Market access and the heterogeneous effect of shocks on wages: Evidence from Chinese cities

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Abstract. New Economic Geography (NEG) models predict that locations with market access advantages have higher wages and larger labour inflows. Using comprehensive prefecture-city level data for China, the study estimates a wage equation derived from a NEG model. The results support the NEG explanation for wage disparities across cities. An application of shock experiments on 230 prefecture-cities in China shows that the average effect of income changes differs greatly across locations. In particular, income shocks generated in core cities have a higher average impact in the rest of the country than shocks generated elsewhere.

JEL classification: R12, F12, O18, O53

Key words: New Economic Geography, China, labour mobility

1 Introduction

The new economic geography (NEG) theories explain that locations within a country are not independent of each other. Market access is at the core of location decisions of firms that exploit economies of scale. Thus, not only the size of local market matters but also how many consumers can be supplied from a single location. From the perspective of a particular location, proximate locations matter more than distant locations, given the existence of transport costs. It is natural then, the role played by ‘core’ regions: as they comprise high levels of income and population, firms and workers prefer to be close to them. This spatial representation of cities according to their relative weight is summarized in the ‘wage equation’, which relates the level of wages to real market access for each location. The wage equation captures the fact that, as a response of their attractiveness, wages in ‘core’ regions are higher than in regions with low market access.

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In theory, perfect labour mobility can counterbalance wage differentials across locations. As workers respond by moving to regions with higher wages, migration will ensure that real wages are equalized across regions. However, in practice this ‘quantity’ adjustment is lower than optimal, resulting in real wage differentials that can be explained by differences in market access (Head and Mayer 2006).

In the case of China, this effect may be aggravated by the fact that labour mobility is restricted under the Hukou system. By law, each Chinese citizen must register in one, and only one, location of permanent residence. Migratory regulations in China vary greatly across cities and towns, ranging from small cities offering ‘free’ local Hukou to large cities imposing prohibitive costs (Chan and Buckingham 2008). Thus, although the number of migrants including illegal migrants around 2006 was estimated in 120 million people, migration is believed to be subdued (Ping and Pieke 2003). Given the relatively low flow of goods and people within the country, the bulk of urban development has been concentrated around a fairly small number of metropolitan or core cities (Keng 2006).

Under these circumstances, a relevant empirical question is if market access is an important determinant of wages at the city level in China. At the province level, Lin (2005) and Ma (2006) find evidence on the effect of market access on the increasing wage gap between coastal and interior provinces. Hering and Poncet (2010) argue that in China, changes in demand are met by changes in wages, not in employment levels, as they consider labour migration restrictions to be tight enough for the ‘price’ effect to prevail over the ‘quantity’ effect. The authors estimate a wage equation using survey data for 6,848 workers from a sample of 56 cities in 11 provinces for 1995. They find that inter-city differences in market access can partly explain individual wage disparities.

However, the existent studies do not identify for which cities this relationship is most important, either because they use data at the province level (Lin 2005; Ma 2006) or because they use a sample of cities (Hering and Poncet, 2010). From the polarization in urban development in China and the predictions of NEG theory, it is expected that for certain cities, the linkages across space are stronger than for other locations that lack connectivity with core cities. In this respect, provincial data can hide substantial intra-provincial differences, and a sample of cities can hide structural patterns. The main contribution of this paper is to give a comprehensive representation of the spatial distribution of economic activity in China at the prefecture-city level. This spatial representation is used to identify for which cities the effect of market access on wages is stronger.

The paper starts by assessing if wages in one location are correlated with wages and income in other locations through an exploratory spatial data analysis (ESDA). The local indicators of spatial association (LISA) show that the spatial relationship between wages and income is positive and significant only for certain areas of China – the most developed areas around the Bohai Bay Area, the Yangtze and the Pearl River Deltas.

The statistical associations found in the ESDA are not causal, however. To establish a causal relationship between wages and market access, the spatial distribution of economic activity is characterized through a wage equation derived from a theoretical NEG model. The theoretical section shows that in the presence of labour mobility restrictions, the testable prediction of the wage equation is that differences in market access can explain some of the variation in wages. In the empirical application, a direct estimation strategy is used that does not require the assumption of perfect labour mobility (Brakman et al. 2004).

