The Externality Impact of Internal Migration in China: Linear and Nonlinear Approach

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Abstract

I analyze the influence of Chinese internal migration on the local labor market outcomes. In this chapter, both linear and quadratic equations are estimated to explore a comprehensive relationship between migrant share and native workers' wages in a city. My findings are twofold. In the ordinary least square regression model, every 10% increase in immigrants would lead to a 5.67% decrease in local labor wages. However, in the non-linear model a turning point is observed. The average wage level decreases when the migrant share is lower than 27.82%, while increases with the migrant share larger than 27.82% complementary, by IV regression.

Key words:

Migration；Urban development；Wage disparities；China；Quadratic function

JEL Classification: J24; J31; J61; O18; R23

Introduction

China staged planned economy before 1980. Before the implementation of Opening up policy in the late 1980s, people were supposed to reside and work only where they had their 'Hukou[1]' (Davin, 1998). Conversely, after 1990s, China has experienced a large-scale internal labor transfer, and the free flow of labor has led to rapid industrialization and urbanization, thereby promoting large-scale population migration and labor mobility (Hering and Poncet 2007). Facts have shown that domestic population mobility is the main driving force of urban population growth (Chen et al., 2016). The direct difference between immigrants (in term of domestic migrants moving cross regions) and natives is what benefits they can get from the city where they live (Démurger et al., 2009), such as public welfare and public education. This situation has strictly restricted population movement for decades.

According to the 2005 national sample survey of 1% of the population, the floating population[2] who have left their household registration place for more than half a year is 147 million, accounting for more than 11% of the total

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1 'Hukou' system was the barrier to migration in China, which was issued in 1958 and stopped in 1979, it made individuals are categorized by the state as either rural or urban and assigned to geographic areas. Travel between these is permitted only under controlled conditions and residents are not given access to jobs, public services, education, healthcare, or food in areas outside of their designated area.

2 The floating population comprises all people with no local residency rights. It includes both migrant workers and their family (non-working people), originating from either rural or urban areas. In contrast, it excludes people who obtained a change in their household registration.

population, of which labor between the ages of 16 and 60 accounts for the floating population 80.2%. Data from the sixth census in 2010 showed that the number of floating populations nationwide was as high as 221 million, an increase of 116.7% compared with 2000.

What are the economic consequences of large-scale labor migration? Will the influx of immigrants really touch the interests of the local people and affect the wage rate of the local labor force? This is a key question many scholars and government officials would raise. It is also of great significance concerning the regional economic development and whether the long-standing “Hukou” system should be cancelled permanently in the future.

Based on the above perspectives, I established a linear and a non-linear model (by adding quadratic term of migrant share) with two types of labor division and production in this chapter to examine the impact of immigration on the wage rate of local labor. Using the 2017 China Household Finance Survey (CHFS), Chinese City Statistics (CCS2017) data and migrant share in 2017 (MS) which is from Wind dataset to conduct empirical analysis.

The basic conclusion is: The linear impact of immigrants in Chinese cities on the wage rate of local labor is significantly negative particularly, for every 10% increase in immigrants, local labor wages will decrease by 5.67%, By controlling for individual characteristics and occupation types. At the position gradually approaching the turning point, the negative external effect of immigration on the local people is gradually weakened, which we can also see from the quadratic term diagram. When the proportion of immigrants is gradually higher than the value of 34.3%, the influence of immigrants on the local labor force also changes from negative to positive, and the positive marginal effect also gradually increases.

Compared with Combes et al. (2015), the research in this chapter analyses the impact of immigrants in Chinese cities on the wage rate of the local labour force in more details. Through using more recent data sets to reflect the reality of immigration issues, therefore, explaining the current government policies and make specific recommendations quantitatively. Previous studies have seldom considered the heterogeneity of the labour force; therefore, the research conclusions are based on the general judgment of the "substitution" or "complementary" relationship between immigrants and native, leading to ignoring the complex interaction between the immigrant labour structure and native.

The following content of the article is arranged as follows: The second part is literature review. The third part introduces database, main variable relations the fourth part shows the empirical models. The fifth part reports the results.

The sixth part summarizes.

Literature Review

Understanding the impact of immigration on local wage rates has important theoretical and policy implications for regional development, so it has attracted the attention of researchers. At the same time, it is more realistic in terms of China's current situation and between cities regional development. Although most literatures take international migration as the research goal or foreign migration as a model for research, in contrast, there are fewer cases in China. In summary, there are three academic viewpoints in the international research literature.

The first perspective is that immigration has a significant negative impact on the wage rate of local labor. Immigration leads to an increase in the supply of local labor, keeping other conditions relatively constant, therefore, the wage rate will inevitably fall when the labor market reaches a new equilibrium. Some empirical research results confirm the theoretical expectations of the competitive labor market under this traditional homogeneity assumption. For instance, Borjas et al (1997) used the US census data from 1980 to 1988 and found that immigrants increased the supply of low-skilled labor, who has high school or below education, in the United States, and significantly reduced the wages of low-skilled laborers. Furthermore, Borjas (2003) divides skill groups according to education and work experience, assuming that immigrants and local manpower in the same skill group are completely replaced, and found that immigrants directly increase labor supply, form competition with local labor, reducing native labor wages within the skill group. Aydemir & Borjas (2007) expanded the method of Borjas's research in 2003 analyzed the impact of immigration on the Canadian labor market and found that immigration has a significant negative effect. Cohen-Goldner & Paserman (2011) studied the impact of the influx of immigrants from the former Soviet Union on the local labor market in Israel and found that there was a significantly negative correlation between the wages of male and female labor and the proportion of immigrants. The migrant share increased by 10%, which in the short term would make local labor wage is reduced by 1 to 3% points.

The second perspective is that immigration has minor or zero impact on the wages of local labor which notes that it will bring out a series of economic adjustments, partially certain adjustments will act as an offsetting force for the decline in wage rates. We could see following potential adjustments by scholars, first is capital flow adjustments. The entry of immigrants is an extreme signal conducive to capital expansion, thereby stimulating the inflow of foreign capital (Leamer & Levinson, 1995), or stimulating local enterprises to increase investment, expand their scale, and create a large number of complementary job opportunities; Time or residence period may also bring more savings to the local area (Chiswick et al, 1992), leading to an increase in capital stock and deriving new labor demand (Hamermesh, 1993). Second, the adjustment of consumer demand. Immigrants are also consumers, which can promote consumption in the local market and stimulate the expansion of local production (Orrenius & Zavodny, 2006). Third, the local labor supply responds. Under the competitive pressure of new immigrants, some local workers may choose to move away (Borjas et al, 1997). This crowding-out effect eases the pressure on the local labor market (Card, 2001). Fourth, inter-regional trade promotes the integration of labor markets in different regions, which can offset the negative impact of immigration on the local labor force to a certain extent (Borjas et al, 1997). There are related papers before and after the study of Borjas et al. to testify to this phenomenon. Card (1990) used the Mariel boatlift incident in 1980 as a natural experiment to analyze the impact of the influx of Mexican immigrants into the Miami area of the United States on the Miami labor market in a short period of time. The results showed that immigrants did not bring the local wage rate to Miami. What a negative impact. Friedberg (2001) used Israeli micro-data to study the impact of immigration from the former Soviet Union on the Israeli labor market and used the occupation before immigration as an instrumental variable to control endogeneity. The conclusion shows that there is insufficient evidence to show that immigration has a negative impact on the wages of local labor.

The third perspective is that immigration has a positive impact on local labor wages which notices that labor is not homogenous. Heterogeneous immigrants and local labor are usually not completely substituting, and sometimes they may be complementary. This is also caused by the externalities of the immigrants' occupation or skills. Some studies have pointed out that immigration will cause firms to change production techniques (Lewis, 2005; Card & Lewis, 2007); leading to the expansion of some industries, usually low-skilled labor industries (Altonji & Card, 1991; Hanson, Slaughter 2002.). If we look at this problem from the occupational classification or skill classification of immigrants and locals. Promote specialized division of labor and occupational redistribution, that is, immigrants and local laborers will choose jobs based on their respective comparative advantages, immigrants are more engaged in manual-intensive work, and local laborers are more engaged in communication-intensive work. In this case, the two types of labor are complementary (Peri & Sparber, 2009). Taking into account the heterogeneity of labor, in different labor groups, immigrants and local labor can have a certain degree of complementarity, at least the two are not completely substitutes (Peri, 2007). Occupation is an important reason for the incomplete substitution between local labor and immigrants within the same education level and experience level group (Ortega & Verdugo, 2011). If we divide immigrants into cities in chronological order, new immigrants also mainly compete with old immigrants, rather than directly competing with local labor (Longhi et al., 2005). Judging from recent research on China's internal immigration issues, Combes et al. in 2015 studied this issue by using data from China's 2005 1% population sample survey. They found that increasing due to complementarity with natives in the production function 6.4%. Regardless of the increase in consumption, the expansion of industries, or the division of labor and specialization that are more complementary to occupations, they all help to increase local productivity. The increase in productivity in the competitive market also means an increase in wage rates.

Although we do not have a common conclusion, the understanding of how immigration affects the local wage rate is no longer a simple static analysis under the assumption of labor homogeneity. The economic adjustment accompanying immigration, as well as the incomplete substitution relationship and even complementarity between immigration and local labor based on labor heterogeneity, have received increasing attention. Theoretically speaking, different types of labor are not completely substituting, and can even be complementary. This will make the combination of the type of structure of immigrants and the type of structure of the local labor force present different economic consequences (Borjas, 2010). It can either increase the local wage rate, or decrease the local wage rate, or increase the wage rate of one type of local labor while the wage rate of another type of labor falls. This is consistent with the conclusions of Combes et al. that the institutional and occupational barriers in the labor market are still high, and certain types of work are legally restricted to local residents. Moreover, due to the low educational level of immigrants, immigrant labor force is naturally classified due to different education levels.

The scale of labor mobility has become an important economic phenomenon and an indisputable fact. However, there are still relatively few literatures on the economic issues of immigration, which directly study the impact of immigration on the wage rate of local labor force, or more concentrated on the issue of international immigration. Whether it is said that the degree of employment competition between immigrants and local labor is increasing (Knight & Yueh, 2009), or it is believed that immigrants and local labor are complementary, labor mobility promotes the division of labor. Or because the labor market is segmented, the substitution of migrant rural labor for urban residents is relatively limited (Meng & Zhang, 2001).

Obviously, different premises and assumptions will lead to different judgments. The substitution relation hypothesis means that immigrants will reduce the wage rate of local labor, the complementary relation hypothesis means that immigrants will increase the wage rate of local labor, and the limited substitution hypothesis means that immigrants will affect the wage rate of local labor is limited.

Therefore, how immigrants affect the wage rate of the local labor force is still a question that requires empirical research in China. Compared with previous study conclusion, which is Combes et al. in 2015, I first use OLS estimation to analyze the linear relation between migrants and natives and 2SLS estimation to adjusting endogenous basis. Secondly, based on OLS estimation, I use the quadratic form model to explore whether there is a nonlinear relation, thereby evaluating the impact of different immigration ratios on local wages from a quantitative perspective.

Data and model

To test whether the immigrant share significantly affects the wage rate of local workers, this chapter uses a national labor market survey data, the Chinese Household Finance Survey (CHFS), which was successfully implemented four times in 2011, 2013, 2015, and 2017 in a nationwide random sample survey of households. For the current regression, I selected 2017 data to form a cross-sectional data set which is the latest publicly available version[3]. The

[3] In our research, we adopt the dataset CHFS (Chinese Household Financial Survey), a large micro-dataset that includes both variables needed in our research and combined native and migrant samples. However, traceable observations during four consecutive waves of this survey are very small, which limits our econometric model to cross-sectional.

survey sample covers 29 provinces (autonomous regions and municipalities directly under the Central Government), 355 counties (districts, county-level cities), 1428 village (residential) committees, and the sample size covers 40011 households. This survey collects a large number of individual-level demographic and socio-economic information, we can identify the impact of the migrant share on the local wage rate on the basis of controlling personal characteristics.

The regression analysis mainly examines whether the proportion of internal immigrants has an impact on the wage level of local labor. According to the analysis in the literature review, the agglomeration effect may promote employment through multiple channels. Agglomeration can increase labor productivity, thereby increasing the labor demand of enterprises. The increase in total urban income brought about by agglomeration will also increase the demand for non-tradable goods, thereby increasing employment opportunities in the non-tradable sector. This situation is especially obvious in cities where there are more concentrated high-skilled workers, because high-skilled workers have relatively high demand for low-skilled services, which leads to "consumption spillovers" of high-skilled people to low-skilled people. There is data in the existing literature that it is easier for workers to find jobs in large cities with larger populations or more university graduates (Glaeser and Lu, 2018). However, the impact of domestic immigration or labor mobility in foreign cities is endogenous to the influx of cities, which is one of the core issues that this article will study.

