

## Urbanisation and Migration Externalities in China

Pierre-Philippe Combes  
Sylvie Démurger  
Shi Li

WP 2013 - Nr 07

# Urbanisation and Migration Externalities in China\*

Pierre-Philippe Combes<sup>†</sup>      Sylvie Démurger<sup>‡</sup>      Shi Li<sup>§</sup>

February 6, 2013

## Abstract

We evaluate the role that cities play on individual productivity in China. First, we show that location explains a large share of nominal wage disparities. Second, even after controlling for individual and firms characteristics and instrumenting city characteristics, the estimated elasticity of wage with respect to employment density is about three times larger than in Western countries. Land area and industrial specialisation also play a significant role whereas the access to external markets does not. Therefore, large agglomeration economies prevail in China and they are more localised than in Western countries. Third, we find evidence of a large positive impact of the local share of migrants on local workers' wages. Overall, these results strongly support the productivity gains that can be expected from further migration and urbanisation in China.

**JEL Codes:** O18, R12, R23, J31, O53.

**Keywords:** urban development; agglomeration economies; wage disparities; migration; China.

---

\*We are very grateful to Matt Turner for his help with maps and to Nancy Qian for sharing her historical data. We thank Jane Golley, John Knight, Florian Mayneris, Xin Meng, Mark Partridge, Sandra Poncet and Jacques-François Thisse for their useful comments on earlier versions of the paper. Any remaining mistakes are our own. This paper is part of the French ANR research programs 'Gender and Ethnic Discrimination in Markets: The Role of Space' and 'Globalization and Governance'. Combes and Démurger are researchers at CNRS whose financial support is gratefully acknowledged.

<sup>†</sup>Aix-Marseille University (Aix-Marseille School of Economics), CNRS & EHESS 2, Rue de la Charité 13236 Marseille cedex 2, France. Email: ppcombes@univmed.fr.

<sup>‡</sup>Université de Lyon, Lyon, F-69007, France; CNRS, GATE Lyon Saint-Etienne, 93 Chemin des Mouilles, Ecully, F-69130, France. Email: demurger@gate.cnrs.fr.

<sup>§</sup>School of Economics and Business Administration, Beijing Normal University, China. Email: lishi@bnu.edu.cn.

## Introduction

The 6th National Population Census conducted in China in November 2010 portrayed a rapidly urbanising country, with the urban population reaching 49.7%, an increase of 13.5 percentage points compared to the 2000 Census. A large share of this above-expectation increase comes from the massive rural-to-urban migration that dramatically accelerated in the 2000s<sup>1</sup>, in sharp contrast with strictly controlled population mobility prevailing in earlier decades. Urbanisation in China has long been highly regulated, in part by means of policies that limited rural-to-urban migration through the dual urban-rural resident system of the *Hukou*, a distinctive feature that imposes strong administrative barriers to migration. Restrictive policies towards urbanisation translated into a relatively low urbanisation rate and the dominance of small or medium-sized cities over large cities (Xu, 2009). Unlike many developing countries that experienced a rapid urbanisation process, China successfully avoided many problems associated with the development of mega-cities, including slums, urban poverty, criminality, and social unrest. However, the restrictive policy towards urbanisation also came at a cost, in terms of capturing the benefits from urban agglomeration. In a recent report, Henderson (2009) argued that there were ‘too many cities with too few people’, with China lacking cities of 1-12 million inhabitants. In 2007, only 3 out of 286 prefecture-level cities had more than 10 million inhabitants, 10 had 5-10 million inhabitants, 39 had 2-5 million inhabitants and 118 had 1-2 million inhabitants (National Bureau of Statistics, 2008). With one billion people expected to live in Chinese cities by 2030, the country now faces extremely challenging policy choices in the management of the expanding urban population, the provision of adequate urban infrastructure and public services, and the securing of public safety and social stability. Yet, the unprecedented pace and scale of urbanisation can also be seen as an opportunity to sustain economic growth by capturing agglomeration economies. This paper aims at assessing the magnitude of such productivity gains from agglomeration and the role migration plays in the process.

The standard explanation provided by economic geography for the positive impact of urban scale on labour productivity is based on a series of agglomeration effects including pure knowledge spillovers, the sharing of inputs, and the pooling of the labour force<sup>2</sup>. Though negative outcomes of agglomeration are often stressed, the empirical literature generally concludes, from Ciccone and Hall (1996), to a positive overall impact of the size of the local economy on local productivity. Yet, most empirical studies focus on developed countries, and somewhat surprisingly, there is very little evidence on the magnitude of agglomeration economies for developing countries, though many of them are witnessing dramatic changes in

---

<sup>1</sup>Rural migrant workers are estimated at 153 million in 2010, a rough doubling over the decade.

<sup>2</sup>See Duranton and Puga (2004) for a thorough review on the micro-foundations of these effects.

economic growth and regional inequality.

This paper contributes filling the gap by testing the presence of agglomeration economies in China. The following research questions are empirically explored: What is the magnitude of the gains from concentrating economic activities over space in China? To what extent does internal migration contribute to these effects through a separate impact on local residents' productivity? To answer these questions, the separate role of the city density, land area, industrial specialisation and diversity, access to other cities and city share of migrants on wage differentials across urban workers is estimated.

We proceed in three steps. We first introduce city-level fixed effects and some other localisation effects in a standard individual wage equation and assess their relative explanatory power; we then explain these fixed effects by incorporating city-level characteristics into the analysis; we finally incorporate in the model an externality arising from rural migration. As detailed in Combes, Mayer and Thisse (2008a), the estimation of agglomeration economies raises a number of specific methodological issues, which we consider here. First, workers may sort spatially depending on personal characteristics (e.g. their abilities), which generally affects their labour outcome. If this is the case, it may be difficult to identify separately the role of agglomeration economies and the role of the workers' characteristics on their wage. As pioneered by Glaeser and Maré (2001) and generalized by Combes, Duranton and Gobillon (2008b), the literature suggests to use individual data to address the issue, a strategy we follow here. Second, the estimation of agglomeration economies is almost inevitably plagued by a reverse causality bias. Large locations increase the productivity of firms, and therefore workers' wages, but higher productivity and wages also attract more firms and more people (if they are sufficiently mobile) in cities, which in turn increases the city size. This issue is addressed in the paper through an instrumentation strategy detailed in section 2.3.

Few contributions on China relate to our approach. Au and Henderson (2006) and Xu (2009) estimate agglomeration economies on real output per worker, while Hering and Poncet (2010) structurally estimate an economic geography model through trade and wage equations. Using aggregate data for 205 prefecture-level cities in 1997, Au and Henderson (2006) estimate a bell-shaped function of real output per worker against city scale and conclude that more than half of the cities in their sample are significantly undersized. In a similar vein, Xu (2009) uses a panel of 155 Chinese cities from 1990 to 1997 and finds clear evidence of agglomeration effects, the optimal city size being estimated at four to five million persons. However, the use of aggregate data prevents both papers from addressing the possible selection bias due to the presence of more skilled workers in cities or the fact that while firm productivity gains in cities directly translate into wages in a perfectly competitive setting, it may not be the case in China. Using individual wage data, as done here, enlarges identification possibilities and clarifies the direction of causalities. Hering and Poncet (2010) use individual data for the

year 1995 but they focus on the impact of aggregate market access and do not specifically study the role of cities. Furthermore, all the aforementioned papers use data from the mid-1990s<sup>3</sup>. Over the last decade, China has been experiencing both huge growth rates and institutional changes, typically regarding mobility that is at the heart of the phenomenon we study. Both may have significantly affected the distribution of economic activities and its impact on local economic outcomes, wage inequality among others. By using data for the year 2007, we provide an updated overview of the determinants of spatial wage inequality and we simultaneously assess the specific impact of migration on local productivity, which none of the above-mentioned papers do. Regarding the latter point, Meng and Zhang (2010) is the only paper we found that tries to specifically evaluate the impact of urban migrants on natives' labour market outcomes in China but it does not emphasise the geographical dimension of local labour markets (e.g. role of local employment density, area and market access). Section 2 provides a comparison of the different strategies used in the literature and highlights our original approach to specify the simultaneous impact of both geography and migration.

We find that location matters for productivity in China. Being located in a twice-denser city increases wage by 8.7%, even after controlling for individual and firms characteristics and instrumenting city characteristics. This is about three times larger than what is usually estimated for Europe or North America with similar specifications. Hence, further productivity gains could result from increasing the size of Chinese cities. Land area and industrial specialisation are also found to play a significant role. Conversely we do not find any robust evidence of an impact of the access to markets outside the city. These findings indicate that agglomeration economies are more localised in China than there are in Western countries: the own-city density matters more, as do own-area and the city specialisation, whereas the size of neighbouring cities matters less. Finally, regarding migration externality, we find evidence of a positive and significant impact of the local share of migrants on local workers' wages, which does not substitute much to other agglomeration gains. For instance, keeping the number of local workers constant, if new migrants move to a city so that their share in total employment jumps from the first quartile (decile respectively) of the distribution across Chinese cities to the last quartile (decile respectively), productivity in the city increases by 10.0% (32.0% respectively). Two-third of the increase result from the externality exerted by migrants and one third results from agglomeration effects induced by the increase in total employment generated by the migrants inflow.

The rest of the paper is organised as follows. Section 1 describes the data sources and provides summary statistics on spatial wage differentials in China in 2007. Section 2 presents

---

<sup>3</sup>Hering and Poncet (2009) study Chinese regional wage differences over a more recent period (1995-2002) in the same framework as Hering and Poncet (2010). However, their analysis relies on province-level data, which deeply reduces the possibility to control for individual characteristics unevenly distributed over space.

the empirical strategy followed in the paper. Sections 3, 4 and 5 discuss the step-by-step econometric results and the estimated magnitude of urbanisation and migration externalities in China. Section 6 concludes.

## 1 Nominal wage dispersion across cities

### 1.1 Data

The data used are drawn from two main complementary sources: 1) individual data extracted from the 2007 Urban Household Survey conducted by the Chinese National Bureau of Statistics (NBS), and 2) city-level data compiled from the annual volume of the *China City Statistical Yearbook* published by the NBS in 2008. Additional data used in sections 4 and 5 come from the 1% 2005 China Population Census and from historical maps.

The raw individual database from the 2007 Urban Household Survey comprises 10,318 households and 30,340 individuals. Only urban *Hukou* holders are surveyed, which excludes an important segment of the urban labour market composed of rural migrants not officially registered in cities. With the number of migrants representing about 17% of China's 1.3 billion people, migrants constitute an important group to be reckoned with, yet clearly marginalized. Lacking the same status as city dwellers, migrant workers face major inequalities in cities. They are denied equal access to public services and to job opportunities; they face poor and unsafe working conditions; and they work primarily in the informal sector (Cai, Park and Zhao, 2008; Démurger, Gurgand, Li and Yue, 2009). Our database being restricted to urban *Hukou* holders only, the observed wage disparities refer to urban residents ('natives') only and one cannot infer that the wage determinants across Chinese cities we identify here would equally apply to migrant workers. Nevertheless, in an effort to assess the possible role of migrants on urban labour productivity, we estimate the externality they exert on local urban workers simultaneously with agglomeration effects, as explained in section 2.2.

Our sample is restricted to individuals aged 16 to 70, who declared working at least part of the year and earning (positive) wages. Owners of private or individual enterprises are excluded because we cannot disentangle wages from profit in their case. Taking into account these restrictions, we are left with 14,590 workers<sup>4</sup>.