Previous papers have assessed the strength and spatial decay of income shocks for one location (Brakman et al. 2004; Hanson 2005). They generate a change of 10 percent in the income of one location and analyze the subsequent changes in every other location within the country. This paper shows that the same shock has different impacts depending on which city it is applied to. To see this, consider the case of two relatively large cities: one is located in the...
coastal area, and is surrounded by growing intermediate satellites cities. The second one is located inland and is surrounded by small towns and rural areas. How will a sudden increase in economic activity in these locations affect wages in their surrounding locations? From NEG theory, one would expect that the first city has a larger impact on its surroundings than the second city. A ‘hierarchy’ of cities is derived based on their spatial externalities by simulating a marginal income (GDP) shock in each of the 230 prefecture-cities of the sample and evaluating the consequent change in wages. The most important empirical result of this paper is to show that spatial linkages seem to be most relevant for core cities (Beijing, Shanghai and Guangzhou).

After the introduction, the paper continues in Section 2 with the ESDA that will motivate the empirical application. The theoretical framework on which the empirical application rests is introduced in Section 3. Section 4 presents the results of the empirical estimation. Section 5 contains the results of a counterfactual experiment where the heterogeneous impact on wages of market access shocks in different locations is assessed. Finally, Section 6 concludes and presents some directions for future research.

2 Exploratory spatial data analysis (ESDA)

What is first noticeable when looking at the map depicting the distribution of employment density at the prefecture-city level in China is the significant variation across and within provinces. In particular, employment density is largest in a handful of coastal prefecture-cities.

Given this distribution of economic activity, are wages spatially dependent or are they randomly determined? The global Moran’s I statistic gives a rough indication of the existence of spatial autocorrelation of wages in China as a whole. Based on wages in 2005, the value of this indicator is 0.26, implying, in a strict sense, that similar values are more spatially clustered than could have been caused by chance.

The local indicators of spatial association (LISA) provide a measure of spatial association for each individual location. Figure 2 shows the LISA cluster map for wages in 2005. The results are quite interesting, as they reveal new patterns that are not evident in studies using data at provincial level or a sample of cities (Ying 2000; Lin 2005; Hering and Poncet 2010). Darker areas indicate that high local wages are associated with high wages in surrounding locations. This ‘high-high’ significant relationship is found for a group of cities located in the Bohai Bay Area (BBA), the Yangtze River Delta (PRD) and the Pearl River Delta (YRD).

The LISA cluster map for wages and GDP (see Figure 3, and Figures 4, 5 and 6 for a close-up on the BBA, YRD and PRD) confirms that for roughly the same group of cities, high wages in one location are associated with high income in surrounding locations. The fact that dark areas are found next to each other confirms a stylized fact of the NEG literature, namely, the tendency of successful locations to ‘cluster’ together.

Up to this point, the ESDA has revealed two issues that will be studied further in the empirical application of this paper. The first is that it is relevant to analyze the change in wages in Chinese cities in terms of what happens in surrounding locations regarding income and wages. In terms of NEG, this is the equivalent of explaining local wages as a function of market access. Sections 3 and 4 are devoted to this empirical application. The second is that, given the
uneven spatial distribution of economic activity, these spatial linkages may be heterogeneous across the country. This is further explored in Section 5.

3 The wage equation

3.1 General framework

Consider the following set-up. In an economy with \( R \) locations, there are two sectors, each of them producing one good. One of them is a tradable good (usually identified as manufactures) and the other one is an homogeneous good that can be tradable or non-tradable across regions. The only input in the economy is labour.\(^6\) There are positive costs for trading manufacture goods between locations. One way to model them is as ‘iceberg’ transport costs, meaning that a part of the good ‘melts away’ when transported, so only a fraction of the unit originally shipped arrives.

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\(^5\) For a formal derivation of the core NEG model see Krugman (1991) and Brakman et al. (2009).

\(^6\) Other versions of the model also include intermediate inputs, see for example Krugman and Venables (1995).
Consumers spend their income on both goods, and maximize their utility accordingly. The manufacturing good can be thought of as an aggregate of differentiated varieties, and the consumption of each variety is determined by its price and by the consumer’s elasticity of substitution, denoted by $\varepsilon$.

On the production side, there is monopolistic competition on the manufacturing sector, where each firm produces under increasing returns to scale one variety of a product differentiated by secondary attributes. For a sufficiently large number of firms, one can assume that each firm has no influence on prices and therefore, faces a downward sloping demand curve. Given that the elasticity of substitution is constant, a measure of scale economies can be derived by taking the ratio between the average cost and the marginal cost, so that the larger the elasticity of substitution, the lower the mark-up a firm can charge on consumers, and the lower the scale economies.