The main purpose of controlling these variables is to reduce the bias of missing variables that may be caused by labor demand factors and supply factors. There is a correlation between the accumulation of capital in a city and the scale of the city, especially the concentration of highly skilled labor in the city, and the employment of urban residents. Due to the benefits of economic agglomeration, larger cities attract more capital, and the increase in capital itself will increase the employment opportunities and wages of urban residents (Glaeser and Lu, 2018). Therefore, ignoring the return of capital accumulation will cause a negative impact on the scale coefficient and biased estimate. Another reason for capital accumulation to be considered is involving the externality of human capital.

When there are frictions in the labor market and there is complementarity between physical capital and human capital, the increase in the level of education of some residents in the city will increase the investment of physical capital by urban enterprises, so that the amount of capital and the high-skilled labors will match the labor force. As a result, at equilibrium, an increase in urban material capital investment will increase labor productivity, thereby increasing the labor demand of enterprises. However, the demand for labor is ultimately limited to a certain extent, and the continuous influx of domestic immigrants has resulted in diversified relationships among different labors. Controlling a city's investment in fixed assets can to a certain extent reduce the bias in the estimation of the impact of urban scale on employment caused by the demand factor. In addition, we controlled the industrial structure of the city in the return. This is mainly because the size of a city is related to its industrial structure. At the same time, the different employment absorption capacity of the secondary and tertiary industries will also make the industrial structure of the city have an impact on the employment of laborers. Controlling the proportion of local government budget expenditures in GDP in the regression process is mainly because in cities of different sizes, the degree of government intervention in the economy is often different, and local government intervention in the economy will affect employment.

Furthermore, to personal data, we also control a series for urban characteristics that may affect employment. The city-level data comes from Chinese City Statistics (CCS2017) which collects city-level data, including the population, area size, public expenditure, and total fixed asset. Finally, the migrant share variable comes from the Wind, a database that pairs over 1.3 million macroeconomic and industry time series with data analysis tools to give financial professionals the most comprehensive insights into China's economy.

In order to carry out follow-up empirical research, necessarily data clean is conducted first: first of all, the regression sample is limited to the working-age population, therefore, keeping the sample of males between 16 and 60 years old, and the sample of females between 16 and 55 years old, and exclude the students who are in school, those who have not obtained employment status and have no salary.

However, in data processing, we found two potential problems. One is that there is an endogenous problem arising from reverse causality between the migrant share and the wage level of locals. Moreover, even though that logarithm of population density ($lnpd$) is not the core explanatory variable in the regression, which I investigate, but as one of the city level control variables, it potentially has the reverse causality with migrant share (ms). The logic behind it is that if the city gets more population, at the meantime, it causes more migrants coming in.

I adopt several different instrument variables in my research to rule out the endogeneity problems arising from the potential reverse casual effect. The first instrument variable, whether the city is a historical one, comes from Combes et.al (2015). About the second instrument, although it is quite difficult to obtain the historical data of the population of different cities, many scholars argue that geographic data can serve as instruments. Jia (2014) used whether the city is a treaty port after the Opium War as an instrument variable. The intuition is that proximity to historical cities is a substitute for being exactly located there since interactions remain possible at not too long distances. In the same spirit, we also consider an overall peripherality index that consists of the average distance of any city to all cities, be they historic or not (Combes et.al 2015). Since the treaty ports are to a large extent the same as the seaports, they also add the average distance to the seaports as an instrument. However, I try to improve this average distance in my research as this variable may underestimate the geographic advantage for those cities near the seaports. To overcome this shortcoming, I use the minimum distance to the nearest distance instead. To obtain this variable, three steps are conducted. First, calculate the spherical distances between the target city and seaport cities using Vincenty's (1975) method. Second, calculate the minimum value of these distances. Third, transform the values into a natural logarithm and obtain the instrument variable. The third instrument is the historic industry structure. With the economic development over the past decades, one key factor that would influence the laborers' wages is the city's industry structure. For example, the international metropolis Shanghai has a large share of finance services, which makes its laborers' average wages comparatively higher than other cities and attracts a lot of migrants. For this reason, we use the GDP created by the service sector divided by the sum of the other three sectors (agriculture, services and manufacturing) to measure the industry structure.

The last instrument variable also comes from Combes et.al (2015), including doctor numbers per capita which measures the level of the public good offered by the cities as theories show that one of the important drivers of migration is the public service offered by the destination city.

Finally, the sample size that satisfies the above empirical research is 8066 individuals. And in my regression, in order to ensure the consistency of the sample results, I keep the number of samples of ordinary least squares (OLS) and two-stage least squares (2SLS) at 8066.

Because the city-level variables are already included in the control variable group, it is equivalent to saying that in the regression process, immigrants in the same city face the same city control group. Therefore, we cannot perform city-level fixed effects on the variables based on the city ID. But different occupations do also affect the rate of return of wages. The original questionnaire asked about the individual's work occupation[4]. The occupational classification standard completely follows the census standard, which refers to

[4] The standard stipulates the classification structure, categories and codes of Chinese occupations, and is applicable to various censuses, survey statistics, administrative management, and domestic and foreign information exchanges. Occupation classification is based on the identity of the nature of the work performed by the working population. According to regulations, the national occupational classification is divided into 8 major categories, namely the first category: heads of state agencies, party organizations, enterprises, and institutions; the second category: professional and technical personnel; the third category: office workers and related personnel ; The fourth category: commercial and service personnel; the fifth category: agricultural, forestry, animal husbandry, fishery, and water conservancy production personnel; the sixth category: production and transportation equipment operators and related personnel; the seventh category: military personnel; the eighth category: others.

the type of social work that practitioners engage in to obtain their main source of livelihood. There are eight occupation types, therefore, we could add seven dummy variables to both the OLS estimation and the Quadratic Model to fix the influence of occupations.

Table 1 shows a summary of explanatory variables[5]

Variable	Description	Data source
lnwage	natural logarithm of the native individual (CNY)	CHFS
educ	Education years at individual level (Year)	CHFS
male	Dummy variable, male=1 if male =0, then female	CHFS
exp	Potential working experience years, calculating by $individual\ person\ age - year\ of\ schooling - 6$ (Year)	CHFS
expsq	The square of working experience (Year Square)	CHFS
marriage	Dummy variable, =1 if ever married; =0 otherwise	CHFS
ms	Migrant share=migrant population/total population (Percentage)	Wind
lnpd	natural logarithm of the population density(10000 person/km2)	CCS
lnpubexp	natural logarithm of public expenditure	CCS
lnexpst	natural logarithm of public expenditure in science and	CCS

5 Gender, working experience and its square term, marriage and education are at individual level, other variables are at city level.

	technology	
lnexpedu	natural logarithm of public expenditure in education	CCS
lnfixedasset	natural logarithm of total fixed asset	CCS

Table 2 Statistic Description

Variable	Obs	Mean	Std. Dev.	Min	Max
wage	8066	19.733	22.005	1	740.741
educ	8066	11.628	3.506	0	22
male	8066	.587	.492	0	1
exp	8066	21.686	11.401	0	40
expsq	8066	600.245	488.573	0	1600
marriage	8066	.834	.372	0	1
ms	8066	.151	.148	.001	.775
pd	8066	1138.802	670.758	124.04	4329.9
pubexp	8066	7341411.9	6343099.6	957303	42110429
expst	8066	279962.58	572248.44	2631	4035240
expedu	8066	1218995.7	814839.22	62808	4147269
fixedasset	8066	31840226	18966699	1571218	74547006
ms_sq	8066	.0445122	.0970559	0	.5991445

Table 3 Occupation classification

Occpuation	**Frequency**	**Percent**	**Cummulation**
The leader of party and state organs, mass organizations, social organizations, enterprises, and public institutions	311	3.86	3.86
Technicians and professionals	1,797	22.28	26.13
Clerks or related staffs	1,966	24.37	50.51
Social production and life service workers	1,547	19.18	69.69

Production operators and support staffs of the industry of agriculture, forestry, husbandry, fishery	101	1.25	70.94
wholesale and retail	1,558	19.32	90.26
Transportation, storage, logistics and mail	8	0.1	90.35
Others without clear classification	778	9.65	100
Total	8,066	100	

Econometric model

Based on extant literature, this chapter also controls the workers' education level, potential work experience and marital status all need to be considered into account. This paper establishes the following linear estimation OLS model:

$$\text{lnwage}_{i,c}^{Native} = \beta_0 + \delta_1 * MS_c + \beta_1 * X_{i,c} + \beta_2 * City_c + \sum_{i=1}^{7} \gamma_i occ_i + \varepsilon_{i,c} \qquad (1)$$

Where the subscripts i and c respectively represent the individual i and its location of city, and $\sum_{i=1}^{7} \gamma_i occ_i$ refers 7 occupational dummy variables and $\varepsilon_{i,c}$ represents the random disturbance term. The explained variable of the model $\text{lnwgae}_{i,c}^{Native}$ represents the natural logarithm of the variable of hourly wage income of the observations, the core explanatory variable of the model is MS, which represents the proportion of domestic immigrants, and its calculation formula is:

$$MS_c = \frac{Migrants_c}{Migrants_c + Natives_c} \quad (2)$$

Here, $Migrants_c$ and $Natives_c$ respectively represent the number of immigrants and the number of local workers in the c city.

On the right side of the regression equation, $X_{i,c}$ is a vector of personal features that may affect wages, including gender, marital status, potential work experience and its square term. We did not include age in the personal characteristics because the variable of potential work experience has been included in the regression, which is derived from $age - year\ of\ schooling - 6$. If both age and work experience are included in the regression, it will bring about the problem of perfect collinearity. MS_c is a measure of the proportion of domestic immigrants, and the positive or negative magnitude and significance of δ_1 are the core coefficient of this chapter. If the entry of domestic immigrant labor into large cities (population size bigger than 3 millions) can have a positive impact on local wages, our expected δ_1 should be significantly positive.

Other urban features that may affect employment are included in the $City_c$ vector, including: the natural logarithm of the average fixed asset, the natural logarithm of the average of the government public expenditure, the natural logarithm of public expenditure in education, the natural logarithm of public expenditure in science and technology and city-level education.

Quadratic Model:

To identify potential non-linearities in the relationship between the migrant share and local wages, I add a quadratic term into the OLS model[6]. These models allow for an observation on the turning point where a larger migrant share might have a reverse effect on the local workers' wage level, namely the substitution effect. This quantitative estimation is of policy significance in controlling the city size. Latest statistics shows that the new-born population has witnessed sharp decrease over the past years. Wang and Mason (2007) and Cai (2010) worried that the population dividend that boomed China's economy for decades will disappear in the near future. This will lead to a decrease in the influx of immigrants from rural areas to urban areas. However, large cities in China have been controlling the population scale with the Hukou system for a long time. Without Hukou, immigrants are outlawed to buy a house in the city where they work. If my study shows that larger cities will increase the native workers' wage level and large cities also need migrant workers. A permanent cancellation on the Hukou system would be both preferable in theory and reality.

The model formula is thus as follows:

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[6] More further estimation technique shows in the Appendix M.

$$\text{lnwage}_{i,c}^{Native} = \beta_0 + \delta_1 * MS_c + \delta_2 * MS_c^2 + \beta_1 * X_{i,c} + \beta_2 * City_c + \sum_{i=1}^{7} \gamma_i occ_i + \varepsilon_{i,c} \quad (3)$$

For my research, the focus is on the marginal influence of migrant share on local labors' wage rate.

$$\frac{\partial \text{lnwage}_{i,c}^{Native}}{\partial MS_C} \approx \widehat{\delta_1} + 2\widehat{\delta_2} * MS_C \quad (4)$$

This interpreting that the marginal influence of MS on local labors' wage rate is not a constant, which follows that the value of MS changes.

About turning point analysis, when the coefficient of MS is negative, but the coefficient of the quadratic term of MS (ms_sq) is positive, the value of $MS \in (0,1)$, which means that the equation with the quadratic term has a U-shaped relationship like a parabola. It shows that at turning point ($MS *$) the marginal influence of MS on local labors' wage rate is zero, before this point ($MS < MS^*$), the influence of MS on dependent variable is negative; and after this point, the influence of MS on MS^* is positive. Therefore, I have the equation (6) in the below.

$$MS^* = -\frac{\widehat{\delta_1}}{2\widehat{\delta_2}} \quad (5)$$

The analysis of the quadratic equation will be discussed in detail in the following data result analysis

Moreover, in the regression of my research, in addition to the standard OLS and 2SLS (dealing with endogeneity), I also added Heteroskedasticity-Robust Standard Error regression and Cluster-Robust standard error regression to solve the potential problems arising from heteroskedasticity and correlated error terms within a cluster, basing on OLS and 2SLS. The reasons and ideas for using heteroscedasticity robust standard errors and clustering robust standard errors are as follows: First, the calculation formula for ordinary standard errors is derived under the Gauss Markov assumption. One of the important assumptions is the homoscedasticity assumption, but the homoscedasticity assumption is generally not satisfied. If heteroscedasticity exists, the ordinary standard error is not the true standard error, and the t-statistic constructed using the ordinary standard error is invalid. (Woodridge 2010).

