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ABSTRACT

Inter-City Spillover and Intra-City Agglomeration Effects among Local Labour Markets in China

We examine how city size affect wage levels of cities (agglomeration externality) and how it influence surrounding cities (spill-over effect) in China for the period between 1995 and 2009. Using spatial fixed-effect panel data models and allowing for endogenous and exogenous spatial dependence, we find strong positive city size effect on real wage levels, which confirms the existence of agglomeration economy within cities. We also find significant differences in both the direct and indirect effect of factors such as FDI between more and less population dense areas.

JEL Classification: C23, R12, R23

Keywords: agglomeration economy, spill-over, spatial econometrics, fixed-effects

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1 Introduction

China's fast economic growth has been associated with a rapid productivity increase. According to the estimates of Feenstra et al. (2015), China's total Factor Productivity (TFP) measured at constant national prices increased from 0.59 in 1990 to 1.04 in 2014. It is often believed that this is at least partly the result of fast urbanisation. As commented by an article in The Economist (Jan 22, 2015): "Breakneck urban growth has propelled China's rise in the past three decades". Indeed, through massive rural-urban migration and increase in the number of cities and towns, by 2016, Chinese urban population has grown to about 57 percent from only about 23 percent in 1985 (World Bank (2017)). According to the 2010 Census, China's migrant population was about 221 million or 16.5 percent of the total population NBS (2011). At the same time, the number of cities at the prefectural level or above increased from 169 in 1986 to 298 in 2017. However, there have been significant and persistent disparities in development across regions. Of the 185 prefectural cities that we have data for, the difference in GDP per capita (in constant prices) between the 9th and 1st decile was about 132 percent in 1994, and became 163 percent in 2009. The dispersion of real wage levels across regions has also been persistent: the difference in the average real wages between the 9th and 1st decile cities has been constant at about 64 percent.

In this paper, we wish to shed some light on the reasons behind the unbalanced economic growth and the persistent gap in real wages across regions from the perspective of agglomeration externalities. We study two types of externalities in Chinese cities: how city size affect real wages(we call it intra-city agglomeration economy) and how cities' real wages are affected by those of surronding cities (we call it the inter-city spillover effect). Our focus is on 185 Chinese cities at and above the prefectural level for the years between 1995 and 2009.

The idea that urbanisation could bring efficiency gain is not new. It could be traced to at least as early as Marshall (1890) who believed that productivity differences across regions are not exogenous and could be explained by agglomeration externalities through mechanisms such as thick labour and intermediate goods markets[1], and knowledge spillover (for a review of the literature, see for example, Johansson and Quigley (2004), Johansson and Forslund Johansson (2008), and Combes and Gobillon (2015)). These effects are important to quantify because the existence of these externalities often leads to optimal choices by individuals not in line with collective objectives that policy makers may have, and has inequality implications. For example, China's policy makers are often concerned about the negative effects of repaid growth in the size of cities and excessive urbanisation (see Jones and Visaria (1997) and Henderson (2003)). Empirically, however, due to its elusive nature, agglomeration externality is often tricky to detect, and the magnitude depends on

[1] A thicker market means higher density of agents or their activities.

factors such as institution settings and environment of specific periods. As discussed in Combes and Gobillon (2015), agglomeration economies are shaped through many different channels. The effects of these mechanisms are not identified separately. What has been estimated in the literature (and also the focus of this paper) is rather the overall impact on local outcomes of spatial concentration. This is, however, ̀crucial for the understanding of firms' and workers' location choices or for the design of economics policies'.

In this strand of literature, which this paper follows, the hypothesis that productivity in more agglomerated areas is higher is tested. Typically, population size or density are used to measure agglomeration, and output per worker, wages, or TFP are used to measure productivity. The elasticity of productivity with respect to population size or density is used to measure the agglomeration economy. These investigations are either conducted at the local level or at the individual level of firms or workers. For example, Sveikauskas (1975) found a positive correlation between output per worker and the population size of US cities. Similarly, by estimating a reduced form labour productivity equation using state-level data of the US, Ciccone and Hall (1996) find that doubling employment density raises productivity (measured by output per worker) by 6 percent. A criticism of these early studies is that they lack of 'solid identification strategy' (Moretti (2011)) to deal with the endogeneity issues of the agglomeration measures. The sources of the endogeneity at the local level could come from omitted variables that are correlated with the agglomeration measures; interdependent across regions, potential reverse-causality between productivity and agglomeration, or errors in the agglomeration measurement. Further, if individual data were used, further endogeneity issue may arise when workers make location choices according to some unobserved factors such as unobserved ability, or to the exact individual outcomes that correlate to local characteristics. Later studies attempt to use various strategies to deal with these issues. For example, Ciccone (2002) use historical variables as instruments for agglomeration with cross-section data to deal with the endogeneity issue. Other studies such as Glaeser and Mare (2001), Henderson (2003), Moretti (2004), and Greenstone et al. (2010) make use of panel data to remove the correlation with unobserved time-invariant factors. Each of these methods by themselves may not be able to deal with the endogeneity issue satisfactorily (see discussion in Combes and Gobillon (2015)). Another drawback of these approaches is that agglomeration economy is assumed to be constant for all cities and they ignore spatial interdependence. In the presence of systematic spatial dependence, the standard fixed effects models will result in an estimate of the average effect but cannot reflect the pattern of the effect across regions. Thus another branch of the literature employs spatial econometric technique to model regional correlations explicitly. In spatial econometrics models, the effect of certain factor is allowed to be a multiple of the direct effect and depends upon proximity to neighbouring regions. The impact of factors originated from neighbouring regions could also be separated out from that of own region. The models are richer than the standard non-spatial linear models. However, these spatial models still suffer from the same omitted variable problem and ignore the potential 'exogenous interaction effects' among cities (Manski (1993)). In other words, without controlling for either fixed-effects or instrumenting the endogenous variables, spatial econometric models still suffer from the endogeneity problem (see the discussion in Gibbons and Overman (2012)). Such examples include Bode (2004), Van Oort (2007), and Ke (2010)) which all use cross-section data and restrict spatial correlation to spatial lags, but do not deal with the endogeneity issue.

As mentioned earlier, the magnitudes of agglomeration effects vary from time to time, and country to country. The estimates also depend upon the measures used. For example, the estimates for the US are around 0.05, and for European countries, the estimates ragnes from 0.05 to 0.13.[2] For China, the estimates have been found to be in a wide range. Chauvin et al. (2017) obtained a few estimates for the elasticity of wage with respect to population size and population density. Depending upon the methods and instrument used, the estimates range from 0.03 to 0.32 (for the elasticity of wage with respect to population size) or from 0.19 to 0.32 (for the elasticity of wage with respect to population density). Yet, Ke (2010), using a cross-sectional spatial econometric model, found the elasticity of wage with respect to employment density to be negative. Au and Henderson (2006), using an IV approach with cross-sectional data, found that 'urban agglomeration benefits are high' and are U-shaped: 'real incomes per worker rise sharply with increases in city size from a low level', and 'level out nearer the peak and then decline very slowly past the peak'. Xu (2009), by estimating a non-spatial panel data model, also concluded that the relationship between population and productivity to be non-linear (U-shaped). These findings may suggest that the agglomeration externality is not constant in China. None of these studies take the advantages of spatial econometrics and treating the endogeneity issue at the same time. In this paper, we attempt to estimate these agglomeration externalities in China using a fixed effect Spatial Durbin panel data model, which both gives a richer insight of intra-city agglomeration externalities and inter-city spillover effects, and controls for time-invariant heterogeneity at the local level. We also use time-lag of population size of city as the explanatory variable to reduce the concern on simultaneity. Intra-city agglomeration externalities are captured by the effects of city size, while the inter-city

[2] The estimates for the US seem to be comparable across different studies. For example, Ciccone and Hall (1996) and Rosenthal and Strange (2008) estimated the elasticity of productivity with respect to population density to be around 0.04-0.05 for the US. Also for the US, Chauvin et al. (2017) estimated the elasticity of male earning with respect to metropolitan area population to be 0.054. For other countries, is seems not to be the case. Ciccone (2002) estimated the productivity elasticity with respect to population density for a few European countries to be 0.05 in 1992. These studies use IV approach on cross-section data to control for the endogeneity issue. However, Brülhart and Mathys (2008), who use a panel of more European countries for the period between 1980-2003 got a much larger estimate of around 0.13.

spillover effects are captured by spatial dependence. We argue that identification is achieved by 1) the inclusion of fixed effects, which takes account of the endogeneity problem due to omitted time-invariant variables; 2) using time-lagged (rather than contemporary) variables as regressors, which reduces the potential simultaneity problem; and 3) by functional form assumptions. Functional form assumptions may be strong in this approach, but this may be the price worth to pay for allowing for a richer structure of the model. Since the variables are strongly correlated, it is possible that using one-year lag is not sufficient to overcome the simultaneity problem. As a robustness check, we estimate and compare the models using time-lags of different period. Admittedly, the endogeneity problem may still not be removed completely with this approach, but we believe by taking into account the spatial independence and controlling for the fixed-effects, our estimates may be improved compared to previous estimates for China and provide the pattern of the effects across regions. Han et al. (2018) is a recent example that use similar approach to study spatial spillover effects of industrial agglomeration on carbon emissions in China.