Under these conditions, the following wage equation is obtained (Krugman 1991):

$$W_r = \left[ \sum_i Y_i I_{Ir} \varepsilon^{-\frac{1}{\varepsilon}} T_{Ir} \right]^{\frac{1}{\varepsilon}}$$

where $r$ refers to location $r$, $W_r$ measures average wage, $Y_i$ measures income or expenditure level, $I_r$ is a composite index price of manufactures and $T_{Ir}$ is a function decreasing in distance.
or transport costs between locations. Given $\varepsilon > 1$, Equation (1) relates wages in location $r$ to 'market access (MA)' (income deflated by the price index) and surrounding locations. Particularly, and given the decreasing transport cost function, Equation (1) describes a 'wage gradient', where wages are systematically higher in locations with better market access, and they are lower in locations located further from these centers.

3.2 Empirical testing

Several papers have shown evidence on the positive effect of market access in wage differentials for the case of China. At the province level, Lin (2005) and Ma (2006) find evidence on the effect of market access on the increasing wage gap between coastal and interior provinces. Hering and Poncet (2010) estimate a wage equation using survey data for 6,848 workers from 56 cities in 11 provinces for 1995. They regress an estimated city market access variable on individual wages and other control variables, and find that there is a significant and positive relationship between Chinese cities’ market access and individual wages.

These papers share the methodology outlined in Redding and Venables (2004) for estimating the wage equation. Under this approach, the market capacity of a location within a country is decomposed into supplier access and market access. Because the market capacity is not directly

Fig. 3. LISA cluster map for GDP and wages, Chinese prefecture-cities, 2005
observable, the wage equation is estimated in two-steps. In the first step, a gravity equation containing the market capacity determinants is estimated using data for trade and distances between sub-national locations and trading partners.\(^7\) In the second step, the resulting market and supplier access estimates are taken as given under the assumption of perfect labour immobility, and the maximum wage that a firm can afford to pay is estimated.

Noting that labour mobility in China is restricted but not prohibited, De Sousa and Poncet (2007) take a different approach by assuming that labour is immobile in the short-run but mobile in the long-run. They estimate a wage equation that includes both an estimated market access term and a variable capturing internal migrant labour supply using data at the province level. They find that the magnitude of internal migrant labour supply exerts a downward pressure on wages, and that this effect is large enough to offset the upward pressure exerted by market access.

While a combined approach including intermediate demand, international and internal trade and labour migration would be highly desirable for the case of China, reliable data on inter-city migration and trade are not available. One of the main purposes of this paper is to estimate a

\(^7\) Given the lack of sub-provincial trade data, Hering and Poncet (2010) allocate the estimated provincial market capacity to each of the cities in their sample according to the GDP share of each city.
NEG-type of wage equation and then use the estimated relationship as a benchmark to assess the impact of changes in market access for each prefecture-city. For this purpose, a comprehensive spatial representation of economic activity at the prefecture-city level is needed.

Hanson (2005) offers an example of such a spatial representation. He takes a direct approach for estimating the wage equation. The market access of a location is approximated by a distance-weighted measure of local income discounted by the price index. The main problem with this direct estimation is that data on the price index is usually not available for high levels of spatial disaggregation. Hanson noticed that for deriving an explicit measure of the price index, one option is to assume that perfect labour mobility results in real wage equalization across locations in the long run. After using housing prices to approximate the cost of an immobile factor (Helpman 1998), he obtained an estimable version of the equation from which the structural parameters of the underlying NEG model can be retrieved.

Given that labour mobility in China is at an intermediate point between fully mobile and immobile, the paper opts for a direct estimation strategy that does not rely on the real wage equalization assumption but that still allows for a comprehensive spatial representation of economic activity. This strategy, introduced by Brakman et al. (2004), is presented in the next section.

Fig. 5. LISA cluster map for GDP and wages, Yangtze River Delta, 2005
4 Empirical implementation

4.1 Estimation strategy

The empirical strategy proposed by Brakman et al. (2004) takes a different approach to derive the wage equation, at the expense of less information on the structural parameters of the model when compared to the Hanson model. The authors start by simplifying the price index outside a region by using an average distance measure, and propose the distance from an economic center as an appropriate measure.