White (1980) proposed a robust standard error of heteroscedasticity, but the data in our model might not meet the assumption of homoscedasticity. Secondly, cross-sectional data usually has heteroscedasticity problems, so for cross-sectional data, heteroscedasticity robust standard errors are generally used. The robust standard error means that the same variance assumption is not necessarily required to estimate the standard error, therefore it is not a must precondition in the White adjusted regression model. If an OLS model does not meet the same variance assumption, it will underestimate the standard error. White-robust regression will only affect the estimated standard error, leaving the coefficient itself the same.

Autocorrelation will not affect the unbiasedness and consistency of the estimator, but it will affect the validity, that is, it will affect the variance of the estimator, and Gauss-Markov's theorem is no longer valid, therefore, it is problematic to use ordinary standard errors or heteroscedasticity robust standard errors, so the t-statistic will also be invalid. Therefore, this also brings out another regression standard, the standard error of clustering robustness. For example, if you use city-level data, each city is a cluster, and the observations in the same cluster are related to each other, while the observations between different clusters are not.

For clustered samples, OLS estimation can still be performed, just use the "clustering-robust standard error" option, it can be treated as a sandwich variance estimator in form, which is manifested in the calculation of variance. The standard error of clustering robustness is a more stringent standard error than the standard error of heteroscedasticity robustness because it does not use the homoscedasticity assumption in the derivation process; therefore, the clustering robust standard errors are all heteroscedasticity robust.

In terms of the value of the standard error, the order from large to small is usually as clustering robust standard error, heteroskedasticity robust standard error and normal standard error. Therefore, in most cases, it may be significant if you use normal standard error, and once you use heteroscedasticity-robust standard error or the cluster robust standard error is no longer significant. In my later results, both adjusted error regression results will be reported.

Result

1) OLS Estimation

Table 4 reports the estimated results of standard OLS regression. The first column reports that only the city-level control variables and occupational effects are added. Columns 2-5 gradually add the individual-level characteristic variables such as education gender, work experience and its square term, and marital status compared to the first column.

Table 4 OLS Estimation Results

	(1)	(2)	(3)	(4)	(5)
	lnwage	lnwage	lnwage	lnwage	lnwage
ms	.422***	.429***	.418***	.439***	.434***
	(.068)	(.066)	(.065)	(.064)	(.064)
lnpd	-.023*	-.034***	-.032***	-.037***	-.037***
	(.012)	(.012)	(.012)	(.011)	(.011)
lnpubexp	.098**	.026	.027	-.021	-.019
	(.04)	(.038)	(.038)	(.037)	(.037)
lnexpst	.067***	.064***	.069***	.075***	.076***
	(.012)	(.012)	(.012)	(.011)	(.011)

lnexpedu	.023	.073**	.064*	.082**	.082**
	(.038)	(.036)	(.036)	(.035)	(.035)
lnfixedasset	-.055***	-.056***	-.055***	-.05***	-.052***
	(.019)	(.018)	(.018)	(.018)	(.018)
occ1	.511***	.286***	.275***	.193***	.194***
	(.042)	(.041)	(.041)	(.04)	(.04)
occ2	.407***	.241***	.236***	.219***	.219***
	(.027)	(.026)	(.026)	(.026)	(.026)
occ3	.21***	.064**	.084***	.067***	.068***
	(.027)	(.026)	(.026)	(.025)	(.025)
occ4	-.057**	-.081***	-.049*	-.044*	-.043*
	(.027)	(.026)	(.026)	(.026)	(.026)
occ5	-.067	-.001	.002	-.003	-.002
	(.066)	(.063)	(.063)	(.061)	(.061)
occ6	.009	.046*	.052**	.046*	.046*
	(.027)	(.026)	(.026)	(.026)	(.026)
occ7	.729***	.441**	.375*	.446**	.445**
	(.221)	(.212)	(.21)	(.206)	(.206)
educ		.057***	.058***	.072***	.071***
		(.002)	(.002)	(.002)	(.002)
male			.182***	.179***	.181***
			(.014)	(.013)	(.013)
exp				.04***	.037***
				(.002)	(.003)
expsq				-.001***	-.001***
				(0)	(0)
marriage					.04*
					(.024)
_cons	.982***	.975***	.856***	.673***	.678***
	(.277)	(.266)	(.263)	(.258)	(.258)
Observations	8066	8066	8066	8066	8066
R-squared	.165	.232	.249	.28	.281

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

The results in column (1) of Table 4 show that the regression coefficient of the proportion of immigrants is 0.422, which is significant at the 1% level. Column (5) further includes education gender, work experience and its square terms, marital status, and the estimated results that reflect urban control variables and occupational fixed characteristic variables. It finds that the regression coefficient of the migrant share is still 0.434 at significance level of 1%. Specifically, given other conditions unchanged, for every 10% increase in the proportion of urban-professional immigrants, the hourly wage of local labor will increase by 4.34%. This means that the influx of immigrants will indeed impact the wages of the local labor market to a certain extent. And after gradually adding personal-level features, the model setting is more stable, with R-squared rising from 0.165 to 0.281.

Comparing the size of different estimation coefficients, the results of previous findings are different. For example, the estimated results of Borjas (2003) show that for every 10% increase in international migration, market wages fall by about 3% to 4%. A study by Card (2001) found that for every 10% increase in international migration, local labor wages fall by about 1.5%. Combes et al. (2015) found China's the large total migrant impact (+10% when one moves from the first to the third quartile of the migrant variable distribution) arises from gains due to complementarity with natives in the production function (+6.4%), and from gains due to agglomeration economies (+3.3%). My finding is consistent with Combes et al. With the development of cities and the migration movement, combined with the cross-sectional data of 2017, we can derive from the data results that there is a complementary situation between domestic immigrants and local labor. When evaluating the impact of immigration on the labor market, there are differences in estimated coefficients. A potential reason is the difference in observation samples and research methods. Nevertheless, my research results once again confirmed the conclusion in the literature that immigration has a positive effect on the wages of the local labor force. This result is consistent with the research on domestic immigration, which also uses China as a case study.

2) Adjust Standard Error OLS Estimation

Moreover, as I mentioned in methodology, cross-sessional data has heteroskedasticity in general, then, I used 'White Test' to proof this situation in my regression. We can see the result in Table5, the chi-square value is $chi2(154) = 310.97$, and the significance is $Prob > chi2 = 0.0000$. Obviously, the null hypothesis Ho: homoskedasticity should be rejected, with heteroscedasticity, which means our estimation result of OLS might be inefficient.

Table 5 White Test Result

Chi2	df	p
310.97	**154**	**0.0000**

Second, a feature in regression is that all observations from a city have the same MS value. This is a version of the classic Moulton (1986) problem. In this case, it allows observations in the same cluster are related to each other, while observations between different clusters are not. It will cause the OLS standard error to shift downward. Therefore, I report the adjusted OLS results in Table 5.

Table6 Ordinary and Adjusted OLS Estimation Results

VARIABLES	(1) OLS lnwage	(2) OLS_Robust lnwage	(3) OLS_Cluster_ Robust lnwage
ms	0.434***	0.434***	0.434***
	(0.0637)	(0.0666)	(0.134)
educ	0.0714***	0.0714***	0.0714***
	(0.00242)	(0.00265)	(0.00422)
male	0.181***	0.181***	0.181***
	(0.0133)	(0.0131)	(0.0131)
exp	0.0371***	0.0371***	0.0371***
	(0.00297)	(0.00330)	(0.00380)
expsq	-0.000715***	-0.000715***	-0.000715***
	(6.31e-05)	(6.87e-05)	(7.90e-05)
marriage	0.0404*	0.0404*	0.0404*
	(0.0244)	(0.0248)	(0.0221)
lnpd	-0.0369***	-0.0369***	-0.0369*
	(0.0114)	(0.0114)	(0.0221)
lnpubexp	-0.0192	-0.0192	-0.0192
	(0.0371)	(0.0375)	(0.0748)
lnexpst	0.0757***	0.0757***	0.0757***
	(0.0115)	(0.0114)	(0.0216)
lnexpedu	0.0817**	0.0817**	0.0817
	(0.0353)	(0.0354)	(0.0685)

lnfixedasset	-0.0516***	-0.0516***	-0.0516
	(0.0177)	(0.0179)	(0.0367)
occ1	0.194***	0.194***	0.194***
	(0.0400)	(0.0437)	(0.0520)
occ2	0.219***	0.219***	0.219***
	(0.0256)	(0.0281)	(0.0311)
occ3	0.0681***	0.0681**	0.0681**
	(0.0253)	(0.0271)	(0.0277)
occ4	-0.0425*	-0.0425	-0.0425
	(0.0256)	(0.0266)	(0.0302)
occ5	-0.00213	-0.00213	-0.00213
	(0.0613)	(0.0713)	(0.0815)
occ6	0.0462*	0.0462*	0.0462
	(0.0255)	(0.0267)	(0.0311)
occ7	0.445**	0.445***	0.445***
	(0.206)	(0.117)	(0.115)
Constant	0.678***	0.678***	0.678
	(0.258)	(0.254)	(0.456)
Observations	8,066	8,066	8,066
R-squared	0.281	0.281	0.281

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

We can see it from the table that in these two procedures make the standard error has been re-adjusted which is larger than the ordinary OLS, from 0.0637 changed to 0.134, however, our results are still consistent with 0.434 when MS increase by 1% and strongly significant at 1% level.

There might be an endogeneity problem in my model arising from reverse causality. Agglomeration effect might increase the wage level due to a decrease in the industry cost and thus increase the average wage level in the large city. However, this would in return attract more immigrants to large cities. This is true when China has numerous rural labors over the past decades.

Furthermore, since I noticed the problem of endogeneity in regression (reverse causality and measurement error), I deal with the problem of endogeneity by using the instrumental variable method (the two-stage least squares method). The results show in the below table7.

The comparison columns (1) and (2), (3) and (4), (5) and (6) respectively show the results of different differences between the least squares method and the instrumental variable method. The difference I am referring to stems from two parts. The first part is because after the instrumental variable method is adopted, the underestimation of OLS results caused by reverse causality and measurement errors is corrected. We can compare the OLS and its corresponding IV results in pairs.

I adopt several different instrument variables in my research to rule out the endogeneity problems arising from the potential reverse casual effect. The first two instrument variables come from Pierre-Philippe Combes et.al (2015), even though, it is quite difficult to obtain the historical data of the population of different cities, many scholars argue that geographic data can serve as instruments. Jia (2014) used whether the city is a treaty port after the Opium War as an instrument variable. The intuition is that proximity to historical cities is a substitute for being exactly located there since interactions remain possible at not too long distances. Secondly, in the same spirit, we also consider an overall peripherality index that consists of the average distance of any city to all cities, be they historic or not (Combes et.al 2015). Since the treaty ports are to a large extent the same as the seaports, they also add the average distance to the seaports as an instrument. However, I try to improve this average distance in my research as this variable may underestimate the geographic advantage for those cities near the seaports. To overcome this shortcoming, I use the minimum distance to the nearest distance. To obtain this variable, three steps are conducted. First, calculate the spherical distances between the target city and seaport cities using Vincenty's (1975) method. Second, calculate the minimum value of these distances. Third, transform the values into a natural logarithm and obtain the instrument variable. The third instrument is the industry structure. With the economic development over the past decades, one key factor that would influence the laborers' wages is the city's industry structure. For example, the international metropolis Shanghai has a large share of financial services, which makes its laborers' average wages comparatively higher than other cities and attracts a lot of migrants. For this reason, we use the GDP created by the service sector divided by the sum of the other two sectors to measure the industry structure. The last set of instrument variables also come from Combes et.al (2015), doctor numbers per capita which are of which measure the level of the public good offered by the cities as theories show that one of the important drivers of migration is the public service offered by the destination city.

For every 10% increase in the proportion of immigrants to the local labor force, the wage level of the local labor force increases by 4.34% to 5.67%. Considering the instrumental variable model specification, we can clearly see that no matter which way (Original Standard Error or Adjust Standard Error), the model passed under-identification, weak-identification, and over-identification. Respectively, the $Chi-sq(3)$ P-value of Anderson LM is equal to 0.000 which is significant at 1% level reject null-hypothesis, Cragg-Donald Wald F statistic is greater than 10 (in theory, if Cragg-Donald Wald F statistic is greater than 10 which means the instrument(s) is strong), and for Hansen P- value is strongly significant at 1% level which means that the model is not over identified.