The earnings variable is the declared income from wage employment, which includes the basic salary as well as all sorts of bonuses, allowances and subsidies (including housing or medical subsidies), other wages (including overtime wages), and other income from work unit. The main drawback to the NBS data is that no working time is recorded, which does not

---

<sup>4</sup>The discrepancy with the total number of observations in the raw database is primarily explained by the age pyramid and the occupational distribution of the population. In the original database, 53% are working individuals, 19% are retired (mostly above the age of 50), 4% are unemployed or waiting for a job, 20% are students (mostly below the age of 16), and 4% are full-time home-makers or others.

allow us either to separate part-time and full-time workers, or to estimate an hourly wage model. Given this constraint, we focus on total earnings from the work unit reported by wage workers who declared strictly positive annual earnings. To check the robustness of the estimated effects, section 4.2 supplements the analysis with a database for the year 2002 that documents individual working time and thus enables us to compute hourly earnings.

City-level data come from the *China City Statistical Yearbook 2008*. The administrative structure in China comprises four levels. In 2007, the mainland territory was divided into 31 province-level regions (excluding the two Special Administrative Regions, Hong Kong and Macao), 333 prefecture-level regions (including 286 prefecture-level cities), 2,859 county-level regions and 40,813 township-level regions (National Bureau of Statistics, 2008). The 87 spatial entities studied here are prefecture-level cities that can be considered as metropolitan areas by international standards, i.e. the city and suburban districts (excluding counties under the jurisdiction of the city government). Any prefecture has at most one such metropolitan area. Unfortunately, not all provinces in China are represented, but only 16 of them<sup>5</sup>. Yet, Kernel density estimations for the distribution of employment density, respectively for all prefectures in China and for the 87 prefectures of our sample, highlight pretty close distribution patterns, as illustrated in Appendix A. Medium-sized cities tend to be slightly under-represented while very large ones are slightly over-represented. However this should not bias our estimates and, if anything, under the standard assumption of diminishing marginal gains from city size, agglomeration economies should be only underestimated.

## 1.2 Summary statistics

Table 1 reports summary statistics for the prefecture-level cities in our sample. The average size of cities is rather large (2,297 square km), with however important differences across urban areas as reflected in a coefficient of variation of 1.35. The largest metropolitan area is Chongqing municipality (26,041 square km), which also hosts the largest urban population in China (15,3 million). The smallest area in our sample is found in Shanxi province, with a city area of only 147 square km. The average employment density is 414 workers per square km, with again large dispersion across cities. The ratio of the ninth to the first decile is 36.9 and the coefficient of variation equals 1.03. To illustrate this geographical dispersion, Figure 1 maps the distribution of employment density across the 87 prefecture-level cities. Unsurprisingly, denser areas are found in coastal provinces, but Figure 1 also highlights pockets of densely populated (in terms of employment) areas in inland provinces, such as in Shanxi or Hunan provinces.

---

<sup>5</sup>Beijing, Shanxi, Liaoning, Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Henan, Hubei, Hunan, Guangdong, Chongqing, Sichuan, Yunnan and Gansu. In the original NBS survey, four autonomous prefectures, all in Yunnan province, are also included. However, since we do not have any information at the city-level such as area or total employment, for these autonomous prefectures, we exclude them from the analysis.

Figure 1: Employment density in the sampled prefecture-level cities

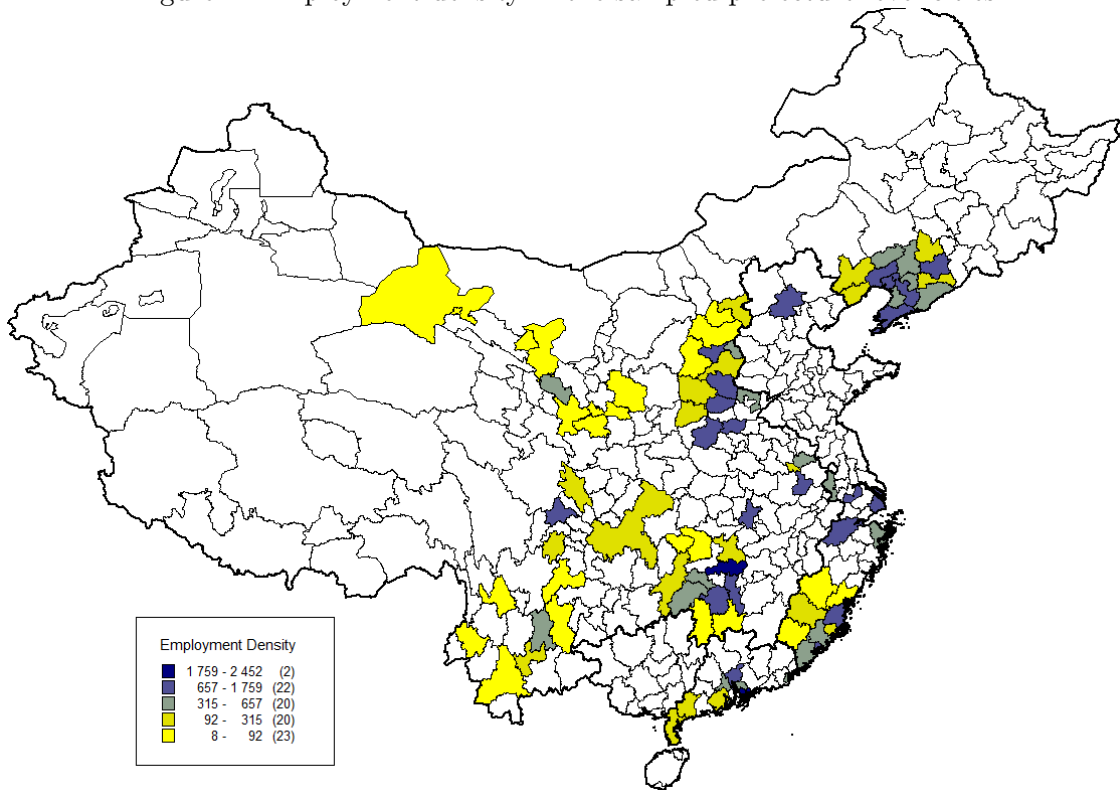


Figure 2: Average wage in the sampled prefecture-level cities

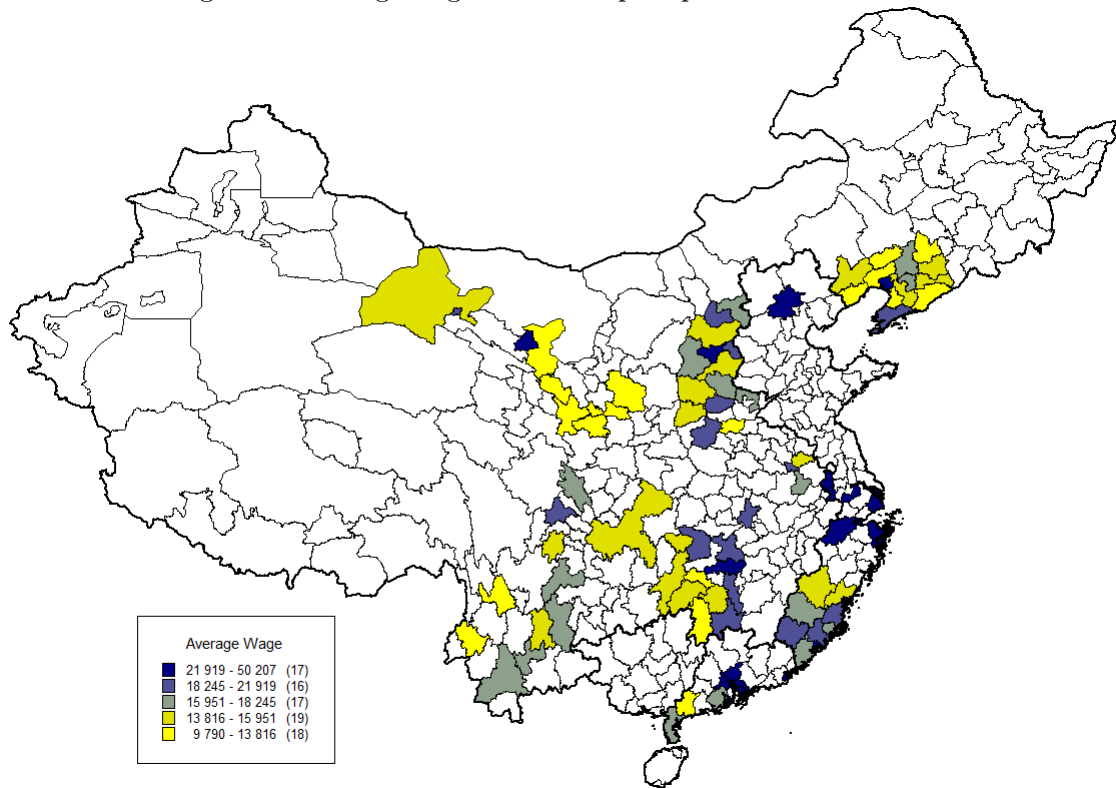




Table 1: Summary statistics for local variables

	Mean	Std. Dev.	p10	p25	p50	p75	p90
Employment density (workers per sq. km)	414.2	426.6	25.44	61.76	315.1	665.0	938.1
log employment density	5.353	1.347	3.236	4.123	5.753	6.500	6.844
Area (sq. km)	2296.8	3098.0	537	835	1623	2718	4225
log area	7.337	0.867	6.286	6.727	7.392	7.908	8.349
Diversity	6.071	1.036	4.553	5.443	6.039	6.840	7.531
log diversity	1.789	0.175	1.516	1.694	1.798	1.923	2.019
Specialisation	0.170	0.0305	0.133	0.146	0.166	0.184	0.220
log specialisation	-1.789	0.175	-2.019	-1.923	-1.798	-1.694	-1.516
Market potential	162875	44600	99812	138752	167345	181594	215843
log market potential	11.96	0.288	11.51	11.84	12.03	12.11	12.28
Distance to seaport	521.5	414.6	82.75	179.2	428.0	721.4	1229.2
log distance	5.619	1.733	4.416	5.189	6.059	6.581	7.114
Migrant share	0.285	0.211	0.0842	0.140	0.208	0.361	0.624
log (1-migrant share) <sup>-1</sup>	0.422	0.540	0.0879	0.150	0.233	0.448	0.978
<i>N</i>	87						

Sources: National Bureau of Statistics (2008); 1% Population Census 2005.

Figure 2 displays the average annual wage at the city-level in 2007 for the 87 cities under study. Huge wage gaps across cities can also be observed, with the ratio of the highest average to the lowest being above 5. Various inequality indicators computed at the city-level confirm the wage gap across cities: the coefficient of variation equals 0.36, and the Gini coefficient is equal to 0.18. In terms of spatial wage distribution, Figure 2 also gives evidence of a clear coastal-inland gap. Higher wages are paid in Guangdong province (especially in Shenzhen, the city that borders Hong Kong, where the average annual earnings is above 50,000 yuan). On the other hand, the lowest wages are paid in inland provinces, such as Wenshan in Yunnan province. As a first insight on possible agglomeration economies in China, a raw comparison between Figure 1 and Figure 2 highlights similarities between the distribution of employment density and the distribution of average wages.

Simple correlations using city-level averages corroborate this observation and reveal a strong correlation between average city-level earnings and either employment density or employment level. The estimated elasticities are respectively of about 0.08 with respect to the former and 0.14 with respect to the latter. As compared to developed countries such as France (Combes et al., 2008b), the estimated unidimensional elasticities for China in 2007 are higher. The explanatory power of employment density is more limited yet (with a  $R^2$  of about 14%

against 51% for France), but it is equivalent for total employment (33% against 34%).