A drawback for allowing for the effects of the explanatory variables to be varying across observations in spatial econometrics models is that the effects cannot be expressed directly as the parameters of the models. Using model estimates, we calculate summary measures of the variable impacts: the average direct (from own city) and indirect effects (from other cities) of some key variables on productivity. These effects are calculated for various city groups. We also propose a new measure of the strength of the spillover effect–the multiplier of the average effect over the initial shock of a variable. [3]

We find a strong positive effect of urban population on the real wage level. This finding confirms the existence of agglomeration economy within regions. We also find significant differences in both the direct and indirect effect of factors such as FDI on productivity between areas with different population densities. This seems to suggest the existence of spillover effects between cities. Disparity between regions in economic growth and productivity could be explained by the statistically significant regional variations in the direct and indirect effects of the explanatory variables. For example, we find that the average direct effect of Foreign direct investment (FDI) increments is about 1.5 times larger in East China than in Northeast.

The contributions of the paper are: 1) identifying within region agglomeration externality and inter-region spillover effects on productivity in urban China using a spatial panel data approach; 2) providing an explanation for the unbalanced economic growth and the persistent gap in productivity

[3]As discussed in Moretti (2011), another approach has also been used to test for agglomeration economies. It is based upon the location decision of firms at equilibrium and to make inference out of observed geographic distribution of employment. For example, by comparing geographic concentration across industries in the US manufacturing sector, Ellison and Glaeser (1997) find that all industries are localised to some degree and that spillover of location, natural environment, and even random shocks could all affect agglomeration. Other examples include Rosenthal and Strange (2003), Duranton and Overman (2005), and Ellison et al. (2010).

across regions; 3) our model considers both endogenous and exogenous spatial interdependence explicitly; and 4) proposing a new measure for the strength of the spillover effects.

The rest of the paper is organised as follows. In Section 2 we describe the output and productivity patterns of the prefectural cities over the period between 1995 and 2009. In Section 3 we present the model. Estimation results are presented and discussed in Section 4. In Section 5, we conclude.

2 Data

Our analysis focuses on 185 cities at or above prefectural levels in China for the years between 1995-2009. A prefectural city[4] in China is a city that directly controlled by a provincial government. According to a 1993 State Council document, they have to be cities that, have a non-agricultural population over 250,000 in their non-suburban areas; have total output of over 3 billion Chinese Yuans (at least 80 percent of which is from non-agriculture); have total GDP of over 2.5 billion Yuans (of which, over 35 percent is from the third (service) sector and more than that from the first (agriculture) sector); have government revenue of above 0.2 billion Yuans; and are centers to several other cities or counties in the region. In addition, four cities, Beijing, Shanghai, Tianjin, and Chongqing, are municipalities directly administrated by the central government.

Data employed in this paper are mainly obtained from China City Statistical Year Books and are supplemented by China Statistics Year Books. In a small number of cases, missing data for specific cities/years are obtained from statistical year books of various provinces. As mentioned in the introduction, the number of cities has been steadily increasing over the years from 206 in 1994 to 298 in 2017. For our analysis, we construct a balanced panel of 185 cities which have already existed in 1994. The panel excludes a few cities whose administrative areas have changed significantly during the period and a couple of cities in Tibet (which are isolated from most of the cities in the country). The location of these cities are shown in Figure 1.

[Figure 1 is here]

The key variable of interest analysed in this paper is average real wage per worker with urban *Hukou*[5], which we use to measure productivity.[6] The explanatory variables include the (lagged)

[4]There are three levels of cities in China, municipality under the central government, prefectural cities, and county level cities.

[5]The *hukou system is the residence registration system in China. Until recently, each citizen was classified in an agricultural or non-agricultural hukou (commonly referred to as rural or urban) and further categorized by location of origin. This two-fold organization structure was linked to employment permission and social policy. Local residents who held non-agricultural (i.e. urban) hukou status received benefits not available to their rural counterparts or non-residents. As a result, internal migration has been tightly controlled by the system. Only in the past few decades have these restrictions been gradually loosened.*

[6]Some papers use TFP as the measure of productivity (e.g., Moretti (2004) and Henderson (2003)). The issue

annal increment in FDI, the stock of total assets (including both fixed and circular assets), the size of urban population, and the shares of employment and output from the second (slightly broader than the manufacture sector) and the third sectors. It is important to take into account the large regional disparity in price levels. Thus, all the variables related to values have been deflated using a spatial price index (SPI) at the provincial level generated using the method proposed in Brandt and Holz (2006).[7]

Table 1 summarises the variables and their descriptive statistics used in this paper. First, the data confirm that productivity in China has increased rapidly over the sample period of 15 years—the average real wages have more than quadrupled. This increase is only slightly slower than the increase in real GDP per capita. Meanwhile, annual FDI inflows (in real terms) have also more than doubled. Since early 1990s, China has been the largest FDI recipient among the developing countries, and since 2003 it has become the largest recipient of the whole world. Second, the average size of cities has increased by about 13 percent over the sample period. Yet, this does not include rural migrant workers and their families. Thus the actual size of the cities would increase by a much larger scale. Thus this measure can only be used as a proxy for the size of the labour force. Due to the *Hukou* system, China's urban labour markets are dichotomous. To a large extent, workers with urban *Hukou* and migrant workers are often segregated into different sectors. And, the former are relatively immobile and the latter highly mobile. Admittedly, if the increases in the size of migrant workers are not in similar proportions, it may affect the estimate of the effect of city size on wage levels. Third, as a sign of urbanisation, the industry structure of the economy has also changed dramatically. On average, the proportion of non-agricultural sector has grown from about 78 percent to about 88 percent. In 2009, the service sector has already employed more than half of the non-agricultural workforce.

[Table 1 is here.]

To see regional disparity of the development, following the convention, we divide China into 7 regions: East China, North China, Central China, South China, Northeast China, Northwest China, and Southwest China (also see the map in Figure 1).[8] Generally speaking, East and South China are the most population dense and economically active regions, and the western parts of

with TFP is that it has to be estimated. And it China, statistics did not include migrant workers until 2010, which means we do not have the correct measure of the total labour input to estimate TFP. Wage does not suffer the same problem if they are paid at marginal product.

[7]Various methods, including Engel Curve methods, of creating SPI have been explored. Also see discussions in Gong and Meng (2008).

[8]East China includes Shandong, Jiangshu, Zhejiang, Anhui, Jiangxi, Fujian, and Shanghai; North China includes Hebei, Shanxi, Inner Mongolia, Tianjin, and Beijing; Central China includes Henan, Hubei, and Hunan; South China includes Guangdong and Guangxi; Northeast China includes Liaoning, Jin Lin, and Heilongjiang; Northwest China includes Shaanxi, Gansu, Ningxia, Qianghai, and Xinjiang; and Southwest China includes Sichuan, Guaizhou, Yunnan, Chongqing, and Tebit.

the country are less developed. In Figures 2 to 4, we present the trends of GDP per capita, wage levels, and FDI inflows of different parts of China together with the country averages. The figures illustrate vast and persistent differences among these regions. Figure 2 shows that cities in Central and Southwest China have the lowest GDP per capita and those in East and North China have the highest, and the differences of output levels have enlarged in the years post 2000. Figure 3 indicates that the pattern of wage increases do not follow exactly the output growth. Wages did not increase until late 1990's while per capita GDP had a continuous increase over the entire period. The speed of increases in wage levels is quite similar among different regions, and the differences in wages have been roughly kept constant (except for South China). This may be a sign of cross dependence in the labour markets. FDI inflows are extremely uneven among regions (Figure 4). In the early years, most of FDI ended up in East and South China. In later years, FDI in other areas picked up, but Northwest is still the region that attracts the least FDI. We also present the average sizes of the cities in terms of urban population in Table 2—in Northeast and Northwest, which are the less populated areas, city sizes are significantly smaller than in other regions.

[Table 2 is here.]

[Figure 2, 3, and 4 are here]

We use highway distances between pairs of cities in kilometers to measure the spatial distances between cities.[9] To show spatial correlation among regions, we calculate and compare in Table 3 the Moran index for log wage per worker. The table shows strong spatial correlations across cities. These correlations are all significant for cities until they are 1500kms apart. The correlations decrease dramatically with the increase of the distances—after the distances over 300kms the influences of other cities are still there, but the correlation coefficients become pretty small. The correlations of cities that are close from each other remain stable over time, but the correlations among cities over a longer distances became stronger in later years. This may suggest that economic links among cities are getting stronger over time, which is in line with the increased levels of economic activities.

[Table 3 is here.]

[9] We do not use absolute geographical distances calculated from geographic coordinates because we believe that highway distances better reflect economic relation between cities. These data are collected using the service provided by Google Map Services.