Comparing (2), (4) and (6), the IV models' Standard Error is adjusted. The few differences show in the below, the Standard Error gets bigger from 0.182 to 0.186, ending at 0.235, fortunately that the results are still showing significant, even though, after using Cluster- Robust Standard Error procedure, the significance of the coefficient of MS is significant at 5% level.

Table 7 Comparing OLS Results and Second Stage IV-Results

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS_Robust	IV_R	OLS_Roubust _Cluster	IV_R_C
VARIABLES	lnwage	lnwage	lnwage	lnwage	lnwage	lnwage

ms	0.434***	0.567***	0.434***	0.567***	0.434***	0.567**
	(0.0637)	(0.182)	(0.0666)	(0.186)	(0.134)	(0.235)
educ	0.0714***	0.0721***	0.0714***	0.0721***	0.0714***	0.0721***
	(0.00242)	(0.00248)	(0.00265)	(0.00272)	(0.00422)	(0.00823)
male	0.181***	0.179***	0.181***	0.179***	0.181***	0.179***
	(0.0133)	(0.0134)	(0.0131)	(0.0132)	(0.0131)	(0.0263)
exp	0.0371***	0.0379***	0.0371***	0.0379***	0.0371***	0.0380***
	(0.00297)	(0.00303)	(0.00330)	(0.00337)	(0.00380)	(0.00273)
expsq	-0.00072***	-0.000731***	-0.000715***	-0.000731***	-0.000715***	-0.000734***
	(6.31e-05)	(6.41e-05)	(6.87e-05)	(6.97e-05)	(7.90e-05)	(4.76e-05)
marriage	0.0404*	0.0361	0.0404	0.0361	0.0404*	0.0358*
	(0.0244)	(0.0248)	(0.0248)	(0.0252)	(0.0221)	(0.0202)
lnpd	-0.0369***	-0.128**	-0.0369***	-0.128**	-0.0369*	-0.128*
	(0.0114)	(0.0613)	(0.0114)	(0.0602)	(0.0221)	(0.0712)
lnpubexp	-0.0192	-0.00510	-0.0192	-0.00510	-0.0192	0.00119
	(0.0371)	(0.0407)	(0.0375)	(0.0403)	(0.0748)	(0.0409)
lnexpst	0.0757***	0.0697***	0.0757***	0.0697***	0.0757***	0.0706***
	(0.0115)	(0.0168)	(0.0114)	(0.0171)	(0.0216)	(0.0246)
lnexpedu	0.0817**	0.0546	0.0817**	0.0546	0.0817	0.0491
	(0.0353)	(0.0397)	(0.0354)	(0.0395)	(0.0685)	(0.0395)
lnfixedasset	-0.0516***	-0.0187	-0.0516***	-0.0187	-0.0516	-0.0203
	(0.0177)	(0.0331)	(0.0179)	(0.0343)	(0.0367)	(0.0389)
occ1	0.194***	0.193***	0.194***	0.193***	0.194***	0.189**
	(0.0400)	(0.0402)	(0.0437)	(0.0440)	(0.0520)	(0.0926)
occ2	0.219***	0.213***	0.219***	0.213***	0.219***	0.209***
	(0.0256)	(0.0261)	(0.0281)	(0.0286)	(0.0311)	(0.0283)
occ3	0.0681***	0.0620**	0.0681**	0.0620**	0.0681**	0.0574
	(0.0253)	(0.0257)	(0.0271)	(0.0275)	(0.0277)	(0.0394)
occ4	-0.0425*	-0.0469*	-0.0425	-0.0469*	-0.0425	-0.0536***
	(0.0256)	(0.0259)	(0.0266)	(0.0270)	(0.0302)	(0.0189)
occ5	-0.00213	-0.0146	-0.00213	-0.0146	-0.00213	-0.0183
	(0.0613)	(0.0621)	(0.0713)	(0.0718)	(0.0815)	(0.0367)
occ6	0.0462*	0.0409	0.0462*	0.0409	0.0462	0.0381
	(0.0255)	(0.0258)	(0.0267)	(0.0271)	(0.0311)	(0.0268)
occ7	0.445**	0.435**	0.445***	0.435***	0.445***	0.432***
	(0.206)	(0.206)	(0.117)	(0.126)	(0.115)	(0.0717)
Constant	0.678***	0.940***	0.678***	0.940***	0.678	0.936**
	(0.258)	(0.313)	(0.254)	(0.318)	(0.456)	(0.438)
Observations	8,066	8,066	8,066	8,066	8,066	8,066
R-squared	0.281	0.275	0.281	0.275	0.281	0.275
IV F-stat		170.4		158.1		66.1
Anderson LM		267.9		254.1		221.6
Cragg-Donald Wald F		69.11		69.11		69.11

statistic			
Hansen-J Statistic	18.11	17.50	8.819
Hansen p-value	0.000117	0.000159	0.0122

Note: The first stage results of IV adjusted quadratic OLS is in the Table 9, Appendix I. About the explanation of the specification of IV is in the Appendix K. In the brackets are the standard errors, the difference of standard errors is showing by between columns (1), (3) and (5), and columns (2), (4) and (6). I use columns (1) and (2) as baseline of ordinary standard errors, columns (3) and (4) are adjusted by robust standard errors, columns (5) and (6) are adjusted by cluster-robust standard errors.

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

I classify immigrant labor with education years less than or equal to 12 years as low-skilled labor, and those with more than 12 years of education as high-skilled labor, to explore the impact of immigrant labor on the wage level of local labor at different skill levels. Here I report only the results after clustering robust standard errors of OLS and IV estimates. From the results of the data, we can find that whether it is a high-skilled labor force or a low-skilled labor force, the wage level of the local labor force has a tendency to promote. Also, we could indirectly proof that as Mincer's wage function which labor's wage rate drives by education.

Table 8 Different skilled influence

	(1)	(2)	(3)	(4)

VARIABLES	OLS_R_C low lnwage	IV_R_C low lnwage	OLS_R_C high lnwage	IV_R_C high lnwage
ms	0.201**	0.309*	0.551***	0.770***
	(0.0895)	(0.251)	(0.0923)	(0.233)
educ	0.0298***	0.0304***	0.181***	0.183***
	(0.00420)	(0.00426)	(0.00985)	(0.00914)
male	0.247***	0.246***	0.126***	0.122***
	(0.0171)	(0.0176)	(0.0199)	(0.0202)
exp	0.0369***	0.0374***	0.0340***	0.0355***
	(0.00567)	(0.00453)	(0.00490)	(0.00487)
expsq	-0.000726***	-0.000736***	-0.000530***	-0.000556***
	(0.000109)	(9.02e-05)	(0.000127)	(0.000124)
marriage	0.0203	0.0183	0.0384	0.0287
	(0.0376)	(0.0350)	(0.0321)	(0.0345)
lnpd	-0.0329**	-0.151*	-0.0636***	-0.214**
	(0.0144)	(0.0805)	(0.0176)	(0.0906)
lnpubexp	-0.148***	-0.138***	0.0886	0.133**
	(0.0493)	(0.0506)	(0.0560)	(0.0658)
lnexpst	0.0980***	0.0961***	0.0541***	0.0422*
	(0.0140)	(0.0219)	(0.0188)	(0.0252)
lnexpedu	0.0942**	0.0698	0.0505	-0.0145
	(0.0445)	(0.0472)	(0.0565)	(0.0685)
lnfixedasset	-0.0311	0.00586	-0.0354	0.0175
	(0.0236)	(0.0419)	(0.0267)	(0.0470)
occ1	0.138	0.121*	0.166***	0.178***
	(0.0871)	(0.0701)	(0.0607)	(0.0578)
occ2	0.159***	0.147***	0.188***	0.187***
	(0.0348)	(0.0331)	(0.0510)	(0.0468)
occ3	0.0987***	0.0889***	0.0456	0.0447
	(0.0323)	(0.0317)	(0.0505)	(0.0464)
occ4	0.000507	-0.00797	-0.0704	-0.0664
	(0.0296)	(0.0299)	(0.0556)	(0.0518)
occ5	-0.0122	-0.0311	-0.0308	-0.0366
	(0.0750)	(0.0669)	(0.170)	(0.172)
occ6	0.0711**	0.0617**	-0.0445	-0.0466
	(0.0293)	(0.0292)	(0.0567)	(0.0564)
occ7	0.0740**	-0.0240	0.473***	0.480**
	(0.0355)	(0.582)	(0.0834)	(0.214)
Constant	2.254***	2.618***	2.047***	1.639***
	(0.325)	(0.412)	(0.422)	(0.487)

Observations	4,865	4,865	3,201	3,201
R-squared	0.115	0.112	0.357	0.343
IV F-stat		34.13		94.04
Anderson LM		149.5		123.5
Cragg-Donald Wald F statistic		38.40		31.92
Hansen Statistic		9.306		8.664
Hansen p-value		0.00953		0.0131

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3) Quadratic Form Model Results

To test whether there is a turning point in the quadratic function, I added ms_sq as migrant share' quadratic form, the results show in table9.

Before we see the results, we need to discuss in equation (6) we can calculate the turning point, but at this time we need to consider the value range of MS, and then we can judge whether the turning point has economic significance or research significance. Therefore, when we calculate the turning point, we should pay attention to whether its value fits the range of the value explored. The core explanatory variable of my study is the proportion of immigrants which is $[0,1]$.

From Table9, we can see that the coefficient of the quadratic form of migrant share is strongly significant at 1% level everywhere, even though, the first-order coefficients are not significant in the regression results. However, what we hope in this part is the regression based on OLS, adding its quadratic term to the core explanatory variable to explore whether there is a nonlinear relationship between the core explanatory variable and the explained variable. Based on the above assumptions, we can allow the quadratic equation to have a non-significant first-order regression (Haans et al. 2016). Moreover, the sign of quadratic term is positive and the sign of first order is negative which means that the graph of function would be U-shape.

Table 9 Quadratic form results of OLS and IV Estimation

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	Robust	IV _R	IV Cluster	IV _R_C
VARIABLES	lnwage	lnwage	lnwage	lnwage	lnwage	lnwage
ms	-0.0468	-0.0603	-0.0468	-0.0603	-0.0468	-0.0603
	(0.0385)	(0.0459)	(0.0372)	(0.0451)	(0.0647)	(0.0804)
ms_sq	0.0753***	0.0880***	0.0753***	0.0880***	0.0753***	0.0880**
	(0.00880)	(0.0259)	(0.00964)	(0.0271)	(0.0135)	(0.0422)
educ	0.0712***	0.0719***	0.0712***	0.0719***	0.0712***	0.0719***
	(0.00242)	(0.00246)	(0.00265)	(0.00271)	(0.00424)	(0.00438)
male	0.180***	0.179***	0.180***	0.179***	0.180***	0.179***
	(0.0133)	(0.0134)	(0.0130)	(0.0132)	(0.0131)	(0.0133)
exp	0.0368***	0.0375***	0.0368***	0.0375***	0.0368***	0.0375***
	(0.00296)	(0.00301)	(0.00329)	(0.00334)	(0.00368)	(0.00384)
expsq	-0. 001***	-0. 001***	-0. 001***	-0. 001***	-0. 001***	-0. 001***
	(6.30e-05)	(6.37e-05)	(6.86e-05)	(6.92e-05)	(7.65e-05)	(7.82e-05)
marriage	0.0385	0.0351	0.0385	0.0351	0.0385*	0.0351

	(0.0244)	(0.0248)	(0.0247)	(0.0252)	(0.0219)	(0.0233)
lnpd	-0.041***	-0.132**	-0.041***	-0.132**	-0.0409*	-0.132
	(0.0114)	(0.0607)	(0.0114)	(0.0582)	(0.0215)	(0.118)
lnpubexp	-0.0657*	-0.0554	-0.0657*	-0.0554	-0.0657	-0.0554
	(0.0387)	(0.0456)	(0.0387)	(0.0455)	(0.0687)	(0.0859)
lnexpst	0.0762***	0.0745***	0.0762***	0.0745***	0.0762***	0.0745**
	(0.0115)	(0.0154)	(0.0113)	(0.0157)	(0.0201)	(0.0295)
lnexpedu	0.118***	0.0983**	0.118***	0.0983**	0.118*	0.0983
	(0.0366)	(0.0397)	(0.0365)	(0.0387)	(0.0642)	(0.0761)
lnfixedasset	-0.0413**	-0.0139	-0.0413**	-0.0139	-0.0413	-0.0139
	(0.0176)	(0.0335)	(0.0177)	(0.0346)	(0.0329)	(0.0607)
occ1	0.195***	0.194***	0.195***	0.194***	0.195***	0.194***
	(0.0399)	(0.0401)	(0.0435)	(0.0438)	(0.0517)	(0.0522)
occ2	0.220***	0.214***	0.220***	0.214***	0.220***	0.214***
	(0.0256)	(0.0260)	(0.0281)	(0.0286)	(0.0311)	(0.0342)
occ3	0.0696***	0.0634**	0.0696**	0.0634**	0.0696**	0.0634**
	(0.0252)	(0.0256)	(0.0271)	(0.0275)	(0.0272)	(0.0289)
occ4	-0.0401	-0.0450*	-0.0401	-0.0450*	-0.0401	-0.0450
	(0.0255)	(0.0258)	(0.0266)	(0.0270)	(0.0302)	(0.0306)
occ5	0.00323	-0.00941	0.00323	-0.00941	0.00323	-0.00941
	(0.0612)	(0.0619)	(0.0712)	(0.0715)	(0.0811)	(0.0824)
occ6	0.0472*	0.0418	0.0472*	0.0418	0.0472	0.0418
	(0.0255)	(0.0258)	(0.0267)	(0.0271)	(0.0308)	(0.0320)
occ7	0.455**	0.448**	0.455***	0.448***	0.455***	0.448***
	(0.205)	(0.206)	(0.117)	(0.125)	(0.113)	(0.125)
Constant	0.841***	1.141***	0.841***	1.141***	0.841*	1.141*
	(0.259)	(0.332)	(0.255)	(0.331)	(0.426)	(0.613)
Observations	8,066	8,066	8,066	8,066	8,066	8,066
R-squared	0.283	0.277	0.283	0.277	0.283	0.277
IV F-stat		162.1		151.9		62.91
Anderson LM		268.8		273.5		210.9
Cragg-Donald Wald F statistic		69.34		69.34		69.34
Hansen-J Statistic		17.06		17.64		11.69
Hansen p-value		0.000197		0.000148		0.0348