With this simplified measure, the real wage equalization no longer has to be invoked, and after taking logarithms the wage equation (Equation (1)) to be estimated becomes:

$$\log(W_r) = \kappa_0 + \epsilon^{-1} \log \left( \sum_{s=1}^{R} Y_s I_s^{r-1} (D_{rs})^{1-\epsilon} \right) + \mu_r \quad (2)$$

8 In particular, from the Hanson version of the wage equation, estimates for the elasticity of substitution, the transport cost parameter and the share of income spent on manufactures can be obtained. Estimates for the two first parameters can be obtained with the strategy proposed by Brakman et al. (2004), but not for the last one.

9 The economic center is the city with the smallest average distance to other cities, where average distance is calculated as: $\overline{Dist_r} = \frac{\sum_{s} Y_s / \sum_{s} Y_s D_{rs}}.$
with
\[
I_s = \left[ \lambda_s (W_s D_{s})^{1-\epsilon} + (1 - \lambda_s) (W_s D_{s-center})^{1-\epsilon} \right]\gamma^{1-\epsilon}
\]

where \( W_s \) the average wage outside location \( s \), \( D_s \) is the internal distance of location \( s \), \( D_{s-center} \) is the distance from location \( s \) to the economic center, weight \( \lambda_s \) is location \( s \)'s share of employment in the manufacturing sector and \( \mu_s \) is an error term. The power distance function 
\[
T_{rs} = \tau r^t \]
with \( t > 0 \) allows the data to decide whether transport costs rise or fall more (if \( \tau > 1 \)) or less (if \( 0 < \tau < 1 \)) than proportionally with increased distance between \( r \) and \( s \) (Brakman et al. 2006).

4.2 Estimation issues

By estimating Equation (2), one can obtain the values of the elasticity of substitution between manufacture varieties (\( \epsilon \)) and the level of transport costs (\( \tau \)). From the theoretical model \( \epsilon > 1 \) and \( \tau > 0 \) are expected.

Equation (2) suffers from possible biases, because there might be a two-sided causality between GDP and wages. Equation (2) is estimated by using non-linear least squares (NLLS) and a generalized method of moments (GMM) estimator, using population density in 1996, elevation (from sea level) and GDP per capita in 1996 as instruments. The validity of the instruments is shown by means of the Hansen J statistic.

Still, estimating Equation (2) may lead to overestimation of the parameters because if a place offers more and better education, it will probably have, on average, more workers with higher skills. In such a case, the wage differential relative to other locations is partly determined by the skill level of workers. Lacking disaggregate information on wages by labour category, an alternative is to explicitly control for the prefecture-city's supply of higher education institutes per 10,000 inhabitants in Equation (2).

A control variable for employment density is included (Ciccone and Peri 2006), and 'first nature' or geographical explanations is also controlled for (Bao et al. 2002) by including a dummy variable that takes the value of one if the prefecture-city has access to the sea and zero otherwise.

4.3 Estimation results

Table 1 summarizes the results for the NLLS and GMM estimations of Equation (2) for data on 230 Chinese prefecture-cities in 2005.

The structural parameters \( \epsilon \) and \( \tau \) are precisely estimated\(^{10}\) under both the NLLS and GMM estimation and their values lie on the range of values found for China and other countries (Brakman et al. 2004; Mion 2004; Hanson 2005; Brakman et al. 2006; Hering and Poncet 2010). The control variable for skill differences is significant even when using the GMM estimator.\(^{11}\)

\(^{10}\) However, the efficiency of the NLLS and GMM estimates can be affected by the presence of spatial autocorrelation in the residuals, without affecting their consistency. A first assessment using an LM error test revealed the presence of this problem. This paper gives more weight to identification issues, so it follows closely the specification suggested by the theoretical model without regarding the issue of spatial autocorrelation, with the remark that the standard errors of the parameters should be interpreted with care.