3 The Approach

The Model

To estimate the agglomeration and spillover effects in productivity, we estimate a fixed effect Spatial Durbin (SDM) Model:

$$y_t = \rho W y_t + X_t\beta + W X_t\theta + a + \sum_{s=1}^{S} d_t^s \iota_n + v_t,\ t = (1, \ldots, T), \tag{1}$$

where $y_t = (y_{1t}, \ldots, y_{nt})'$ is the (log) average real wage of the cities in year t, $X_t = (X_t^1, \ldots, X_t^R)$ (each $X_t^r = (X_{1t}^r, \ldots, X_{nt}^r)'$, $r = 1, \ldots, R$) is a matrix of R explanatory variables, W is a given spatial matrix for the autoregressive components, $a = (a_1, \ldots, a_n)'$ is the vector of city fixed effect, d_t^s $(s = 1, \ldots, S)$ are the dummy time effects, ι_n is a vector of ones, and $v_t = (v_{1t}, \ldots, v_{nt})'$ is an i.i.d. normally distributed error term. Included in X are (log) asset, lagged (log) population size of the city, relative size of each sector in the economy, and lagged (log) FDI. Including lagged population size and FDI is to reduce the endogeneity issue caused by simultaneity. We specify W as the inverse of highway distances between cities, standardised by the maximum of its eigenvalues.

In this model, potential intra-city agglomeration externality is captured by the impact of population size. The impacts of demand shock are captured by the coefficients of the lagged FDI. The inter-city spillover effect is considered to be from two sources. The first is from ρ, the coefficient of the spatial lag of the dependent variable. It reflects that the productivity of a city varies with that of its neighbouring cities. The second is from θ, the coefficients of the spatial lag of the explanatory variables. It reflects the fact that the productivity of a city may vary with the characteristics of its neighbouring cities. These two sources correspond to what Manski (1993) labelled as the 'endogenous interaction effects' and the 'exogenous interaction effects' (Elhorst (2014)).

One of the advantages of the SAR or SDM model is that they allow for the impacts of factors to vary for each city. The price to pay is the loss of straightforward interpretation of the model parameters. The model coefficients cannot be explained as the marginal effects of the variables. For example, β's could be explained as the initial round of direct shock of the corresponding variable on the dependent variable, and $W\theta$ could be explained as the initial round of exogenous interaction effects from other cities. The complete effects of the variables include the feedback effects (see next sub-section for details).

In the standard non-spatial linear models (including Spatial Error models), none of the two inter-city spillover effect is allowed. In those models, both ρ and θ's are set to zeros, although spatial correlation in the error terms can be allowed. In the presence of spatial correlation through lagged spatial dependent variables, the OLS or fixed effect estimates would be inconsistent. Although IV or GMM approaches could yield consistent estimates. The consistency of IV or GMM estimates depends crucially on the validity of instruments. And even if in the rare cases where valid instruments could be found, the inter-regional impacts are restricted to be constant and it is difficult to obtain the pattern of the varying effects.

In the Spatial Autoregressive (SAR) Models, which are probably the most popular spatial econometrics models, only the first (endogenous) spillover effect is allowed. In these models, θ's are set to zero. A potential problem is that if there exist exogenous interaction effects, the Maximum likelihood estimator would be inconsistent. The presence of these effects could be tested using a simple Likelihood ratio test (there is a large literature discussing various models, see for example, LeSage and Pace (2009) and Elhorst (2010)).

Marginal effects

Unlike in the non-spatial models, where the coefficients of the explanatory variables measure the marginal effect of those variables, the marginal impacts of explanatory variables in SAR or SDM models are more complicated. The effects depend upon the spatial correlation coefficient ρ, the spatial weighting matrix W, along with the β's (and θ's in the case of SDM). They also differ from units to units.[10] For example, the marginal impact of X_{it}^r, the r-th variable in X_t of city i at time t on Ey_{jt}, the expected wage level of city j at time t is given by

$$\partial E\{y_{jt}|X_t\}/\partial X_{it}^r = S_r(W)_{ji}, (i,\ j = 1, \ldots, n; t = 1, \ldots, T) \tag{2}$$

where $S_r(W)_{ji}$ is the j, i-th element of the matrix

$$S_r(W) = (I_n - \rho W)^{-1}(I_n \beta_r + W\theta_r)$$

(I_n is a $n \times n$ identity matrix).

LeSage and Pace (2014) propose calculating three averages of these varying impacts as summary measures. The first is the Average Direct Effects (ADE), which is the average impact of changing the value of the explanatory variable on the real wage of the same city:

$$ADE_r = n^{-1}tr(S_r(W)) \tag{3}$$

[10] It is worth pointing out that, many empirical studies wrongly interpret the coefficients as the marginal effects (as noted by LeSage and Pace (2009)).

This measure has the similar interpretation as the typical (non-spatial) regression coefficients. Due to spatial dependence, this effect is different from the initial impact β. From this measure, we propose to calculate the ratio,

$$\bar{\eta}_r = ADE_r/\beta_r, \tag{4}$$

which is the average multiplier of the initial direct shock of X_r and reflects the strength of the feedback or repercussion effects. For example, a multiplier of 1.10 could be interpreted as that the accumulated effect is about 10 percent larger than the original shock. The further apart the multiplier from the unity, the stronger is the interdependence across regions and are the repercussion effects among each other. A larger than unity multiplier means the direct impact is stronger than the initial shock, while a smaller than unity multiplier means the direct impact is weaker than the initial shock. In the SDM models, the multipliers are different for each explanatory variable, but in the SAR models, the multiplier is restricted to be the same for all variables. This is another advantage of the SDM models over the SAR models.

The second is the Average Total Effect (ATE)[11] to (or from) an observation, which is the average impact of changing the values of the explanatory variables of all observations on a city's wage level:

$$ATE_r = n^{-1}\iota_n'(S_r(W))\iota_n. \tag{5}$$

The difference of the ATE and the ADE is called the Average Indirect Effects (AIE),

$$AIE_r = ATE_r - ADE_r \tag{6}$$

The AIE measures the average effects of changing the values of the explanatory variable of all except own observation on a city's wage level. In another words, AIE measures the average radiation effects originated from all other observations if the values of the corresponding variable change simultaneously. In our case, it measures the average cross-city effects. It should be noted AIE and ADE should not be compared directly because ADE measures the effect originated from one (own city), and AIE measures the sum of the effects from all other cities.

In fact all these measures could be extended to any selection of cities. For example, of a group of cities s, we can define an ADE_r^s as

$$ADE_r^s = n_s^{-1}(S_r(W)_d\iota_{n_s}) \tag{7}$$

where n_s is the number of cities in the group, $S_r(W)_d = (S_r(W)_{11}, \dots, S_r(W)_{nn})'$ is the row vector of the diagonal elements of $S_r(W)$, and ι_{n_s} is the vector of indicators of city group s.

[11]For all cities, the ATE's from and to a city are numerically identical.

Similarly the average of the total effects from all cities on city group s (ATE^s_{rf}) could be defined as

$$ATE^s_{rf} = n_s^{-1}\iota'_{n_s}(S_r(W))\iota_n \tag{8}$$

The average of the total effects to all cities from city group s (ATE^s_{rt}) could be defined as

$$ATE^s_{rt} = n_s^{-1}\iota'_n(S_r(W))\iota_{n_s} \tag{9}$$

ATE^s_{rt} and ATE^s_{rf} may be different if W is asymmetric.

Estimation

The model (Equation 1) is estimated by the (concentrated) maximum likelihood method (ML). First of all, the fixed effects are removed by demeaning the data:

$$\tilde{y}_t = \rho W\tilde{y}_t + \tilde{X}_t\beta + W\tilde{X}_t\theta + \sum_{s=1}^{S} d^s_t(1-1/T)\iota_n + \tilde{v}_t, t = 1, \ldots, T) \tag{10}$$

where $\tilde{y}$ and $\tilde{X}$ are demeaned variables. Secondly, for a given ρ, β's, d_t's, θ's and the variance of error terms are estimated by OLS of $\tilde{y} - \rho W\tilde{y}$ on $\tilde{X}$, $W\tilde{X}$, and the transformed time dummies, and hence just a function of ρ (denoted as $\hat{\beta}_\rho$, $\hat{\theta}_\rho$, $\hat{d}_t$, and $\hat{\sigma}^2_\rho$, respectively). Thus, the concentrated likelihood function to be maximised (against ρ) is

$$\ln L = -nT/2 * (ln(\pi) + ln(\sigma^2_\rho) + 1) + (T-1) * \ln|I_n - \rho W|, \tag{11}$$

where $|I_n - \rho W|$ is the determinant of the matrix $(I_n - \rho W)$, $\sigma^2_\rho = e'e/(nT) * T/(T-1)$ is the variance of the error terms,, and $e = \tilde{y} - \rho W\tilde{y} - \tilde{X}\hat{\beta}_\rho - W\tilde{X}\hat{\theta}_\rho - \sum_{s=1}^{S}\hat{d}^s_t$.[12] We include the correction factor $T/(T-1)$ in σ^2_ρ following Lee and Yu (2010).

At the maximum, the asymptotic distribution of parameter estimates $(\hat{\rho}, \hat{\beta}, \hat{\theta}, \hat{d}_t, \hat{\sigma}^2)'$ is normal. The variance and co-variance matrix of the parameter estimates can be estimated from Hessian calculated analytically, numerically, or the mixture of the two. We use the mixed analytical and numerical methods (for details see, LeSage and Pace (2009)).

