analysis on the migrant-native wage gap based on exogenous variations in the hukou quota induced by the policy shock; (2) before-after decompositions of the migrant-native wage gap; (3) analysis on wage-setting power and worker allocation and their relationships with the hukou system.

Table 3: Decomposition of the Migrant-Native Wage Gap

	(1) Decomposition	(2) Alternative Decomposition
Wage Gap (Migrant - Native, same below)	0.190	0.190
1. Person Effect Gap	0.375	0.375
2. Covariates Gap	-0.162	-0.162
3. Employer Effect Gap	-0.024	-0.024
3.1. Wage-Setting Effect	-0.048	-0.062
3.2. Sorting Effect	0.024	0.038
3.2.1. Skill-Based Sorting Effect	0.072	0.076
3.2.2. Residual Sorting Effect	-0.048	-0.039
Observations	2280272	2280272

Notes: Results are conducted based on estimations of the two-way fixed effects in equation 1 and decomposition in equation 2. Only observations in the largest connected set are included. The wage gap is calculated as the difference in log-transformed wages.

4.1 Institutional background

4.1.1 The hukou system

The household registration system (hukou) in China categorizes individuals' residence status based on their work in the agriculture or non-agriculture sector in a specific location. Access to local (usually at the prefecture city level) public services is highly dependent on hukou status. Basically, temporary residents without a local hukou are often excluded from accessing local education, medical care, and social security resources (Song, 2016). Moreover, they may also face restrictions in purchasing houses and vehicles.

Basically, one's initial hukou status following birth depends on the hukou of their parents. However, the hukou status is not permanent for an individual. While people may obtain the hukou in another city, most cities have set criteria for non-local residents to acquire local hukou. The most common method is through reunification with one's spouse, children, or parents who possess local hukou. To obtain hukou without a relative network, non-local residents are generally required to have proofs of stable sources of income, a residential address, and a minimum duration of residency in the city. Buying houses and starting a business are also common ways of getting hukou. The central government has delegated the authority to each prefecture city to establish its own hukou policies. As a result, the difficulty of obtaining local hukou varies significantly across different cities (Fan, 2019).

In a metropolis like the one studied, where rich public services and resources are provided to local residents but strict restrictions are imposed on non-local temporary residents, having a local hukou is highly valuable. There is ample anecdotal evidence highlighting the significance of hukou. For instance, a lot of anecdotal evidence indicates that a "black market" for hukou has long existed in the studied city. Obtaining a local hukou in the studied city is very challenging. The local government set up the hukou quota system to control the total number of newly minted migrating graduates who can obtain local hukou and stay in the city. Employees must request their employers to apply for the hukou quota on their behalf, similar to the H1-B visa process in the US.

Unlike the H1-B visa lottery system, the allocation of hukou quotas is determined by the government. The process of hukou quota allocation follows the following procedure. First, employers in each district of the city report their demand for hukou quotas to the corresponding district's handling department. Then, the municipal government consolidates the demand and distributes hukou quotas to each district based on the total number of quotas for the year and the districts' demand. Finally, each district allocates the quotas to employers based on their demand. According to the enrollment rules for non-native graduates in the city, employers in the public sector are more likely to acquire hukou quotas for their workers.

The hukou quota ensures the right to obtain a local hukou. However, in practice, employees with a hukou quota need to wait for a period ranging between six months and three years before actually receiving the hukou. During this period, they are granted a working residence permit, which provides access to most, but not all, local public services available to residents with a local hukou. Most employees who obtain a hukou quota sign fixed-term contracts with their employers, which set minimum requirements for the duration of their employment. Early termination of the contract may result in significant fines, often amounting to hundreds of thousands of yuan. However, there are still many cases in which employees break the contract and leave after obtaining a hukou, indicating that the hukou policy grants monopsony power to employers, leading to suboptimal job matches.

4.1.2 The 2011 reform on hukou quota

During the National People's Congress and the Chinese People's Political Consultative Conference (the "Two Sessions") in 2011, which marked the beginning of China's 12th five-year plan, the city recognized significant population pressure as a crucial challenge. The local governments in the studied city responded to this challenge by setting explicit and stringent population control targets in their development plans following the Two Sessions.[6] To achieve these targets, the governments proposed a range of population control policies, with a primary focus on restricting the inflow of migrants, as migration was identified as the main driver of population growth in the city. The government adopted three main methods to address this issue. First, they restricted the provision of local hukou to migrants. Closely related to our study, the total number of hukou quotas was reduced by about one-third, decreasing from about 16,000 to around 10,000 (see Figure 1). Second, they strengthen the monitoring of migrants to ensure the tracking of every temporary resident without local hukou. Third, they advanced structure transformation in the city, trying to phase out low-value-added, labor-intensive manufacturing and service companies.

The policy change towards stricter population control did result in a slowdown in the growth of non-local residents moving into the city (see Figure 1). However, the total number of migrants continued to increase over time. Given that the absolute number of hukou quotas decreased significantly, obtaining a hukou became more challenging.

The policy shock on the hukou quota can be regarded as largely exogenous to individual labor market outcomes for two primary reasons. First, although speculations and subjective media predictions regarding the reduction were widespread before the official announcement by the government, the actual magnitude of the reduction in the hukou quota was not anticipated by the public before its implementation. Second, the allocation of hukou quotas is determined on a case-by-case basis, making it difficult for individual employers to accurately predict how their quota numbers will be affected.

According to documents released by the local Human Resources and Social Security Bureau at both municipal and district levels, which are in charge of the allocation of hukou quotas, hukou quotas were still allocated tilted towards the public sector after the

[6] Details of these targets can be found in Table E1. Ten districts out of 16 proposed explicit population control targets in their developing plans, while the remaining districts also emphasized the importance of population control.

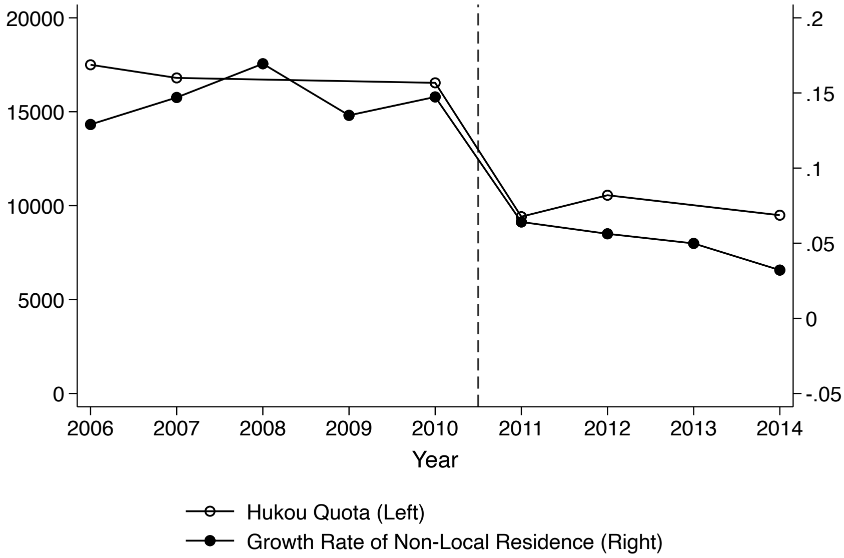


Figure 1: Total Hukou Quota, 2006 – 2014

Notes: Data source: Yearbooks of the studied city, and Statistical Yearbook of the studied city. Data in some years is missing because the total hukou quota is not publicly reported every year. Only non-local residents who live in the city for more than half a year are included.

policy shock. In this case, employers in the private sector that used to have hukou quotas experienced the most significant reduction in their hukou quota allocation. This policy variation in hukou quota reduction across sectors provides an opportunity to see how changes in the probability of obtaining hukou affect employers' wage-setting power for migrant workers, the wage gap between migrants and native workers, and the allocation of migrants across employers.

4.2 Descriptive evidence of the role of hukou

Before proceeding to the next section, I briefly discuss some descriptive analyses of the heterogeneity of the migrant-native wage gap and its components across different workers and employers. The results shed light on the potential role of the hukou system in driving the migrant-native wage gap, which serves as a motivation and building block to the analysis below.

First, I document a smaller migrant-native wage gap (i.e., lower relative wage of migrants) in the public sector and among young workers under the age of 35 (see Figure 2). This pattern holds when: (1) I control for education levels, focusing on a restricted subsample with the information on education; (2) I control for estimated person effect of workers. A lower relative wage of migrants in the public sector is consistent with the fact that the public sector is more likely to provide hukou quotas for migrants and thus has higher monopsony power among migrants while migrants on average accept a lower wage in exchange for hukou. A lower relative wage of migrants among young workers is in line with the case where young workers have a higher demand for hukou. I argue that this is true because young workers can benefit from hukou for a longer period than old workers under a system where a migrant holds the hukou forever once obtained it.

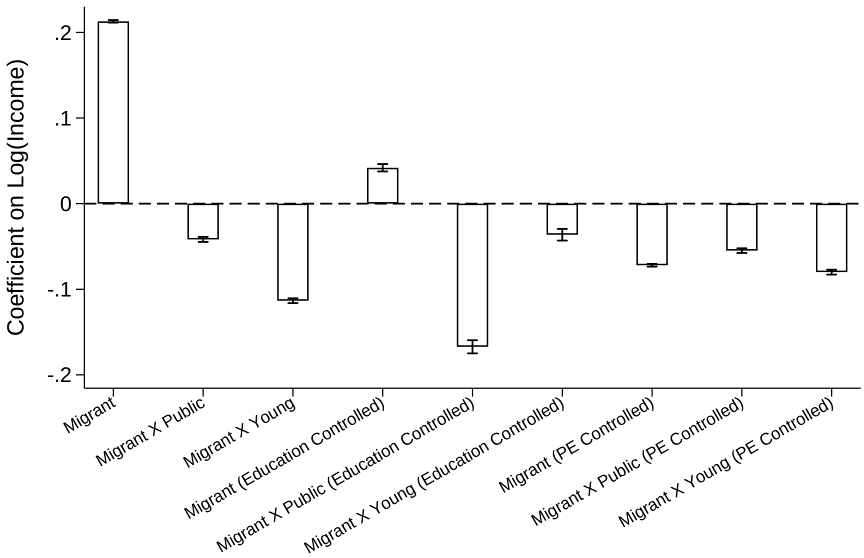


Figure 2: Migrant-Native Wage Gap

Notes: Each bar show a coefficient of interest in separate regressions as shown on the x axis. Capped vertical lines indicate the 95% confidence interval of the coefficient. The regression models are specified as below:

$$\ln y_{it} = \beta_0 + \beta_1 Migrant_i + \beta_2 Migrant_i \times Treat_{ijt} + \beta X_{it} + \gamma W_{j(i,t)t} + \lambda_t + \varepsilon_{it}$$

Where $Treat_{ijt}$ indicates the public sector for the second and the fifth bars from the left, and it indicates young workers for the third and the sixth bars from the left. The first three bars on the left come from regression results on the data set of this study. The other three bars come from regression results on the subsample with education information available. In the three bars on the right, education information is controlled for in the regression.

Second, I find that the person effect gap between migrants and natives is increasing with the proportion of native workers of an employer, which is also correlated with the probability of the employer being in the public sector. On the contrary, the migrant-native employer effect gap is decreasing in the proportion of native workers sector (see

Figure 3). Theoretically, high-skilled migrants should not choose the public sector that offers lower wage premiums. However, when high-skilled migrants have a higher demand for hukou compared with low-skill migrants, which is likely the case, they will opt for the public sector that offers more hukou quotas.

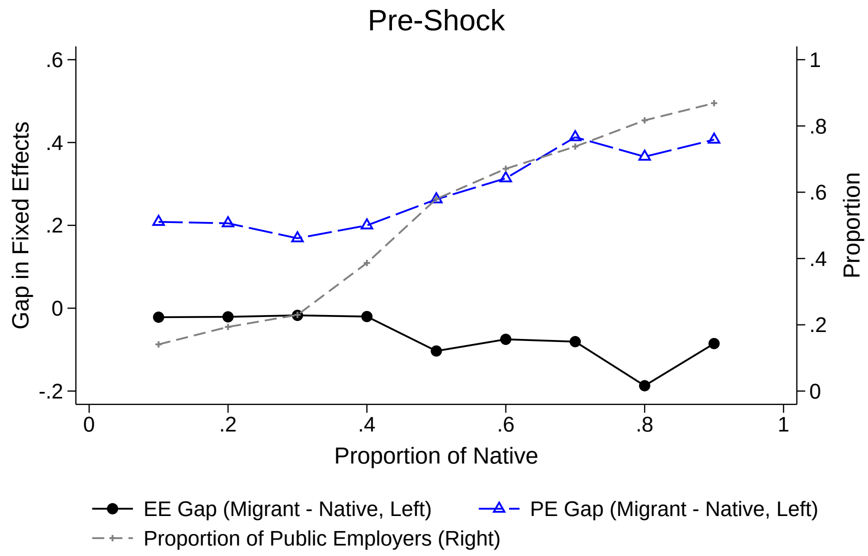


Figure 3: PE and EE Gaps across Employers

Notes: Person effects and employer effects are estimated with the AKM method. Each dot, triangle, and plus indicate the average value of within a bin of employers sorted by the proportion of native workers. This figure is generated with the sample in the pre-shock period.

Lastly, in Appendix D, I adopt a simplified version of revealed-preference estimation of worker-employer match values following Sorkin (2018). Conditional on the assumptions that job-to-job transitions are endogenous (i.e., workers switch jobs for higher utilities), and worker utilities depend on wage and amenities, I can back out the values of amenity of each worker-employer match, allowing employers to offer different amenities to migrants and native workers. Results show that employer wage premium is negatively correlated with amenities, attesting to a compensating differential narrative in the wage-setting policy. It is worth noting that this analysis does not rule out the role of monopsony power in generating the migrant-native wage gap. Instead, it validates the existence of a trade-off between wage premium and the non-pecuniary value of a job. Nonetheless, when such a trade-off is absent, amenities will not contribute to employers' monopsony power.