## 2 Empirical strategy

Our general objective is first to evaluate the relative contribution of location as compared to individual characteristics in the explanation of wage differentials across urban workers, and then to determine the factors that shape the location effect. This section presents the framework for the estimation of agglomeration effects, and extends it to introduce a migration externality. It finally reviews the instrumentation strategy we follow to address reverse causality and missing variables issues.

### 2.1 The estimation of agglomeration effects

We start with a simple model that describes our key identification assumptions. Firm  $j$  located in city  $c$  (in a given sector not made explicit here) operates under constant marginal cost (once fixed costs are paid). Its output  $y_j$  is given by:

$$y_j = A_j k_j^\theta \left( \sum_i e_i \ell_i \right)^{1-\theta}, \quad (1)$$

where  $A_j$  is the technology level,  $\ell_i$  is the number of hours worked by worker  $i$ ,  $e_i$  measures worker  $i$ 's efficiency and  $k_j$  inputs other than labour. Under the assumption of competitive markets for final goods and inputs, and once logarithms are taken, the first-order condition for profit maximisation leads to:

$$\log w_i = \log \Phi_{j(i)} + \log e_i, \quad (2)$$

where  $w_i$  is the hourly wage of worker  $i$  and  $\Phi_{j(i)}$  is a wage shifter for firm  $j(i)$  that employs worker  $i$  defined as:

$$\Phi_j \equiv (1 - \theta) \theta^{\theta/(1-\theta)} \left( \frac{p_j A_j}{r_j^\theta} \right)^{1/(1-\theta)}, \quad (3)$$

with  $p_j$  the revenue per unit sold (net of intermediate consumption and trade costs, if any, born on exported units) and  $r_j$  the cost of  $k_j$ .

Equations (2) and (3) summarise the key explanations for higher wages in cities. Labour productivity, which directly translates into nominal wages, is higher in cities where firms benefit from workers with high efficiency  $e_i$ , or from pure knowledge externalities that increase their technology level  $A_j$ . Wages are also higher when the access to final goods markets is good as it implies higher prices net of trade costs  $p_j$ . Finally, wages are higher when the cost

of inputs  $r_j$  other than labour is low<sup>6</sup>.

To get to the estimated specification, we need further assumptions on the determinants of the two right-hand side terms in (2). We assume that worker  $i$ 's efficiency  $e_i$  is a function of a vector of her own personal characteristics  $C_i$ , and the firm  $j$  productivity shifter is a function of both a vector of its own characteristics  $F_j$  and of some local effects. As all possible local effects cannot be identified because of missing data, the literature usually estimates a two-equation specification as follows:

$$\log w_i = C_i a_1 + F_{j(i)} a_2 + L_{c(i)s(j(i))} a_3 + \delta_{c(i)} + \varepsilon_i \quad (4)$$

$$\delta_c = U_c \alpha + \nu_c \quad (5)$$

In a first step, equation (4) isolates the impact of worker  $i$ 's and firm  $j$ 's characteristics on individual productivity from the impact of location. Local effects are captured by both a vector  $L_{cs}$  of agglomeration effects in city  $c$  that are specific to the firm's industry  $s$  (the so-called "localisation effects") and a city fixed effect  $\delta_c$ . The city fixed effect captures both the agglomeration effects that operate between industries in location  $c$  (the so-called "urbanisation effects") and the role of any other local characteristic that affects individual productivity (e.g. local public goods, specific technology or endowment, or local geography).  $\varepsilon_i$  is an individual random component that affects worker  $i$ 's efficiency. In a second step, specification (5) explains the estimated city fixed effect by a vector of observable urbanisation effects,  $U_c$ , which includes employment density.

The vector of individual characteristics that affect productivity,  $C_i$ , includes gender, experience<sup>7</sup>, education and occupation. Within-the-firm experience is sometimes also considered but, unfortunately, such information is not reported in the data set we use. Firm  $j$ 's characteristics,  $F_j$ , include sectoral dummies, which allows us focusing on the spatial variations of productivity only. In the specific case of China, the ownership of firms is another important determinant of workers' wages (Chen, Démurger and Fournier, 2005). We take state-owned enterprises as the reference group, and we add dummy variables for urban collective firms, private or individual firms, and "other" firms (including foreign-owned firms).

As for agglomeration effects,  $L_{cs}$  typically includes the role of the sector local size, measured by the share in the local economy of employment in the firm's sector. A positive impact of such a specialisation variable reflects the presence of localisation economies arising for instance from the sharing of specific inputs or labour skills or from the presence of sector specific knowledge spillovers. Then most agglomeration effects are identified through the second step estimation. The main variable of interest in  $U_c$  is the city employment density. The larger it

---

<sup>6</sup>More than the cost of capital, which generally varies little between various locations in the same country, these effects include the price of land and the cost of intermediate inputs used in production.

<sup>7</sup>We use the actual number of years of work experience, i.e. participation to the labour force, reported in the survey.

is, the stronger technological spillovers, the larger the final goods or inputs markets, the better the matching between firms and workers, all possible reasons for which employment density is expected to positively impact productivity and then wages. However, the effect of density could be also negative if congestion on land or on the local transport network dominates and reduces productivity. Besides employment density, the city land area is also included in  $U_c$ . Whereas density captures the thickness of the location, land area, once density is controlled for, assesses over which land surface such a density effect holds. If agglomeration economies dominate, land area should also have a positive impact on productivity even after controlling for density. Moreover, following Jacobs (1969), one may also expect that a diverse local economic environment can favour innovation and productivity, which is another aspect of urbanisation economies. This intuition is usually captured by introducing the inverse of a sector concentration Herfindhal index, which should as well have a positive impact on productivity.

Beyond the city own characteristics, its location within the network of all other cities may also matter. Typically, if workers do benefit from the density of their own city, they should also benefit, though probably to a lower extent, from the density of neighbouring cities since they most likely interact with them. Economic geography models have emphasised such a role of the access to distant markets. Empirically, it is usually captured by market potential variables. We use the Harris (1954) definition, which simply corresponds to the inverse-distance weighted sum of densities over all Chinese cities other than the city considered. Following Au and Henderson (2006), we add as another control for the proximity to external markets the distance to the closest seaport,<sup>8</sup> which reflects the access to foreign markets. Some studies, as Hering and Poncet (2010) for China, use a structural version of market potential, which makes sense when the purpose is to test whether a particular economic geography model is valid. The specification we choose here allows us to identify separately the specific roles of the city own size, the proximity to other large Chinese cities, and the proximity to foreign markets. Contrary to the assumption made in economic geography models, there are many reasons to think that the access to these three types of markets has a different impact on local productivity. For instance, while at short distance, proximity induces gains from both knowledge spillovers and demand effects, when the distance increases, especially for international markets, the role of the demand size dominates. From a policy perspective, it is therefore important to assess these roles separately, and our findings confirm that they indeed differ<sup>9</sup>.

---

<sup>8</sup>Among the 12 majors coastal seaports in China (defined by the volume of freight handled), which are, by decreasing order, Shanghai, Ningbo, Guangzhou, Tianjin, Qingdao, Qinhuangdao, Dalian, Rizhao, Yingkou, Yantai, Lianyungang and Zhanjiang.

<sup>9</sup>Harris (1954) market potential is also probably less endogenous from an econometric point of view than the structural market potential since it is not based on trade flows determinants estimated simultaneously in structural approaches. In any case, it has been shown that the correlation between the two types of market potential is very high and that both perform very similarly in regressions (Head and Mayer, 2004). By splitting

Table 1 reports the summary statistics for all the variables related to urbanisation economies. Density and land area present the largest spatial variations, as typically observed in most countries. On the contrary, diversity and specialisation vary little, while spatial variations in access to external markets are intermediate.

A number of issues must be kept in mind. First, only the total effect of agglomeration is identified and the effect of spatial concentration on each channel that appears in equation (3) cannot be identified separately. In other words, as it has been acknowledged in the literature for long, urban scale may raise wages through a variety of channels (better technology, higher labour efficiency, higher prices of goods, and lower costs of other factors) but very few studies to date managed to give their relative importance. Likewise, if agglomeration induces negative effects, they cannot be identified separately from the positive ones. This could be the case for instance if competition on local goods markets is tough (e.g. if goods are not so much differentiated), which would induce prices of goods to be lower in larger cities. The less tradable the inputs other than labour, or the less mobile their input suppliers, the more responsive their price is to an increase in demand, which can make them higher in large cities, as it is true at the extreme for land. Finally, pure congestion effects may also decrease efficiency. Notwithstanding these caveats, estimating the total net effect of agglomeration is meaningful in a policy perspective since a positive estimate means that gains from agglomeration dominate losses, and implies that increasing the size of cities for instance would improve productivity.

Second, the assumption of competitive markets for inputs and final goods may raise some concerns, especially for an economy like China. However, we only need wages to be proportional to labour productivity, which implies that these concerns should not be too strong. For instance, if the firms' monopsony power depends on location, and is typically lower in denser areas, this is estimated as part of the positive effects of agglomeration (for workers).

## 2.2 Migration and agglomeration effects

Beyond the estimation of agglomeration effects, a contribution of the paper consists in proposing an empirical strategy to simultaneously assess the extent to which internal migration contributes to Chinese urban residents' productivity and wages. From the initial contributions of Sjaastad (1962) and Topel (1986), a pretty large literature has attempted to evaluate the impact of international migrants on their host country labour markets. This literature provides contrasted evidence and migrants' impact on local wages remains a highly debated issue. While earlier studies concluded to dominating negative effects on natives outcomes (Borjas,

---

market potential into three distinct variables, our approach identifies more effects, which is very much in the spirit of what is done by Au and Henderson (2006) (and also by Chen and Partridge (2011) in their study of the determinants of city growth).

Friedman and Katz, 1997), more recent contributions are somewhat more optimistic (Card, 2005; Ottaviano and Peri, 2012; Peri, 2012). Importantly, most studies focus on OECD countries (Docquier, Ozden and Peri, 2011), and in all cases the concern is about international migration.

Our perspective is different for two reasons: we focus on an urban-level, and not a country-level, context and we study the impact of labour mobility within the country, i.e. internal migration. The share of migrants in local employment sharply increased over the last decades in China<sup>10</sup> and some concerns were raised regarding their potentially negative impact on local residents' labour market outcomes. As rural migrants are significantly less educated than their urban counterparts, a major concern is that by increasing the relative supply of unskilled workers in cities, the inflow of rural migrants would exert a downward pressure on wages, particularly for unskilled local urban residents. This mirrors similar concerns for developed countries and international migrants. However, the only existing study we are aware of for China finds no significant impact of the rural migrant inflow on average wages of urban workers (Meng and Zhang, 2010). The non-negative impact of migrants on local wages can find its sources in the presence of complementarities between native and migrant workers. In that case, the induced positive externality from migrants to local workers may offset the negative effect due to the increase in (unskilled) labour supply. In what follows, we propose further exploring this issue by explicitly accounting for the role of internal migration when estimating agglomeration economies.