Using the parameter estimated, the marginal effects could be calculated directly and their standard errors are calculated by bootstrapping. Given the estimates of the variance-covariance

[12] If the number of cross-section units is too large, calculating $|I_n - \rho W|$ or $(I_n - \rho W)^{-1}$ directly could be inefficient, LeSage and Pace (2009) discuss alternative methods of estimating them. In our case, the number of cross-section units is 185, which is not very big. The differences in the estimates of these quantities using different methods are negligible.

matrix of the parameter estimates, bootstrapping is straightforward: draw B sets of parameter estimates from its distribution, for each set of estimates calculate the marginal effects described above, and the standard errors of the marginal distribution are given by the standard deviation of the empirical distribution of the B estimated marginal effects.

4 Results

Comparison of models

As indicated in Table 3, there are strong spatial correlations in our data. Therefore, estimates from non-spatial OLS and fixed effects that do not take into account of spatial correlations are likely to be inconsistent. For comparison purposes, Table 4 presents parameter estimates of 4 models: non-spatial OLS, non-spatial fixed effects, fixed effect SAR, and fixed effect SDM. It is apparent that the coefficient estimates from non-spatial OLS and fixed effects models are quite different from the results of both SAR and SDM models. Meanwhile, the interpretation of the coefficients are not directly comparable.

The estimates of βs, which measure the initial round direct impact of each variable on own city, are quite similar from both the SAR and SDM models. However, the null hypothesis of no exogenous spatial interdependence is strongly rejected by a likelihood ratio test between the SAR and SDM model, which means that the SAR model is rejected—the test statistics is 156.36.[13] Most of the estimates of the coefficients of WX in the SDM model (the θ's) are significant. This implies the existence of both strong endogenous and exogenous interdependence between these cities. In addition, the estimate of the spatial autoregressive coefficient (ρ) from the SDM model (0.80) is also different from that from the SAR model (0.53).

[Table 4 is here.]

Marginal effects

In Table 5, the marginal effects of the explanatory variables from these models are presented. The non-spatial OLS and fixed-effects coefficients are also own marginal effects, which have the same spirit as the ADE's of the SAR and SDM models. Again, they are very different from the latter two models. Most of the ADE estimates from the SAR and the SDM are not too far apart, but the AIE estimates are very different. Even with much larger standard errors, at least some of the AIE estimates from the SDM model are still significantly different from those from the SAR model. Again, the SAR restricts the multiplier to be the same for all variables (estimated to be 1.017) and

[13]The critical value of the $\chi^2(6)$ at the 5 percent level is 12.6.

the SDM allows them to be different for each variable. In the rest of the paper, our interpretation of the results will be based upon the SDM model.

[Table 5 is here.]

The last three columns of Table 5 reveal some interesting insights of productivity in urban China. Firstly, the ADEs of all variables are significant. The ADE of urban population on real wages confirms the existence of intra city agglomeration externality in Chinese cities. The estimate of 0.542 is an elasticity, which means that on average, if a city's own population increases by one percent, the real wage would increase by about 0.54 percent. The multiplier of 1.06 could be interpreted that the accumulated effect is about 6 percent larger than the original impact, and it is significantly different from one. This estimate confirms that agglomeration economy in China is much stronger than those for the US and for Europe. Such a strong agglomeration economy may provide a good explanation for the rapid urbanisation in China and why policies aim to limit the size of city growth may not be effective. The estimate from the SDM model is also larger than the estimates from other studies for China, which either do not take into account spatial dependence or control for the endogeneity issue. The ADE of FDI implies that every one percent increase in FDI would push up the local wage by 0.01 percent. A multiplier of 1.5 (which is significantly different from one) implies that, through repercussions between neighbour cities, it is amplified to about 1.5 times of the original impact. The impacts of the other variables also have the expected signs. For example, higher capital stock (measured by total value of the assets) also leads to higher wage (with an elasticity of 0.11); the larger are the non-agriculture sectors (measured by the proportion of second and third sector GDP), the higher is the wage; and the larger the second sector employment relative to the third sector (measured by the proportion of second sector employment out of the non-agriculture sectors), the lower the wage is. For some of these variables, a somewhat significantly less than one multiplier suggests that the accumulative impacts are weaker than the original impacts due to the inter-city spillover effects.

Secondly, it is worth noting that the fact that most of the multipliers are significantly different from one illustrates strong inter-city spillover. Thirdly, these inter-city spillover effects differ from factor to factor, where that of FDI is the strongest, and that of city size is probably the weakest. Fourthly, the inter-city spillover effects are also reflected in the AIE's. From the estimates of the AIEs we find that for most factors, the inter-city spillover is very strong, which means that a large part of productivity increase is due to effects originated from cities other than own. For example, if the population size of all other cities increases by one percent, on average, a city's real wage would be pushed up by 4.8 percent. If FDI of all other cities increases by one percent, on average, a city's real wage would be pushed up by 0.53 percent. Similarly, if the size of the second sector out of the non-agriculture sectors of all other cities increases by one hundred percentage points (which means the whole economy swings away massively from the service sector), the real wage of an average city would decrease by about 18 percent. Again, these inter-city spillover effects vary from factor to factor. The multiplier and the AIE of FDI also suggest that the inter-regional spillover effects of FDI contribute significantly to productivity increase of a much wider scope than where the FDI locates. This may be due to the transfer of knowledge, management skills, and so on, or due to that—unlike the State Owned firms who often require workers to have local *Hukou*—the foreign firms could draw from the more mobile part of the urban labour force.

Differences across regions

To illustrate the regional differences, we present the measures of the marginal effects for the seven regions in Table 6.[14] From the table, we can see that both the multiplier and the AIE exhibit some variations across regions. The pattern seems to be that these effects are somewhat larger in more population dense areas such as East, South, and Central China, but smaller in less population dense areas such as Northeast and Northwest. To further illustrate the differences across regions, we further analyse Northeast and East China. Northeast China is an area with a relative low (but not the least) population density. It is the 'old' industrial base where many heavy industries such as machinery locate. Economic growth in Northeast China has been slow. As a contrast, East China is an area with a high population density. It is the economic powerhouse in the last few decades. East China is also the destination of most of the FDI inflow. As the results show, the multiplier of the FDI impact for Northeast China is about 1.4, but that in East China, it is about 1.6. This means that the impact of FDI on productivity would be 1.6 times of its initial shock in East China and about 1.4 times in Northeast China. For the AIE, a similar conclusion could be made. We conduct a formal test for the significance of these differences and present the test results in Table 7. The results show that the differences of the multipliers and the AIE's for most of the variables are significant at least at the 10 percent level.

The disparity in growth and productivity across regions can be explained by the variations in the effects of these factors. In addition, these variations suggest that the strength of inter-regional spillover correlates with population (and thus city) density. This can be seen as another form of agglomeration economy.

[Table 6 is here.]

[Table 7 is here.]

[14]The results from the SAR model is presented in Table 8.

Robustness of the results

The reason to use time lagged variable for population size (and FDI) is to reduce the potential endogeneity of the variables, even though the fixed-effect is controlled for. To check whether using lagged variable is sufficient to control for this issue, we calculated the correlation between the spatial lag variable Wy and the estimated residuals. A low correlation between the two can be a sign that the endogeneity issue is not a serious issue. For the SDM model, the correlation is 0.007, which is very small.

To further check whether using one-year lag is sufficient, we also estimated a set of alternative models and compared the results of the benchmark models. In these alternative models, we replace the population size with lags of various years (up to $t-5$). The parameter estimates for the SDM models are presented in Table 9 (the results for SAR models are presented in Table 11 of the Appendix). In these alternative models, we restrict the cities to those with five more years of data. Thus the number of observations used is smaller than in the benchmark models. From the table, we can see that the results are quite robust to the specifications. The parameter estimates of all variables except for those of the population size are almost identical for all models, no matter which lag is used for the population size. The magnitudes of the coefficients of the population size are somewhat different when different lag is used (which is not surprising), but the difference is not large and the sign and the significance remain the same. The estimates of the spatial coefficient ρ are also very close to each other. In addition, the value of the likelihood are also similar.

We also checked the stability of the estimates over time. We partitioned the sample into three periods (1994–1999, 2000–2004, 2005–2009) and estimated the model for each sub-period. The estimates of the parameters, the ADEs, and the AIEs for the SDM models are presented in Tables 10 (the results for SAR models are presented in Table 12 in the Appendix). It should be noted that for the estimates to be consistent, both the number of cross-section units and the number of time periods need to be large. However, the samples of each sub-period only consists of five years of data, which is rather small. The magnitudes of the estimates for different periods do differ and the estimate of the spatial coefficient become smaller in later period. However, the signs and the significance for most of the parameters are consistent over time. The results may imply that in a fast evolving economic system like China, the assumption that the economic relationship remains constant could be restrictive or unrealistic. Time-varying coefficient models, which allow for changing economic relationships, may be more appropriate for such cases.