Note: The first stage results of IV adjusted quadratic OLS is in the Table 10, Appendix J. About the explanation of the specification of IV is in the Appendix K. In the brackets are the standard errors, the difference of standard errors is showing by between columns (1), (3) and (5), and columns (2), (4) and (6). I use columns (1) and (2) as baseline of ordinary standard errors, columns (3) and (4) are adjusted by robust standard errors, columns (5) and (6) are adjusted by cluster-robust standard errors.

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

From $Equation\ 5$, we can calculate the turning point. However, before calculating the turning point, we have another issue to solve. Because of avoiding the multicollinearity, I standardized the size or dimension of the variable of the quadratic term of migrant share. This leads to a decrease of the mean of the quadratic term from 0.0397 to zero and the standard deviation increase from 0.09 to 1. Therefore, the coefficient of ms_sq has been standardized either, moreover, if we use it to calculate the turning point will be biased , also when calculating the marginal effect in the non-linearity estimation.

In principle, we need to de-normalize the coefficient of ms_sq. By Frieman, Saucie and Miller mentioned in 2017, we can denormalized the standardized coefficient, which using the standardized coefficient of the variable (ms_sq) divided by standard deviation of the variable (ms_sq), then minus the mean of the original value of the variable (ms_sq) to have the true value. Therefore, if simply using OLS estimation, the turning point is 0.1085, therefore, in this case, it means that after the migrant share at 10.85%, the marginal impact of immigration on the wages of native labour varies from negative to positive. After using IV estimation to dealing with endogenous problem and looking into where is the turning point and tendency overall, the turning point is 0.2782, which means the true turning point is at 27.82%. The graphs of the quadratic term estimation for OLS and IV are shown below (Graph 1 and 2).

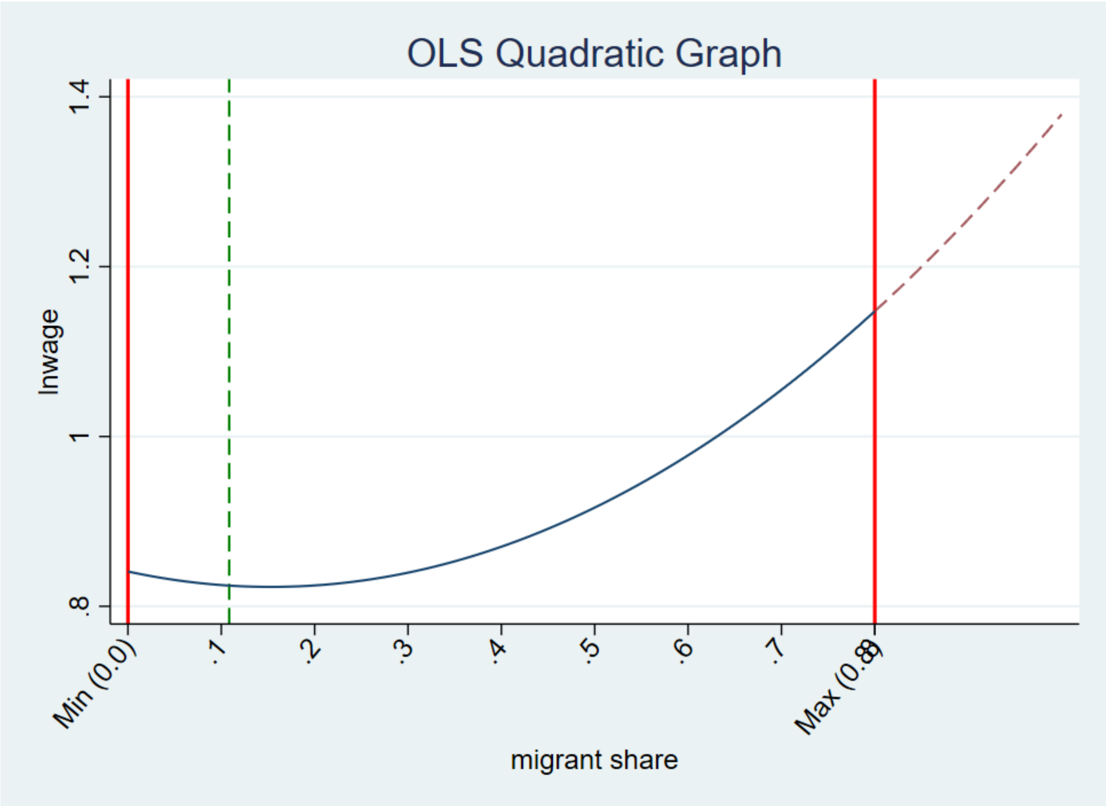


Figure 1 OLS Quadratic Estimation

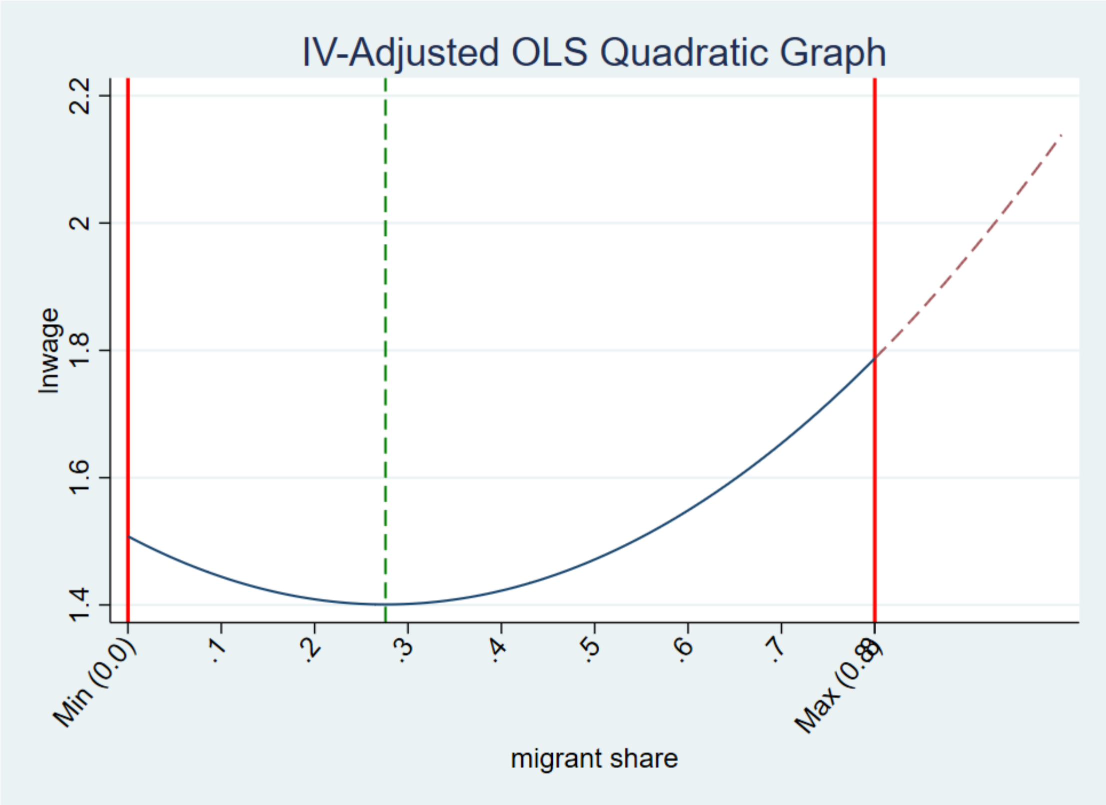


Figure 2 IV Quadratic Estimation

For ease of viewing, I also marked the minimum and maximum values of the explanatory variable MS in Figures 1 and 2 with solid red lines. Obviously, the turning point calculated in this example is to the right of the mean of the MS. There is a U-shaped relationship, the coefficient of MS is significantly positive, and the turning point occurs near the mean value of MS, so the marginal effects in Figures 1 and 2 show a characteristic of turning from negative to positive. This means that there is a non-linear relationship between MS and $lnwage$, which is mainly manifested in the trend of decreasing first and then increasing the marginal effect, and the relationship between the two is not always monotonically increasing.

We can understand that the emergence of this phenomenon is that the relationship between local labor and foreign labor is no longer alternative or complementary, and a situation of structural compatibility between the two has formed.

The impact of migration on local wage levels is phased. The result is a process of urban labor market adaptation. In the first range of immigration level (in the case where the average proportion of urban immigrants is less than 27.82%), I found that the influx of domestic immigrants hurt the wages of natives. This empirical result supports the first finding in the literature. The degree of employment competition between immigrants and local labor is increasing (Knight & Yueh, 2009). Immigration will lead to an increase in the local labor supply. In a unit time (in my case will be a year), it is difficult for capital inflows and technological development to increase, resulting in a decline in wages.

Around the turning point ($MS = 27.82\%$), the marginal impact, no matter positive or negative, is essentially small. Moreover, the tendency of migrant flow is continuous, it is like growing by a margin (year by year), therefore, when MS gets more, cities are also being developed. Cities would have time to react to the migrant impact or be prepared. This is the second perspective in the supporting literature. We can understand it from the perspective of Leamer & Levinson 1995 and Chiswick et al. in 1992 that external capital found that the labor supply in the region was higher than the demand, and the wage level was lower. The re-influx of capital and the increase in labor demand for enterprises are beneficial to both local labor and immigrants. It is also possible that cities with immigrants in this range have better industrial structures, labor markets, and cities' carrying capacity. The inflow of immigrants in a short period of time, as shown in Card's 1990 research conclusion, has no effect on the inflow of immigrants into cities.

For the case where MS is greater than 27.82%, immigrant laborers find their job counterparts in the labor market where they flow into cities. Even if the labor force may have barriers due to occupation, skills, or education. In the process of adaptation, in the corresponding technical level of the occupation, it will be in healthy competition with the local labor force, and it will be complementary with industry-related occupations (such as babysitting and high-intensity workers). For the case where the proportion of immigrants is greater than 0.323, immigrant laborers find their job counterparts in the labor market where they flow into cities. Even if the labor force may have barriers due to occupation or skills, in the process of adaptation, in the corresponding technical level of the occupation, it will be in healthy competition with the local labor force, and it will be complementary with industry-related occupations (such as babysitting and high-intensity work)(Peri & Sparber 2009, Peri, 2007 and Ortega & Verdugo, 2011).

Conclusion

This article contributes to the literature on the impact of migration share on local economies by investigating migration externalities in Chinese cities. China is an interesting case study, first there is a relatively clear point in time as the beginning of internal migration behavior. Second, urbanization has long been regulated by administrative means, but labor mobility accelerated dramatically in the 2000s, driving urbanization and raising concerns about the potential impact of immigrant inflows on local residents. Therefore, assessing the role of immigration in this process is a critical step in assessing the possible scope of regional and urban policies in China.