4.3 Reduced-Form analysis of hukou quota reduction

In this section, I leverage the exogenous reduction in hukou quota to conduct reduced-form analyses on the migrant-native wage gap. The reduction in hukou quotas directly affects the amenity values offered by employers to migrants, generating two effects. First, it affects how employers set the wage compensation for migrant workers (wage-setting effect). Second, it affects the matching process between workers and employers (sorting effect), as both wage compensation and available amenities have changed. Therefore, the overall impact of the policy shock depends on the relative magnitude of these two effects.

As argued above, the private sector suffered a more significant decrease in hukou quotas. Consequently, the impact of increasing wage compensation for migrants should be more salient in the private sector. In addition, the hukou quota reduction affects different workers differently. A worker is entitled to the hukou once he/she obtained it. Therefore, young workers have a higher demand for hukou as they can enjoy the benefits of hukou for an extended period.[7] In this case, it is expected that the reduction in hukou quotas will have a larger impact on the wage gap between young migrants and young native workers.

To estimate the aggregate impact of the policy shock on the migrant-native wage gap, I apply the difference-in-differences (DID) method and estimate the following empirical model:

$$\ln y_{it} = \alpha_i + \gamma_1 \cdot g_i \times Post_t + \gamma_2 \cdot g_i + \lambda_t + X'_{it}\beta_X + W'_{j(it)t}\beta_W + \varepsilon_{it} \tag{4}$$

Where $\ln y_{it}$ is the log wage of employee i in year t. g_i indicates whether individual i is a migrant or a native worker. X_{it} captures observed employee-side characteristics with differential impacts before and after the policy shock,[8] α_i is the estimated person effect from the AKM model, and ε_{it} is the error term. Controlling for the estimated person effect helps address the selection issue of migrants having different skills compared with native workers.

Here, I consider two specifications. The first one does not include $W_{j(it)t}$ that captures employer-side characteristics with differential impacts before and after the policy shock,

[7] There could be other reasons for young workers to have a higher demand for hukou other than life-cycle considerations. For example, they are around the time of getting marriage and would like to purchase a house, which is restricted to individuals without a local hukou.

[8] There is an abuse of notation here. In practice, time-variant individual (and employer) characteristics, along with their interactions terms with $Post_t$ are included in the regression model.

and the second one controls for $W_{j(it)t}$. Under the first specification, I allow comparisons between migrants and native workers who work for employers with different features. That is, I allow the change in the distribution of workers across different employers to affect the migrant-native wage gap following the policy shock. Under the second specification, I restrict the comparisons between migrants and native workers within employers with comparable observed characteristics. By doing so, I largely control for potential changes in sorting effect that affects the migrant-native wage gap. Rather, the results reflect changes in the wage-setting effect. Hence, comparing the results under these two specifications sheds light on the relative importance of the wage-setting effect and sorting effect in determining the migrant-native wage gap.

To test for the heterogeneous effects on different sectors and on different workers, I apply the triple-difference (DDD) method and estimate the following empirical model:

$$\begin{aligned} \ln y_{it} =& \alpha_i + \gamma_1 \cdot g_i \times Treat_{i,j(it)} \times Post_t + \\ & \gamma_2 \cdot g_i \times Treat_{i,j(it)} + \gamma_3 \cdot g_i \times Post_t + \gamma_4 \cdot Treat_{i,j(it)} \times Post_t + \\ & X'_{it}\beta_X + W'_{j(it)t}\beta_W + \varepsilon_{it} \end{aligned} \tag{5}$$

where $\ln y_{it}$, g_i, X_{it}, $W_{j(it)t}$, α_i, and ε_{it} are defined as in equation 4 above. $Treat_{i,j(it)}$ represents different treatment groups, i.e., employers in the private sector and employees younger than 35 years old. Same as the analysis above, I consider two specifications: one that includes $W_{j(it)t}$ in the model and one that does not.

The results of the estimation of equation 4 are shown in the columns (1) and (4) of Table 4. It turns out that migrants' relative wages increased following the policy shock under both specifications. It is worth noting that the positive coefficient in column (4) is larger, suggesting that wage setting effect is the main driving force of increased relative wage of migrants. Meanwhile, the sorting effect tends to generate negative impact on the relative wage of migrants. The results of the estimation of equation 5 are shown in columns (2) – (3) and (5) – (6) of Table 4. We can see that the coefficients for the triple-difference term are significantly positive in all four columns. This indicates that following the reduction in hukou quotas in 2011, the relative wage of migrants, compared to native workers, increased to a larger extent for the treatment groups defined above. Importantly, these results go beyond a simple before-after analysis of the policy shock in 2011, which could be confounded by other simultaneous policy changes following the launch of the 12^{th} 5-year plan. Thus, we can have confidence that the results are explained by the change in the provision of hukou quotas, rather than other policy changes.

Table 4: Regression Results of the Hukou Quota Reduction

VARIABLES	(1) Log(Income)	(2) Log(Income)	(3) Log(Income)	(4) Log(Income)	(5) Log(Income)	(6) Log(Income)
Migrant	-0.0991***	-0.138***	-0.0280***	-0.0808***	-0.115***	-0.0268***
	(0.00113)	(0.00155)	(0.00209)	(0.000864)	(0.00127)	(0.00151)
Migrant × Post	0.0298***	-0.00366**	-0.0211***	0.0543***	0.0127***	0.0217***
	(0.00120)	(0.00171)	(0.00216)	(0.000973)	(0.00146)	(0.00161)
Migrant × Post × Private		0.111***			0.0652***	
		(0.00216)			(0.00164)	
Migrant × Post × Young Workers			0.0668***			0.0426***
			(0.00246)			(0.00174)
Constant	-3.211***	-3.403***	-3.464***	-0.350***	-0.682***	-0.558***
	(0.0119)	(0.0118)	(0.0122)	(0.0107)	(0.0111)	(0.0109)
Observations	5,383,805	5,107,887	5,383,805	4,829,027	4,602,333	4,829,027
R-squared	0.635	0.658	0.636	0.809	0.816	0.810
Sample	Largest Connected	Largest Connected	Largest Connected	Largest Connected	Largest Connected	Largest Connected
Worker Controls × Post	Yes	Yes	Yes	Yes	Yes	Yes
Employer Controls × Post				Yes	Yes	Yes

Notes: All estimations are conducted in the largest connected set within employers that are presented in both periods. Person effects are estimated in equation 1 using AKM method. Worker controls include age, age squared, gender, and job tenure. Employer controls include the proportion of natives of the employer, the proportion of females of the employer, the average age of the employer, the average wage of the employer, and the average turnover rate. Year fixed effects are included. The numbers of observations are different in columns because of missing values or the fact that controlling for turnover rate reduce one year of available sample. Robust standard errors clustered at the individual level are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Accordingly, I can estimate the corresponding event-study model to test the assumption of parallel pre-trends of the treatment as well as to estimate time-varying treatment effects. The empirical model is specified as below:

$$\ln y_{it} = \alpha_i + \sum_{m=-4, m\neq -1}^{3} \gamma_m \cdot g_i \times t_{0+m} + \gamma_2 \cdot g_i + \lambda_t + X_{it}'\beta_X + W_{j(it)t}'\beta_W + \varepsilon_{it} \tag{6}$$

where t_{0+m} is a set of dummies indicating an eight-year window around the year of hukou quota reduction (i.e., the year 2011). In the regression, I use the group where $m = -1$ as a benchmark.

The corresponding event study result is shown in Panels (a) and (b) of Figure 4. Before the policy shock, the coefficients of being a migrant worker on log-transformed wage were around zero. After the policy shock, the coefficients increased and remained consistently positive in the years following. Consistent with the results above, when we include employer characteristics in the model, the positive effect is more statistically and economically significant in the post-shock period.

I also estimate a corresponding event-study analysis on the triple-difference model.[9] The empirical model is specified as follows:

$$
\begin{aligned}
\ln y_{it} =& \alpha_i + \sum_{m=-4, m\neq -1}^{3} \Big[\gamma_1^m \cdot g_i \times Private_{j(it)} \times t_{0+m} + \gamma_2^m \cdot g_i \times t_{0+m} + \\
& \gamma_3^m \cdot Private_{j(it)} \times t_{0+m} \Big] + \gamma_4 \cdot g_i \times Private_{j(it)} + \lambda_t + \\
& X_{it}' \beta_X + W_{j(it)t}' \beta_W + \varepsilon_{it}
\end{aligned}
\tag{7}
$$

where $Private_{j(it)}$ indicates whether employer j is in the private sector.

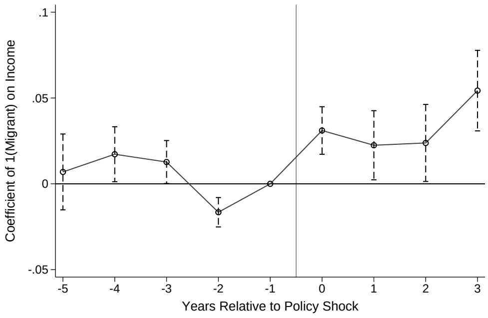
Results are shown in Panels (c) and (d) of Figure 4. Estimating the relative treatment effect of private employers across different years, I find non-significant or close-to-zero relative treatment effects in the pre-shock period, and large significant positive effects following the policy shock.

The results above support the argument that changes in the hukou system affect the migrant-native wage gap. The estimated treatment effects are unlikely to be explained by other simultaneous policy shocks for several reasons. First, I leverage the variations in hukou quota reduction across sectors to estimate the heterogeneous treatment effects. Any confounding policy shocks should generate heterogeneous treatment effects following the same pattern that the private sector witnesses a larger increase in migrants' relative wages in order to explain the treatment effect. Second, I also leverage the variations in demand for hukou across different age groups. Suppose another simultaneous population control policy affects another type of amenity for migrants, say employer-sponsored health insurance. Then, it would be more valuable to old workers than to young workers, generating different results than what I have found.

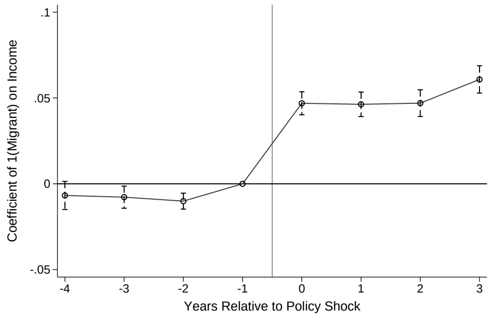
4.4 Decompositions of the migrant-native wage gap before and after the policy shock

While the last section shows the policy effect on the migrant-native wage gap, here I try to dig deeper into the change in each component of the migrant-native wage gap following

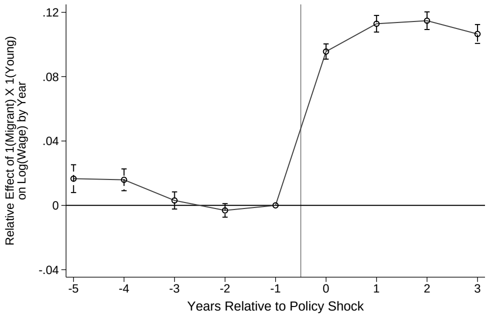
[9] Results of using young workers as the treatment group is presented in Figure F1.



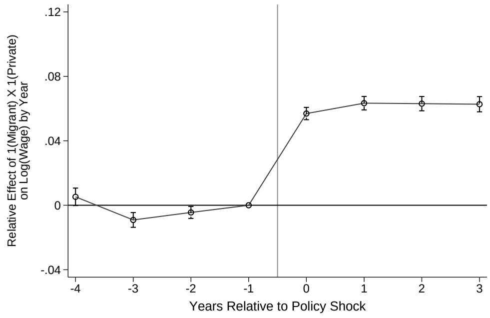
(a) Two-Way, w/o $W_{j(it)t}$



(b) Two-Way, w/ $W_{j(it)t}$



(c) Three-Way, w/o $W_{j(it)t}$



(d) Three-Way, w/ $W_{j(it)t}$

Figure 4: Event Study Results

Note: In Panels (a) and (c), each circle indicates the point estimations of the treatment effect (i.e., the coefficient of $g_i \times t_{0+m}$). In Panels (c) and (d), each circle indicates the point estimations of the relative treatment effect (i.e., the coefficient of $g_i \times Treat_{j(it)} \times t_{0+m}$). Each vertical dashed line indicates the 95% confidence interval of the treatment effect. In Panels (a) and (c), employer controls $W_{j(it)t}$ are not included in the model. In Panels (b) and (d), $W_{j(it)t}$ are included.

the policy shock. To do so, I compare decompositions of the migrant-native wage gap in the period of 2006 to 2010 with that in the period of 2011 to 2014. I first estimate the AKM model in equation 1 separately for migrants and native workers for the sample in the post-shock period. Variance decomposition results of the AKM model are shown in Table C2. It turns out that the AKM model yields high R^2 in wage determination. While the variance of wage explained by employer effect decreased in the post-shock period compared with that in the pre-shock period, the correlation between person and employer effects increased, resulting in a comparable role of the employer in driving wage dispersion when we combine the employer effect with the covariance of employer and person effects. Based on the AKM estimations, I normalize the estimated person effects and employer effects following the method in Section 3.

The before-after difference in each component of the migrant-native wage gap provides suggestive evidence of the impact of hukou quota reduction on the migrant-native wage gap. On one hand, it is expected that the wage-setting effect to be higher in the post-shock period because the hukou quota reduction diminishes the amenity values to migrants, reducing their incentive to accept lower wages in exchange for the amenity values. On the other hand, a more negative residual sorting effect against migrants is also expected. This is because the reduction of hukou quotas mainly occurred in the private sector. As a result, some migrants with a high demand for hukou, who would have otherwise chosen the private sector, may now prefer the public sector that offers hukou quotas. When the private sector has higher wage premiums than the public sector, the residual sorting would be lower.

Decomposition results are shown in Table 5. After the policy change, migrants experienced an increase in wage-negotiating power, although there remains a 1.6 pp negative wage gap attributed to wage-setting effects. Looking at the sorting effect, we can find a larger negative residual sorting effect that explains a 6.5 pp negative wage gap.