5 Conclusions

In this paper, we analysed the intra-city agglomeration economies and inter-city spillovers in productivity of urban China using a spatial econometrics approach. the productivity is measured with the average real wage of each city, which is adjusted using a spatial price index. We compared various specifications including non-spatial linear models, the fixed-effect SAR model, and the fixed-effect SDM model. We showed that in presence of a strong spatial interdependence, the fixed-effect SDM is preferred. The fixed-effect SDM model allows for both the endogenous and exogenous interdependence, and allows for non-linear spillover effects between cities. The results are summarised using measures such as ADE and AIE as proposed by LeSage and Pace (2014). We also proposed a multiplier of the ADE to measure the strength of the inter-city spillover effects.

From the results for the 185 cities at or above the prefectural levels, we could draw the following conclusions. First, our estimate shows that the average elasticity of wage with respect to population size of cities was about 0.5 for the period between 1994 and 2009, which means that if the population size of the city is increased by one percent, productivity would increase by 0.5 percent. This is much larger than those found for the developed countries, but consistent with findings that for developing countries such as China, India, and Brazil, agglomeration economy is usually larger. This could help to explain why rapid urbanisation happens in these countries and could explain why policies aiming to limit city sizes may not be effective. Secondly, we find that agglomeration economy may exist as the forms of both intra-city agglomeration and inter-city spillover effects. A significant positive effect of urban population on the real wage level confirms the existence of intr-city agglomeration effects, while the significant differences in the multipliers and AIE's between more and less population dense areas seem to suggest that the agglomeration economy may also exist in the form of inter-city spillovers. Thirdly, the disparity between regions in economic growth and productivity could be explained by the statistically significant regional variations in the multipliers and AIE's. For example, we find that the multiplier of the direct effect of FDI is larger in East China than in Northeast. This is probably why we see the emergence of the fast growing city groups in areas such as the Yantz River Delta, Pearl River Delta, and so on.

The results are rather robust to alternative specifications in which various time lags are used. The correlation between the spatial lagged variable and the residuals is very low. These findings suggest that our identification strategy works well. However, the results are different for various sub-periods, which may suggest that a more flexible model such as time-varying coefficient model that allows for evolving economic relationships could be more appropriate. This is a direction for future research.

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Figures

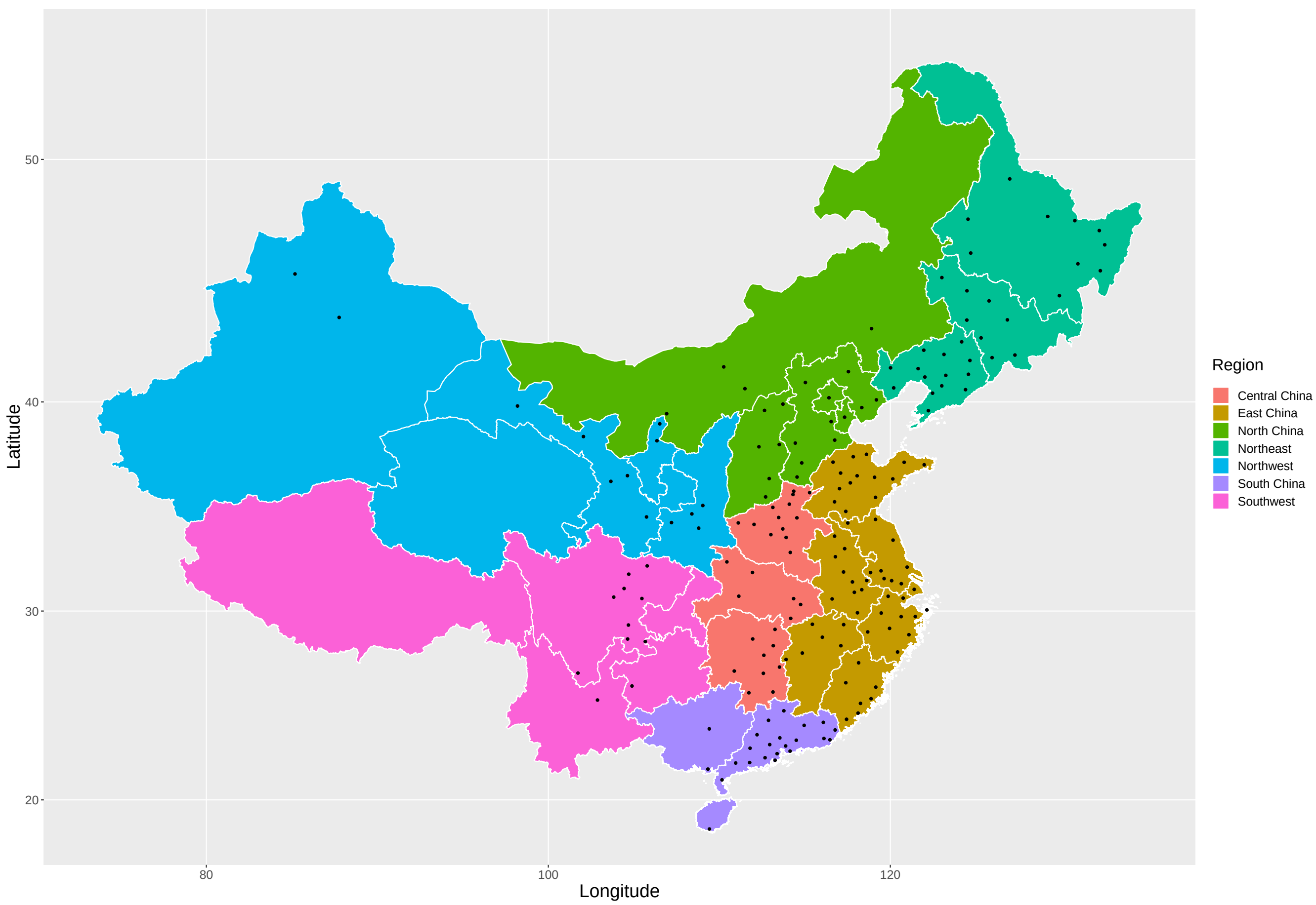

Figure 1: Cities (black dots) included in the analysis.