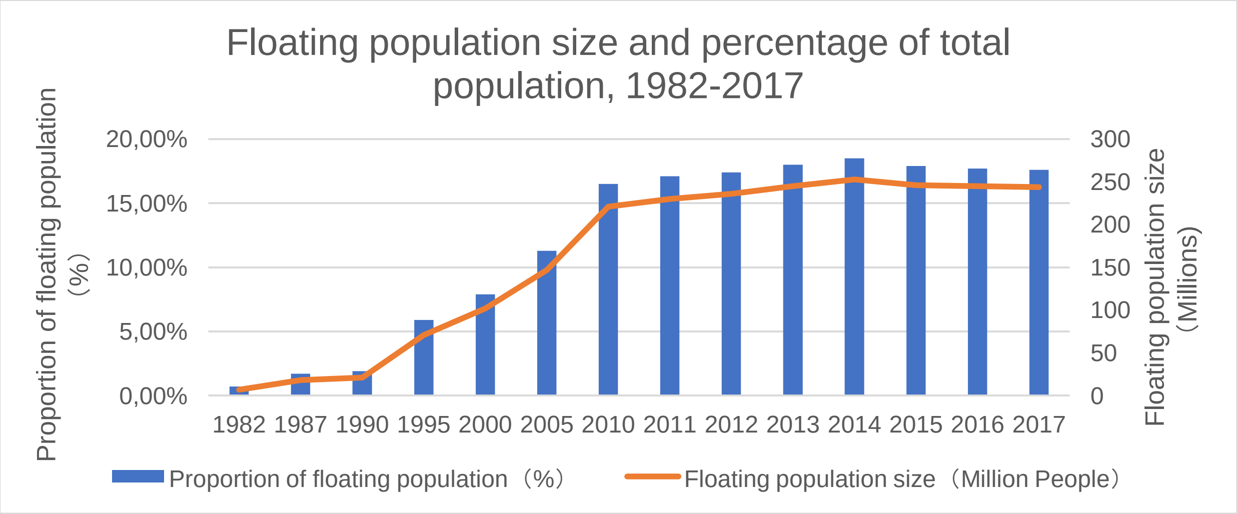
Using CHFP 2017 microeconomic data, we find evidence of a strong positive correlation between the urban share of migrants and the wages of natives. The increase in the wage level of local labor by Chinese domestic immigration shows a trend of increasing by 5.67% for every 10% increase in the wage level of local labor. In addition, I added the quadratic term of the proportion of immigrants to the linear OLS model, and the result is significant, which can prove that the proportion of immigrants has a non-linear relationship with the wage level of the local labor force. From the quadratic IV adjusted OLS model and the results, we can calculate the inflection point of the nonlinear relationship and chart it. When the proportion of immigrants is less than

27.82%, there is a crowd-out effect between immigrant labor and local labor, and immigrant labor will cause the wage level of local labor to drop. However, the result of this side effect is a gradual decrease. When the value is higher than this value, the aggregation effect between immigrants and natives will be more obvious.

My findings on immigration support the hypothesis that immigration brings complementarity, rather than exclusion, to local workers. And this complementary trend exists not only among high-skilled workers but also among low-skilled workers. First, institutional barriers in the labor market remain high, with certain types of work legally restricted to local residents. Second, because migrants have relatively low levels of education on average, which in turn can represent low skill levels, they are "naturally" classified, increasing the productivity of skilled local workers by providing cheap labor to low-skilled sectors. The results show that there is a greater positive effect on skilled locals, while it remains positive on unskilled people. And the positive impact among high-skilled labor is even greater.

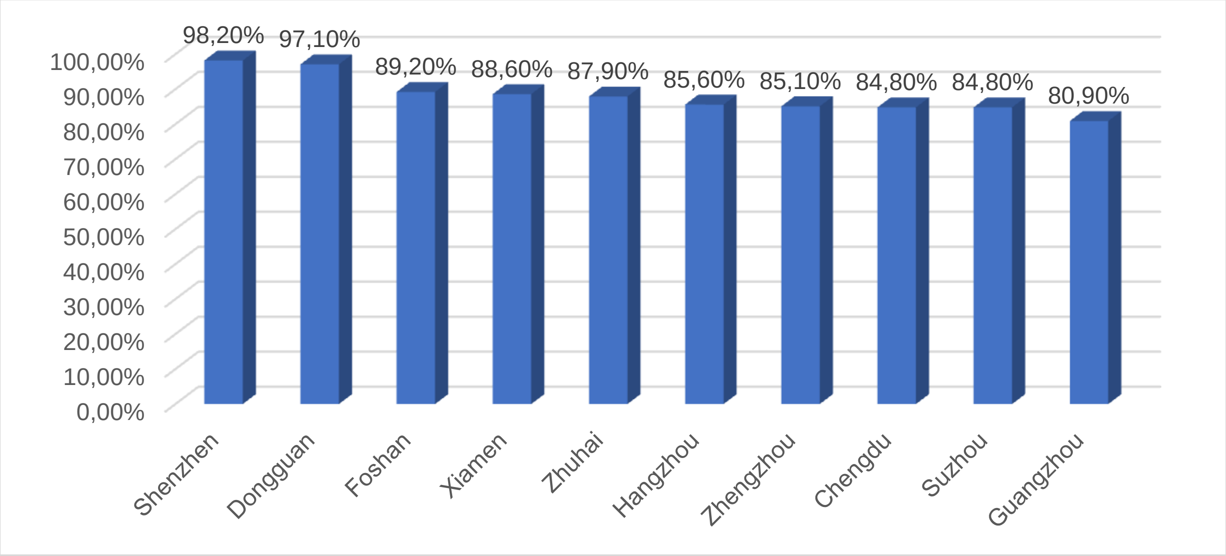
Appendix

Appendix A Floating population size and percentage of total population, 1982-2017



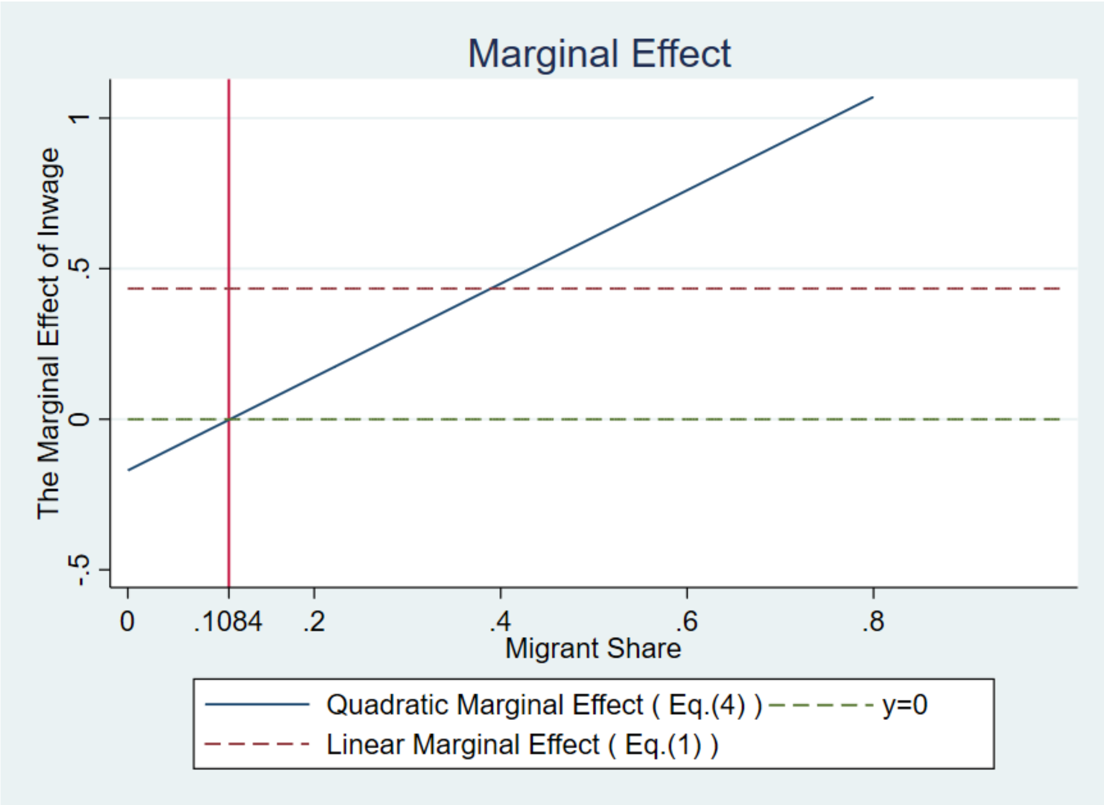
1982-2000, 2010 from national censuses, 2005 from 1% sample survey and 2011-2017 from NBS (National Bureau of Statistics) annual reports.

Appendix B The top ten cities with Migrant Share in 2017



Data from 2017 Chinese City Statistics

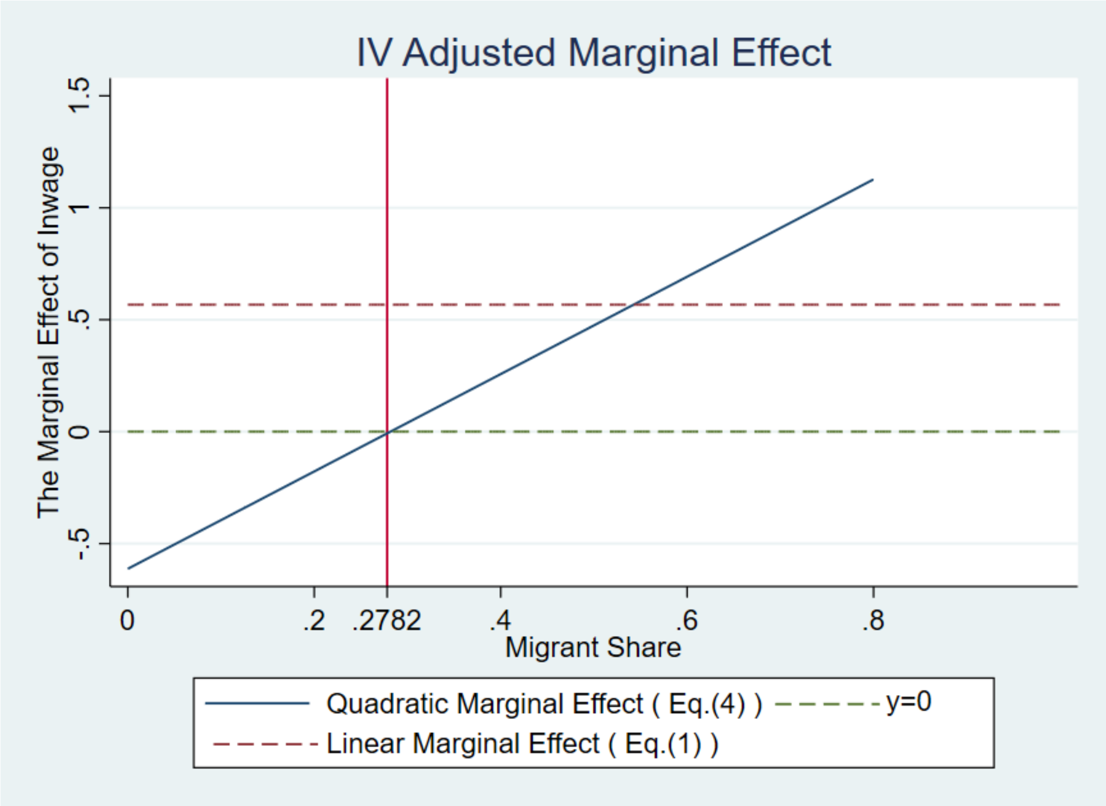
Appendix C the Marginal Effect of OLS Quadratic Function



By the same sprite in the finding turning point part, the marginal effect of OLS is abnormally larger than the quadratic regression results due to my standardized treatment of the quadratic term of migrant share, as an effort to mitigate the multicollinearity problem. The change of the value from its original form to standardized lead to the downward shift of the marginal effect of the quadratic results.

We can clearly find from the image that with the gradual increase in the proportion of immigrants, its marginal effect on the wage level of the local labour force first decreases and then increases. We can also see that the turning point is at 0.1084.