\(^{11}\) This result holds when using student enrollment per 10,000 inhabitants as an alternative control for skill differences.
The relevance of human capital differences in explaining wage differentials in China is in accordance with findings at the provincial level (Lin 2005; Ma 2006; De Sousa and Poncet 2007). The Hansen J statistic does not reject the validity of the set of instruments for both years. Controls for employment density and access to coast, turned out to be insignificant in the GMM estimation (see column 2 of Table 1).12

Given these results, the GMM estimations with controls for skills are used as the preferred specification. Internal market access and the educational variable can explain 36 percent of the variation in wage differences across cities. The impact of market access on wages, which depends only (and inversely) on the elasticity of substitution, is 0.33. On average, doubling market access increases average wages by 33 percent. This seems to be on the high side when compared to the values found by Au and Henderson (2006) and Hering and Poncet (2010) for China. However, these estimates are not strictly comparable because these studies rely on different methodologies, levels of aggregation and coverage of the data.

The transport cost parameter is also significant. The value is lower compared to the values found by Brakman et al. (2006) for the European Union, but it is worth noticing that the transport cost parameter is affected by the way distance is measured and the relative size of the country.

The results of the direct estimation of the wage equation using prefecture-city level data confirm that part of the variation in wage differentials can be explained by differences in market access. With the spatial representation given by the wage equation we now turn to the main question of this paper: are spatial spillovers different across cities?

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12 Equation (2) is also estimated using a two-stage instrumental variables (TS-IV) estimator, which in theory is a special case of the GMM estimator (Baum et al. 2003). The point estimates and standard errors are roughly the same as the GMM’s and are therefore not shown here.
5 Market access and the heterogeneous effect of shocks

Do the effects of a location-specific shock differ from city to city? With perfect labour mobility, labour supply is infinitely elastic (so the wage curve is a flat line), and the higher real wage generated by a positive shock in an area attracts an inflow of migrant workers until real wages (wages minus the cost of living) are again equalized across areas. Given this, the area experiencing the positive shock ends up with a larger population but the same real wage. On the other extreme, if labour is perfectly immobile, all of the impact of a positive shock is met by changes in wages, so the region that generated the shock ends up with a larger real wage and the same population as before the shock. What about the intermediate case? This question is particularly interesting for the case of China, where the wage curve is somewhere in the middle of these two extremes.

Combes et al. (2005) state that the implications for the way in which the urban system adjusts to shocks varies in the presence of labour mobility restrictions. Particularly, it depends on the relative slope of the real wage and supply curves. It is reasonable to assume that each city faces a different real wage and labour supply curve. In this case, cities may experience population gains and losses together with changes in the real wage. It is not possible to estimate the real wage curve and labour supply for each city, but generating the same shock over all locations and comparing the changes in wages due to this shock may give an idea of the changes in population that may follow, or the possible effects of labour mobility restrictions.

To address these issues, a methodology is proposed that has been applied for the case of one city, (Brakman et al. 2004; Mion 2004; Hanson 2005) but not used in a systematic manner across all cities for comparative purposes. The elasticity of wages are calculated in each location \(s\) to a change in income (GDP) in location \(i\). This experiment is performed for each of the prefecture-cities included in the sample, using the estimated values of \(\tau\) and \(\varepsilon\) of the preferred specification (see Table 1, third column). In this way, it is possible to separate the change in wages that is due to spatial externalities for each location, and compare the effects across cities. Although in practice, changes in income (a rise or fall in export demand, for example) are likely to affect many locations at the same time, this exercise seeks to isolate the pure effect of each location, in order to compare both the spatial decay and strength of the effects.

Formally, the elasticity of wages in location \(s\) to an income change in location \(i\) can be expressed as:

\[
\frac{\partial \ln W_i}{\partial \ln Y_i} = \frac{1}{\varepsilon} \sum_s Y_s I_s^{\tau - 1} D_{ri}^{\varepsilon (1 - \tau)} Y_i I_i^{\tau - 1} D_{ir}^{\varepsilon (1 - \tau)} \left[ \frac{1}{\varepsilon} \frac{M_{ar}}{M_{ir}} \right]
\]  

This elasticity is directly proportional to the contribution of location \(i\) to location \(r\)'s market access. From the functional form of the transport cost function that has been defined, and the signs of the parameter value estimates, it can be readily deduced that the effects of a local shock will ‘fade’ as one moves further away from the epicentre. But are these effects different depending on where the shock is generated?

Figure 7 contains the results of the shock experiment for all provincial capitals and municipalities. The effects are divided between the own location, the average of locations within 100 km, 200 km and beyond 200 km,13 so the spatial decay of the shocks is evident. It is readily seen, for example, that a 1 percent change in Shanghai’s income causes not only a 0.28 percent change in local wages, but also a 0.04 percent, 0.02 percent and 0.005 percent average change.