Table 5: Decomposition of the Migrant-Native Wage Gap

	(1) Pre-shock	(2) Post-shock	(3) Difference (Post-Pre)
Wage Gap (Migrant - Native, same below)	0.190	0.199	0.010
1. Person Effect Gap	0.375	0.307	-0.068
2. Covariates Gap	-0.162	-0.083	0.079
3. Employer Effect Gap	-0.024	-0.025	-0.001
3.1. Wage-Setting Effect	-0.048	-0.016	0.032
3.2. Sorting Effect	0.024	-0.009	-0.033
3.2.1. Skill-Based Sorting Effect	0.072	0.055	-0.017
3.2.2. Residual Sorting Effect	-0.048	-0.065	-0.016
Observations	2280272	2437044	–

Notes: Results are conducted based on estimations of the two-way fixed effects in equation 1 and decomposition in equation 2. Only observations in the largest connected set are included. The wage gap is calculated as the difference in log-transformed wages. Column (3) shows the results of column (2) minus column (1).

I present the results of the alternative decomposition in Table C3. Qualitative conclusions remain consistent. First, the wage-setting effect increased after the policy shock.

Second, the residual sorting effect is negative and becomes more negative in the post-shock period than in the pre-shock period.

4.4.1 Change in wage-setting effects

I further explore the impacts of hukou quota reduction by constructing the employer-level wage-setting effects as the dependent variable of interest. By examining the changes in the gap of wage-setting effect, we can investigate how the reduction in hukou quota affects wage-setting powers.

According to equation 2, I define employer-level wage-setting effect as the following:

$$Wage\_Setting_j = (\psi_j^M - \psi_j^N) \cdot \pi_j^M / \pi_j$$

Compared with the wage-setting term in equation 2, I rescale employer-level wage-setting effect by the share of employment to avoid extreme values of wage-setting effect. The employer-level empirical model is as follows:

$$Wage\_Setting_{j \cdot Post_t} = \beta_1 \cdot Private_j \times Post_t + \beta_2 \cdot Private_j + \lambda_t + W_{jt}'\beta_W + \varepsilon_{jt} \quad (8)$$

where $Wage\_Setting_{j \cdot Post_t}$ is the aforementioned wage-setting effect. Here I can calculate wage-setting effect separately for two periods.

The results of the estimation of equation 8 are shown in Table 6. In columns (1) – (2), I find that the wage-setting effect becomes larger after the policy shock, suggesting the reduction in hukou quotas increased wage-setting power of migrants. This is consistent with the case where migrants ask for higher wage compensation for the reduced value of hukou. Also, this is consistent with the case where employers as a whole lost part of their monopsony power, because fewer jobs with hukou quota that are hard to be substituted remained in the labor market after the policy shock. In column (3), I find that the positive treatment effect is more salient in private-sector employers. This is consistent with the argument that the private sector witnessed a larger reduction in hukou quotas.

4.4.2 Misallocation of Workers

The formation of worker-employer matches is endogenous, which means that the hukou policy not only affects pay policies within worker-employer pairs but also influences how workers are distributed among employers in the first place. Because the hukou quota reduction is not evenly distributed among employers, migrants may be more (less) likely

Table 6: Hukou Quota Reduction and Wage-Setting Effect

VARIABLES	(1) Wage-Setting	(2) Wage-Setting	(3) Wage-Setting
Post	0.0220***	0.0221***	
	(0.00563)	(0.00576)	
Private Sector × Post			0.0460***
			(0.0111)
Constant	-0.0536***	0.197***	0.0443
	(0.00448)	(0.0402)	(0.0454)
Observations	126,227	126,227	126,227
R-squared	0.001	0.012	0.019
Controls	No	Yes	Yes
Year FE	No	No	Yes

Notes: All estimations are conducted in the largest connected set within employers presented in both periods. Other controls include the proportion of females of the employer, the proportion of native workers of the employer, the average wage of the employer, the average age of the employer, and the average turnover rate. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

to work for high-premium employers when the reduction mainly occurs in low- (high-)premium employers. Results above indicates that on aggregate level, migrants are less likely to work for high-premium employers. Here, I conduct employer-level regression analysis on the residual sorting effect. Suppose employers with high wage premiums also have high productivity, residual sorting reflects the misallocation of workers. Similar to the analysis in Section 4, I define employer-level residual sorting effect as follows:

$$Resid\_Sorting_j = \psi_j^N \left[\left(\pi_{Mj} - \pi_{Mj}^* \right) - \left(\pi_{Nj} - \pi_{Nj}^* \right) \right] / \pi_j$$

Compared with the wage-setting term in equation 2, I rescale employer-level residual sorting effect by the share of employment to avoid extreme values of residual sorting effect. The employer-level empirical model is as follows:

$$Resid\_Sorting_{j \cdot Post_t} = \beta_1 \cdot Private_j \times Post_t + \beta_2 \cdot Private_j + \lambda_t + W_{jt}' \beta_W + \varepsilon_{jt} \qquad (9)$$

where $Resid\_Sorting_{j \cdot Post_t}$ is the residual sorting effect calculated for two periods. Regression results are shown in Table 7. As expected, I find that the residual sorting effect decreased after the policy shock (columns (1) and (2)). It is worth noting that I do not explicitly predict the sign of β_1 because it depends on whether those who opt out of the private sector choose high- or low-premium employers in the public sector. Based on the results in column (3), migrants who would have joined the private sector chose relatively low-premium employers in the public sector after the policy shock.

Table 7: Hukou Quota Reduction and Residual Sorting Effect

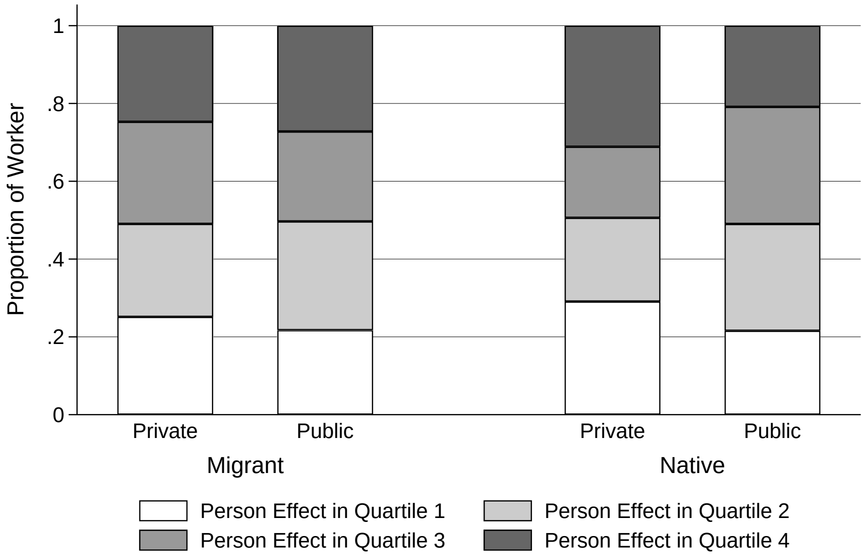
VARIABLES	(1) Residual Sorting	(2) Residual Sorting	(3) Residual Sorting
Post	-0.0161*	-0.0939***	
	(0.00828)	(0.00869)	
Private Sector × Post			-0.0328**
			(0.0152)
Constant	-0.0499***	-0.0311	-0.101
	(0.0104)	(0.0520)	(0.0736)
Observations	144,818	144,818	144,818
R-squared	0.000	0.265	0.267
Controls	No	Yes	Yes
Year FE	No	No	Yes

Notes: All estimations are conducted in the largest connected set within employers presented in both periods. Other controls include the proportion of females of the employer, the proportion of native workers of the employer, the average wage of the employer, the average age of the employer, and the average turnover rate. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

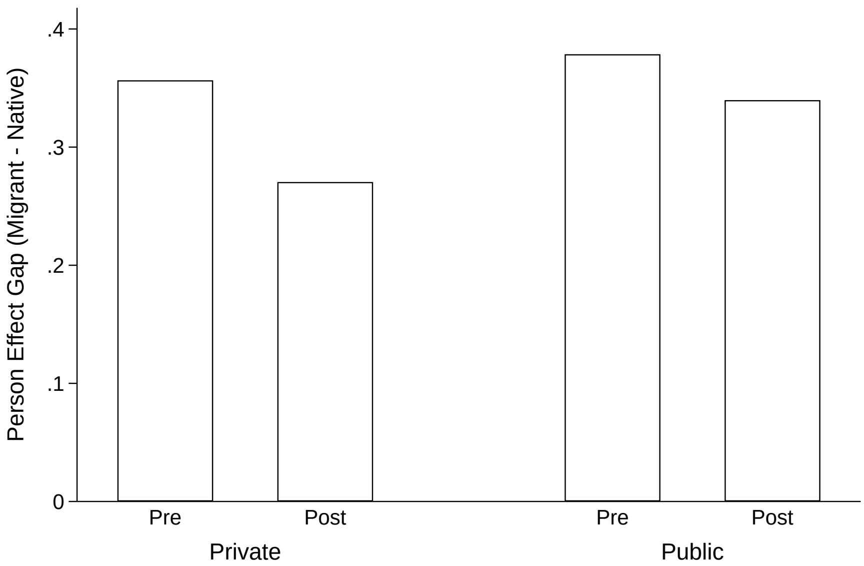
Another way to investigate the impact of hukou quota reduction on the allocation of workers is through the sectoral distribution of workers. Employers with hukou quotas can be more selective in hiring migrants in a case where the amenity value is not fully compensated and high-productivity workers have greater demands for hukou. In Panel (a) of Figure 5, it is demonstrated that high-skilled migrants (defined as those in the top quartile of person effect) are more likely to work in the public sector, while high-skilled native workers prefer to work in the private sector.

It is worth noting that hukou quotas tend to be allocated more towards the public sector. Furthermore, empirical evidence from previous literature consistently finds that state-owned enterprises are less productive than private-owned ones Berkowitz et al., 2017; Brandt et al., 2008, 2022; Hsieh and Klenow, 2009; Hsieh and Song, 2016; Song et al., 2011. Therefore, employers with more hukou quotas have lower productivity than others. In Figure G1, I use the Annual Survey of Industrial Firms (ASIF) 2006 – 2007 in the studied city to verify that employers in the public sector indeed have lower profitability, a proxy for productivity, compared to other employers.[10]

[10]Variables to calculate profitability following Song et al. (2011) is only available in the ASIF data before



(a) Allocation of Workers Across Sectors



(b) Person Effect Gaps Across Sectors

Figure 5: Worker Allocation Patterns

Note: In Panel (a), each bar shows the skill composition of migrants/native workers in a sector. Workers are categorized into four groups according to their relative levels of estimated person effect compared with other workers in the same group. Workers with person effect in the 4^{th} quartile are defined as high-skilled workers. In Panel (b), Each bar shows the gap (migrant worker minus native worker) between the average person effect in each period-sector group.

2007.

In this case, consider the assumption that there are positive productivity gains in assortative matching between high-productivity workers and high-productivity employers. Under this assumption, the allocation of hukou quotas would lead to a concentration of high-productivity migrants in low-productivity employers, resulting in a misallocation of talent.

After the policy shock, high-productivity private-sector employers are less likely to have hukou quotas. While they increase wage compensation as shown in Table 4, they are unable to fully offset the decline in amenity values because of individual-level heterogeneous preference. Consequently, workers with higher demand for hukou, who would have otherwise joined a high-productivity employer, now opt for low-productivity ones. Therefore, the reduction of hukou quotas together with their allocation favoring low-productivity employers exacerbates worker misallocation.

To see this, I calculate the gaps between the average person effects of migrants and native workers separately within the private sector and the public sector. These gaps show the extent of the distorted distribution of high-skilled migrants across different employers. Then, I make a before-after comparison between the average person effect gaps. Results are shown in Panel (b) of Figure 5. It shows that in both periods, the person effect gaps are always positive, which is consistent with the fact that migrants have higher skill levels in the data. More importantly, it shows that after the policy shock, the person effect gap decreased by a larger margin in the private sector, compared with that in the public sector. This result suggests that high-skilled workers prefer the low-productivity public sector after the policy shock, thereby exacerbating the misallocation of workers.

I also provide formal empirical evidence by conducting a regression analysis on the sector choice of workers following the empirical model below:

$$\begin{aligned}
Private_{it} = & \alpha_i + \gamma_1 \cdot g_i \times Skilled_i^g \times Post_t + \\
& \gamma_2 \cdot g_i \times Skilled_i^g + \gamma_3 \cdot g_i \times Post_t + \gamma_4 \cdot Skilled_i^g \times Post_t + \\
& X_{it}'\beta_X + W_{j(it)t}'\beta_W + \varepsilon_{it}
\end{aligned} \tag{10}$$

where $Private_{it}$ indicates whether individual i works in the private sector in year t. $Skilled_i^g$ is a dummy indicating whether i ranks in the top quartile of workers in the same group g.

Results are shown in Table 8. It shows that high-skilled migrants are about 3.7% less likely to work in the private sector before the policy shock. The relative probability dropped by an additional 3.8% afterward, even though high-skilled native workers are more likely to work in the private sector after the policy shock. The corresponding event-study result of workers' sector choice is shown in Figure G2. It turns out that the policy change not only decreased the probability of high-skilled migrants working in the private sector but also broke the rising trend before the policy change.

Table 8: Sectoral Choice of Workers

VARIABLES	(1) Work in the Private Sector	(2) Work in the Private Sector
Migrant	0.00705***	0.0366***
	(0.00107)	(0.00123)
Migrant × Post	-0.00671***	0.00223*
	(0.00101)	(0.00129)
Migrant × High-Skilled		-0.0373***
		(0.00201)
High-Skilled × Post		0.0122***
		(0.00207)
Migrant × High-Skilled × Post		-0.0386***
		(0.00230)
Constant	3.200***	3.649***
	(0.0141)	(0.0154)
Observations	4,602,333	4,602,333
R-squared	0.497	0.500
Controls	Yes	Yes

Notes: The model is estimated by OLS regression. Other controls include age, age squared, gender, estimated person effect, proportion of females of the employer, proportion of native workers of the employer, average wage of the employer, average age of the employer, and average turnover rate. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

5 Robustness Checks

All the empirical results above depend on a series of assumptions, sample selection, and model specifications. In this section, I present a set of robustness checks, encompassing a range of alternative methods, sample selections, and specifications, to further validate the conclusions. While the results in previous sections provide rich supports to the argument that the hukou system affect the migrant-native wage gap, we still lack direct evidence of the impacts of obtaining hukou on wages and job search behaviors, due to data limitations. In this section, I present a set of supplemental analysis on the subsample of workers who used the housing provident fund to apply for a housing mortgage. For this subsample, I observe the hukou location of them at the time of mortgage application. Therefore, I can provide more direct evidence on the role of hukou in determining the migrant-native wage gap. The detailed results of these robustness checks can be found in the appendix.