We argue that for a correct interpretation of the role of migrants and a consistent discussion of endogeneity, we need to specify the role of migrants in relation with the way urbanisation effects are taken into account. As emphasised above, the main focus of economic geography is on the role of the city total employment density,  $Den_c^T$ , and the specification estimated is typically the following:

$$\delta_c = \beta \log Den_c^T + \tilde{U}_c \eta + \nu_c, \quad (6)$$

where  $\tilde{U}_c$  is the vector of urbanisation effects other than density. The literature on international migration usually specifies the role of the share of migrants in local employment. A parallel can be done with the formulation adopted in economic geography when assessing the externality effects of more educated workers on other local workers (see Moretti (2004) for instance), which also considers the impact on productivity of their share in local employment. Under that perspective, one could simply estimate:

$$\delta_c = \beta \log Den_c^T + \lambda MigSh_c + \tilde{U}_c \eta + \epsilon_c, \quad (7)$$

---

<sup>10</sup>Using the 2000 Census data, Cai et al. (2008) estimate that migrants account for 19.6% of the employment in China's cities (excluding townships).

where  $MigSh_c$  is the share of migrants in total employment. However, such a specification is difficult to interpret because total density is itself a function of the share of migrants, namely  $Den_c^T = \frac{Den_c^N}{1-MigSh_c}$  where  $Den_c^N$  is the density of native employment. This leads to

$$\delta_c = \beta \log Den_c^N + \beta \log \left( \frac{1}{1-MigSh_c} \right) + \lambda MigSh_c + \tilde{U}_c \eta + \epsilon_c. \quad (8)$$

When migrant employment is poorly measured and the city density variable mostly reflects native employment, the estimation of the migrant externality,  $\lambda$ , is blurred by the fact that migrants simultaneously shape total employment density. Equation (8) also underlines the role of the specification adopted for the migrant externality. If one assumes that the externality is proportional to  $\log \left( \frac{1}{1-MigSh_c} \right)$  instead of  $MigSh_c$ , which is in either case ad hoc (and almost identical as long as  $MigSh_c$  is small), one gets:

$$\delta_c = \beta \log Den_c^N + (\beta + \lambda) \log \left( \frac{1}{1-MigSh_c} \right) + \tilde{U}_c \eta + \zeta_c. \quad (9)$$

This specification uses the impact of the density of native employment to identify agglomeration effects and the migrant effect corresponds to the sum of the agglomeration effect and the migrant externality. Therefore the respective impact of density and migrants is better disentangled. Given the better measurement of native employment than of migrant employment in our data, we prefer to report estimates corresponding to specification (9). It is also preferable for endogeneity concerns as detailed below.

### 2.3 Endogeneity concerns and instrumentation

OLS estimates for specification (9) can clearly suffer from endogeneity bias. A simple model of migration consists in assuming that migrants are attracted by higher expected wages in the city (i.e. a high  $\delta_c$ ), as well as by other amenities found in dense areas. In other words, one could specify for instance:

$$\log \left( \frac{1}{1-MigSh_c} \right) = \phi \delta_c + \rho \log Den_c^N + \vartheta_c, \quad (10)$$

where  $\phi$  is a positive parameter and  $\rho$  can be either positive or negative (depending on whether urban disamenities more than compensate amenities for workers). In that case, one can easily show that a correlation between  $\log \left( \frac{1}{1-MigSh_c} \right)$  and  $\zeta_c$  exists, even when  $\log Den_c^N$  is not correlated to  $\zeta_c$ .<sup>11</sup> Therefore OLS estimates of (9) are biased and one has to deal with such

---

<sup>11</sup> $Cov \left( \log \left( \frac{1}{1-MigSh_c} \right), \zeta_c \right) = Cov \left( \phi \delta_c + \rho \log Den_c^N + \vartheta_c, \zeta_c \right) = Cov \left( \phi \beta \log Den_c^N + \phi \tilde{U}_c \eta + \phi (\beta + \lambda) \log \left( \frac{1}{1-MigSh_c} \right) + \phi \zeta_c + \rho \log Den_c^N + \vartheta_c, \zeta_c \right)$ . Even if we assume  $Cov \left( \log Den_c^N, \zeta_c \right) = Cov \left( \tilde{U}_c, \zeta_c \right) = Cov \left( \vartheta_c, \zeta_c \right) = 0$ , we have  $Cov \left( \log \left( \frac{1}{1-MigSh_c} \right), \zeta_c \right) = \frac{\phi}{1-\phi(\beta+\lambda)} Var \left( \zeta_c \right) \neq 0$ .

a reverse causality.

Interestingly, acknowledging the endogeneity of migration also allows us to correctly interpret the reduced-form specification (11) obtained when (10) is plugged back into (9):

$$\delta_c = \frac{\beta + (\beta + \lambda)\rho}{1 - \phi(\beta + \lambda)} \log Den_c^N + \tilde{U}_c \frac{\eta}{1 - \phi(\beta + \lambda)} + \xi_c. \quad (11)$$

Though looking similar to (6), this specification leads to a different interpretation of the elasticity of density, which encompasses both agglomeration economies and the externality from migrants, and the two can no longer be identified separately. Therefore, one needs to be careful when interpreting (6) or (11) and make sure that the correct density variable, either total or native employment, is used. OLS estimates of (11) should also suffer less from endogeneity bias since the migrant variable does not enter explicitly. This is also why estimating (9) should also be more robust than (7): native density should be less endogenous than total density.

Economic geography stresses that OLS estimates of agglomeration effects can be biased not only because of reverse causality between wages and migration but also because of missing productive amenities in the productivity specification. For instance, dense areas can benefit from better public infrastructure (e.g. large train stations or airports, universities), which are in general not controlled for in the specification. In that case, even the native employment density is correlated to the random productivity component and must be instrumented.<sup>12</sup>

To sum up, once instrumented, specifications (7) and (9) identify the same parameters but we expect (9) to lead to cleaner interpretation and to be the easiest to instrument because there are less elements that make  $Den_c^N$  endogenous than  $Den_c^T$ . Equation (11) identifies one parameter less but also requires to instrument one variable less. Finally, note that most variables in  $\tilde{U}_c$  depend on local employment and have to be instrumented too on grounds similar to density. We start by estimating (11) in section 4 as it is consistent with both the model including the role of migrants and the usual estimations of agglomeration economies in the literature. Then we move to the estimation of (9) in section 5, which allows us to emphasise the role of migrants.

To address endogeneity, we take an instrumental variable approach and we use several sets of instruments as sources of exogenous variation for the suspected endogenous variable(s). The standard practice since Ciccone and Hall (1996) to instrument for urban size or density is to use historical variables such as long lags of population density. The rationale is that the spatial distribution of population is persistent over time but the sources of productivity differences differ over time. Following this approach, our first series of instruments relates

---

<sup>12</sup>A survey of endogeneity concerns when estimating agglomeration economies and solutions implemented for Western countries can be found in Combes et al. (2008a).



to historical data. We use a set of important cities in China at the end of the 19th century, which is composed of major historic cities, including 48 treaty ports conceded to foreign countries between 1842 and 1920<sup>13</sup>. Although we do not have historical population, this set of important cities at the turn of the 20th century can be considered as a relevant instrument since, as stated by Banerjee, Duflo and Qian (2012): “[in] the late 19th and early 20th century, the Chinese government and a set of Western Colonial powers built railroads connecting the historical cities of China to each other and to the newly constructed so-called treaty ports” (p. 5). From these historical data, we compute several indicators. First, we use a dummy variable for cities that are either historic major cities or former treaty ports. Second, we compute a ‘peripherality’ index (the average distance) to these historic cities. We also consider a purely geographic peripherality index that consists in the average distance of any city to all cities, be they historic or not. Economic geography shows that “being central” influences productivity and employment growth. Theory also implies that distance should be weighted by the level of economic activity, for the same reason as why both local density and market potential variables are introduced in the specification. This is also the reason why our peripherality instruments are not weighted. Therefore, they remain correlated with the instrumented variables but should not be too much correlated with current wages and productivity shocks.

The second set of instruments is borrowed from Au and Henderson (2006), who use 1990 data on city characteristics and amenities. We use the shares of manufacturing and services respectively in total employment, the share of non-agricultural employment in total employment and the share of doctors in the population, all measured for the year 1990. The intuition is that the past industrial composition of the cities should have influenced their total employment growth. On the other hand, with a twenty-year lag over a period of major reforms in China, past industrial composition should not be too much correlated with current wages and productivity shocks. The presence of doctors can reflect amenities or the occupational composition of overall employment that may similarly have influenced the development of cities without being correlated to current productivity shocks.

Finally, the third set of instruments is composed of “Henderson instruments” (as defined by Combes, Duranton and Gobillon, 2012), which are computed for occupations and for sectors. The index corresponds to the population that the city would have, would its workers be located in a city with total employment corresponding to the mean city employment (nation-wide) for the workers sharing the same occupation (employed in the same sector respectively). More precisely, for each occupation (sector resp.), we compute the mean city employment. Then for each city, we compute the instrument by interacting the local share of employment of an

---

<sup>13</sup>The treaty ports were part of the ‘unequal treaties’ that China signed with Western countries in the late Qing dynasty. The system was abolished in 1943 after China signed new treaties with Britain and the US (Jia, 2012).

occupation (sector resp.) with the mean employment at the city level for this occupation (sector resp.) before summing across occupations (sectors resp.). Put differently, a city with a high proportion of managers will be predicted to be large because on average over China, managers locate in larger cities, while an urban area with a high proportion of blue-collar occupations will be predicted to be small. This sort of instrument is interesting because it removes from city size the part that is not explained by its occupation or sectoral structure, typically the one that could relate to possibly missing variables in the wage equation and that makes the city actually larger or smaller. Therefore, such instruments should be fairly exogenous to the wage random component and simultaneously be strong enough because the employment structure necessarily affects at least part of the city size. Using instruments from fairly different families should reduce the risk of facing weak instrument issues and give more credence to the over-identification tests.

### 3 Individual wages and city fixed effects

We first estimate simple regressions that successively include the different sets of explanatory variables: location effects, individual characteristics, and firm characteristics. They are first introduced separately and then combined with each other. At this stage, our interest being in the relative contribution of the different sets, we do not report the estimation results but only focus on their adjusted  $R^2$ , which are reported in Table 2. Unsurprisingly, individual characteristics alone explain 25% of the variations of individual wages in 2007. The explanatory power of firm characteristics alone amount to 13%. Interestingly, and much less documented in the case of China, we find that location accounts for a non-negligible share of the variations in individual wages. Indeed, city dummies and specialisation together exhibit a substantial explanatory power, with an adjusted  $R^2$  of 17%. Another finding worth mentioning is the fairly strong orthogonality of the three groups of effects. City effects and individual characteristics together explain 41% of wage disparities when the sum of their individual  $R^2$  is 0.42, and 30% for city and firms effects for a sum of their individual  $R^2$  at 0.28. Individual and firms effects are a bit more correlated. As a consequence, the explanatory power of the city effects cannot be fully attributed to differences in the composition of the labour force and in the type of firms present in the city.

Table 7 in Appendix B reports a full variance analysis. It shows that the main factor explaining individual wage disparities are individual characteristics but location effects matter also and come second before firms effects. It also indicates that among local effects, specialisation explains very little of wage disparities. These results closely match those obtained for developed countries. On the other hand, the absence of sorting of workers across cities in China depending on their skills is corroborated by the absence of correlation between

Table 2: Explanatory power of various sets of right-hand side variables

<i>Adj. R<sup>2</sup> for individual wages in 2007 (log wage) as a function of:</i>	
City effects	0.17
Individual characteristics	0.25
Firm characteristics	0.13
City effects and Individual characteristics	0.41
City effects and Firm characteristics	0.32
Individual characteristics and Firm characteristics	0.28
All three sets	0.44
<i>N</i>	14,590

*Notes:* City effects include both city fixed effects and a localisation effect measured by sector specialization.

individual characteristics effects and city-level dummies (with a non-significant correlation coefficient at 0.0012). This is in sharp contrast with what is usually obtained in developed countries, where a large fraction of the explanatory power of city effects arises from the sorting of workers<sup>14</sup>.