Appendix D the Marginal Effect of IV Adjusted Quadratic Function



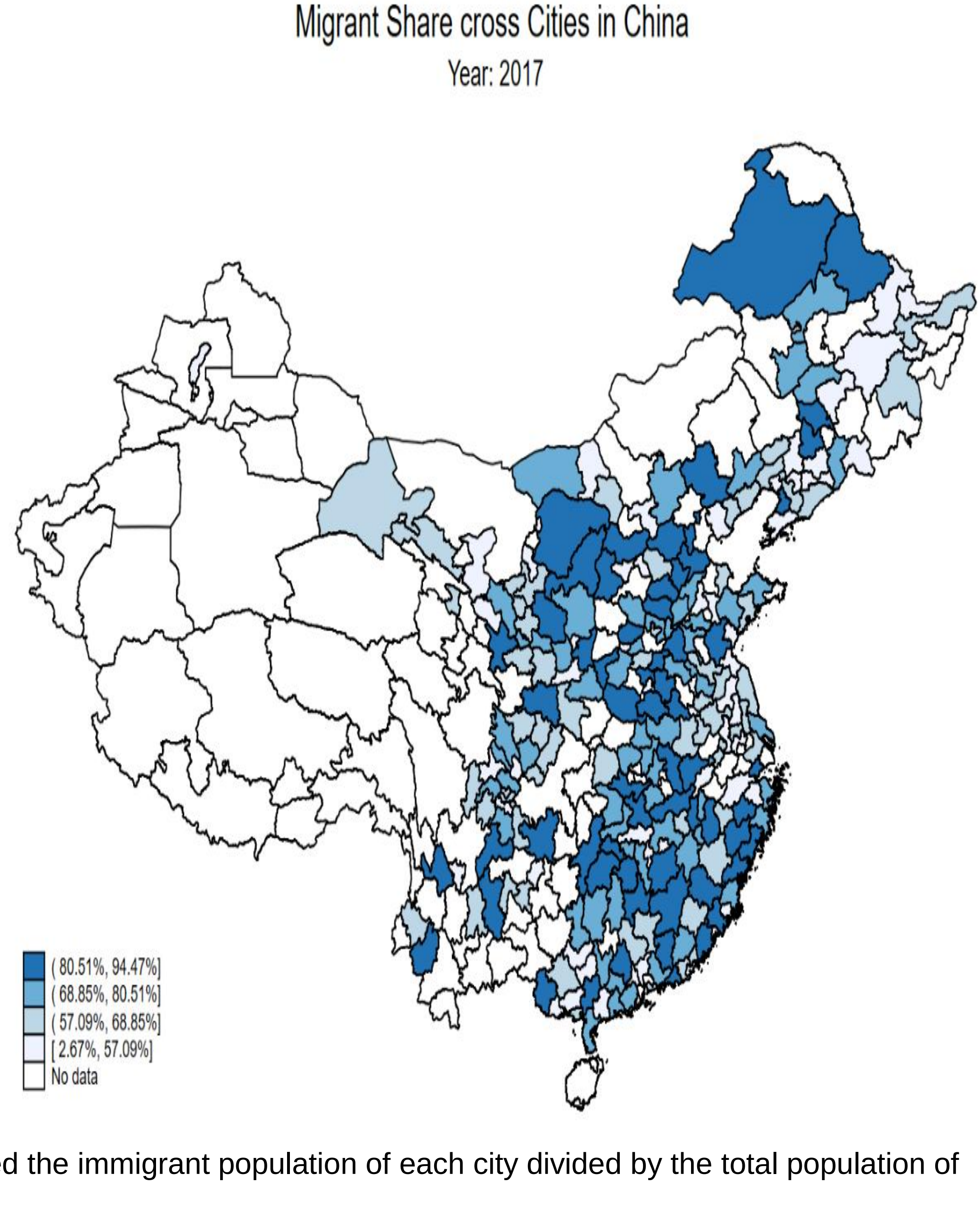
We can clearly find from the image that with the gradual increase in the proportion of immigrants, the turning point changes from 0.1084 to 0.2782 and consistent with U-shape relationship between $lnwage$ and ms.

Appendix E Data cleaning process

20736 observations were obtained after preliminary data clean, which samples are limited to the working-age population and have not obtained employment status and have no salary. The sample was first restricted to 17814 after dropping the observations with missing city identification. And then reduced to 10603 after merging with the city level control variables. Finally, we drop the samples with an unknown migrant status, and this makes our final sample at

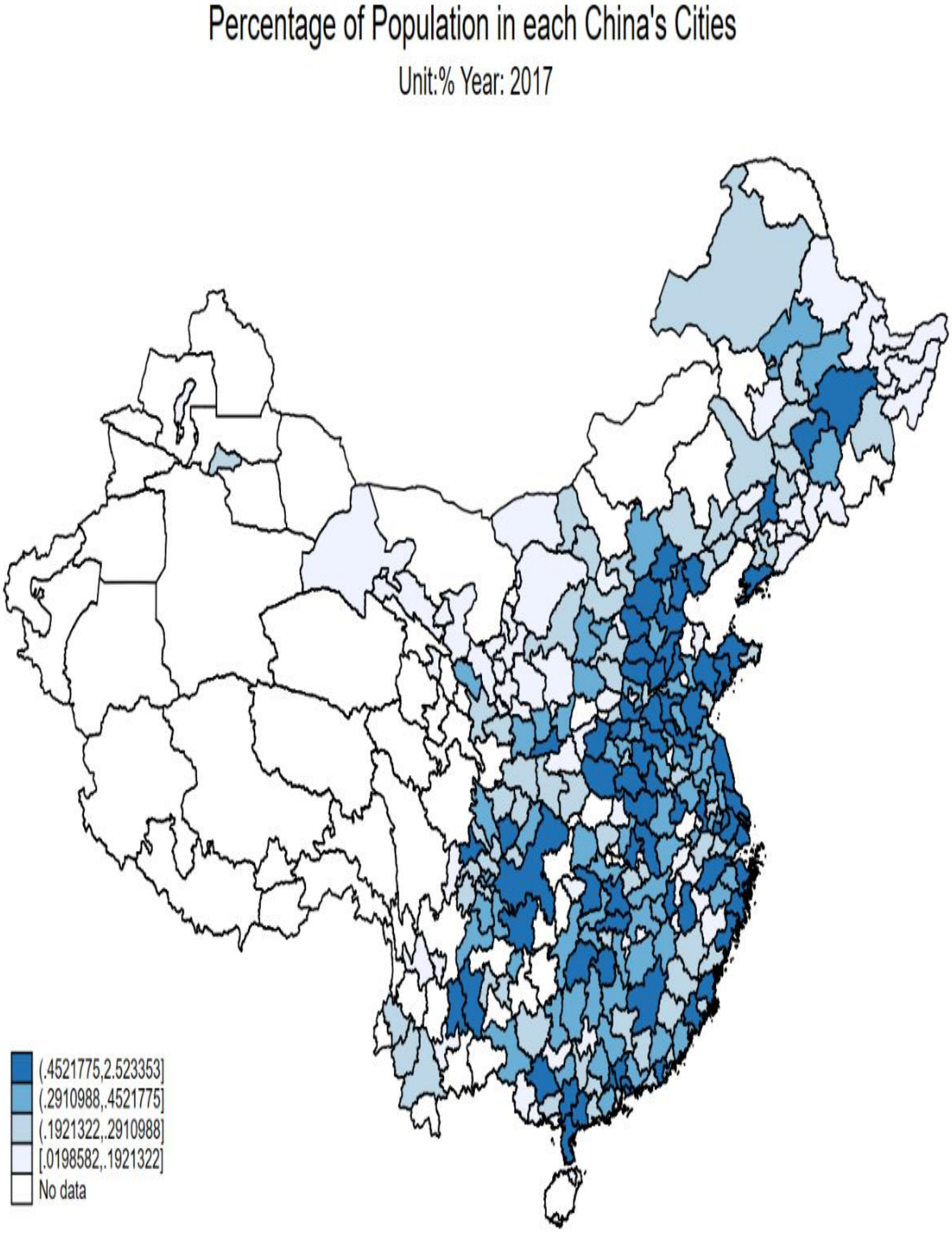
8066 observations.

Appendix F Migrant Share Cross Cities in China



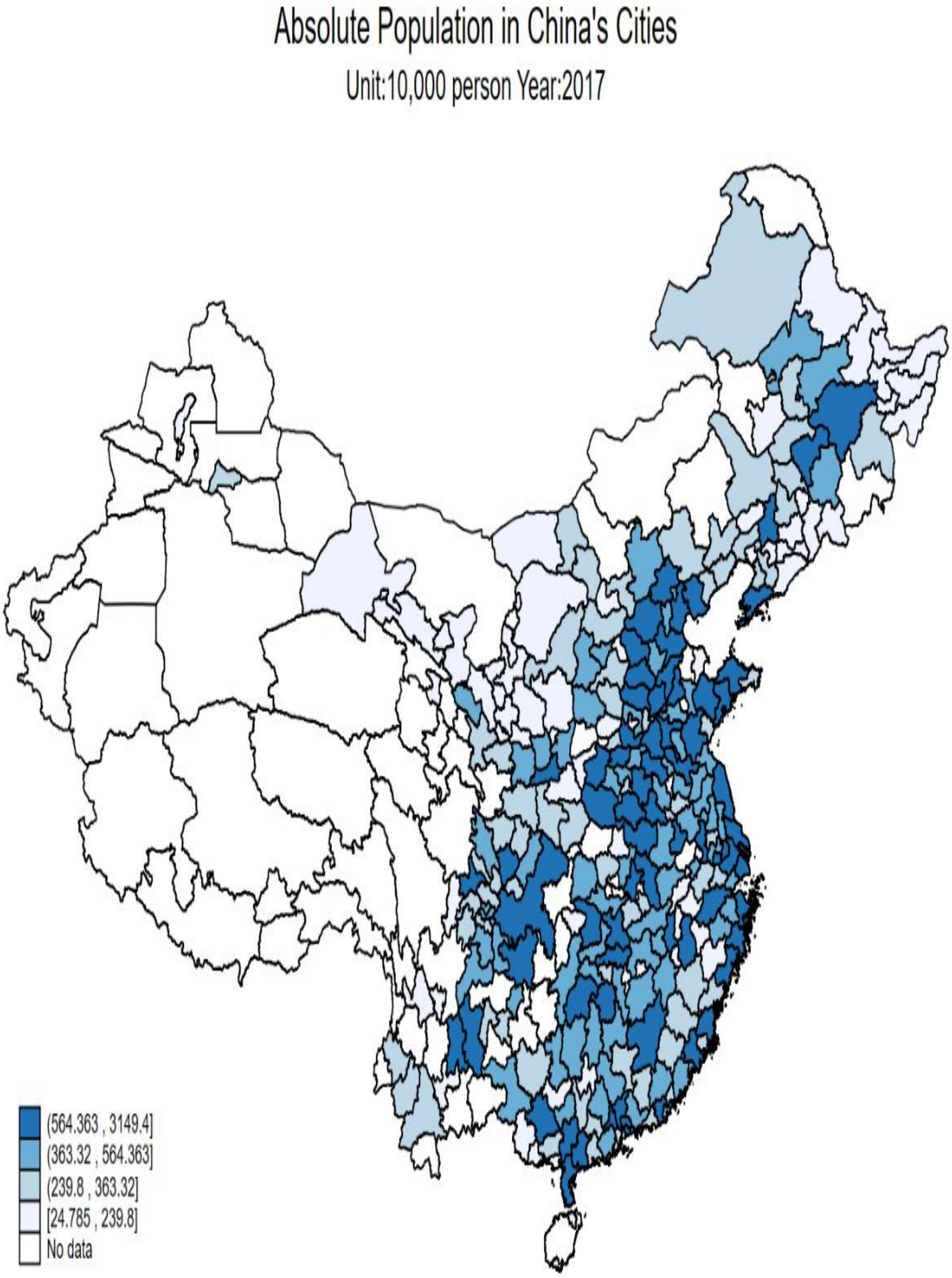
I used the immigrant population of each city divided by the total population of each city to calculate the proportion of immigrants in each city at the city level and marked it on the map of China through colour blocks by different colours, and the unit is percentage.

Appendix G China's cities as a percentage of the total population



Obtained by dividing the total population of each city in 2017 by the total population of China in 2017 and the unit is percentage.

Appendix H China's cities as a percentage of the total population



Obtained by dividing the total population of each city by the area of each city's municipal district and the unit is 10000 people per km.