13 The average impact over 100, 200 and beyond 200 km is calculated as \(\frac{1}{N_{km}} \sum_{r \in R_{km}} \frac{\partial \ln W_i}{\partial \ln Y_i} = \frac{1}{\varepsilon N_{km}} \sum_{r \in R_{km}} \frac{M_{ar}}{M_{ir}}, d_i \geq km \leq 100; 100 \geq km \leq 200; km > 200.\)
in wages in prefecture-cities located within 100 km, between 100 and 200 km, and beyond 200 km from Shanghai, respectively. In contrast, originating the same shock in Urumqi, the capital of Xinjiang province, causes a change of 0.27 percent in the local wages, but has virtually no effect in the wages of other locations.

Figure 8 shows a map with the average impact of the shocks on each location.\textsuperscript{14} It allows comparison of the strength of the effect on average wages of an equal change in income. As can be seen in Figure 7, the shocks generated in economic centres (Beijing, Shanghai and Guangzhou), marked with the larger dark grey circle, have the largest average impact on the rest of the country. Put differently, these cities exhibit a larger elasticity of wages to shocks (changes in income), when considering not only local wages, but wages in all of the other prefecture-cities in the sample.\textsuperscript{15}

The larger responsiveness of economic centers is likely to generate more than proportional potential migration flows to these centers, and the cities around them (given the spatial decay mentioned above; see also Figures 4–6). In this sense, the impact on wages ultimately depends on the degree of labour mobility. On the one hand, if migration to economic centers is tightly restricted, the shock will ultimately translate in higher wages in economic centers and greater wage disparities with respect to the rest of the country. On the other hand, if migration flows are loosely restricted, there will be an increase in wages accompanied by an increase of population, but as long as mobility remains imperfect, it is expected that the change in population does not completely offset the increase in wages.

6 Conclusions

This paper has assessed whether the predictions of a wage equation derived from a new economic geography model are consistent with the observed wage differences across locations in China.

Given the existence of both labour mobility restrictions and significant inter-city migration, an empirical version of the wage equation is opted for that does not assume real wage

\begin{equation}
\frac{1}{N} \sum_{i=1}^{N} \frac{\partial \ln W}{\partial \ln Y} = \frac{1}{\varepsilon N} \sum_{i=1}^{N} MA_i
\end{equation}

\textsuperscript{14} The average impact over all N locations is calculated as

\textsuperscript{15} See Table A1 in Appendix 2 for a complete list of the percentage average impacts by prefecture-city.
equalization but that allows labour mobility. The results of the estimation give support to the idea that market access differences can explain part of the variation in wages across cities in China. The results are consistent with the findings of previous papers that use different methodologies or spatial scales.

In the analysis of shock experiments for each location, confirmation is found for the idea of heterogeneous effects of income shocks on wages across China. Thus, even though wages are spatially correlated across locations (as shown in Section 2), there are some areas where these effects are stronger. In particular, they seem to be most relevant for Beijing, Shanghai and Guangdong as core cities, and their adjacent areas.

The results give an indication of further concentration of economic activity and population in these core cities and their surrounding satellite cities. However, it is difficult to forecast the long-run population distribution from a partial equilibrium approach. The cumulative causation present in NEG models requires a different modeling strategy, in particular, one that accounts for the spillover effects on a general equilibrium framework. Furthermore, as pointed out by Redding (2009), the permanent or transitory nature of the shock depends on the existence of multiple equilibria. This is an area open for further research.

Fig. 8. Average impact of income shocks on wages for Chinese prefecture-cities
Appendix 1

Data description

The People’s Republic of China administers 33 province-level divisions, including 22 provinces, five autonomous regions (Guangxi, Inner Mongolia, Ningxia, Xinjiang and Tibet), four municipalities (Beijing, Tianjin, Chongqing and Shanghai), and two special administrative regions (Hong Kong and Macau, not included in this paper). The prefecture level is the second level in the administrative hierarchy of the People’s Republic of China. This structure consists of 333 divisions composed of 283 prefecture-cities, 17 prefectures, 30 autonomous prefectures and 3 leagues. For empirically estimating the wage equation for China, data is used at the prefecture-city level, which is generally composed of an urban center and surrounding rural areas.