To further examine the sorting hypothesis, we run additional regressions not reported here. The underlying idea of the sorting test is that if individuals were sorted across cities according to their abilities, the city-level employment density would be correlated with individual characteristics such as education or occupation. Hence, one would expect the estimated coefficient for employment density in the second step of the estimation to change when individual characteristics are not incorporated in the first step wage equation. This is typically what arises for Western countries, the density elasticity being multiplied by a factor of 2 in the case of France. As for China, the elasticity of employment density is found to be very stable across specifications, with and without individual controls in the first step. The absence of sorting may not be surprising since labour mobility towards urban areas with a change in *Hukou* has been strictly restricted for decades and remains controlled<sup>15</sup>.

Table 3 displays estimation results for the first step specification (4), section 2.1. We confirm usual findings on the role of gender, education and experience in urban wage settings in China. Everything else equal, male workers benefit from a wage premium of about 25% as compared to female workers. The returns to education are slightly above 6% for one additional year of education and we find the usual concave form for actual work experience, with

<sup>14</sup>See for instance Combes et al. (2008b) for France where the correlation between individual and location fixed effects is found to be large, at 0.29. See also Mion and Naticchioni (2009) for Italy and Bacolod, Blum and Strange (2009) for the US even if the spatial sorting of skills there is somewhat less strong.

<sup>15</sup>Since our database covers urban *Hukou* holders only, the sorting hypothesis refers to this part of the urban population only. Migrants may be included in the sub-sample, provided that they obtained a change in their *Hukou*.

a wage peak achieved at about 24 years of participation to the labour force. As for occupation, administration staff and professional or technical staff earn a 30% to 36% premium as compared to the reference category. Regarding firm characteristics, almost all sector dummies are significant (the reference sector is manufacturing) and have signs consistent with existing evidence on China. In particular, we find that oligopolistic sectors (such as finance and insurance, public utilities, real estate) pay higher wages than the competitive manufacturing sector. The impact of ownership variables also corresponds to what is usually found for China, with higher wages still being paid in the public sector, the reference category (Démurger, Fournier, Li and Wei, 2007). Finally, the elasticity for specialisation is found at the upper bound of what is usually estimated for developed countries. Doubling the size of the sector within the city, that is roughly moving from the first to the ninth decile of the specialisation variable, increases productivity by almost 4%. To the best of our knowledge, this is the first evidence of the presence of relatively strong localisation economies for China that arise from within-sector city externalities, all other city characteristics being controlled for.

## 4 Explaining the location effect

### 4.1 Main OLS and IV estimations

Table 4 reports a series of estimations of specification (11) either using OLS or instrumenting the city characteristics to tackle the endogeneity issues we detailed in section 2.3<sup>16</sup>.

OLS estimations displayed in Columns (1) to (3) highlight a strong and significant impact of local employment density on individual earnings. As shown in Column (1), the estimated elasticity is about 0.10 when introduced alone in the specification. Columns (2) and (3) add local variables contained in  $\tilde{U}_c$  that include land area, the Herfindhal diversity index, market potential and distance to the closest seaport. Whereas land area and market potential are both significant at one percent level neither the Herfindhal diversity index nor the distance to the closest seaport is significant<sup>17</sup>. Employment density remains significant and its estimated impact is fairly close to the one obtained with no additional control. The impact of density is higher when land area and diversity are included but it reduces when market potential and distance to seaport are included. Specification OLS2 thus seems to suffer from a missing variable problem when market potential is not controlled for, due to the positive correlation

---

<sup>16</sup>As some of the instruments are available for 83 cities only, the sample is reduced to these cities for all the estimations done in the second stage (Table 4 and Table 6). OLS estimates on the whole sample of 87 prefecture-level cities provide very similar results.

<sup>17</sup>Regarding the diversity index, this is a standard finding when urbanisation economies variables are simultaneously introduced in the specification. Moreover, in our case, the sector classification is not much detailed since we have only 11 sectors. Being computed on a too small number of sectors, our index may not properly account for the effective industrial diversification, which in turn may affect the significance of the diversity variable.

Table 3: Individual wage disparities - OLS estimates for the first stage

<i>Log(wage)</i>		
Male	0.252***	(0.00992)
Years of education	0.0643***	(0.00217)
Experience	0.0398***	(0.00162)
Experience squared	-0.000838***	(0.0000389)
<i>Occupation</i>		
Administration staff	0.358***	(0.0331)
Prof. and technical staff	0.304***	(0.0278)
Office worker or manager	0.169***	(0.0262)
Service worker	-0.0121	(0.0276)
Unskilled worker	0.0690**	(0.0276)
<i>Enterprise ownership</i>		
Urban collective enterprises	-0.274***	(0.0207)
Private or individual enterprises	-0.226***	(0.0175)
Other ownership	-0.224***	(0.0128)
<i>Economic sector</i>		
Agriculture, mining	0.162***	(0.0397)
Electricity, gas and water	0.238***	(0.0328)
Construction	0.0975***	(0.0337)
Transport, storage, telecom	0.0926***	(0.0194)
Wholesale and retail trade	-0.0313	(0.0207)
Finance and insurance	0.253***	(0.0330)
Real estate	0.113***	(0.0315)
Social services	-0.186***	(0.0213)
Health, education, culture and research	0.0412**	(0.0177)
Government and party agencies	0.0329*	(0.0186)
Specialization	0.0552***	(0.0103)
City dummies	Yes	
<i>N</i>	14,590	
adj. <i>R</i> <sup>2</sup>	0.442	

*Notes:* Standard errors in brackets. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . Reference groups: for occupation: other occupation (including soldiers); for enterprise ownership: state-owned enterprises; for economic sector: manufacturing.

between density and market potential on the one hand, and between market potential and wages on the other hand (see Appendix C).

Table 4: The determinants of city effects - OLS and IV estimates for the second stage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS1	OLS2	OLS3	IV1	IV2	IV3	IV4	IV5
Density	0.099*** (0.024)	0.150*** (0.025)	0.095*** (0.028)	0.090*** (0.035)	0.138*** (0.038)	0.121*** (0.041)	0.125*** (0.037)	0.123*** (0.038)
Land area		0.176*** (0.035)	0.165*** (0.034)		0.168*** (0.039)	0.162*** (0.038)	0.168*** (0.037)	0.247*** (0.058)
Diversity		-0.027 (0.170)	0.084 (0.162)		0.008 (0.186)	0.017 (0.178)	0.008 (0.172)	-0.024 (0.174)
Market potential			0.381*** (0.109)			0.106 (0.141)	0.116 (0.132)	0.225 (0.155)
Distance to seaport			-0.010 (0.016)			-0.020 (0.017)	-0.018 (0.017)	-0.010 (0.018)
<b><i>Instruments:</i></b>								
Peripherality				Y	Y	N	N	N
Historic city				N	N	Y	Y	Y
Distance to historic				N	N	Y	Y	Y
Manufacturing share				Y	Y	Y	N	Y
Services share				N	N	N	Y	N
Henderson industries				N	Y	Y	N	N
Henderson occupations				N	N	N	N	Y
Doctors share				N	N	N	Y	Y
R <sup>2</sup>	0.18	0.39	0.48					
Hansen p-value				0.623	0.955	0.849	0.879	0.214
Cragg-Donald				33.8	18.1	16.3	24.9	5.1
1st Shea part. R <sup>2</sup> , den				0.46	0.41	0.47	0.58	0.57
1st part. Fisher, den				33.84	13.04	12.69	25.40	14.52
1st Shea part. R <sup>2</sup> , mp						0.60	0.68	0.51
1st part. Fisher, mp						5.28	40.01	7.82
1st Shea part. R <sup>2</sup> , area								0.34
1st part. Fisher, area								6.05

*Notes:* 83 observations for each regression. Standard errors in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . In columns (4) and (5), employment density only is instrumented. In columns (6) and (7), employment density and market potential are instrumented. In column (8), employment density, market potential and land area are instrumented. The instruments are: the logarithm of the average distance of any city to all cities (peripherality), the logarithm of the average distance to historic cities (distance to historic), a dummy for historic major cities (historic city), the logarithm of the share of manufacturing in total employment in 1990 (manufacturing share), the logarithm of the share of services in total employment in 1990 (services share), the share of doctors in the population in 1990 (doctors share), the Henderson index for sectors (Henderson industries), the Henderson index for occupation (Henderson occupations).

As for urbanisation economies other than density, a remarkable finding concerns land area that is usually not found to significantly impact productivity in Western countries when included together with density. In China, further gains from increasing the city land area,

keeping density constant, would exist. The important role of land area also appears through the  $R^2$  that more than doubles when area is introduced, which is not the case for Western countries.

Finally, the estimated elasticity of market potential (0.38) is close to what is usually found in Western countries, and it leads to a further 9 percentage point increase in the  $R^2$ . Hence, OLS results indicate that access to other cities matters for local productivity, which could reflect either better trade opportunities or technological spillovers from neighbouring cities. Note that such an effect cannot be directly compared to the positive impact of market potential obtained in structural estimations by Au and Henderson (2006) and Hering and Poncet (2010) because their variable includes both the own city size and other cities' size whereas our approach disentangles the two and excludes the own city size from the market potential variable. Our OLS estimates conclude to a positive impact of both components. By contrast, the proximity to seaports, which could reflect a better access to international export opportunities, does not have any significant effect. Again, this cannot be directly compared with Hering and Poncet (2010) who include international markets within their single market potential variable but it is consistent with Au and Henderson (2006) who also conclude to a non-significant role of the access to sea. Moreover, as we control for firm ownership (and foreign ownership in particular) in the first step of the estimation and for the effect of many other local variables in the second step -all variables strongly correlated to the distance to seaport-, it is not surprising that this counterbalances the negative uni-dimensional impact of lack of access to sea (see Appendix C). Only a multi-variate approach as ours allows not to misinterpret the correlation between productivity and access to sea.

Columns (4) to (8) display IV regression results for different specifications and variants on the instruments used. IV1 considers density only as an explanatory (instrumented) variable. If instruments are valid, it should be enough to get the correct elasticity for the impact of density. Several diagnostic tests are used to ascertain the validity of the instruments. In general the difficulty lies in finding exogenous instruments. Here, over-identification tests are passed according to the Hansen p-value and instruments are not weak given the Cragg-Donald statistics<sup>18</sup> at 33.8 and the high first-stage partial  $R^2$ . The elasticity of employment density slightly decreases by comparison with OLS1. This is consistent with usual findings for Western countries and with the presence of reverse causality and/or missing variables that slightly bias OLS estimates. IV2 controls for both land area and diversity, with density only being instrumented. This implies that land area is also used as an instrument. There are debates on that point. Typically, if one thinks that local or central authorities react to the expansion of cities by increasing their spatial extent, land area may well be endogenous too. However, Ciccone (2002) and a number of followers argue that area is a licit instrument.

---

<sup>18</sup>Equal to the Fisher test since there is for the moment only one instrumented variable.

This is what estimation IV2 does too. Instruments still pass over-identification and weak instruments tests. The density elasticity increases quite significantly. The positive impact of land area on wages, and the absence of a diversity effect, found in OLS are confirmed.