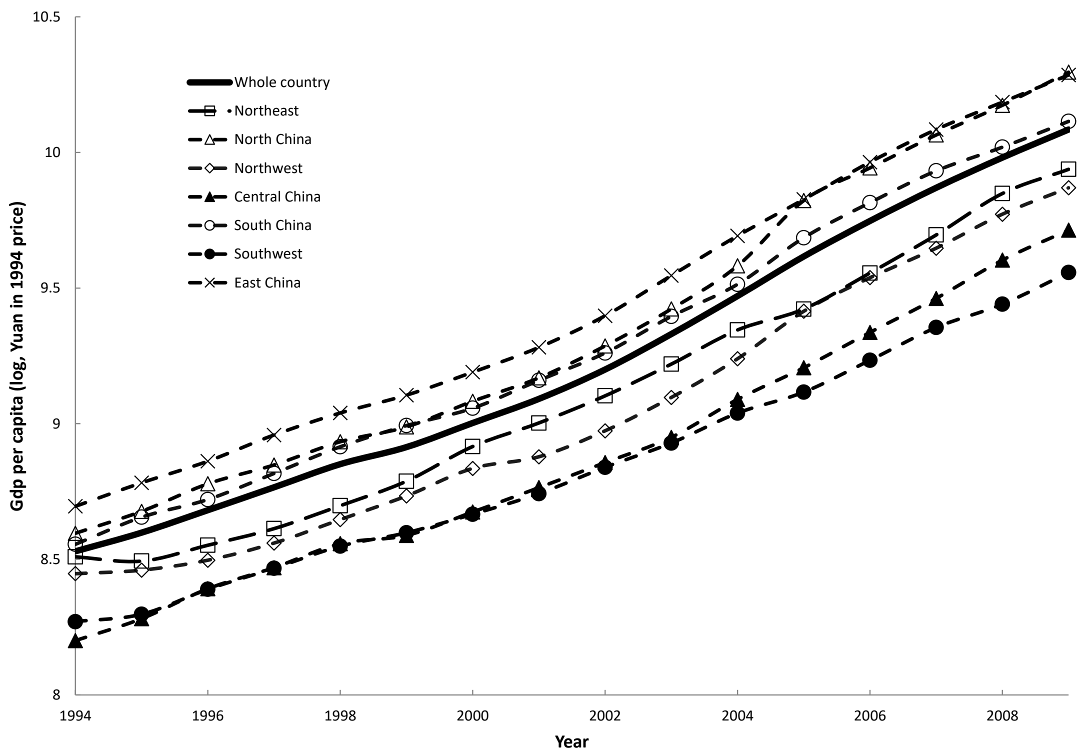

Figure 2: Trend of log GDP per capita of different regions

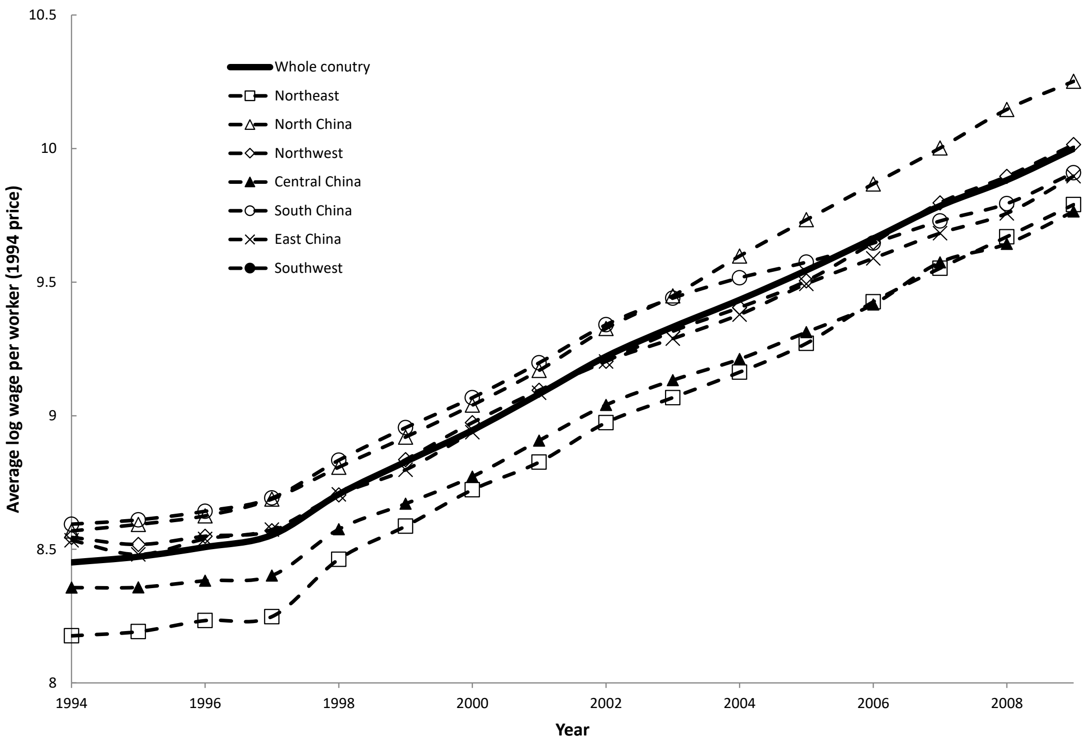

Figure 3: Trend of Wage per worker of different regions.

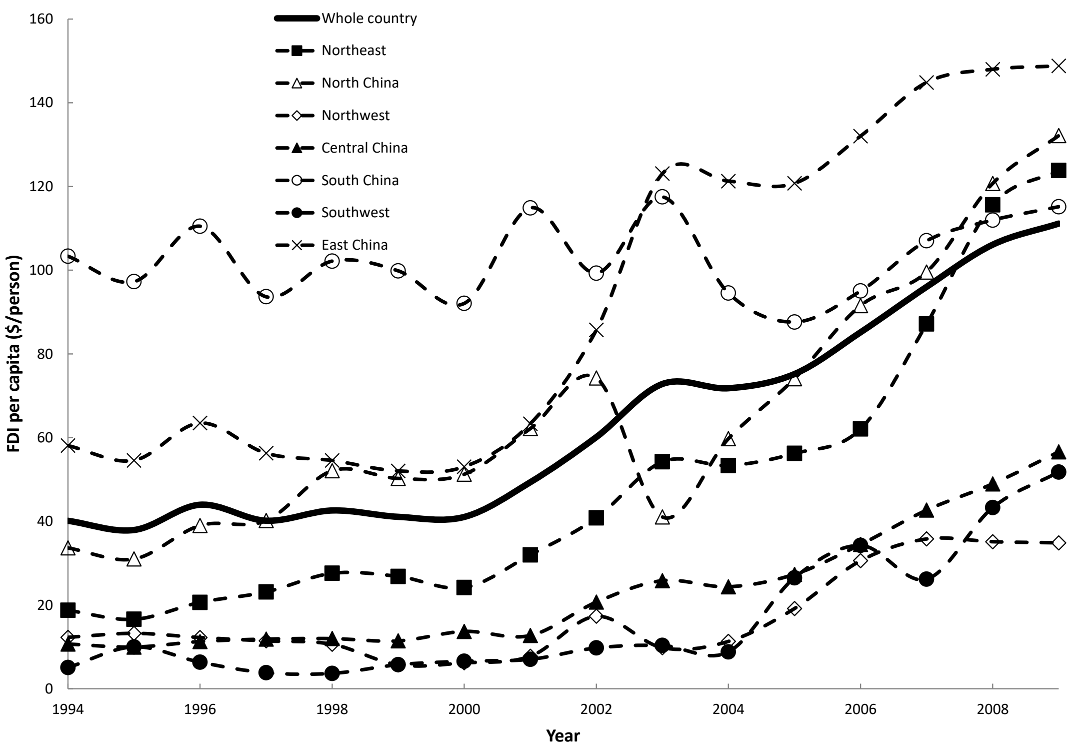

Figure 4: Trend of FDI of different regions

Tables

Table 1: Variable definition and Sample statistics

Variable	Definition	Sample statistics			
		1994	1999	2004	2009
wage	wage per worker	4390.28	6071.11	10798.75	18961.0
		(1077.7)	(1628.93)	(3109.5)	(4766.5)
fdi	FDI (10,000 yuans)	127198.2	130954	236396.8	316040.0
		(290713.4)	(282552)	(486765.7)	(614322.8)
gdp	GDP per capita (10,000 yuans)	5354.94	7512.80	13079.95	23866.5
		(4619.5)	(6887.4)	(12584.8)	(19878.7)
Asset	Total asset (million yuans)	22969.68	31521.85	50053.04	118982.80
		(31896.7)	(44273.05)	(72168.94)	(158168.5)
pop	Population (10,000 persons)	367.81	385.16	397.82	416.29
		(232.4)	(242.0)	(247.1)	(260.2)
gdp_m	The manufactural sector GDP (proportion)	.478	.461	.503	.517
		(.11)	(.10)	(.11)	(.10)
gdp_s	The services sector GDP (proportion)	.300	.351	.349	.368
		(.07)	(.07)	(.07)	(.09)
emp_{ms}	Employment in the manufactural sector	.545	.498	.484	.487
	out of the non-agricultural sector	(.10)	(.11)	(.12)	(.13)

Standard errors are in the parentheses. Values are in 1994 prices

Table 2: Average city sizes by region

Regions	No of cities	1994	2009
Whole country	185	367.81(232.4)	416.29(260.2)
Northwest	13	201.40(191.1)	246.46(223.1)
Northeast	32	262.29(150.9)	280.65(168.1)
South China	23	295.41(170.4)	369.13(211.4)
East China	57	415.44(252.2)	459.49(271.4)
Southwest	11	423.22(234.3)	483.32(273.3)
North China	21	427.34(291.7)	491.40(332.0)
Central China	28	461.78(194.7)	518.28(223.0)

Populations are in 10 thousands of persons. Standard deviations are in the parentheses.

Table 3: Moran's I for log wage per worker

year	<200km	<300km	<500km	<1000km	<1500km	<2000km
1994	.432 (.051)	.309 (.035)	.179 (.022)	0.102 (.010)	0.071 (.006)	0.036 (.004)
1995	.407 (.051)	.304 (.035)	.180 (.022)	0.100 (.010)	0.063 (.006)	0.023 (.004)
1996	.388 (.051)	.295 (.035)	.168 (.022)	0.090 (.010)	0.049 (.006)	0.011 (.004)
1997	.408 (.051)	.342 (.035)	.195 (.022)	0.098 (.010)	0.054 (.006)	0.011 (.004)
1998	.365 (.051)	.280 (.035)	.153 (.022)	0.073 (.010)	0.054 (.006)	0.011 (.004)
1999	.378 (.051)	.298 (.035)	.158 (.022)	0.069 (.010)	0.051 (.006)	0.010 (.004)
2000	.351 (.051)	.284 (.035)	.148 (.022)	0.050 (.010)	0.035 (.006)	0.003 (.004)
2001	.385 (.051)	.324 (.035)	.185 (.022)	0.072 (.010)	0.050 (.006)	0.015 (.004)
2002	.410 (.051)	.347 (.035)	.197 (.022)	0.069 (.010)	0.048 (.006)	0.009 (.004)
2003	.456 (.051)	.387 (.035)	.224 (.022)	0.080 (.010)	0.053 (.006)	0.010 (.004)
2004	.413 (.051)	.377 (.035)	.232 (.022)	0.085 (.010)	0.049 (.006)	0.005 (.004)
2005	.401 (.051)	.366 (.035)	.238 (.022)	0.084 (.010)	0.033 (.006)	-0.006 (.004)
2006	.391 (.051)	.360 (.035)	.243 (.022)	0.094 (.010)	0.033 (.006)	-0.008 (.004)
2007	.414 (.051)	.381 (.035)	.266 (.022)	0.119 (.010)	0.048 (.006)	-0.003 (.004)
2008	.414 (.051)	.380 (.035)	.273 (.022)	0.126 (.010)	0.050 (.006)	0.000 (.004)
2009	.405 (.051)	.392 (.035)	.297 (.022)	0.142 (.010)	0.055 (.006)	-0.003 (.004)

Standard errors are in the parentheses.