The source of all data is the China City Statistical Indicators database provided by the China Data Center of the University of Michigan. The original data are reported by the National Bureau of Statistics, which is collected from local statistical bureaus in all counties and cities in China. The data is comprehensive for nearly all prefecture-cities, but is adjusted for missing observations in some of the variables. As a measure of market size, gross domestic product measured in thousands of current Yuan is used.

As a measure of wages, the average wage of on-post staff and workers in current Yuan is used. The category ‘staff and workers’ does not include persons employed in small-scale private establishments and self-employed individuals, migrants employed in the informal sector or those who are not reported (Banister 2005). Therefore, a word of caution is needed on the interpretation of this ‘wage’ measure, because it is not directly comparable to international statistics on labour compensation.

Hering and Poncet (2007) propose GDP per capita as proxy for wages, instead of average wages for staff and workers. This has two caveats. First, the variable GDP per capita for China is likely to be biased upwards because population numbers do not include most of the floating migrant population. Second, in a cross-section of cities, the underlying assumption is that the share of wages in income is roughly similar. This is not accurate for China, because the share of income accrued to the government differs considerably across locations. Therefore, in this paper the use of average wages for staff and workers as proxy for wages is preferred. The assumption that wages in the private sector have followed the same tendency as wages for the non-private sector across cities does not seem so unreasonable given the observed increasing mobility of labour across sectors (Zhao 2005).

Information on the share of employees in the manufacturing sector is readily available in the China City Statistical Indicators database. The paper measures distance between every pair of locations using the great distance circle formula and proxy internal distance by $2/3\sqrt{\text{area}/\pi}$.

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16 Prefectures and leagues are historical categories that have been replaced almost entirely by prefecture-cities, although some of them can still be found mostly in Xinjiang, Tibet and Inner Mongolia. Autonomous prefectures are prefectures with one or more designated ethnic minorities. A large part of the prefectures, leagues and autonomous prefectures are located in remote areas with difficult geographical and climatic conditions, which cover a vast territory in the west of China. Although this territory is not covered in the prefecture-city levels sample (N/A observations in Figure 1), aggregate population data for all prefecture-city levels accounts for roughly 90 percent of the national figures.

17 However, throughout the article the terms ‘prefecture-city’ and ‘city’ are used indistinctively.


19 Lin (2005) and Ma (2006) have used similar wage data at the provincial level. Statistics on wages for the private sector, self-employed individuals and units below designated size have never been published in China for any level of spatial disaggregation.

20 For example, at the province level, the income accruing to government in Shanghai in 2002 was 28.9 while it was 17.4 percent for Zhejiang. Consequently, and given an almost identical share of corporate profits on income, the shares of employee compensation were 41 percent for Shanghai and 53 percent in Zhejiang.
### Table A1. Percentage average impact of income shocks, by prefecture-city

<table>
<thead>
<tr>
<th>Prefecture-city</th>
<th>Province</th>
<th>Percentage average impact</th>
<th>Prefecture-city</th>
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Papers in Regional Science, Volume 90 Number 1 March 2011.
Resumen. Los modelos de la Nueva Geografía Económica (NEG, siglas en inglés) predicen que las localizaciones con ventajas de acceso a mercados ofrecen salarios más elevados y mayor afluencia de mano de obra. Mediante la utilización de datos a nivel de ciudad-prefectura en China, este estudio estima una ecuación salarial a partir de un modelo NEG. Los resultados apoyan la explicación que da la NEG a las disparidades salariales entre ciudades. Una aplicación de experimentos de choque en 230 prefecturas en China muestra que el efecto promedio de cambios en los ingresos difiere en gran medida entre localizaciones. En particular, las conmociones salariales generadas en las ciudades principales tienen un impacto promedio mayor en el resto del país que las conmociones generadas en otros lugares.

要約 新経済地理学（NEG）モデルでは、市場へのアクセスが便利なロケーションでは、賃金がより高く、労働力の流入規模がより大きいことが予測される。本論文では、中国の地級市レベルの包括的なデータを用いて、NEGモデルから導出した賃金方程式を評価する。推計結果は、都市間の賃金格差は新経済地理学的説明により裏付けられるものである。中国の230の地級市にショック実験を適用した場合、ロケーションにより所得変化の効果の平均値が大きく異なることが示された。特に、中核都市で生じる所得ショックが中国のほかの地域に与えるインパクトの規模の平均値は、他の地域で生じたショックに比べて大きくなる。