The conclusions still hold when market potential is introduced in the specification and is instrumented. If one thinks that density is endogenous, market potential, which corresponds to density in neighbouring regions, might be endogenous too. We provide two sets of regressions that instrument both density and market potential (IV3 and IV4). They should provide consistent estimates for two different sets of instruments since both the over-identification and weak instrument tests are passed. Instrumenting leaves the elasticities of density and land area almost unaffected with respect to column IV2. However, by comparison with column OLS3, the market potential impact is not significant any more. This is an important result. It is actually fairly difficult to identify separately the effect of density and market potential because these variables are pretty much correlated (the correlation coefficient amounts to 0.55, see Appendix C). OLS would conclude that both variables impact wages significantly. However, the IV3 estimation shows that the market potential effect must be attributed to density, whose real effect is higher than it appears in OLS1 or OLS3 for instance. Importantly, one should note that the non-significance of market potential in IV3 and IV4 is not due to a too imprecise estimation but rather to a decrease in the magnitude of the effect. The IV standard error is close to the OLS one but the elasticity of market potential decreases by a factor of more than 3. Hence, market potential would not matter for local productivity in China. This is not in contradiction with results from Au and Henderson (2006) and Hering and Poncet (2010) since their market potential includes both the own city size and other cities' size. When the two are disentangled, first by using two different variables, second by instrumenting, only the own city size seems to matter.<sup>19</sup>

Finally, to relax the exogeneity assumption for land area (even when over-identification and weak instruments tests are passed), we instrument all three variables (density, land area and market potential) simultaneously in column IV5. Density and market potential effects are very close to those obtained in columns IV3 and IV4, and the area effect gets larger. The over-identification test is passed but instruments are a bit weak. This may not be surprising given that instrumenting the three variables simultaneously is very demanding. First, area usually expands when density does but its variations present more inertia over time. Finding variables that instrument both correctly and are not weak is not easy in that case. Furthermore, and generally speaking, many econometricians find the simultaneous instrumentation of more than two variables a bit doubtful and difficult to interpret even when tests are passed. Given

---

<sup>19</sup>Although city growth and not productivity in China is studied by Chen and Partridge (2011), which corresponds to different underlying mechanisms, our conclusion is consistent with their findings of a positive effect of market access to medium-sized cities but a negative effect for the market access to mega-cities.



these various points of view, we are somewhat agnostic about the fact that area should be instrumented or not. In any case, regressions that do or do not instrument area simultaneously with density and market potential (IV3, IV4 and IV5) all lead to very similar conclusions. The elasticity of employment density is about 0.12, the elasticity for land area is at least 0.17, possibly a bit higher, whereas diversity, access to sea, and market potential are not significant. These findings imply that agglomeration economies would be more localized in China than in Western countries: the own-city density matters more, and own-area matters also, while the size of neighbouring cities matters less.

At about 0.12, the estimated elasticity for local employment density is three times higher than in Western countries for similar specifications, implying that the doubling of density would increase individual wages of any worker by 8.7%. Another interesting point is that the dispersion of density is also much larger in China than in Western countries. A worker moving from a city at the first quartile (decile, respectively) of density to a city at the third quartile (last decile, respectively) would experience a wage gain of 27% (53%) respectively. The same figures for France for instance would be around 2.5% and 5%, respectively, both because the density elasticity is lower (at 0.03) and because inter-deciles and quartiles are around 10 times lower.

The estimated coefficient of about 0.17 for land area means that if we compare two cities with the same employment density, but one 20% larger than the other, workers in the largest city gain 3.2% more than workers in the smallest city. A direct implication of this finding is that labour productivity could be improved in China by simultaneously increasing the density and the physical size of cities. For example, if the population of a city was increased by 50% with its land area simultaneously expanded by 20%, the wage gain for workers would be about 6.4%. Though not directly comparable with Au and Henderson (2006) due to the presence of a non-log linear effect of city size in their specification and a structural approach, the order of magnitude of agglomeration economies is rather similar in both studies, at least as regards the part of their curve where productivity is increasing with city size, which regards 90% of the cities in their sample.

## 4.2 Further robustness tests

To assess the robustness of the magnitude of the estimated impact of density, we supplement the analysis with another individual database. The data used in this section come from a nationally representative household income survey for the year 2002, which is part of the China Household Income Project (CHIP)<sup>20</sup>. The main advantage of using these data is that

---

<sup>20</sup>The China Household Income Project is an internationally joint research project established in 1987, and coordinated by the Institute of Economics, Chinese Academy of Social Sciences, with assistance from the National Bureau of Statistics (NBS). It includes three waves: 1988, 1995, and 2002 that have been widely used

the survey provides a more complete measure for individual wages. The main weakness of the database is that the number of cities is much reduced compared to the 2007 database, which does not allow us to provide a comprehensive set of tests. In particular, as explained below, we stick to OLS estimations only and confirm that they are fully consistent with OLS results from 2007.

The CHIP-2002 urban survey includes 6,835 households and 20,632 individuals in 12 provinces (Anhui, Beijing, Gansu, Guangdong, Henan, Hubei, Jiangsu, Liaoning, Shanxi, Chongqing, Sichuan, and Yunnan). As compared to the 2007 NBS dataset, it covers fewer provinces, and fewer prefecture-level cities as well since only 49 prefecture-level cities are surveyed, though most cities included in the 2002 survey are also included in the 2007 survey.

Earnings and working time are documented in great detail in the CHIP-2002 data, which makes it possible to account for location differences in working time as well as in non-productivity compensation payments. Regarding earnings, cash labour compensations are divided into several categories that distinguish the basic salary from bonuses, allowances and subsidies paid by the work unit<sup>21</sup>. Regarding working time, the number of declared hours worked in a year reported in the survey enables us to compute hourly wages. Four different dependent variables are thus considered to assess the importance of not controlling for work hours or for non-productivity compensation payments for the 2007 estimations. As a reference, the first dependent variable is the log of total annual earnings defined in the same way as in the 2007 database. Then, we consider only the (still annual) basic wage paid to workers, which excludes all sorts of benefits paid by the work unit. Finally, we account for working time by considering the hourly earnings/wage instead of the annual earnings/wage. We replicate the two-stage empirical strategy presented in section 2.1 on the 2002 database. In a first stage, equation (4) is estimated on 2002 individual wage data through OLS. In a second stage, equation (11) is estimated on 2002 city-level variables, defined in a way strictly similar to 2007. The estimation results for the first stage are reported in Appendix D for reference.<sup>22</sup> Table 5 reproduces estimation results that are comparable with Columns OLS2 and OLS3 in Table 4, with four different dependent variables used in the first stage.

A rapid comparison of the estimated coefficients across the four columns highlights very stable results, which indicates that the bias brought by the use of annual earnings instead of basic salary and/or hourly compensation should not be too severe to the extent that it contaminates our results. Interestingly, the coefficient estimates for the location variables

---

to investigate income inequality in China. For the year 2002, a detailed description of the survey can be found in Li, Luo, Wei and Yue (2008).

<sup>21</sup>A description of the various categories of these benefits can be found in Démurger et al. (2007).

<sup>22</sup>All explanatory variables are defined consistently with 2007 for both steps. The only exception is for enterprise ownership, which contains two additional categories not included in the 2007 classification: foreign-invested firms and government agencies. Foreign-invested firms are implicitly included in the ‘other ownership’ category in 2007, while government agencies are implicitly included in the state-owned enterprises category.

Table 5: Individual wage disparities, 2002 - OLS estimates for the second stage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	DEP1	DEP2	DEP3	DEP4	DEP1	DEP2	DEP3	DEP4
Density	0.122** (0.0475)	0.128** (0.0482)	0.105*** (0.0355)	0.111*** (0.0364)	0.104** (0.0500)	0.107** (0.0503)	0.0976** (0.0379)	0.101** (0.0386)
Land area	0.102** (0.0453)	0.110** (0.0460)	0.0735** (0.0338)	0.0814** (0.0347)	0.118** (0.0516)	0.131** (0.0520)	0.0825** (0.0392)	0.0949** (0.0399)
Diversity	0.116 (0.201)	0.176 (0.204)	0.108 (0.150)	0.169 (0.154)	0.105 (0.203)	0.167 (0.205)	0.106 (0.154)	0.168 (0.157)
Market potential					0.242 (0.207)	0.294 (0.209)	0.115 (0.157)	0.166 (0.160)
Distance to seaport					-0.0265 (0.0462)	-0.0274 (0.0466)	-0.00742 (0.0351)	-0.00893 (0.0357)
$N$	49	49	49	49	49	49	49	49
$R^2$	0.164	0.188	0.196	0.225	0.202	0.238	0.208	0.248

Notes: Standard errors in brackets. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . DEP1 to DEP4 refer to 4 different dependent variables for the first stage, as follows: DEP1 is for Log(earnings); DEP2 is for Log(hourly earnings); DEP3 is for Log(wage); DEP4 is for Log(hourly wage).

remain of comparable magnitude, though a bit smaller, as compared to estimations provided in Table 4. More precisely, the wage elasticity with respect to employment density is consistently close to 0.12, although variations can be observed across regressions, notably between earnings (DEP1 and DEP2) and wages (DEP3 and DEP4). Hence, taking into account non ‘pure’ wage compensations paid by the work unit reduces the elasticity of wage with respect to employment density by 11 to 14 percent. In comparison, taking into account the working time does not alter much the results, as shown in the comparison between DEP1 and DEP2, as well as between DEP3 and DEP4.

Two other results deserve additional comments. First, regarding the impact of land area, the estimated amplitude is smaller than in 2007, and more importantly, while it is not much affected by working time differences, it is particularly reduced when ‘pure’ wage is used as a dependent variable. The reduction in the estimated effect is bigger than for the employment density, at about 27 to 31 percent. Second, the impact of market potential on wage differentials is not only reduced in amplitude but it also becomes non-significant for both earnings and wage variables. Distance to seaport remains not significant either. Therefore, as for 2007 we find that access to other cities and to international markets is not a cause of higher productivity in Chinese cities.

To sum up, the aforementioned robustness checks with 2002 data indicate that the amplitude of the density effect is remarkably stable over the various definitions of wages, which gives credit to our measured elasticity with respect to density of about 0.12 for 2007, around 20%

higher than the one estimated for 2002. These findings suggest that not only agglomeration economies matter in China but they also seem to have been reinforcing over recent years.

## 5 The migration externality

The extent to which internal migration contributes to local residents' productivity is another contribution of the paper. As described in section 2.2, we measure this contribution by estimating specification (9) where the (logarithm of the inverse of 1 minus the) local share of migrants is introduced in the specification together with the density of local residents' employment and other urbanisation effects. Results are provided in Table 6, which displays both OLS and IV estimations as a parallel to Table 4.

Before discussing the estimation results, the definition of the local share of migrants deserves some comments. Aggregate data available at the city level account for officially registered population only, which we loosely refer as "natives", and rural migrants are set aside. Since official figures including non-registered urban residents are not available, we resort to the 1% Population Census issued in 2005 to compute the share of the migrant population in cities. The rural migrants are defined as working individuals aged 16 to 60 who are not living in the same county as their county of *Hukou* registration<sup>23</sup>.

Column (1) in Table 6 introduces employment density and the migrant share only in an OLS estimation. Both variables exhibit a highly significant positive effect, which suggests that on top of employment density the presence of rural migrants creates a positive externality that increases the wages of all (native) workers. As expected from the derivations in section 2.2, the elasticity of density is now lower than when the role of migration was not considered since it does not encompass anymore the positive externality of migrants. This clearly appears when one compares (9), where the elasticity of density is  $\beta$ , to (11), where it is  $\beta + (\beta + \lambda)\rho > \beta$  even if one ignores the reverse causality role of expected wages.<sup>24</sup> One also needs  $\rho > 0$ , ie migrants are indeed attracted by city amenities beyond the expected wage, which is confirmed empirically.

Columns (2) and (3) go on to incorporate additional local variables in a way similar to what is done in Table 4. Column (2) confirms that assessing simultaneously the role of land area increases the density elasticity. Land area has a positive impact on wages but it is lower compared to estimations that do not assess the role of migrants separately. The same reasoning as for density holds. If city amenities that attract migrants are correlated to both density and land area, which is consistent with the positive correlation between these two

---

<sup>23</sup>The duration of migration can also be added in the definition of a migrant. The standard definition from the NBS is to consider only individuals who have resided in the city for at least 6 months. Yet, adding this time dimension does not affect our results.