Table 4: Parameter estimates of different models

	OLS	Fixed-effect	Fixed-effect SAR	Fixed-effect SDM
	Main			
$ln(fdi)$	0.002	0.015**	0.011**	0.008**
	[1.22]	[6.91]	[6.60]	[4.92]
$ln(asset)$	0.211**	0.284**	0.098**	0.109**
	[27.61]	[25.24]	[9.64]	[10.61]
$ln(pop)$	-0.158**	0.221**	0.340**	0.510**
	[-19.00]	[3.24]	[6.45]	[9.40]
gdp_m	0.961**	1.193**	0.732**	0.909**
	[13.69]	[11.86]	[9.33]	[11.68]
gdp_s	0.630**	1.418**	0.838**	1.271**
	[8.36]	[11.39]	[8.63]	[12.99]
emp_{ms}	-0.879**	-0.953**	-0.632**	-0.488**
	[-19.40]	[-17.90]	[-15.07]	[-11.40]
$T00-04$	0.415**	0.338**	0.166**	0.127**
	[42.94]	[36.79]	[19.23]	[7.76]
$T05-09$	0.816**	0.660**	0.346**	-0.144**
	[77.01]	[48.25]	[25.00]	[-4.47]
$Cons$	7.112**			
	[147.01]			
σ_e^2			0.012**	0.011**
			[4.00]	[3.30]
	Spatial			
ρ			0.527**	0.798**
			[34.76]	[20.68]
	WX			
$ln(fdi)$				0.711**
				[2.11]
$ln(asset)$				-5.440**
				[-11.00]
$ln(pop)$				-6.242**
				[-12.74]
gdp_m				-1.756**
				[-7.41]
gdp_s				0.178**
				[18.65]
emp_{ms}				0.367**
				[27.52]
lnL			2764.86	2906.60
Obs.	2775			

Table 5: Average marginal effects from different models

	OLS	Fixed-effect	Fixed-effect SAR		Fixed-effect SDM		
			ADE	AIE	ADE	AIE	$\bar{\eta}^{\#}$
$ln(pop)$	-0.158**	0.221**	0.342**	0.378**	0.542**	4.791**	1.063**
	[-19.00]	[3.24]	[6.72]	[6.37]	[10.65]	[2.48]	[2.25]
$ln(fdi)$	0.002	0.015***	0.011**	0.012**	0.011**	0.527**	1.504**
	[1.22]	[6.91]	[6.58]	[6.09]	[6.52]	[4.12]	[3.03]
$ln(asset)$	0.211**	0.284***	0.098**	0.109**	0.107**	-0.140	0.985*
	[27.61]	[25.24]	[9.14]	[10.47]	[9.84]	[-1.00]	[-1.74]
gdp_m	0.961**	1.193***	0.737**	0.813**	0.773**	-17.767**	0.850**
	[13.69]	[11.86]	[8.88]	[8.02]	[9.29]	[-2.97]	[-3.74]
gdp_s	0.630**	1.418***	0.843**	0.930**	1.120**	-19.488**	0.881**
	[8.36]	[11.39]	[8.78]	[8.00]	[11.38]	[-3.09]	[-3.95]
emp_{ms}	-0.879**	-0.953***	-0.636**	-0.702**	-0.550**	-8.803**	1.127**
	[-19.40]	[-17.90]	[-14.93]	[-11.88]	[-11.99]	[-4.03]	[4.39]
$\bar{\eta}^{\#}$			1.006**				
			(12.74)				
Obs.	2775						

t-statistic in brackets. # t-statistic for Multiplier is for $h_0 : multiplier = 1$.
* $p < 0.1$, ** $p < 0.05$

Table 6: Average marginal effects for regions (Fixed-effect SDM model)

	Whole country			North China		
	ADE	$\bar{\eta}^{\#}$	AIE	ADE	$\bar{\eta}^{\#}$	AIE
$ln(pop)$	0.542**	1.063**	4.791**	0.538**	1.056**	5.045**
$ln(fdi)$	0.011**	1.504**	0.527**	0.011**	1.443**	0.600**
$ln(asset)$	0.107**	0.985*	-0.140	0.107**	0.987*	-0.260*
gdp_m	0.773**	0.850**	-17.767**	0.789**	0.868**	-21.281**
gdp_s	1.120**	0.881**	-19.488**	1.139**	0.896**	-23.595**
emp_{ms}	-0.550**	1.127**	-8.803**	-0.542**	1.111**	-9.682**
	East China			South China		
	ADE	$\bar{\eta}^{\#}$	AIE	ADE	$\bar{\eta}^{\#}$	AIE
$ln(pop)$	0.551**	1.080**	6.061**	0.541**	1.061**	4.398**
$ln(asset)$	0.106**	0.981*	-0.313*	0.107**	0.985*	-0.227*
$ln(fdi)$	0.012**	1.641**	0.720**	0.011**	1.486**	0.523**
gdp_m	0.736**	0.810**	-25.565**	0.777**	0.856**	-18.552**
gdp_s	1.079**	0.849**	-28.345**	1.126**	0.886**	-20.569**
emp_{ms}	-0.567**	1.161**	-11.632**	-0.548**	1.122**	-8.441**
	Central China			North East		
	ADE	$\bar{\eta}^{\#}$	AIE	ADE	$\bar{\eta}^{\#}$	AIE
$ln(pop)$	0.554**	1.087**	6.180**	0.532**	1.045**	3.829**
$ln(asset)$	0.106**	0.979*	-0.319*	0.107**	0.989*	-0.198*
$ln(fdi)$	0.013**	1.695**	0.734**	0.010**	1.357**	0.455**
gdp_m	0.721**	0.794**	-26.067**	0.812**	0.894**	-16.149**
gdp_s	1.063**	0.836**	-28.902**	1.164**	0.916**	-17.905**
emp_{ms}	-0.573**	1.175**	-11.860**	-0.532**	1.090**	-7.347**
	North West			South West		
	ADE	$\bar{\eta}^{\#}$	AIE	ADE	$\bar{\eta}^{\#}$	AIE
$ln(pop)$	0.525**	1.031**	3.220**	0.522**	1.024**	3.110**
$ln(asset)$	0.108**	0.993*	-0.166*	0.108**	0.994*	-0.160*
$ln(fdi)$	0.009**	1.244**	0.383**	0.009**	1.194**	0.370**
gdp_m	0.843**	0.927**	-13.583**	0.856**	0.942**	-13.116**
gdp_s	1.198**	0.942**	-15.060**	1.213**	0.954**	-14.542**
emp_{ms}	-0.518**	1.062**	-6.180**	-0.512**	1.049**	-5.968**

* $p < 0.1$, ** $p < 0.05$

\# t-test for Multiplier is $h_0 : \bar{\eta} = 1$.

Table 7: Equality test of marginal effects for Northeast and East China

Variables	$H_0 : \bar{\eta}_{ne} = \bar{\eta}_{ec}$		$H_0 : AIE_{ne} = AIE_{ec}$	
	Diff.	$t-$stat.	Diff.	$t-$stat.
$ln(pop)$	-0.036**	(1.78)	-2.232**	[-2.39]
$ln(fdi)$	-0.284**	[-1.99]	-0.265**	[-4.59]
$ln(asset)$	0.009	[1.56]	0.115*	[1.65]
gdp_m	0.084**	[2.86]	9.416**	[3.40]
gdp_s	0.067**	[2.97]	10.440**	[3.60]
emp_{ms}	-0.071**	[-3.35]	4.284**	[4.39]

Table 8: Average marginal effects for regions (Fixed-effect SAR model)

	Whole country		North China		East China		South China	
	ADE	AIE	ADE	AIE	ADE	AIE	ADE	AIE
$ln(pop)$	0.342**	0.378**	0.342**	0.348**	0.342**	0.411**	0.342**	0.312**
$ln(fdi)$	0.011**	0.012**	0.011**	0.011**	0.011**	0.013**	0.011**	0.010**
$ln(asset)$	0.098**	0.109**	0.098**	0.100**	0.099**	0.118**	0.099**	0.090**
gdp_m	0.737**	0.813**	0.736**	0.749**	0.737**	0.884**	0.737**	0.671**
gdp_s	0.843**	0.930**	0.842**	0.858**	0.844**	1.012**	0.844**	0.768**
emp_{ms}	-0.636**	-0.702**	-0.635**	-0.647**	-0.636**	-0.764**	-0.636**	-0.579**
$\bar{\eta}^{\#}$	1.006**		1.005**		1.007**		1.006**	
	Central China		North East		North West		South West	
	ADE	AIE	ADE	AIE	ADE	AIE	ADE	AIE
$ln(pop)$	0.343**	0.420**	0.342**	0.275**	0.341**	0.227**	0.341**	0.223**
$ln(fdi)$	0.011**	0.013**	0.011**	0.009**	0.011**	0.007**	0.011**	0.007**
$ln(asset)$	0.099**	0.121**	0.098**	0.079**	0.098**	0.065**	0.098**	0.064**
gdp_m	0.738**	0.905**	0.736**	0.592**	0.735**	0.489**	0.734**	0.481**
gdp_s	0.845**	1.036**	0.842**	0.678**	0.841**	0.560**	0.840**	0.550**
emp_{ms}	-0.637**	-0.781**	-0.635**	-0.511**	-0.634**	-0.422**	–0.634**	-0.415**
$\bar{\eta}^{\#}$	1.007**		1.005**		1.003**		1.002**	

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

t-test for Multiplier is $h_0 : multiplier = 1$.