5.1 An alternative AKM model

To examine the impact of the policy shock, it is necessary to estimate two sets of equations for equation 1, one for the pre-shock period and the other for the post-shock period. Following recent growing literature (Engbom et al., 2023; Lachowska et al., 2023), we can incorporate the dynamics feature of employer effects by estimating an extended AKM model that incorporates two sets of employer fixed effects in the model. The extended model is presented below:

$$\ln y_{git} = \alpha_{gi} + X'_{git}\beta_g + \psi^g_{j(g,i,t_1)} + \phi^g_{j(g,i,t_2)} + \varepsilon_{git}$$

Where $\ln y_{git}$, α_{gi}, X_{git}, and ε_{it} follows the definition in equation 1. $\psi^g_{j(g,i,t_1)}$ is a wage premium paid at employer j to workers in group g in the pre-shock period. $j(g,i,t_1)$ is an index function indicating the employer for worker i in group g in year t_1 before the policy shock. $\phi^g_{j(g,i,t_2)}$ is a wage premium paid at employer j to workers in group g in the post-shock period. $j(g,i,t_2)$ is an index function indicating the employer for worker i in group g in year t_2 after the policy shock.

Estimation of Section 5.1 requires redefining the connectedness of employers following the discussion in Engbom et al. (2023). The intuition is to treat an employer j in pre-shock and post-shock periods as two employer-period units when forming the connected sets. The estimated employer-period fixed effects capture the relative employer-period fixed effects relative to a normalized employer-period. To facilitate between-group comparisons, I need to conduct normalization on the estimated fixed effects by choosing a proper set of benchmark employers that are assumed to have no wage premium on workers. In this regard, I adopt the same definition of benchmark employers as in our baseline specification.

With the estimation results as shown in Table H1, I conduct a similar triple difference analysis as in Section 4 to estimate the differential impacts of hukou quota reduction on the migrant-native wage gap across employers. Results shown in Table H2 confirm that the previous conclusions hold. Also, I replicate the estimation of equation 8 to investigate the change in wage-setting power following the policy shock. Results are generally in line with our baseline results, although the increase in wage-setting effect is non-significantly larger in the private sector than in the public sector ($p = 0.142$. See Table H3 for details). In Table H4, I find that employer-level residual sorting decreased after the policy shock as in the baseline result.

5.2 Alternative measures, samples, and specifications

The normalization of estimated employer effects and person effects is crucial to ensure that these estimates are comparable across different groups of workers. To enhance the robustness of the results, I introduce an alternative set of benchmark employers for the normalization process. These benchmark employers are defined as being in the private sector, ranking among the bottom 5 to 10 percentiles of average wages, and ranking among the bottom 10 percentiles of the observed migrant-native wage gap. This alternative definition of benchmark employers aims to capture employers that are less likely to obtain rent from the hukou quota system in our context. With this alternative definition of benchmark employers, I replicate four sets of empirical analyses. First, I replicate the estimation of equation 5. Results shown in Table H5 provide consistent qualitative conclusions as the baseline results in the last section. Second, I replicate the estimation of equation 8. Results shown in Table H6 also find that the wage-setting effect increased after the policy shock, while the increase is more pronounced in the private sector. Finally, Table H7 shows a reduced residual sorting effect as in the baseline results.

In the baseline estimation, I restricted the construction of connected sets to employers that were presented in both the pre-shock and post-shock periods. Here I consider two alternative samples: 1) employers whose employees were presented in both periods; and 2) employers that once hired at least one job mover. Based on these two alternative samples, I estimate the AKM model and replicate the estimation of equation 5, equation 8, and equation 9. Results are shown in Table H8 to Table H10 for the first alternative sample, and Table H11 to Table H13 for the second alternative sample. All qualitative conclusions still hold.

In addition, I include job stayers in the largest connected set in the estimation of equation 1. This inclusion significantly increases the sample size of the estimation. As shown in Table H14, the three-way interaction terms remain significantly positive across all columns, which is consistent with our baseline results. Other results on the wage-setting effect and residual sorting also align with the baseline results (see Table H15 and Table H17). Notably, to study the sectoral choice of workers, a preferred specification should take all workers into account, including job movers and job stayers. Therefore, I also replicate the estimation of equation 10 using this alternative sample. Results in Table H16 show that the policy shock led more migrants, especially high-skilled ones, to prefer the public sector.

Finally, I tried to exclude non-firm employers (e.g., government agencies, schools, and hospitals, etc.) in the empirical analysis, trying to exclude the impact of underlying differences between firms and other types of employers. Results show that the main empirical conclusion holds as well (see Table H18).

Combining all the results on alternative measures, samples, and specifications, we can be confident that the empirical conclusions are robust to the empirical setups. Importantly, the results on the wage-setting effect, workers' sector choice, and residual sorting effect further prove that our proposed mechanisms of the migrant-native wage gap are at play.

5.3 Analysis on the subsample with hukou information

In this section, I try to provide more direct evidence by focusing on the subsample of workers who used the housing provident fund to apply for house mortgages. This is still not perfect data to work on, because the decision of applying for a house mortgage is highly selected. Also, I cannot know the exact timing of obtaining hukou. Nonetheless, working on this subsample provides further validation that hukou plays a non-negligible role in determining the migrant-native wage gap.

Of the 403,343 workers that applied for house mortgages, I document the hukou location of 389,351 (97%) workers. Of these, about 24% are migrants with local hukou at the time of applying for a house mortgage. another 18% of the workers are migrants without local hukou at the time of applying for a house mortgage. The left are natives. For this part of the analysis, I focus on this subsample to exclude the substantial differences between house buyers and other individuals.

The analysis consists of two parts. First, I examine the heterogeneous treatment effect of the policy shock on migrants who have already obtained hukou before the policy shock. The basic idea is that migrants who have obtained hukou should be "immune" to a policy shock that affects the provision of hukou quotas, except for potential general equilibrium effects. Therefore, migrants who have obtained hukou should witness a significantly smaller income increase following the policy shock. This is indeed the case as shown in Table H19, which shows the results of a triple-difference regression alike equation 5, but with the treatment group defined as migrants who applied for house mortgage before 2011 and had obtained a local hukou at that time. The relative treatment effect of migrants who have obtained a local hukou compared with other migrants is negative and statistically significant. It is worth noting that the definition here miscategorizes migrants who obtained a local hukou before 2011 but applied for a house mortgage after that as the control group. Therefore, the negative relative treatment effect is over-estimated, i.e., the underlying relative treatment effect should be negative and larger in magnitude.

Second, I try to verify the theoretical predictions regarding the sector choice pattern of migrants who obtained local hukou. Because the public sector offers more hukou quotas, we would expect those who obtained local hukou to be more likely to work in the public sector than other workers. Moreover, we should expect those workers who obtained local hukou to gradually leave the public sector to pursue higher wage incomes. These two predictions are supported in the data (see Figure H1). Combining these two pieces of evidence together, I am confident that the hukou system plays a non-negligible role in determining the migrant-native wage gap.

6 Conclusion

This study investigates the labor market conditions of migrants and native workers in the formal sector of a Chinese metropolis. The specific focus is on investigating the impact of a major type of internal migration restriction, the hukou system, on the wage gap between migrants and native workers, as well as its influence on the allocation of workers across different employers.

The empirical analyses of this study yield several novel findings. First, migrants are willing to accept lower wages in exchange for hukou quotas, while government-granted hukou quotas provide employers with monopsony power in hiring migrants. Together they result in reduced wage-setting power for migrants compared to native workers. Second, migrants are less likely to be employed by high-paying employers than native workers, after controlling for observed characteristics and person effects. This pattern is driven by the fact that migrants may prefer jobs with hukou quotas in low-paying employers to jobs in high-paying employers without hukou quotas. Third, following a large reduction in hukou quotas in 2011, the wage-setting power of migrants increased. This effect is consistent with both reduced amenity value of hukou quota in the aggregate, as well as decreased monopsony power of employers that used to have access to hukou quotas. Notably, the relative income of migrants experiences a more substantial improvement in private sector employers that witnessed a larger reduction in hukou quota. Fourth, the unequal distribution of hukou quotas tilted towards low-productivity public sector employers leads to the misallocation of workers. The reduction in hukou quotas exacerbated this misallocation because the private sector suffered a larger reduction in hukou quotas.

Our results highlight the importance of internal migration restrictions in determining the migrant-native wage effect. The empirical findings suggest that granting hukou quotas to high-productivity employers may improve the allocation efficiency of migrants. Moreover, equalizing the amenity values for the migrants and native workers may be crucial in mitigating the migrant-native wage gap.

To my best knowledge, this study is the first to use longitudinal matched employer-employee data in China to estimate the AKM model. By investigating how employers make use of group-specific preferences for observed amenities to tailor their wage-setting policy and hiring practices for different workers, this study adds to the previous literature on the monopsony power of employers and frictions in the labor market.

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ALL APPENDICES BELOW ARE FOR ONLINE PUBLICATION ONLY

A Data Representativeness

Table A1: Summary Statistics

	HPF Data	Aggregate Data	Source
Income (2006-2014)	71872.34	72339.76	Statistical Yearbook of the studied city (2007-2015)
Income (2010)	67519.86	65683.00	Statistical Yearbook of the studied city 2011
Female (2010)	0.45	0.43	Census 2010
Age (2010)	35.16	36.13	Census 2010
Native (2010)	0.60	0.54	Census 2010
College (2010)	0.47	0.43	Census 2010

Notes: For census data, only individuals aged between 25 to 50 years old and are currently working are included.

B Observed migrant-native wage gap

In this section, I provide descriptive evidence on the observed wage gap between migrants and native workers. I conduct a simple wage regression based on the model below:

$$\ln y_{it} = \beta_0 + \beta_1 Migrant_i + \beta X_{it} + \gamma W_{j(i,t)t} + \lambda_t + \varepsilon_{it} \tag{11}$$

where $\ln y_{git}$is the log-transformed wage of worker i in period t. $Migrant_i$ is a dummy variable indicating if individual i is a migrant ($Migrant_i = 1$) or a native worker ($Migrant_i = 0$). β_1 captures the migrant-native wage gap. X_{it} is a vector of observed characteristics of employees, including the gender, age, age squared, and job tenure. $W_{j(i,t)t}$ is a vector of observed characteristics of employer j in which individual i work in period t, including the proportion of females of the employer, the average age of the employer, the total employment of the employer, and the average turnover rate of the employer. I further control for year fixed effect λ_t. ε_{it} is the error term.

Results are shown in Figure B1. Migrants in our sample have a 21.3% higher observed wage income compared to native workers, as depicted by the first bar on the left.

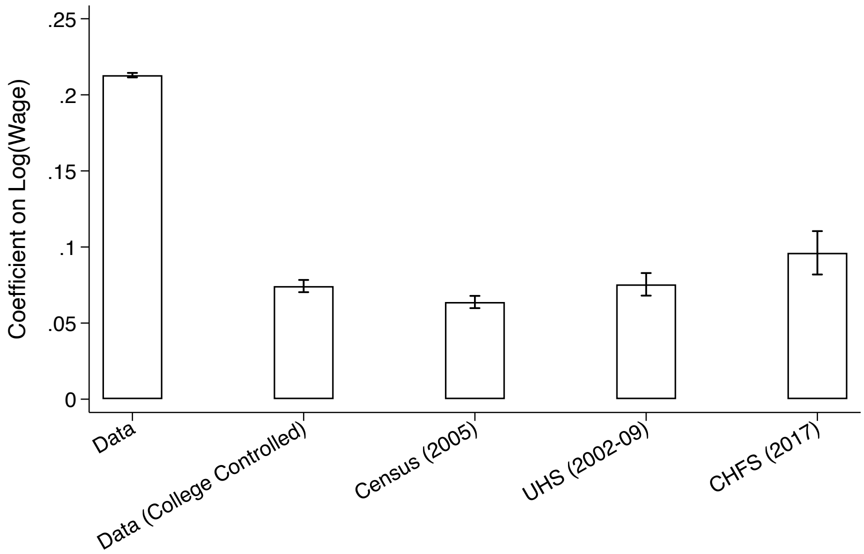


Figure B1: Migrant-Native Wage Gap

Notes: Each bar show the coefficient of $Migrant_i$ in equation 11 in separate regressions. The first two bars on the left come from regression results on the data set of this study. The other three bars come from regression results on 2005 population census, UHS 2002 – 2009, and CHFS 2017 data. In the first bars on the left, I controlled for age, age squared, gender, job tenure, proportion of females of the employer, average age of the employer, total employment of employer, average turnover rate of employer, and year fixed effects. In the second bar, I further control for the dummy of college degree.

To address the concerns of selection into formality in the data set, I utilize several nationally representative data sets in China to investigate the observed migrant-native wage gap following the definition of migrants in this paper. The first one is the 2005 1% population survey data, also known as the "mini" census, conducted every ten years in the middle of two formal population census waves. The 2005 1% population survey data randomly surveys 1% of the population in the country. The sampling method ensures national representativeness of the data. It provides comprehensive information of individual characteristics, including age, gender, education, industry, location, employment status, and migration and registration status information. Notably, the 2005 1% population survey also collect wage income of working individuals. The second data set used is the Urban Household Survey (UHS) from 2002 to 2009, also conducted by the National Bureau of Statistics of China. It is the most comprehensive data set available on households in urban regions in the country, covering 185 cities (out of about 300). The sampling method of UHS is similar to the Current Population Surveys (CPS) in the US. The multi-stage probabilistic sample and stratified design ensures national representativeness. It contains rich information of individual characteristics and income. The third data set is the China Household Finance Survey (CHFS) organized and managed by China Household Financial Survey and Research Center, Southwestern University of Finance and Economics. A relatively large proportion of the sample comes from rich, urban areas. Yet, the mutil-stage PPS sampling method ensures representativeness. Besides basic demographics information of individuals, the CHFS data also contains detailed information on household asset holdings, income, consumption, and other variables on household finances.