<sup>24</sup>If we do not assume  $\phi = 0$ , the gap is even larger.

Table 6: The migration externality - OLS and IV estimates for the second stage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS1	OLS2	OLS3	IV1	IV2	IV3	IV4
Density	0.046** (0.018)	0.086*** (0.022)	0.067*** (0.024)	0.118*** (0.029)	0.103*** (0.034)	0.104*** (0.033)	0.103*** (0.033)
Migrants	0.369*** (0.043)	0.314*** (0.044)	0.279*** (0.046)	0.381*** (0.097)	0.327*** (0.084)	0.322*** (0.069)	0.311*** (0.077)
Land area		0.100*** (0.029)	0.103*** (0.030)	0.114*** (0.034)	0.116*** (0.034)	0.117*** (0.033)	0.118*** (0.032)
Diversity		-0.072 (0.133)	-0.014 (0.135)	-0.209 (0.157)	-0.132 (0.151)	-0.130 (0.150)	-0.124 (0.151)
Market potential			0.182* (0.096)		0.082 (0.119)	0.086 (0.114)	0.078 (0.116)
Distance to seaport			-0.005** (0.013)		0.002 (0.014)	0.002 (0.014)	0.001 (0.015)
<b><i>Instruments:</i></b>							
Peripherality	N	N	N	Y	Y	N	Y
Historic city	N	N	N	Y	Y	Y	Y
Distance to historic	N	N	N	Y	Y	Y	Y
Manufacturing share	N	N	N	N	Y	Y	Y
Non-agr. empl. share	N	N	N	Y	N	Y	Y
R <sup>2</sup>	0.57	0.63	0.65				
Hansen p-value				0.585	0.457	0.454	0.469
Cragg-Donald				4.1	7.1	10.8	5.9
1st Shea part. R <sup>2</sup> , den				0.58	0.48	0.48	0.49
1st part. Fisher, den				18.49	15.97	16.08	14.95
1st Shea part. R <sup>2</sup> , mig				0.21	0.29	0.43	0.35
1st part. Fisher, mig				4.13	7.30	12.97	6.49
1st Shea part. R <sup>2</sup> , mp							0.65
1st part. Fisher, mp							31.90

Notes: 83 observations for each regression. Standard errors in parentheses. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . In columns (4), (5) and (6), employment density and the share of rural migrants are instrumented. In column (7), employment density, the share of rural migrants and market potential are instrumented. The instruments are: the logarithm of the average distance of any city to all cities (peripherality), the logarithm of the average distance to historic cities (distance to historic), a dummy for historic major cities (historic city), the logarithm of the share of manufacturing in total employment in 1990 (manufacturing share), and the share of non-agricultural employment in total employment in 1990 (non-ag. empl. share).

variables and the migrant share reported in Appendix C, the elasticity of these two variables is larger when migrants are omitted from the specification.

Interestingly, OLS estimates reported in Column (3) conclude to a small but significant impact of both external market potential and the distance to the closest seaport. Finally, one can note that the inclusion of the migration externality largely increases the explanatory power of the model, by almost 40 percentage points in the specification with density only, by 17 percentage points in the complete specification. All variables together explain about two-third of the city effects, which is very similar to what is found for Western countries. However, for these countries, almost all the explanatory power comes from density only.

Columns (4) to (7) present IV estimations. As shown in specifications IV1 to IV3, the simultaneous instrumentation of employment density and the share of migrants does not affect much the migrants' and area's impacts but largely increases the impact of density by comparison with OLS specifications (OLS2 and OLS3). Looking at (9), this corresponds to either a reverse causality effect similar to the role played by parameter  $\phi$  but when migrants take their migration decision on the exact wage proposed in the city (i.e. including the random component), or to missing city variables that increase productivity (public goods for instance). The estimated elasticity is now much closer to the magnitude found for the specifications without migrants. As explained above, the remaining difference between the two is consistent with a positive externality arising from the presence of migrants. This is confirmed by the elasticity of the migrant variable itself since, according to (9), the pure migrant externality effect corresponds to the difference between the density and the migrant elasticities. Because the effect of the migrant variable is not only positive but significantly larger than the density elasticity, our estimations show evidence of a positive externality of migrants on natives' productivity.

When market potential and the distance to the closest seaport are controlled for (specifications IV2 to IV4), both turn to a non-significant impact, as it was the case in the IV specifications without a separate effect for migrants. The elasticities of employment density and of the migrant share are slightly reduced compared to specification IV1 but the latter remains significantly larger. The estimated area elasticity is not affected by the introduction of market potential and distance to seaport controls. The quality of the instruments for columns IV2 and IV3 is decent, both in terms of over-identification and weak instruments tests, without being exceptional. Instruments are a bit weak. This is particularly true in column IV4 that simultaneously instruments market potential together with density and migrant share but results remain very similar to those obtained for specifications IV2 and IV3. Again, the comments we made in section 4 about the difficulty to instrument this type of specifications apply here since the migrant variable is also instrumented. The overall consistence of our results across various OLS and IV estimations makes us confident that we evaluate the correct

order of magnitude for the impact of both agglomeration and migrant variables.

To sum up, the overall impact of employment density, including the migrant externality is estimated at 0.12 and the estimated impact of land area is about 0.17 in that case. When migrants externalities are controlled for separately in the specification, both effects are reduced, at about 0.10 for density and 0.12 for area, and the separate impact of migrants is about 0.32. Hence, when estimations do not consider the role of migrants separately, about 15% of the density elasticity and 30% of the area elasticity are due to the migration externality. Going back to (9), our estimations indicate that  $\beta = 0.10$  and that the pure migrant externality  $\lambda = 0.32 - 0.10 = 0.22$ . From that, one may compute the productivity gain from increased migration. If new migrants move to a city at a constant number of local residents and if this move increases their share in total employment from the first quartile (decile respectively) of the distribution across Chinese cities to the last quartile (decile respectively), then productivity in the city increases by 10.0% (33.0% respectively). Two-third of that number comes from the externality exerted by migrants and one third results from agglomeration effects induced by the increase in total employment generated by the migrant inflow. On the other hand, if migrants replace natives in local employment, thus keeping total employment density constant, the productivity of natives increases by 6.8% (21.6% respectively) just by the externality effect. Even in that situation, migrants exert a large positive impact on local wages.

## 6 Conclusion

This paper contributes to a large literature on agglomeration economies by investigating urbanisation and migration externalities in China. China is an interesting case study because urbanisation has long been regulated by administrative means but rural labour mobility has been sharply accelerating during the 2000s, feeding urbanisation and concomitantly raising concerns on the potential impact of migrant inflows on local residents' outcomes. Therefore, evaluating the magnitude of agglomeration economies and the role that migration plays in the process is a crucial step to assess the degree to which the Chinese population is efficiently distributed over the territory and the possible scope for regional policy in China.

Using 2007 microeconomic data from the National Bureau of Statistics, we find that location matters a lot for urban workers' wages. Even after controlling for individual and firms characteristics and instrumenting city characteristics, the elasticity of wage with respect to employment density is about three times larger than in Western countries. Land area and specialisation also play a significant role whereas the access to other cities' markets or to seaports does not. Therefore, large agglomeration economies prevail in China and they are more localised than in Western countries. Moreover, we find evidence of a significant and

large positive impact of the local share of migrants on local workers' wages. Hence, migration not only increases productivity through the increase of employment density it leads to, but also because migrants exert a positive externality on local workers' wages.

Overall, our estimates support Henderson (2009)'s statement on 'too many cities with too few people' in China based on evidence for the mid-1990s and they indicate that there is still room for urban areas to further expand. The accelerating urbanisation pace that is being observed since the early 2000s in China is contributing to filling the gap. However, a related and highly debated issue in China remains opened on the optimal size of the future cities: should the expansion of already existing mega-cities or the development of medium-sized cities be favoured? What our findings suggest is that in 2007, there were potentially high efficiency losses due to a too strong dispersion of the population and that in comparison with 2002, agglomeration economies had not been fading out significantly despite a growing flow of rural-to-urban migration.

Regarding migration policies, our findings on migration externalities add another evidence of rural migrants' contribution to the country's economic growth and industrialisation. They support the hypothesis of a complementarity (rather than a crowding out) that migrants bring in to local workers, which is fully consistent with rural migrants being mainly concentrated in low-end labour-intensive industries that feed other local industries, thus contributing to an overall improvement of urban productivity.

Beyond the overall large estimated impact of employment density on urban productivity, there may be heterogeneous effects of agglomeration across individuals depending on skills, occupations, gender, etc. Heterogeneity in the effect of place-based externalities on individual earnings is not covered in the paper but in terms of optimal local economic structure, there is potential for future research along such lines. Furthermore, whether spatial concentration increases individual welfare is not under study here either. To evaluate that, one should also estimate how the cost of living increases with city size and compare the productivity gains we exhibit to these costs. The literature on that topic is only burgeoning, even for Western countries, but it is clearly another interesting direction to explore for China.

## References

- Au, C. and Henderson, V. (2006), 'Are Chinese cities too small?', *The Review of Economic Studies* **73**, 549–576.
- Bacolod, M., Blum, B. S. and Strange, W. C. (2009), 'Skills in the city', *Journal of Urban Economics* **65**(2), 136–153.
- Banerjee, A., Duflo, E. and Qian, N. (2012), 'On the road: Access to transportation infrastructure and economic growth in China', *NBER Working Paper Series* **17897**.