Table 9: Estimates of SDM models using different lags for population

	$ln(pop)_{t-1}$	$ln(pop)_{t-2}$	$ln(pop)_{t-3}$	$ln(pop)_{t-4}$	$ln(pop)_{t-5}$
			Main		
$ln(pop)$	0.381**	0.419**	0.419**	0.488**	0.558**
	[5.28]	[5.77]	[5.77]	[6.85]	[8.03]
$ln(fdi)$	0.007**	0.007**	0.007**	0.007**	0.0064**
	[3.45]	[3.48]	[3.48]	[3.49]	[3.43]
$ln(asset)$	0.120**	0.120**	0.120**	0.116**	0.112**
	[10.23]	[10.31]	[10.31]	[10.08]	[9.75]
gdp_m	0.733**	0.723**	0.723**	0.694**	0.689**
	[7.16]	[7.10]	[7.10]	[6.89]	[6.87]
gdp_s	0.714**	0.704**	0.704**	0.665**	0.634**
	[5.80]	[5.73]	[5.73]	[5.46]	[5.22]
emp_{ms}	-0.575**	-0.565**	-0.565**	-0.551**	-0.543**
	[-10.13]	[-9.98]	[-9.98]	[-9.78]	[-9.66]
$T00-04$	0.064**	0.067**	0.067**	0.064**	0.065**
	[5.21]	[5.48]	[5.48]	[5.26]	[5.36]
$T05-09$	0.216**	0.219**	0.219**	0.212**	0.206**
	[13.92]	[14.12]	[14.12]	[13.72]	[13.39]
σ_e^2	0.009**	0.009**	0.009***	0.009**	0.008**
	[31.79]	[31.79]	[31.79]	[31.79]	[31.80]
			Spatial		
ρ	0.778**	0.776**	0.776**	0.761**	0.757**
	[15.52]	[15.45]	[15.45]	[14.58]	[14.35]
			Wx		
$ln(pop)$	0.915	1.221**	1.221**	1.944**	1.815**
	[1.85]	[2.51]	[2.51]	[3.94]	[3.72]
$ln(fdi)$	0.056**	0.060**	0.060**	0.071**	0.076**
	[2.89]	[3.14]	[3.14]	[3.69]	[3.94]
$ln(asset)$	-0.054	-0.0528	-0.053	-0.019	-0.008
	[-1.45]	[-1.51]	[-1.51]	[-0.60]	[-0.25]
gdp_m	-3.764**	-4.196**	-4.196**	-5.435**	-5.565**
	[-5.51]	[-5.99]	[-5.99]	[-7.07]	[-7.16]
gdp_s	-4.542**	-5.067**	-5.067**	-6.203**	-6.324**
	[-5.67]	[-6.13]	[-6.13]	[-7.06]	[-7.08]
emp_{ms}	-2.824**	-2.817**	-2.817**	-2.897**	-2.800**
	[-9.48]	[-9.49]	[-9.49]	[-9.70]	[-9.42]
lnL	1929.13	1935.11	1935.11	1949.48	1957.78
Obs.			2035		

t statistic in brackets.

* $p < 0.1$, ** $p < 0.05$

Table 10: Estimates of SDM models for different periods

	1995-1999			2000-2004			2005-2009		
	β	ADE	AIE	β	ADE	AIE	β	ADE	AIE
$ln(pop)$	0.534**	0.506	-6.722	0.756**	0.860**	14.25*	0.560**	0.514**	-9.714*
	[5.57]	[0.22]	[-0.02]	[6.13]	[6.73]	[1.85]	[4.52]	[4.24]	[-1.93]
$ln(fdi)$	-0.003	-0.002	0.081	0.001	0.003	0.266	-0.001	-0.0001	0.153
	[-1.56]	[-0.07]	[0.02]	[0.62]	[1.16]	[1.40]	[-0.45]	[-0.02]	[1.47]
$ln(asset)$	0.018	0.011	-0.984	0.035	0.040**	1.009	0.079**	0.081**	0.337
	[1.05]	[0.04]	[-0.02]	[1.77]*	[2.14]	[1.62]	[5.94]	[6.25]	[1.07]
gdp_m	0.694**	0.691	-0.253	0.807**	0.688**	-18.580*	0.997**	1.086**	14.21
	[5.51]	[0.43]	[-0.00]	[4.14]	[3.49]	[-1.82]	[5.39]	[5.65]	[1.21]
gdp_s	0.502**	0.693	30.480	0.441**	0.347	-15.21*	0.675**	0.752**	12.54
	[3.24]	[0.77]	[0.21]	[2.01]	[1.60]	[-1.70]	[3.12]	[3.44]	[1.00]
emp_{ms}	-0.071	0.009	12.08	-0.358**	-0.374**	-3.225	-0.675**	-0.756**	-14.11
	[-1.42]	[0.01]	[0.08]	[-4.49]	[-4.74]	[-1.60]	[-6.70]	[-6.18]	[-1.24]
ρ	0.935**			0.768**			0.673**		
	[34.68]			[9.96]			[6.53]		
Obs.	925								

t statistic in brackets.

* $p < 0.1$, ** $p < 0.05$

Appendix

Parameter estimates of alternative SAR models.

Table 11: Estimates of SAR models using different lags for population

	$ln(pop)_{t-1}$	$ln(pop)_{t-2}$	$ln(pop)_{t-3}$	$ln(pop)_{t-4}$	$ln(pop)_{t-5}$
			Main		
$ln(pop)$	0.263**	0.306**	0.306** *	0.393**	0.471**
	[3.70]	[4.31]	[4.31]	[5.63]	[6.91]
$ln(fdi)$	0.009**	0.009**	0.009**	0.009**	0.009**
	[4.63]	[4.65]	[4.65]	[4.59]	[4.54]
$ln(asset)$	0.113**	0.112**	0.112**	0.111**	0.107**
	[9.90]	[9.95]	[9.95]	[9.89]	[9.62]
gdp_m	0.711**	0.705**	0.705**	0.680**	0.665**
	[7.01]	[6.97]	[6.97]	[6.75]	[6.62]
gdp_s	0.512**	0.503**	0.503**	0.472**	0.439**
	[4.10]	[4.03]	[4.03]	[3.79]	[3.54]
emp_{ms}	-0.885**	-0.880**	-0.880**	-0.869**	-0.857**
	[-16.43]	[-16.34]	[-16.34]	[-16.16]	[-15.97]
$T00-04$	0.076**	0.0751**	0.075**	0.072**	0.069**
	[8.16]	[8.10]	[8.10]	[7.71]	[7.48]
$T05-09$	0.193**	0.191**	0.191**	0.185**	0.180**
	[13.95]	[13.85]	[13.85]	[13.34]	[12.95]
σ_e^2	0.010**	0.010**	0.010**	0.010**	0.009**
	[31.89]	[31.89]	[31.89]	[31.89]	[31.89]
			Spatial		
ρ	0.644**	0.644**	0.644**	0.646**	0.648**
	[38.13]	[38.14]	[38.14]	[38.42]	[[38.71]
lnL	1832.12	1834.52	1834.52	1841.03	1848.88
Obs.			2035		

t statistic in brackets.

* $p < 0.1$, ** $p < 0.05$

Table 12: Estimates of SAR models for different periods

	1995-1999			2000-2004			2005-2009		
	β	ADE	AIE	β	ADE	AIE	β	ADE	AIE
$ln(pop)$	0.526**	0.565**	4.726**	0.757**	0.799**	4.537**	0.429**	0.451**	1.403**
	[5.72]	[6.18]	[3.05]	[6.43]	[6.91]	[4.75]	[3.58]	[3.85]	[3.74]
$ln(fdi)$	-0.002	-0.003	-0.021	0.001	0.001	0.004	0.001	0.001	0.003
	[-1.48]	[-1.41]	[-1.26]	[0.26]	[0.29]	[0.28]	[0.39]	[0.42]	[0.40]
$ln(asset)$	0.001	0.001	-0.003	0.048**	0.049**	0.269**	0.084**	0.086**	0.265**
	[0.08]	[0.04]	[-0.02]	[2.51]	[2.57]	[2.69]	[6.38]	[6.65]	[7.57]
gdp_m	0.643**	0.677**	5.648**	0.682**	0.706**	3.954**	- 1.100**	1.122**	3.502**
	[5.48]	[5.73]	[3.05]	[3.68]	[3.81]	[3.89]	[[6.17]	[6.37]	[5.53]
gdp_s	0.411**	0.433**	3.470**	0.442**	0.460**	2.558**	0.717**	0.730**	2.270**
	[2.99]	[3.15]	[3.16]	[2.17]	[2.23]	[2.23]	[[3.41]	[3.53]	[3.48]
emp_{ms}	-0.025	-0.023	-0.172	-0.386**	-0.396**	-2.242**	-0.898**	-0.911**	-2.858**
	[-0.50]	[-0.44]	[-0.36]	[-4.99]	[-5.01]	[-4.04]	[[-9.05]	[-9.03]	[-5.57]
ρ	0.902**			0.865**			0.778**		
	[38.92]			[39.91]			[31.46]		
Obs.	925								

t statistic in brackets.

* $p < 0.1$, ** $p < 0.05$