Using these data sets, I replicate the estimation of equation 11. The rich individual characteristics enable me to control for a larger set of relevant covariates including education, health, and job characteristics, etc. Results are shown in the three bars on the right of Figure B1, as well as Table B1. After controlling for positive sorting of migration to high-paying cities by including city fixed effects and controlling for a set of individual characteristics, the migrant-native wage gap is consistently significantly positive across different data sets.

The results provide empirical support to the relevance of the migrant-native wage gap documented in this paper. More importantly, it highlights that migrants' disadvantage labor market conditions may be masked by a higher observed income compared with native workers.

Table B1: Migrant-Native Wage Gap

VARIABLES	(1) Log(Wage)	(2) Log(Wage)	(3) Log(Wage)	(4) Log(Wage)
Panel A: Census 2005				
Migrant	0.0994***	-0.0660***	0.0485***	0.0638***
	(0.00252)	(0.00264)	(0.00215)	(0.00205)
Constant	6.785***	6.849***	6.064***	5.969***
	(0.00148)	(0.00146)	(0.00974)	(0.0141)
Observations	370,188	370,188	370,186	370,186
R-squared	0.006	0.162	0.431	0.507
Individual Controls	No	No	Yes	Yes
City FE	No	Yes	Yes	Yes
Job Characteristics	No	No	No	Yes
Panel B: UHS 2002 – 2009				
Migrant	0.144***	0.141***	0.0895***	0.0755***
	(0.00461)	(0.00448)	(0.00393)	(0.00378)
Constant	9.614***	9.615***	9.004***	9.134***
	(0.00310)	(0.00284)	(0.00963)	(0.00960)
Observations	139,473	139,472	139,472	139,470
R-squared	0.022	0.150	0.321	0.372
Individual Controls	No	No	Yes	Yes
Year FE	No	Yes	Yes	Yes
City FE	No	Yes	Yes	Yes
Job Charateristics	No	No	No	Yes
Panel C: CHFS 2017				
Migrant	0.193***	0.142***	0.118***	0.108***
	(0.00825)	(0.00791)	(0.00670)	(0.00650)
Constant	7.927***	7.949***	6.855***	6.936***
	(0.00539)	(0.00513)	(0.0846)	(0.0810)
Observations	23,968	23,968	23,926	23,494
R-squared	0.027	0.148	0.392	0.440
Individual Controls	No	No	Yes	Yes
City FE	No	Yes	Yes	Yes
Job Characteristics	No	No	No	Yes

Note: For Panel A, Individual characteristics include gender, age, age squared, ethnicity, education, and health condition. Job characteristics include type of company, industry, occupation, and whether sign a formal contract. For Panel B, Individual characteristics include gender, age, age squared, ethnicity, and education. Job characteristics include industry and occupation. For Panel C, Individual characteristics include gender, age, age squared, and education. Job characteristics include type of company, industry, and occupation.

C Supplemental Results related to the AKM model

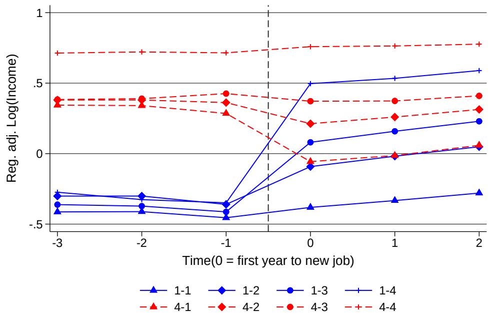
I show the test results that validate the assumptions of the AKM model, following previous literature (Card et al., 2013, 2018). Results show that the wage changes of job switches across different employer quartiles are largely symmetric. Also, before the job switch, there is no pre-trend in wages.

Table C1 below shows the summary statistics of the largest connected set and the leave-one-out connected set. For most variables, the mean and standard errors are comparable across two types of connected sets. However, the sample size of the leave-one-out connected sets are much smaller than those of the largest connected sets.

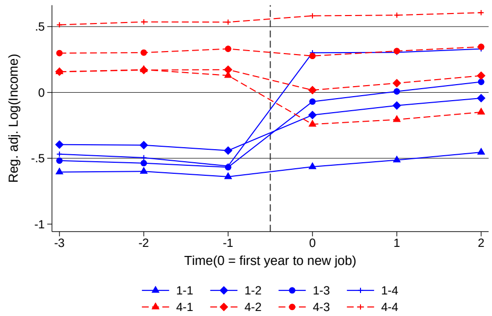
Table C2 shows the results of estimating the AKM model and conducting variance decomposition with both the traditional method and the KSS method with data in the post-shock period. We can see consistent variance decomposition patterns regarding the role of employers in explaining wage variations with those in the pre-shock period.

Table C3 shows the wage gap decomposition results based on the alternative decomposition benchmark, i.e., using the employer effect for migrants as the measure of employers' wage premiums. Qualitative conclusions are the same as in the baseline wage gap decomposition. We can see that both wage-setting effect and residual sorting effect to be negative. Also, wage-setting effect increased in the post-shock period, while residual sorting effect decreased.

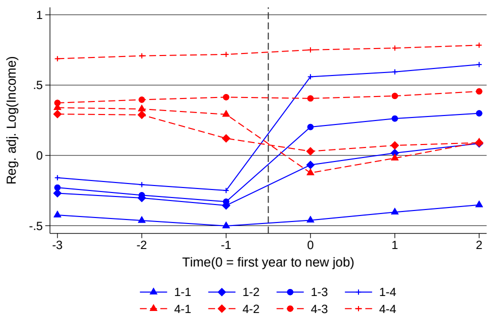
In the decomposition of the migrant-native wage gap, we can see a substantial positive person effect gap but a negative covariates gap. Figure C3 shows that the selection pattern of migrants in terms of person effect gaps, are largely consistent across different ages. This pattern rules out the case where the positive person effect gap arise because younger cohorts have higher person effects and migrants are in general younger in the sample. Moreover, the person effect of young workers are lower than elder workers in the data.



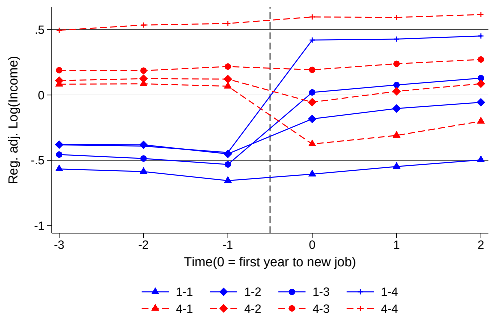
(a) Native, Pre-shock



(b) Migrant, Pre-shock



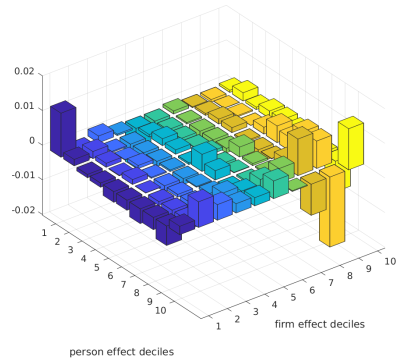
(c) Native, Post-shock



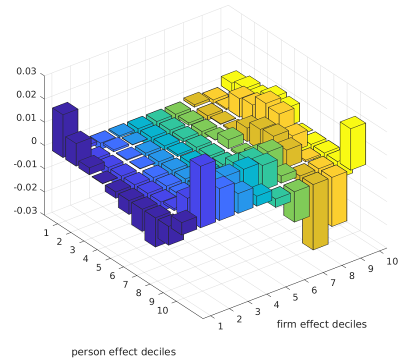
(d) Migrant, Post-shock

Figure C1: Event Study

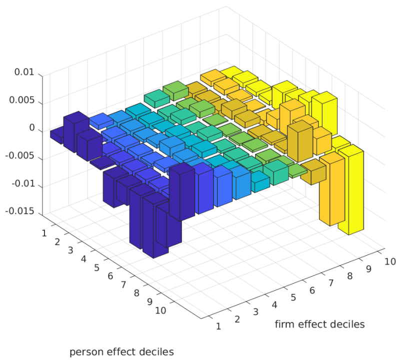
Note: Figure shows the change of regression-adjusted log income of native and migrant workers who changed his/her job in pre-shock or post-shock periods. Each job is classified into quantiles according to the level of estimated employer effect in the AKM model.



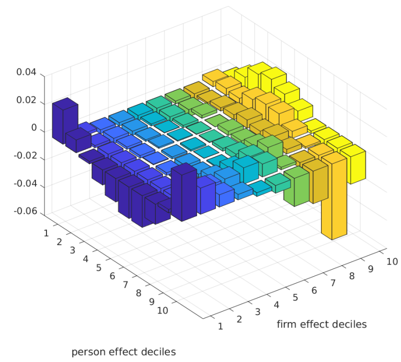
(a) Native, Pre-shock



(b) Migrant, Pre-shock



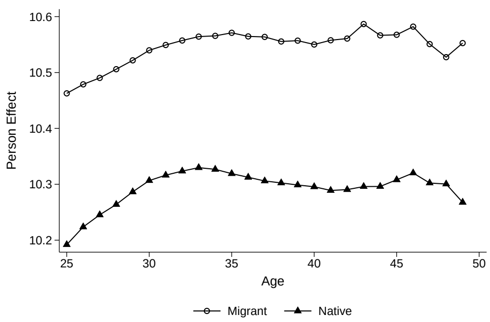
(c) Native, Post-shock



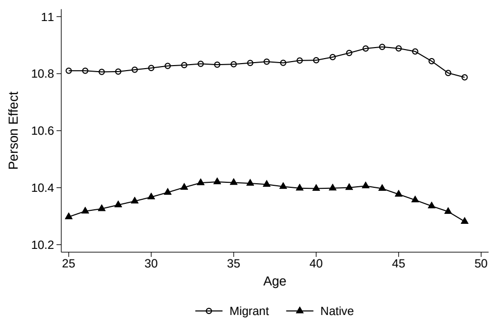
(d) Migrant, Post-shock

Figure C2: Mean Residuals of Person Effect and Employer Effect Deciles

Note: Figure shows the mean residuals in each cell defined by deciles of estimated person effect and employer effect in equation 1.



(a) Female



(b) Male

Figure C3: Person Effects across Different Ages

Note: Person effects are estimated with AKM method on the largest connected set.

Table C1: Summary Statistics of Connected Sets

Mean/sd	(1)	(2)	(3)	(4)
Income	68072.39	90690.36	72062.75	87918.12
	(62384.94)	(67151.16)	(65983.50)	(61343.37)
Average Coworker Income	65018.73	85230.37	67182.73	85377.73
	(45774.42)	(49125.00)	(47669.44)	(48885.44)
Female	0.42	0.43	0.41	0.42
	(0.49)	(0.50)	(0.49)	(0.49)
Age	33.33	34.73	33.98	32.97
	(6.62)	(6.64)	(6.74)	(6.17)
Native	0.58	0.51	0.59	0.45
	(0.49)	(0.50)	(0.49)	(0.50)
Job Tenure	19.83	30.39	16.00	22.53
	(14.94)	(23.33)	(11.61)	(22.12)
Total Employment	714.35	896.26	749.47	787.60
	(1341.14)	(1619.53)	(1370.75)	(1456.06)
Period	Pre-Shock	Post-Shock	Pre-Shock	Post-Shock
Sample	Largest Connected	Largest Connected	Leave-Out Connected	Leave-Out Connected
Number of Observations	2629309	2754496	1284344	1038339
Number of Movers	846860	956911	327660	308866
Number of Employers	34597	33412	25877	25495

Notes: Each cell shows the average of each connected set in different periods. Standard deviations are in parentheses.

Table C2: Estimated Two-Way Fixed Effects – Post-Shock

	Native AKM (1)	Migrant AKM (2)	Native KSS (3)	Migrant KSS (4)
Standard deviation of log wages	0.697	0.723	0.665	0.679
Mean log wages	11.073	11.291	10.973	11.322
Variance decomposition				
SD of person effects	0.539	0.47	0.377	0.344
SD of employer effects	0.351	0.434	0.319	0.409
SD of covariates	0.155	0.203	–	–
Correlation of person/employer effects	0.058	0.091	0.190	0.207
Adjusted R^2 of model	0.931	0.917	0.654	0.748
Adjusted R^2 with match effect	0.944	0.939	–	–
Percentage of variance of log wages due to:				
Person effect	59.8	42.2	32.1	25.7
Employer effect	25.3	35.7	23.0	36.4
Covariance of person and employer effects	4.5	7	10.3	12.7
Emp. effects + covariance person and emp. effects	29.8	42.7	33.3	49.1
Number of employers	27132	26390	19712	19346
Number of movers	465279	491632	134999	173867
Number of person-year observations	1410318	1344178	467176	571163

Notes: Models include dummies for individual workers and individual employers, year dummies, and quadratic terms in age interacted with gender dummies. Samples in columns (1) and (2) include only observations in the largest connected set. Samples in columns (3) and (4) include only observations in the leave-one-out connected set. In columns (3) and (4), I partial out covariates before KSS estimations. Therefore, the standard deviation of log wages and mean log wages represent the standard deviation of *residualized* log wage and the mean of *residualized* log wages, respectively.

Table C3: Decomposition of Migrant-Native Wage Gap – Alternative Benchmark

	(1) Pre-Shock	(2) Post-Shock	(3) Difference
Wage Gap (Migrant - Native, same below)	0.190	0.199	0.010
1. Person Effect Gap	0.375	0.307	-0.068
2. Covariates Gap	-0.162	-0.083	0.079
3. Employer Effect Gap	-0.024	-0.025	-0.001
3.1. Wage-Setting Effect	-0.062	-0.049	0.012
3.2. Sorting Effect	0.038	0.024	-0.014
3.2.1. Skill-Based Sorting Effect	0.076	0.070	-0.006
3.2.2. Residual Sorting Effect	-0.039	-0.046	-0.008
Observations	2280272	2437044	–

Notes: Results are conducted based on two-way fixed effects estimated with AKM method. Only observations in the largest connected set are included. Wage gap is calculated as difference in log-transformed income. Column (3) shows the results of column (2) minus column (1).