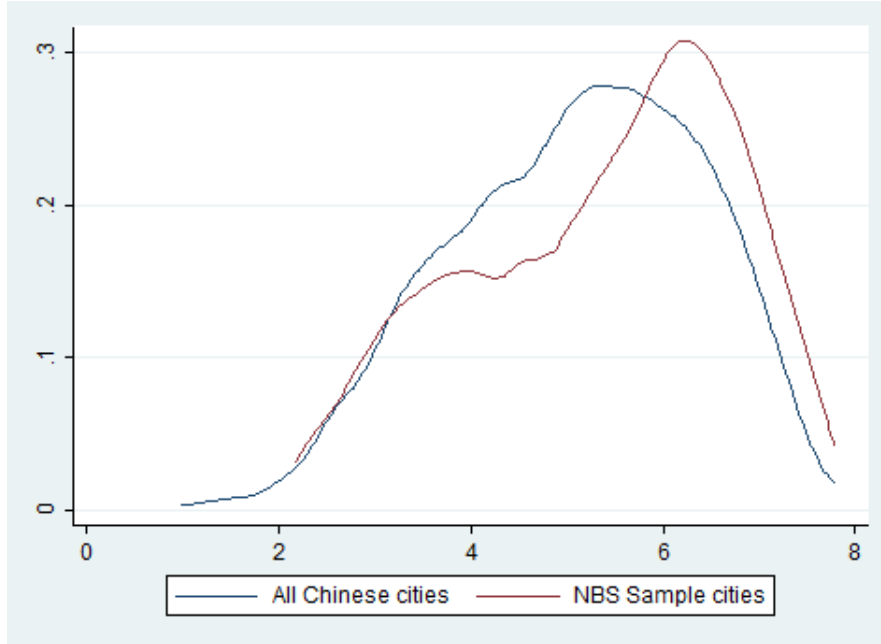
- Borjas, G. J., Friedman, R. B. and Katz, L. F. (1997), ‘How much do immigration and trade affect labor market outcomes?’, *Brookings Papers on Economic Activity* **28**(1), 1–90.
- Cai, F., Park, A. and Zhao, Y. (2008), The Chinese labor market in the reform era, in L. Brandt and T. Rawski, eds, ‘China’s Great Economic Transformation’, Cambridge University Press, pp. 167–214.
- Card, D. (2005), ‘Is the new immigration really so bad?’, *Economic Journal* **115**(507), F300–F323.
- Chen, A. and Partridge, M. D. (2011), ‘When are cities engines of growth in China? Spread and backwash effects across the urban hierarchy’, *Regional Studies* .
- Chen, Y., Démurger, S. and Fournier, M. (2005), ‘Earnings differentials and ownership structure in Chinese enterprises’, *Economic Development and Cultural Change* **53**(4), 933–958.
- Ciccone, A. (2002), ‘Agglomeration effects in Europe’, *European Economic Review* **46**(2), 213–227.
- Ciccone, A. and Hall, R. (1996), ‘Productivity, and the density of economic activity’, *American Economic Review* **86**, 54–70.
- Combes, P.-P., Duranton, G. and Gobillon, L. (2008b), ‘Spatial wage disparities: Sorting matters!’, *Journal of Urban Economics* **63**(2), 723–742.
- Combes, P.-P., Duranton, G. and Gobillon, L. (2012), ‘The costs of agglomeration: Land prices in French cities’, *CEPR Discussion Paper* **9240**.
- Combes, P.-P., Mayer, T. and Thisse, J.-F. (2008a), *Economic Geography: The integration of Regions and Nations*, Princeton University Press, Princeton.
- Démurger, S., Fournier, M., Li, S. and Wei, Z. (2007), ‘Economic liberalization with rising segmentation in China’s urban labor market’, *Asian Economic Papers* **5**(3), 58–101.
- Démurger, S., Gurgand, M., Li, S. and Yue, X. (2009), ‘Migrants as second-class workers in urban China? a decomposition analysis’, *Journal of Comparative Economics* **37**(4), 610–628.
- Docquier, F., Ozden, C. and Peri, G. (2011), ‘The wage effects of immigration and emigration’, *The World Bank Policy Research Working Paper Series* **5556**.
- Duranton, G. and Puga, D. (2004), Micro-foundations of urban agglomeration economies, in V. Henderson and J.-F. Thisse, eds, ‘Handbook of Regional and Urban Economics’, Vol. 4, North-Holland, Amsterdam, pp. 2063–2117.
- Glaeser, E. L. and Maré, D. C. (2001), ‘Cities and skills’, *Journal of Labor Economics* **19**(2), 316–342.
- Harris, C. (1954), ‘The market as a factor in the localization of industry in the United States’, *Annals of the Association of American Geographers* **44**(4), 315–348.
- Head, K. and Mayer, T. (2004), The empirics of agglomeration and trade, in V. Henderson and J.-F. Thisse, eds, ‘Handbook of Regional and Urban Economics’, Vol. 4, North-Holland, Amsterdam, pp. 2609–2669.
- Henderson, J. V. (2009), ‘Urbanization in China: Policy issues and options’, *Report for the China Economic Research and Advisory Programme* .
- Hering, L. and Poncet, S. (2009), ‘The impact of economic geography on wages: Disentangling the channels of influence’, *China Economic Review*, **20**(1), 1–14.

- Hering, L. and Poncet, S. (2010), 'Market access and individual wages: Evidence from China', *Review of Economics and Statistics*, **92**, 145–159.
- Jacobs, J. (1969), *The Economy of Cities*, Random House, New York.
- Jia, R. (2012), The legacies of forced freedom: China's treaty ports. Mimeographed, IIES, Stockholm University.
- Li, S., Luo, C., Wei, Z. and Yue, X. (2008), The 1995 and 2002 household surveys: Sampling methods and data description, *in* B. Gustafsson, S. Li and T. Sicular, eds, 'Inequality and Public Policy in China', Cambridge University Press, pp. 337–353.
- Meng, X. and Zhang, D. (2010), 'Labour market impact of large scale internal migration on Chinese urban 'native' workers', *IZA Discussion Paper* **5288**.
- Mion, G. and Naticchioni, P. (2009), 'The spatial sorting and matching of skills and firms', *Canadian Journal of Economics* **42**, 28–55.
- Moretti, E. (2004), 'Workers' education, spillovers, and productivity: Evidence from plant-level production functions', *American Economic Review* **94**(3), 656–690.
- National Bureau of Statistics (2008), *China City Statistical Yearbook*, China Statistics Press, Beijing.
- Ottaviano, G. and Peri, G. (2012), 'Rethinking the effects of immigration on wages', *Journal of the European Economic Association* **10**(1), 152–197.
- Peri, G. (2012), 'The effect of immigration on productivity: Evidence from U.S. states', *The Review of Economics and Statistics* **94**(1), 348–358.
- Sjaastad, L. A. (1962), 'The costs and returns of human migration', *Journal of Political Economy* **70**(5), 80–93.
- Topel, R. H. (1986), 'Local labor markets', *Journal of Political Economy* **94**(3), S111–43.
- Xu, Z. (2009), 'Productivity and agglomeration economies in Chinese cities', *Comparative Economic Studies* **51**, 284–301.

## APPENDIX

### A Kernel density estimates for employment density

Figure 3: Kernel density estimates for employment density



Source: National Bureau of Statistics (2008).

### B First stage variance analysis

Table 7 presents a full variance decomposition of the first step estimation reported in Table 3. It consists in computing, for each worker, the effect of a set of variables (by summing over the variables the estimated parameter times the value of the variable), and then the variance of this effect across all individuals and its correlation with the dependent variable. These computations allow measuring the explanatory power of each set of variables as well as its correlation with the other sets, so as to assess to what extent the observed effects are intertwined. Unsurprisingly, individual characteristics have the highest explanatory power. Their standard deviation (0.30) is half that of wages (0.75) and their correlation with wages (0.5) is the highest among all the effects (except residuals). Of particular interest here, city fixed effects also have a substantial explanatory power: the set of city dummies comes second after individual characteristics, with a similar standard deviation and a correlation with wages slightly lower. Sector dummies explain less than location, but ownership is fairly important. This fully corroborates the conclusions presented in section 3.

Table 7: Summary statistics for the variance decomposition

	Mean	St. dev.	Simple correlation with lwage
log wage	9.780	0.745	1
<b>Effect of:</b>			
Individual characteristics	1.477	0.303	0.497***
Sector dummies	0.0268	0.0969	0.243***
Enterprise ownership	-0.102	0.115	0.285***
Location variables	8.378	0.315	0.398***
Among which:			
<i>City dummies</i>	8.490	0.314	0.398***
<i>Localisation effect</i>	-0.112	0.0381	0.00441
Residuals	1.12e-10	0.555	0.744***
<i>N</i>	14,590		

Notes: The variance decomposition is based on estimation displayed in Table 3 column (1). \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

## C Pairwise correlation coefficients for local variables and wage

Table 8: Pairwise correlation coefficients for local variables and wage

	Wage	Employment density	Area	Diversity	Market potential	Distance to seaport	Migrant share
Wage	1						
Employment density	0.37***	1					
Area	0.25*	-0.43***	1				
Diversity	0.22*	0.38***	0.08	1			
Market potential	0.43***	0.55***	-0.24*	0.06	1		
Distance to seaport	-0.33**	-0.39***	-0.04	-0.19	-0.38***	1	
Migrant share	0.71***	0.34**	0.18	0.26*	0.41***	-0.31**	1

Notes: All variables are in logarithm. The migrant share variable is defined consistently with the description given in section 2.2. \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

## D Robustness checks with 2002 data

Table 9: Robustness checks with 2002 data

	(1)	(2)	(3)	(4)
	Log(earnings)	Log(hourly earnings)	Log(wage)	Log(hourly wage)
Male	0.141*** (0.0135)	0.101*** (0.0141)	0.114*** (0.0144)	0.0730*** (0.0150)
Years of education	0.0515*** (0.00301)	0.0543*** (0.00315)	0.0417*** (0.00322)	0.0444*** (0.00336)
Experience	0.0436*** (0.00258)	0.0397*** (0.00270)	0.0386*** (0.00277)	0.0347*** (0.00289)
Experience squared	-0.0008*** (0.00006)	-0.0007*** (0.00007)	-0.0007*** (0.00007)	-0.0006*** (0.00007)
<i>Occupation</i>				
Administration staff	0.377*** (0.0565)	0.347*** (0.0597)	0.303*** (0.0607)	0.278*** (0.0639)
Prof. and technical staff	0.311*** (0.0547)	0.294*** (0.0578)	0.239*** (0.0587)	0.227*** (0.0619)
Office worker or manager	0.228*** (0.0532)	0.214*** (0.0563)	0.184*** (0.0571)	0.174*** (0.0603)
Service worker	-0.00806 (0.0567)	-0.0260 (0.0600)	-0.0307 (0.0609)	-0.0436 (0.0643)
Unskilled worker	0.0344 (0.0560)	0.0221 (0.0593)	-0.0143 (0.0602)	-0.0227 (0.0635)
<i>Enterprise ownership</i>				
Urban collective enterprises	-0.183*** (0.0254)	-0.215*** (0.0265)	-0.140*** (0.0271)	-0.174*** (0.0282)
Private or individual enterprises	-0.135*** (0.0196)	-0.203*** (0.0205)	-0.0615*** (0.0210)	-0.131*** (0.0218)
Foreign enterprises	0.183*** (0.0405)	0.124*** (0.0425)	0.230*** (0.0435)	0.165*** (0.0454)
Government administration	0.112*** (0.0233)	0.107*** (0.0244)	0.109*** (0.0250)	0.101*** (0.0261)
<i>Economic sector</i>				
Agriculture, mining	0.0654 (0.0479)	0.100** (0.0501)	0.0114 (0.0511)	0.0449 (0.0533)
Electricity, gas and water	0.307*** (0.0441)	0.387*** (0.0461)	0.208*** (0.0472)	0.286*** (0.0492)
Construction	0.0459 (0.0441)	0.0705 (0.0461)	0.0157 (0.0472)	0.0368 (0.0491)
Transport, storage, telecom	0.187*** (0.0301)	0.182*** (0.0315)	0.163*** (0.0322)	0.157*** (0.0336)
Wholesale and retail trade	-0.0379 (0.0308)	-0.0328 (0.0322)	-0.0623* (0.0330)	-0.0597* (0.0344)
Finance and insurance	0.180*** (0.0488)	0.239*** (0.0512)	0.111** (0.0522)	0.164*** (0.0545)
Real estate	0.160** (0.0656)	0.237*** (0.0683)	0.128* (0.0712)	0.206*** (0.0739)
Social services	-0.140*** (0.0299)	-0.129*** (0.0312)	-0.109*** (0.0320)	-0.101*** (0.0333)

(Continued on next page)

Health, education, culture and research	0.153*** (0.0284)	0.195*** (0.0297)	0.116*** (0.0304)	0.158*** (0.0317)
Government and party agencies	0.0904*** (0.0331)	0.125*** (0.0346)	0.0564 (0.0355)	0.0909** (0.0370)
Specialization	0.0143 (0.0137)	0.0318** (0.0143)	0.000973 (0.0147)	0.0179 (0.0153)
City dummies	Yes	Yes	Yes	Yes
<i>N</i>	7,536	7,469	7,443	7,376
adj. $R^2$	0.41	0.41	0.29	0.29

*Notes:* Standard errors in brackets. \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ . In this Table, earnings refer to total wage compensation, including subsidies, and wage refers to basic wage, excluding all kinds of subsidies. Hourly earnings and wages are calculated by dividing the annual amount by the effective working time reported by workers. Reference groups: for occupation: other occupation (including soldiers); for education level: primary school or below; for enterprise ownership: state-owned enterprises; for economic sector: manufacturing.