Appendix I First stage result of IV Estimation

Table 9 First stage regression for instrumented regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	IV_First	IV_First	IV_First _R	IV_First _R	IV_First _R_C	IV_First _R_C
VARIABLES	ms	lnpd	ms	lnpd	ms	lnpd
educ	-0.001	0.008***	-0.001	0.008***	-0.001**	0.008***
	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)	(0.003)
male	0.004**	-0.014	0.004**	-0.014	0.004	-0.015
	(0.002)	(0.013)	(0.002)	(0.013)	(0.003)	(0.013)
exp	-0.001**	0.008***	-0.001**	0.008***	-0.001**	0.008***
	(0.000)	(0.003)	(0.000)	(0.003)	(0.001)	(0.003)
expsq	0.000	-0.000**	0.000	-0.000**	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
marriage	0.013***	-0.042*	0.013***	-0.042*	0.012***	-0.043*
	(0.004)	(0.023)	(0.004)	(0.023)	(0.004)	(0.024)
lnpubexp	0.096***	0.207***	0.096***	0.207***	0.096***	0.207***
	(0.007)	(0.042)	(0.007)	(0.043)	(0.014)	(0.077)
lnexpst	0.077***	0.072***	0.077***	0.072***	0.077***	0.072***
	(0.002)	(0.011)	(0.002)	(0.010)	(0.003)	(0.025)
lnexpedu	0.053***	-0.144***	0.053***	-0.144***	0.053***	-0.143**
	(0.006)	(0.038)	(0.007)	(0.045)	(0.012)	(0.071)
lnfixedasset	-0.163***	0.108***	-0.163***	0.108***	-0.163***	0.108***
	(0.003)	(0.017)	(0.004)	(0.017)	(0.007)	(0.022)
occ1	-0.002	-0.022	-0.002	-0.022	-0.002	-0.023
	(0.006)	(0.038)	(0.006)	(0.042)	(0.004)	(0.056)
occ2	-0.005	-0.071***	-0.005	-0.071***	-0.005	-0.071**
	(0.004)	(0.024)	(0.004)	(0.027)	(0.005)	(0.034)
occ3	0.001	-0.052**	0.001	-0.052*	0.001	-0.053
	(0.004)	(0.024)	(0.004)	(0.027)	(0.004)	(0.036)
occ4	-0.008*	-0.047*	-0.008*	-0.047*	-0.008	-0.047
	(0.004)	(0.024)	(0.004)	(0.027)	(0.005)	(0.034)
occ5	-0.010	-0.155***	-0.010	-0.155***	-0.010*	-0.157***
	(0.010)	(0.058)	(0.010)	(0.057)	(0.005)	(0.060)
occ6	-0.003	-0.063***	-0.003	-0.063**	-0.003	-0.063*
	(0.004)	(0.024)	(0.004)	(0.027)	(0.004)	(0.033)
occ7	0.002	-0.160	0.002	-0.160	0.002	-0.159**
	(0.033)	(0.196)	(0.034)	(0.149)	(0.034)	(0.068)
lmin_dis	0.016***	-0.010***	0.016***	-0.010***	0.016***	-0.010*
	(0.001)	(0.004)	(0.001)	(0.002)	(0.001)	(0.005)
historical	0.049***	-0.054***	0.049***	-0.054***	0.049***	-0.053**
	(0.003)	(0.016)	(0.004)	(0.014)	(0.005)	(0.022)

structure_90	-0.074***	-0.286***	-0.074***	-0.286***	-0.074***	-0.288***
	(0.003)	(0.018)	(0.003)	(0.016)	(0.005)	(0.026)
lndoc_1990	0.005**	0.182***	0.005**	0.182***	0.005	0.182***
	(0.003)	(0.015)	(0.002)	(0.015)	(0.004)	(0.027)
Constant	-0.181***	2.765***	-0.181***	2.765***	-0.179**	2.753***
	(0.046)	(0.274)	(0.049)	(0.265)	(0.090)	(0.319)
Observations	8,066	8,066	8,066	8,066	8,066	8,066

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix J First stage result of IV Quadratic Estimation

VARIABLES	(1) IV_FIRST ms_sq	(2) IV_FIRST lnpd	(3) IV_FIRST ms	(4) IV_FIRST_R ms_sq	(5) IV_FIRST_R lnpd	(6) IV_FIRST_R ms	(7) IV_FIRST_R_C ms_sq	(8) IV_FIRST_R_C lnpd	(9) IV_FIRST_R_C ms
educ	-0.001**	0.008***	-0.001	-0.001**	0.008***	-0.001	-0.001*	0.008**	-0.001
	(0.003)	(0.002)	(0.000)	(0.003)	(0.002)	(0.000)	(0.007)	(0.005)	(0.001)
male	0.031**	-0.013	0.004**	0.031**	-0.013	0.004**	0.031**	-0.013	0.004*
	(0.016)	(0.013)	(0.002)	(0.016)	(0.013)	(0.002)	(0.014)	(0.012)	(0.002)
exp	-0.002**	0.007***	-0.001**	-0.002	0.007***	-0.001**	-0.002*	0.007*	-0.001
	(0.003)	(0.003)	(0.000)	(0.003)	(0.003)	(0.000)	(0.008)	(0.004)	(0.001)
expsq	-0.000	-0.000**	0.000	-0.000	-0.000**	0.000	-0.000	-0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
marriage	0.077***	-0.045*	0.012***	0.077***	-0.045**	0.012***	0.077*	-0.045	0.012
	(0.029)	(0.023)	(0.004)	(0.028)	(0.023)	(0.004)	(0.056)	(0.030)	(0.008)
lnpubexp	1.130***	0.227***	0.101***	1.130***	0.227***	0.101***	1.130*	0.227	0.101
	(0.052)	(0.043)	(0.007)	(0.060)	(0.044)	(0.007)	(0.654)	(0.390)	(0.067)
lnexpst	0.451***	0.057***	0.074***	0.451***	0.057***	0.074***	0.451***	0.057	0.074***
	(0.014)	(0.011)	(0.002)	(0.012)	(0.012)	(0.002)	(0.120)	(0.103)	(0.016)
lnexpedu	0.169***	-0.202***	0.044***	0.169***	-0.202***	0.044***	0.169	-0.202	0.044
	(0.049)	(0.040)	(0.007)	(0.039)	(0.048)	(0.006)	(0.359)	(0.407)	(0.052)
lnfixedasset	-1.230***	0.153***	-0.157***	-1.230***	0.153***	-0.157***	-1.230***	0.153	-0.157***
	(0.023)	(0.019)	(0.003)	(0.037)	(0.020)	(0.004)	(0.420)	(0.174)	(0.043)
lmin_dis	0.041***	0.043***	0.026***	0.041***	0.043***	0.026***	0.041*	0.043*	0.026*
	(0.016)	(0.013)	(0.002)	(0.014)	(0.013)	(0.002)	(0.146)	(0.122)	(0.019)
historical	-0.017*	-0.049***	0.050***	-0.017*	-0.049***	0.050***	-0.017*	-0.049*	0.050*
	(0.020)	(0.016)	(0.003)	(0.029)	(0.014)	(0.004)	(0.04)	(0.03)	(0.040)
structure_90	-0.295***	-0.167**	-0.087***	-0.295***	-0.167**	-0.087***	-0.295*	-0.167*	-0.087*
	(0.092)	(0.075)	(0.013)	(0.077)	(0.081)	(0.011)	(0.170)	(0.131)	(0.099)

lndoc_1990	0.059***	0.186***	0.006**	0.059***	0.186***	0.006***	0.059*	0.186**	0.006*
	(0.019)	(0.015)	(0.003)	(0.014)	(0.015)	(0.002)	(0.051)	(0.046)	(0.020)
lmin_dis_sq	0.201***	-0.132***	-0.024***	0.201***	-0.132***	-0.024***	0.201*	-0.132*	-0.024*
	(0.037)	(0.030)	(0.005)	(0.033)	(0.033)	(0.005)	(0.159)	(0.071)	(0.049)
structure_90_sq	-0.152***	-0.044**	0.008	-0.152***	-0.044**	0.008	-0.152*	-0.044*	0.008*
	(0.041)	(0.033)	(0.006)	(0.034)	(0.032)	(0.005)	(0.152)	(0.163)	(0.046)
occ1	-0.032	-0.026	-0.003	-0.032	-0.026	-0.003	-0.032	-0.026	-0.003
	(0.047)	(0.038)	(0.006)	(0.047)	(0.041)	(0.006)	(0.059)	(0.071)	(0.008)
occ2	-0.038	-0.072***	-0.005	-0.038	-0.072***	-0.005	-0.038	-0.072	-0.005
	(0.030)	(0.024)	(0.004)	(0.030)	(0.027)	(0.004)	(0.039)	(0.054)	(0.006)
occ3	0.011	-0.052**	0.001	0.011	-0.052*	0.001	0.011	-0.052	0.001
	(0.029)	(0.024)	(0.004)	(0.030)	(0.027)	(0.004)	(0.039)	(0.064)	(0.005)
occ4	-0.052*	-0.048*	-0.008*	-0.052*	-0.048*	-0.008*	-0.052	-0.048	-0.008
	(0.030)	(0.024)	(0.004)	(0.029)	(0.027)	(0.004)	(0.043)	(0.063)	(0.006)
occ5	-0.101	-0.158***	-0.010	-0.101	-0.158***	-0.010	-0.101	-0.158	-0.010
	(0.072)	(0.058)	(0.010)	(0.074)	(0.056)	(0.010)	(0.085)	(0.097)	(0.011)
occ6	-0.025	-0.066***	-0.004	-0.025	-0.066**	-0.004	-0.025	-0.066	-0.004
	(0.030)	(0.024)	(0.004)	(0.028)	(0.027)	(0.004)	(0.045)	(0.068)	(0.007)
occ7	-0.160	-0.160	0.003	-0.160	-0.160	0.003	-0.160	-0.160	0.003
	(0.240)	(0.196)	(0.033)	(0.198)	(0.150)	(0.033)	(0.204)	(0.185)	(0.033)
Constant	-4.138***	2.244***	-0.244***	-4.138***	2.244***	-0.244***	-4.138***	2.244***	-0.244**
	(0.363)	(0.296)	(0.050)	(0.358)	(0.309)	(0.049)	(0.371)	(0.263)	(0.057)
Observations	8,066	8,066	8,066	8,066	8,066	8,066	8,066	8,066	8,066

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix K The Specifications of 2SLS Model

Regarding the specification of the instrumental variable method, we need to pass three tests, namely the under-identification test, the weak identification test and over-identification test.

The under-identification test is a Lagrange Multiplier (LM) test of whether the equation is identified, i.e., that the excluded instruments are "relevant", meaning correlated with the endogenous regressors. The test is essentially the test of the rank of a matrix: under the null hypothesis that the equation is under-identified. The null hypothesis H_0: IV(s) and endogenous variables are not correlated. The two-stage estimation results show that the p-value for this test is 0.0122, thus rejecting the null hypothesis that IV and endogenous variables are not correlated at the 5% significance level. This test verifies the existence of weak instrumental variables to a certain extent, but it cannot replace the test of weak instrumental variables. Therefore, it brings the second specification which is Weak Identification.

The Weak identification test gives the Cragg-Donald Wald F-statistics along with the critical value (when it is greater than 10, which is also the minimising value), which is given by the study of Stock and Yogo (2005). In the above estimation results, the Cragg-Donald Wald F statistic exceeds the minimum critical value, so my instrumental variables are detected by weak instrumental variables,

Because in my 2SLS regression, I have four instrument variables which is more than number of endogenous variables (which is two), therefore, I need to run over-identification. The premise of the over-identification test is that there are at least as many valid instrumental variables as there are endogenous explanatory variables. The null hypothesis for over-identification is H_0: all instrumental variables are exogenous, and the intuitive idea is to test whether the IV estimators produced by different combinations of instrumental variables converge to the same value. The over-identification test showing Hansen J p-value is 0.0122 (linear) and 0.0348 (quadratic) at second stage after cluster-robust standard error, which is significant at 5% level. It means that instrumental variables are not over-identified in this case.

Appendix L The Quadratic term IV

Compared with traditional OLS models, one obvious difference lies in the addition of quadratic form. It will make our instrument estimation a little different since it's a nonlinear term. However, our model is still a linear one despite the nonlinearity of the quadratic form. This makes our estimation process, both the first and second stage, remain the same and the traditional econometric theory is still applicable in this related part. Based on this fact, I add the corresponding quadratic terms of instrument variables as the new instrument variables and rerun the previous codes to get the unbiased coefficients of the quadratic term.

Appendix M The Quadratic Estimation Technique

Compared with traditional OLS models, one obvious difference in my research lies in the inclusion of a quadratic term. It will make our instrument estimation a little different since it's a nonlinear term. However, our model is still a linear one despite the nonlinearity of the quadratic form. The process is the same as the ordinary linear process.

That is to solve the following formula:

$$\operatorname{argmin} \sum_{i=i}^{n} (lnwage_{i,c}^{native} - \beta_0 - \delta_1 * MS_c - \delta_2 * MS_c^2 - \beta_1 * X_{i,c} - \beta_2 * City_c - \sum_{i=1}^{7} \gamma_i occ_i)^2$$

we generalize the above formula as the following:

$$\mathrm{Y} = \mathbf{X\beta} + MS_c^2\gamma + \mathrm{e}$$

Where X is a vector including all the independent variables other than the quadratic term in my research. We can thus rewrite the formula in this form:

$$\mathrm{Y} = \mathbf{Z\delta} + \mathrm{e}$$

Where Z is a vector that combines all the independent variables and $\boldsymbol{\delta}$ a new vector that combines $\boldsymbol{\beta}$ and γ. Based on the OLS estimation, we can get the estimated results of the coefficients as:

$$\widehat{\boldsymbol{\delta}} = (Z^T Z)^{-1} Z^T Y$$

In this process, we treat the quadratic as a whole and take it as a common linear term in the estimation progress. The estimated results of the coefficients are thus unbiased and consistent. It also makes our estimation process, both the first and second stage, remain the same and the traditional econometric theory is still applicable in this related part. Based on this fact, I add the corresponding quadratic terms of instrument variables as the new instrument variables and rerun the previous codes to get the unbiased coefficients of the quadratic term.

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