D Revealed-Preference estimations of amenity value

I start by introducing a simple random on-the-job search framework, following Burdett and Mortensen (1998) and Sorkin (2018). In the model, a worker's utility is determined by both wage and non-wage amenities. I allow for separate supplies of amenities for migrants and native workers, as well as separate valuations of these amenities.

Employers: The are J employers in the economy. Each employer is characterized by the number of employee e_j. I consider employers as relatively passive agents due to the nature of the available data, which primarily focuses on the labor supply side of the market.

Workers: Each worker i is characterized by d_i that summarizes the skill level, experience, and other factors that are equally compensated across different employers. Additionally, workers have a migration status $g_i = m, n$ that represents migrants and native workers, respectively. The worker's indirect utility of being employed in a specific job match is determined by both wage income, amenities and an idiosyncratic valuation of working in employer j:

$$V_{ij} = \ln(w_{ij}) + \ln(a_j^g) + \varepsilon_{ij}$$

It is worth noting that wages are individual specific, and employers can offer different levels of amenities to migrants and natives workers. However, the level of amenities remains consistent within each group of workers. I further assume that ε_{ij} follows a type I extreme value distribution.

Analogous to the setting in the AKM model above, wage is determined by the following equation:

$$\ln(w_{ij}) = d_i + \psi_j^g$$

I abstract the idiosyncratic match component from the equation following our empirical findings that the match component is not relevant in determining wage differences. ψ_j^g is a employer wage premium specific to worker group g.

Job Search: For simplicity, I only consider endogenous job switch between employers. That is, workers only transit to a new job when it profferes a higher levels of utility. Workers meet random job offers both on-the-job and in unemployment, with a common probability λ. Upon receiving a job offer, the worker makes a binary choice between their current job (including unemployment) and the new job.

The probability of choosing employer k instead of employer j can be written as:

$$\begin{aligned}
P(V_{ik} > V_{ij}) &= P(d_i + \psi_k^g + \ln(a_k^g) + \varepsilon_{ik} > d_i + \psi_j^g + \ln(a_j^g) + \varepsilon_{ij}) \\
&= P(\varepsilon_{ij} < \varepsilon_{ik} + [\psi_k^g + \ln(a_k^g)] - [\psi_j^g + \ln(a_j^g)]) \\
&= P(\varepsilon_{ij} < \varepsilon_{ik} + \bar{V}_k - \bar{V}_j) \\
&= \frac{\exp(\bar{V}_k)}{\exp(\bar{V}_k) + \exp(\bar{V}_j)}
\end{aligned}$$

Where the third equation holds when I summarize the common value of working in employer j as $\bar{V}_j \equiv \psi_k^g + \ln(a_k^g)$. The fourth equation holds based on the distribution assumption of ε.

Following Sorkin (2018), I can get the following estimation equation about employers' common values:

$$\frac{\sum_{j \in J} M_{kj} \exp\left(\bar{V}_j\right)}{\sum_{j \in J} M_{jk}} = \exp\left(\bar{V}_k\right) . \forall j \neq k \in J$$

$\Rightarrow$

$$S^{-1} M \exp\left(\bar{V}\right) = \exp\left(\bar{V}\right) \tag{12}$$

Where M_{kj} is the number of workers leaving employer j to enter employer k. S is a diagonal matrix with the k^{th} diagonal entry being $S_{kk} = \sum_{j \in J} M_{jk}$, that is, the total number of workers leaving employer k. M is a matrix where the entry of the j^{th} row and the k^{th} column being M_{jk}. $\exp(\bar{V})$ is a $|J| \times 1$ vertor where the k^{th} entry being $\exp(\bar{V}_k)$.

Following the method and argument in Sorkin (2018), I can solve the fixed point of equation (12) for employers in the strongly connected set. This set consists of employers for which both entering and leaving workflows are observed in the data. With the estimated common value of each employer, I conduct a "plug-in" calculation of amenities in each employer based on the AKM estimations of the employer's wage premium. Specifically, the amenities for group g in employer j are given by: $\widehat{\ln(a_j^g)} = \hat{\bar{V}}_j - \widehat{\psi_j^g}$. I estimate the amenity values separately for the two groups of workers and the two periods.

Figure D1 demonstrates the relationship between a employer's wage premium and the value of amenities it offers. It turns out that high-premium employers offer lower levels of amenities for workers, suggesting that compensating differential is at play in employer's wage-setting policy. This result is also consistent with our previous findings that migrants may forgo a part of their wage compensation in exchange for hukou.

When we look at the within-employer amenity gaps, we can see in Figure D2 that migrants have higher amenities in employers with more hukou quotas. This pattern holds true for both pre-shock and post-shock periods. In the post-shock period, the within-employer amenity gaps are smaller in magnitude for employers with more hukou quotas, which is consistent with the overall decrease in the supply of hukou quotas during the post-shock period.

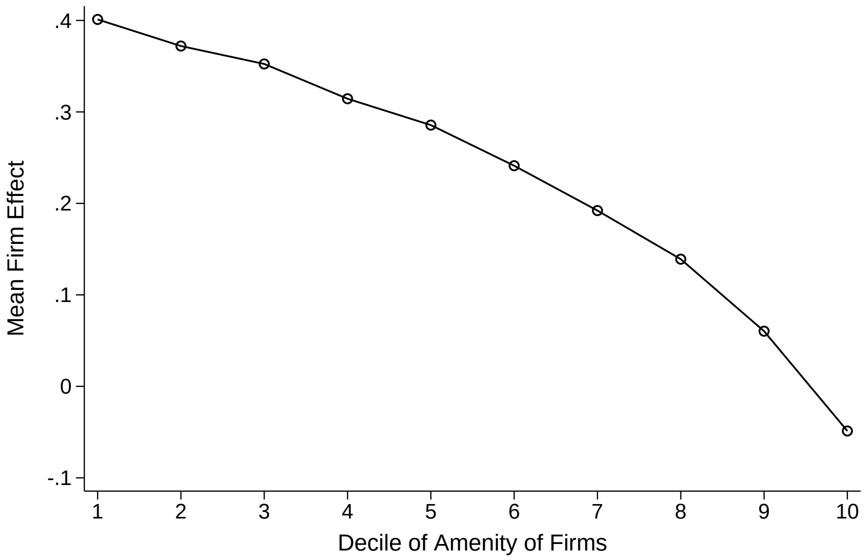
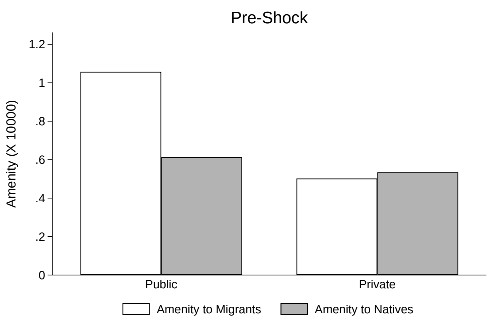
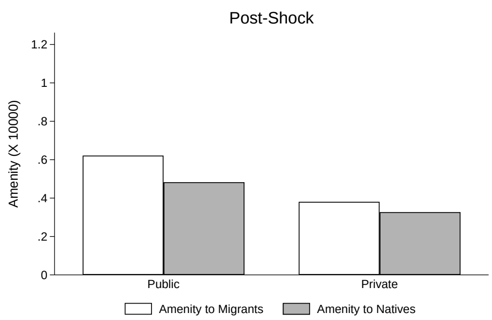


Figure D1: Employer Effects and Amenities

Note: Each circle indicates the average level of employer effect in a decile of employers sorted by amenities. Employer effects are estimated in equation 1. Amenities are plug-in estimations based on employer value in equation 12 and employer wage premium.



(a) By Sector, Pre-shock



(b) By Sector, Post-shock

Figure D2: Within-Employer Amenity Gaps

Note: Amenities are estimated based on the following equation: $\widehat{\ln(a_k^g)} = \widehat{V}_j - \widehat{\psi_k^g}$, in which $\widehat{V}_j$ is estimated based on the fixed point of equation 12, $\widehat{\psi_k^g}$ is estimated based on AKM estimation of equation 1.

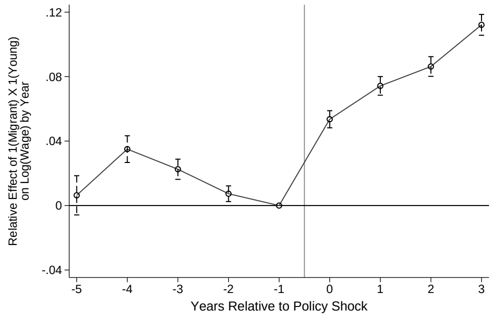
E The 12^{th} Five-Year Plan Population Control Targets

Table E1: Population Control Targets

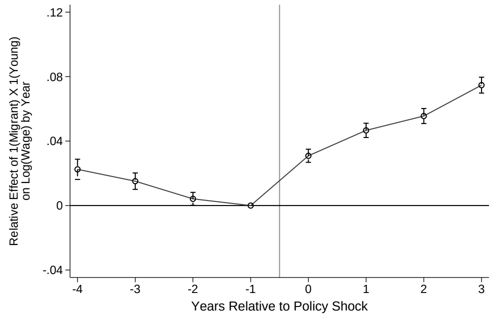
District	Target	District	Target
1	100k reduction in population	6	population<3.8 million
2	population<720k	7	annual population growth<2%
3	population<1.1 million	8	population meet the studied city's target
4	population<870k, migrants<240k	9	population<454k
5	population with Hukou<450k, population<530k	10	population<1.45 million

Data Source: the 12^{th} Five-Year Plan for National Economic and Social Development of each district. Summarized by the authors.

F Supplemental Results on Reduced-Form Analysis



(a) Three-Way, w/o $W_{j(it)t}$



(b) Three-Way, w/ $W_{j(it)t}$

Figure F1: Event Study Results on Model with Young Workers as the Treatment Group

Note: Each circle indicates the point estimations of the relative treatment effect (i.e., the coefficient of $g_i \times Young_{i,j(it)} \times t_{0+m}$). Each vertical dashed line indicates the 95% confidence interval of the treatment effect. In Panel (a), employer controls $W_{j(it)t}$ are not included in the model. In Panel (b), $W_{j(it)t}$ are included.

G Supplemental Results on Allocation of Talents

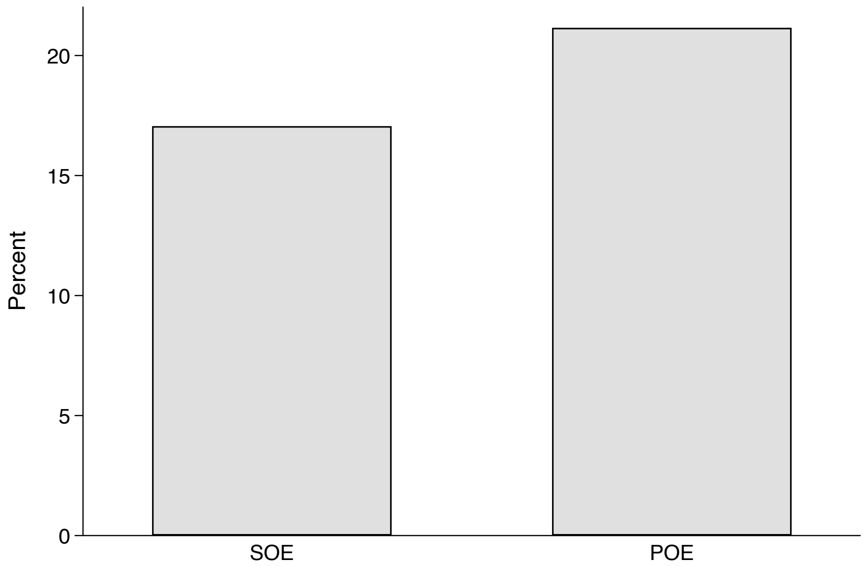


Figure G1: Total Profits over Net Value of Fixed Assets

Note: Figure shows the ratio of total profits on the net value of fixed assets (total value of fixed assets subtracted depreciation). "SOE" stands for state-owned enterprises, which serves as the counterpart to the public sector in this study. Data Source: Annual Survey of Industrial Firms, 2006 – 2007. Only include the sample in the studied city. The data covers state-owned enterprises and industrial employers with annual sales above 5 million yuan.

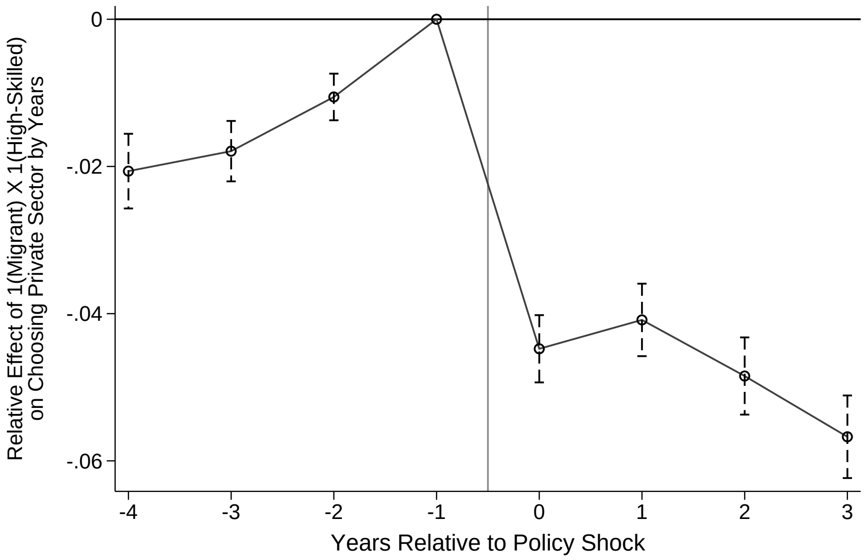


Figure G2: Event Study Results on Sector Choice

Note: Each circle indicates the point estimations of the relative treatment effect (i.e., the coefficient of $g_i \times Skilled_i^g \times t_{0+m}$). Each vertical dashed line indicates the 95% confidence interval of the treatment effect.

H Details of Robustness Checks

Table H1: Variance Decompositions based on the Alternative AKM Model

	Native	Migrant
	(1)	(2)
Largest connected set		
Standard deviation of log wages	0.699	0.723
Mean log wages	10.757	10.970
AKM decomposition:		
SD of person effects	0.493	0.437
SD of estab. effects	0.373	0.442
SD of covariates	0.145	0.215
Correlation of person/establishment effects	0.131	0.148
Adjusted R^2 of model	0.895	0.881
Adjusted R^2 with match effect	0.927	0.921
Percentage of variance of log wages due to:		
Person effect	49.7	36.5
Establishment effect	28.5	37.4
Covariance of person and establishment effects	9.8	11
Estab. effects + covariance person and estab. effects	38.3	48.4
Number of establishments	66723	63855
Number of movers	548313	571299
Number of person-year observations	3002748	2521925

Notes: Models include dummies for individual workers and individual employers, year dummies, and quadratic terms in age interacted with gender dummies. Samples include only observations in the largest connected set.

Table H2: Triple-Difference Result of Hukou Quota Reduction - Alternative AKM model

VARIABLES	(1) Log(Income)	(2) Log(Income)	(3) Log(Income)	(4) Log(Income)	(5) Log(Income)	(6) Log(Income)
Migrant	-0.141***	-0.188***	-0.0608***	-0.0982***	-0.142***	-0.0338***
	(0.00109)	(0.00146)	(0.00201)	(0.000851)	(0.00123)	(0.00147)
Migrant × Post	-0.0036***	-0.00323**	-0.0313***	0.0164***	0.00547***	3.95e-07
	(0.00118)	(0.00163)	(0.00206)	(0.00101)	(0.00144)	(0.00162)
Migrant × Post × Private		0.0425***			0.0129***	
		(0.00213)			(0.00169)	
Migrant × Post × Young Workers			0.0299***			0.0166***
			(0.00240)			(0.00178)
Constant	-3.997***	-4.170***	-4.259***	-1.072***	-1.397***	-1.298***
	(0.0128)	(0.0126)	(0.0130)	(0.0107)	(0.0107)	(0.0109)
Observations	5,524,673	5,193,054	5,524,673	4,954,048	4,677,964	4,954,048
R-squared	0.618	0.641	0.619	0.797	0.804	0.798
Sample	Largest Connected	Largest Connected	Largest Connected	Largest Connected	Largest Connected	Largest Connected
Worker Controls × Post	Yes	Yes	Yes	Yes	Yes	Yes
Employer Controls × Post				Yes	Yes	Yes

Notes: All estimations are conducted in the largest connected set within employers presented in both periods. Person effects are estimated in equation 1 using AKM method. Worker controls include age, age squared, gender, and job tenure. Employer controls include the proportion of natives of the employer, the proportion of females of the employer, the average age of the employer, the average wage of the employer, and the average turnover rate. Year fixed effects are included. The numbers of observations are different in columns because of missing values or the fact that controlling for turnover rate reduce one year of available sample. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Table H3: Hukou Quota Reduction and Wage-Setting Effect - Alternative AKM model

	(1)	(2)	(3)
VARIABLES	Wage-Setting	Wage-Setting	Wage-Setting
Post	0.00561***	0.0110***	
	(0.00124)	(0.00238)	
Private Sector × Post			0.00423
			(0.00288)
Constant	-0.0440***	0.171***	0.0279
	(0.00296)	(0.0293)	(0.0356)
Observations	157,184	157,184	157,184
R-squared	0.000	0.014	0.024

Notes: All estimations are conducted in the largest connected set within employers presented in both periods. Other controls include the proportion of females of the employer, the proportion of native workers of the employer, the average wage of the employer, the average age of the employer, and the average turnover rate. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Table H4: Hukou Quota Reduction and Residual Sorting Effect - Alternative AKM model

	(1)	(2)	(3)
VARIABLES	Residual Sorting	Residual Sorting	Residual Sorting
Post	0.0308***	-0.0589***	
	(0.00577)	(0.00494)	
Private Sector × Post			-0.0519***
			(0.00848)
Constant	-0.0942***	-0.0327	-0.0921
	(0.0102)	(0.0515)	(0.0758)
Observations	149,816	149,816	149,816
R-squared	0.001	0.401	0.404

Notes: All estimations are conducted in the largest connected set within employers presented in both periods. Other controls include the proportion of females of the employer, the proportion of native workers of the employer, the average wage of the employer, the average age of the employer, and the average turnover rate. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Table H5: Triple-Difference Result of Hukou Quota Reduction - Alternative Normalization

VARIABLES	(1) Log(Income)	(2) Log(Income)	(3) Log(Income)	(4) Log(Income)	(5) Log(Income)	(6) Log(Income)
Migrant	-0.137***	-0.177***	-0.0657***	-0.109***	-0.143***	-0.0545***
	(0.00114)	(0.00156)	(0.00210)	(0.000876)	(0.00128)	(0.00151)
Migrant × Post	0.0473***	0.0142***	-0.00355	0.0667***	0.0255***	0.0341***
	(0.00122)	(0.00172)	(0.00217)	(0.000984)	(0.00147)	(0.00162)
Migrant × Post × Private		0.111***			0.0652***	
		(0.00216)			(0.00164)	
Migrant × Post × Young Workers			0.0668***			0.0426***
			(0.00246)			(0.00174)
Constant	-3.130***	-3.322***	-3.384***	-0.290***	-0.619***	-0.498***
	(0.0119)	(0.0117)	(0.0122)	(0.0106)	(0.0111)	(0.0108)
Observations	5,383,805	5,107,887	5,383,805	4,829,027	4,602,333	4,829,027
R-squared	0.635	0.658	0.636	0.809	0.816	0.810
Sample	Largest Connected	Largest Connected	Largest Connected	Largest Connected	Largest Connected	Largest Connected
Worker Controls × Post	Yes	Yes	Yes	Yes	Yes	Yes
Employer Controls × Post				Yes	Yes	Yes

Notes: All estimations are conducted in the largest connected set within employers presented in both periods. Person effects are estimated in equation 1 using AKM method. Normalization is based on alternative definition of benchmark employers whose observed average wage ranks in the bottom 5 to 10 percentile in the sample, and the observed migrant-native wage gap ranks in the bottom 10 percentile in the sample. Worker controls include age, age squared, gender, and job tenure. Employer controls include the proportion of natives of the employer, the proportion of females of the employer, the average age of the employer, the average wage of the employer, and the average turnover rate. Year fixed effects are included. The numbers of observations are different in columns because of missing values or the fact that controlling for turnover rate reduce one year of available sample. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Table H6: Hukou Quota Reduction and Wage-Setting Effect - Alternative Normalization

	(1)	(2)	(3)
VARIABLES	Wage-Setting	Wage-Setting	Wage-Setting
Post	-0.0617***	-0.0476***	
	(0.00550)	(0.00563)	
Private Sector × Post			0.0197*
			(0.0110)
Constant	-0.0747***	0.138***	-0.0633
	(0.00436)	(0.0402)	(0.0456)
Observations	126,227	126,227	126,227
R-squared	0.012	0.028	0.036

Notes: All estimations are conducted in the largest connected set within employers presented in both periods. Normalization is based on alternative definition of benchmark employers whose observed average wage ranks in the bottom 5 to 10 percentile in the sample, and the observed migrant-native wage gap ranks in the bottom 10 percentile in the sample. Other controls include the proportion of females of the employer, the proportion of native workers of the employer, the average wage of the employer, the average age of the employer, and the average turnover rate. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Table H7: Hukou Quota Reduction and Residual Sorting Effect - Alternative Normalization

	(1)	(2)	(3)
VARIABLES	Residual Sorting	Residual Sorting	Residual Sorting
Post	0.00230	-0.0980***	
	(0.00963)	(0.00934)	
Private Sector × Post			-0.0509***
			(0.0164)
Constant	-0.0707***	0.00397	-0.0502
	(0.0133)	(0.0641)	(0.0888)
Observations	115,626	115,626	115,626
R-squared	0.000	0.415	0.418

Notes: All estimations are conducted in the largest connected set within employers presented in both periods. Normalization is based on alternative definition of benchmark employers whose observed average wage ranks in the bottom 5 to 10 percentile in the sample, and the observed migrant-native wage gap ranks in the bottom 10 percentile in the sample. Other controls include the proportion of females of the employer, the proportion of native workers of the employer, the average wage of the employer, the average age of the employer, and the average turnover rate. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Table H8: Triple-Difference Result of Hukou Quota Reduction - Alternative Sample I

VARIABLES	(1) Log(Income)	(2) Log(Income)	(3) Log(Income)	(4) Log(Income)	(5) Log(Income)	(6) Log(Income)
Migrant	-0.0489***	-0.102***	0.0233***	-0.0461***	-0.0838***	0.00843***
	(0.00112)	(0.00151)	(0.00212)	(0.000847)	(0.00124)	(0.00150)
Migrant × Post	0.0890***	0.0838***	0.0239***	0.108***	0.0785***	0.0667***
	(0.00118)	(0.00166)	(0.00214)	(0.000973)	(0.00143)	(0.00159)
Migrant × Post × Private		0.0761***			0.0479***	
		(0.00216)			(0.00165)	
Migrant × Post × Young Workers			0.0865***			0.0536***
			(0.00250)			(0.00175)
Constant	-2.545***	-2.845***	-2.745***	0.284***	-0.0959***	0.0993***
	(0.0148)	(0.0143)	(0.0153)	(0.0123)	(0.0126)	(0.0127)
Observations	5,539,248	5,063,528	5,539,248	4,757,505	4,444,538	4,757,505
R-squared	0.602	0.643	0.603	0.802	0.814	0.802
Sample	Largest Con- nected	Largest Con- nected	Largest Con- nected	Largest Con- nected	Largest Con- nected	Largest Con- nected
Worker Controls × Post	Yes	Yes	Yes	Yes	Yes	Yes
Employer Controls × Post				Yes	Yes	Yes

Notes: All estimations are conducted in the largest connected set within workers that present in both periods. Person effects are estimated in equation 1 using AKM method. Worker controls include age, age squared, gender, and job tenure. Employer controls include the proportion of natives of the employer, the proportion of females of the employer, the average age of the employer, the average wage of the employer, and the average turnover rate. Year fixed effects are included. The numbers of observations are different in columns because of missing values or the fact that controlling for turnover rate reduce one year of available sample. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Table H9: Hukou Quota Reduction and Wage-Setting Effect - Alternative Sample I

	(1)	(2)	(3)
VARIABLES	Wage-Setting	Wage-Setting	Wage-Setting
Post	0.0520***	0.0375***	
	(0.00536)	(0.00549)	
Private Sector × Post			0.0363***
			(0.0107)
Constant	-0.0103**	0.237***	0.112***
	(0.00419)	(0.0346)	(0.0397)
Observations	136,995	136,995	136,995
R-squared	0.007	0.025	0.030

Notes: All estimations are conducted in the largest connected set within workers that present in both periods. Other controls include the proportion of females of the employer, the proportion of native workers of the employer, the average wage of the employer, the average age of the employer, and the average turnover rate. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Table H10: Hukou Quota Reduction and Residual Sorting Effect - Alternative Sample I

	(1)	(2)	(3)
VARIABLES	Residual Sorting	Residual Sorting	Residual Sorting
Post	0.0167*	-0.124***	
	(0.00993)	(0.00932)	
Private Sector × Post			-0.00734
			(0.0172)
Constant	-0.0584***	0.0278	-0.0422
	(0.0124)	(0.0623)	(0.0866)
Observations	125,074	125,074	125,074
R-squared	0.000	0.395	0.398

Notes: All estimations are conducted in the largest connected set within workers that present in both periods. Other controls include the proportion of females of the employer, the proportion of native workers of the employer, the average wage of the employer, the average age of the employer, and the average turnover rate. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Table H11: Triple-Difference Result of Hukou Quota Reduction - Alternative Sample II

VARIABLES	(1) Log(Income)	(2) Log(Income)	(3) Log(Income)	(4) Log(Income)	(5) Log(Income)	(6) Log(Income)
Migrant	-0.0431***	-0.0904***	0.0384***	-0.0412***	-0.0783***	0.0190***
	(0.00107)	(0.00147)	(0.00202)	(0.000795)	(0.00120)	(0.00141)
Migrant × Post	0.0247***	0.0268***	-0.0292***	0.0731***	0.0455***	0.0431***
	(0.00112)	(0.00161)	(0.00206)	(0.000880)	(0.00137)	(0.00149)
Migrant × Post × Private		0.0767***			0.0431***	
		(0.00206)			(0.00154)	
Migrant × Post × Young Workers			0.0706***			0.0387***
			(0.00239)			(0.00162)
Constant	-3.412***	-3.604***	-3.674***	-0.446***	-0.797***	-0.660***
	(0.0116)	(0.0115)	(0.0118)	(0.00967)	(0.0102)	(0.00983)
Observations	6,552,311	5,856,197	6,552,311	5,567,091	5,129,880	5,567,091
R-squared	0.605	0.648	0.607	0.811	0.822	0.812
Sample	Largest Connected	Largest Connected	Largest Connected	Largest Connected	Largest Connected	Largest Connected
Worker Controls × Post	Yes	Yes	Yes	Yes	Yes	Yes
Employer Controls × Post				Yes	Yes	Yes

Notes: All estimations are conducted in the largest connected set within all workers and employers. Person effects are estimated in equation 1 using AKM method. Worker controls include age, age squared, gender, and job tenure. Employer controls include the proportion of natives of the employer, the proportion of females of the employer, the average age of the employer, the average wage of the employer, and the average turnover rate. Year fixed effects are included. The numbers of observations are different in columns because of missing values or the fact that controlling for turnover rate reduce one year of available sample. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Table H12: Hukou Quota Reduction and Wage-Setting Effect - Alternative Sample II

VARIABLES	(1) Wage-Setting	(2) Wage-Setting	(3) Wage-Setting
Post	0.0352***	0.0199***	
	(0.00477)	(0.00500)	
Private Sector × Post			0.0376***
			(0.00944)
Constant	0.00254	0.250***	0.128***
	(0.00401)	(0.0339)	(0.0374)
Observations	152,440	152,440	152,440
R-squared	0.004	0.028	0.034

Notes: All estimations are conducted in the largest connected set within all workers and employers. Other controls include the proportion of females of the employer, the proportion of native workers of the employer, the average wage of the employer, the average age of the employer, and the average turnover rate. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Table H13: Hukou Quota Reduction and Residual Sorting Effect - Alternative Sample II

VARIABLES	(1) Residual Sorting	(2) Residual Sorting	(3) Residual Sorting
Post	-0.0283***	-0.177***	
	(0.00969)	(0.00888)	
Private Sector × Post			0.0133
			(0.0165)
Constant	-0.0597***	0.00613	-0.113
	(0.0123)	(0.0605)	(0.0829)
Observations	139,043	139,043	139,043
R-squared	0.001	0.435	0.439

Notes: All estimations are conducted in the largest connected set within all workers and employers. Other controls include the proportion of females of the employer, the proportion of native workers of the employer, the average wage of the employer, the average age of the employer, and the average turnover rate. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Table H14: Triple-Difference Result of Hukou Quota Reduction - Include Job Stayers

VARIABLES	(1) Log(Income)	(2) Log(Income)	(3) Log(Income)	(4) Log(Income)	(5) Log(Income)	(6) Log(Income)
Migrant	-0.0638***	-0.101***	-0.00169	-0.0532***	-0.0770***	-0.0066***
	(0.000661)	(0.000808)	(0.00110)	(0.000523)	(0.000652)	(0.000802)
Migrant × Post	-0.0134***	-0.0176***	-0.0406***	0.0324***	0.00737***	0.0143***
	(0.000679)	(0.000844)	(0.00113)	(0.000562)	(0.000703)	(0.000846)
Migrant × Post × Private		0.0780***			0.0475***	
		(0.00126)			(0.000896)	
Migrant × Post × Young Workers			0.0396***			0.0282***
			(0.00138)			(0.000956)
Constant	-2.659***	-2.824***	-2.933***	0.0291***	-0.227***	-0.209***
	(0.00620)	(0.00631)	(0.00649)	(0.00542)	(0.00582)	(0.00558)
Observations	18,023,351	17,376,913	18,023,351	16,237,307	15,687,718	16,237,307
R-squared	0.650	0.666	0.651	0.817	0.823	0.818
Sample	Largest Con- nected	Largest Con- nected	Largest Con- nected	Largest Con- nected	Largest Con- nected	Largest Con- nected
Worker Controls × Post	Yes	Yes	Yes	Yes	Yes	Yes
Employer Controls × Post				Yes	Yes	Yes

Notes: All estimations are conducted in the largest connected set with all workers in employers that presented in both periods. Job stayers are included. Person effects are estimated in equation 1 using AKM method. Worker controls include age, age squared, gender, and job tenure. Employer controls include the proportion of natives of the employer, the proportion of females of the employer, the average age of the employer, the average wage of the employer, and the average turnover rate. Year fixed effects are included. The numbers of observations are different in columns because of missing values or the fact that controlling for turnover rate reduce one year of available sample. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Table H15: Hukou Quota Reduction and Wage-Setting Effect - Include Job Stayers

VARIABLES	(1) Wage-Setting	(2) Wage-Setting	(3) Wage-Setting
Post	0.0399***	0.0433***	
	(0.00509)	(0.00560)	
Private Sector × Post			0.0612***
			(0.0101)
Constant	-0.0585***	0.137***	0.00228
	(0.00401)	(0.0354)	(0.0405)
Observations	127,905	127,905	127,905
R-squared	0.004	0.012	0.020

Notes: All estimations are conducted in the largest connected set with all workers in employers that presented in both periods. Job stayers are included. Other controls include the proportion of females of the employer, the proportion of native workers of the employer, the average wage of the employer, the average age of the employer, and the average turnover rate. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Table H16: Sectoral Choice of Workers - Include Job Stayers

VARIABLES	(1) Work in the Private Sector	(2) Work in the Private Sector
Migrant	0.0115***	0.0252***
	(0.000648)	(0.000716)
Migrant × Post	-0.0130***	-0.0136***
	(0.000555)	(0.000683)
Migrant × High-Skilled		0.00736***
		(0.00117)
High-Skilled × Post		-0.0105***
		(0.00101)
Migrant × High-Skilled × Post		-0.0171***
		(0.00127)
Constant	3.609***	4.035***
	(0.00877)	(0.00966)
Observations	15,687,718	15,687,718
R-squared	0.483	0.486

Notes: All estimations are conducted in the largest connected set with all workers in employers that presented in both periods. Job stayers are included. The model is estimated by OLS regression. Other controls include age, age squared, gender, estimated person effect, proportion of females of the employer, proportion of native workers of the employer, average wage of the employer, average age of the employer, and average turnover rate. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Table H17: Hukou Quota Reduction and Residual Sorting Effect - Include Job Stayers

	(1)	(2)	(3)
VARIABLES	Residual Sorting	Residual Sorting	Residual Sorting
Post	-0.0271***	-0.131***	
	(0.00861)	(0.00862)	
Private Sector × Post			-0.0521***
			(0.0158)
Constant	-0.0319***	0.165***	0.0213
	(0.0114)	(0.0447)	(0.0740)
Observations	117,167	117,167	117,167
R-squared	0.001	0.387	0.391

Notes: All estimations are conducted in the largest connected set with all workers in employers that presented in both periods. Job stayers are included. Other controls include the proportion of females of the employer, the proportion of native workers of the employer, the average wage of the employer, the average age of the employer, and the average turnover rate. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Table H18: Triple-Difference Result of Hukou Quota Reduction - Firms Only

VARIABLES	(1) Log(Income)	(2) Log(Income)	(3) Log(Income)	(4) Log(Income)	(5) Log(Income)	(6) Log(Income)
Migrant	-0.0766***	-0.118***	-0.0126***	-0.128***	-0.163***	-0.0413***
	(0.000949)	(0.00167)	(0.00172)	(0.00123)	(0.00192)	(0.00234)
Migrant × Post	0.0637***	0.0318***	0.0284***	0.0677***	0.0324***	0.00470*
	(0.00108)	(0.00198)	(0.00186)	(0.00133)	(0.00219)	(0.00245)
Migrant × Post × Private		0.0423***			0.0818***	
		(0.00206)			(0.00251)	
Migrant × Post × Young Workers			0.0452***			0.0830***
			(0.00199)			(0.00277)
Constant	-0.613***	-0.938***	-0.823***	-3.604***	-3.784***	-3.849***
	(0.0118)	(0.0121)	(0.0119)	(0.0130)	(0.0128)	(0.0132)
Observations	4,043,708	3,817,014	4,043,708	4,520,642	4,244,724	4,520,642
R-squared	0.810	0.818	0.811	0.640	0.664	0.642
Sample	Largest Connected	Largest Connected	Largest Connected	Largest Connected	Largest Connected	Largest Connected
Worker Controls × Post	Yes	Yes	Yes	Yes	Yes	Yes
Employer Controls × Post				Yes	Yes	Yes

Notes: All estimations are conducted in the largest connected set with all workers in firms that presented in both periods. Non-firm employers including government departments, schools, and hospitals are excluded. Person effects are estimated in equation 1 using the AKM method. Worker controls include age, age squared, gender, and job tenure. Employer controls include the proportion of natives of the employer, the proportion of females of the employer, the average age of the employer, the average wage of the employer, and the average turnover rate. Year fixed effects are included. The numbers of observations are different in columns because of missing values or the fact that controlling for turnover rate reduce one year of available sample. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

The following table (Table H19) shows the results of the regression model below:

$$\ln y_{it} = \alpha_i + \gamma_1 \cdot g_i \times Hukou\_pre_i \times Post_t + \gamma_2 \cdot g_i \times No\_Hukou\_pre_i \times Post_t +$$
$$\gamma_3 \cdot g_i \times Hukou\_pre_i + \gamma_4 \cdot Hukou\_pre_i \times Post_t + X'_{it}\beta_X + \varepsilon_{it}$$

where $Hukou\_prei$ is a dummy variable that equals one if an individual i applied for a house mortgage before 2011 and had obtained local hukou at that time. No_Hukou_prei is a dummy variable that equals one if an individual i applied for a house mortgage after 2011 and had not obtained local hukou at that time. The coefficients of interest are γ_1 and γ_2, which captures the treatment effect of migrants who obtained local hukou before the policy shock, and that of migrants who did not obtain local hukou before the policy shock. I predict that γ_1 should be close to zero and $\gamma_2 > 0$.

Table H19: Triple-Difference Result of Hukou Quota Reduction - Mortgage Appliers

VARIABLES	(1) Log(Income)
Migrant	-0.137***
	(0.0196)
Migrant × Post × With Hukou Before Policy	0.00583
	(0.00437)
Migrant × Post × No Hukou Before Policy	0.104***
	(0.0212)
Constant	-1.875***
	(0.0432)
Observations	576,684
R-squared	0.633
Sample	Mortgage Applier w/ Hukou Status
Individual Controls × Post	Yes
Employer Controls × Post	No

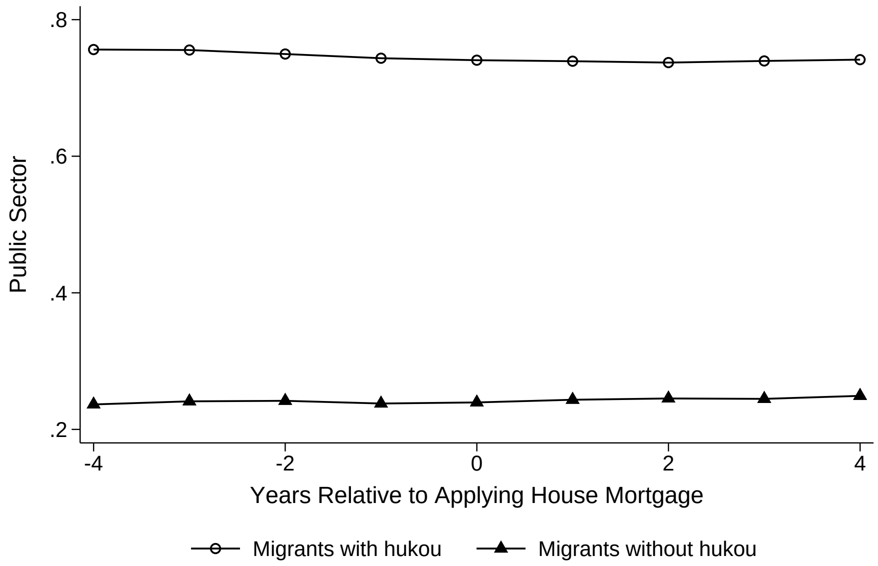
Notes: All estimations are conducted in the sample who used the housing provident fund to apply for the house mortgage. ”With Hukou Before Policy” is a dummy variable defined as those who applied for a house mortgage before 2011 and had obtained local hukou at that time. ”No Hukou Before Policy” is a dummy variable defined as those who applied for a house mortgage after 2011 and did not obtain local hukou at that time. Person effects are estimated in equation 1 using the AKM method and controlled for. Other controls include age, age squared, gender, and job tenure. ***, **, and * denote significance at the 1, 5, and 10 percent level, respectively.

Panel (a) of Figure H1 shows the proportion of migrants working in the public sector. I focus on a balanced panel of migrants who applied for house mortgages in 2010 such that I focus on those with the same time window around the application. It shows that migrants who have obtained local hukou mainly work in the public sector, which is in sharp contrast to other migrants who mainly work in the private sector.

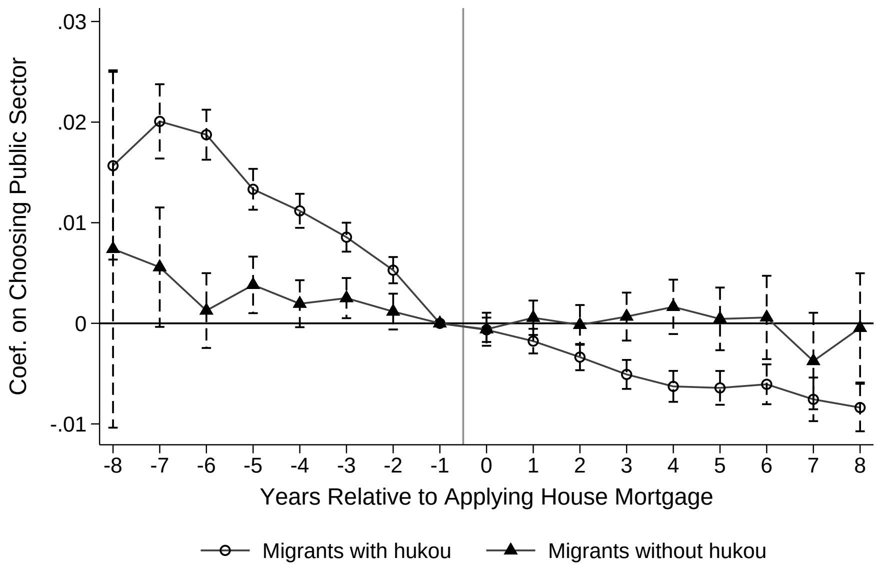
Panel (b) of Figure H1 shows the coefficients of the following regression model on two separate samples – migrants with or without hukou:

$$Public_{it} = \alpha_i + \sum_{m=-8, m\neq -1}^{8} \gamma_m \cdot Hukou_i \times t_{0+m} + \gamma_2 \cdot Hukou_i + \lambda_t + X'_{it}\beta_X + \varepsilon_{it}$$

where $Hukou_i$ is a dummy variable indicating whether individual i have obtained a local hukou at the time of applying for house mortgage. t_{0+m} captures the year relative to the year of mortgage application. Results show that for migrants who did not obtain local hukou, the coefficients are almost consistently insignificant in the $\pm$8-year window around mortgage application. On the contrary, we can see that migrants who have obtained local hukou keep leaving the public sector in the time window.



(a) Proportion of public sector



(b) Relative change in sector choice

Figure H1: Sector Choice of Mortgage Appliers

Note: In panel (a), the figure shows the proportion of workers in the public sector across years relative to the mortgage application. It only shows the proportions of migrants who applied in 2010. In panel (b), the figure shows the relative effect of choosing the public sector compared with one year before mortgage application.