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« Regional Assessment of Openness and Productivity Spillovers in China from 1979 to 2006: A Space-Time Model »

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Regional Assessment of Openness and Productivity Spillovers in China from 1979 to 2006: A Space-Time Model

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Abstract

This study investigates the impact of inward foreign direct investment (FDI) flows and international trade on labour productivity in 30 Chinese provinces over the period 1979-2006. Since China launched the "open door" policy in 1978, the country has been attracting a growing share of FDI flows and its international trade has been expanding considerably. China's accession into the WTO in 2001 has also started a new era in its integration into the world economy.

In this paper, we model labour productivity as dependent on FDI, foreign trade and other traditional variables such as capital intensity, infrastructure and human capital development. Our empirical analysis improves the existing wide literature by taking into account spatial effects and potential econometric issues they imply. Using recently developed spatial data analysis tools, we explore the pattern, (weather it be negative or positive) and the extent of spatial interaction of labour productivity between regions. Thereby, we extend previous research by testing the explanatory power of additional variables such as spatially lagged independent and dependent variables. The explicit consideration of spatial dependence in the modelling scheme provides us a better understanding of the regional spillovers process.

Our results indicate a general trend of spatial autocorrelation in labour productivity during the study period. Put differently, in China, the productivity of a given region is highly determined by those of surrounding regions. In addition, our empirical outcomes yield support for positive and significant impacts of FDI and foreign trade on labour productivity. Furthermore, in China, FDI and trade exhibit a positive spatial pattern and give rise to interregional productivity spillovers among provinces. These findings are robust to a number of alternative spatial weighting matrix specifications.

Keywords: FDI, China, spillovers, spatial autocorrelation, labour productivity.
JEL classification: O11, O18, P20, R10.

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I. Introduction

Since the introduction of the economic reform policy in the early 1980's, China has undergone a continuous and spectacular economic growth (at an average official rate of 10 percent). Along with the impressive economic take off over the past decades, China has observed a rapid expansion of its foreign trade and attracted increasing amounts of foreign capital. Thereby, since the last decade, China became the second largest recipient of foreign direct investment (FDI) flows in the world, after the United States, and the largest host country among developing countries. Furthermore, ranked 32nd in 1978, China outpaced major trading countries and turned to be the world's 3rd largest trading partner in 2006.

In developing countries, the nexus between openness to the outside world and economic development has been an issue of considerable interest. Policy makers and scholars generally perceive FDI and foreign trade as key vehicles of economic growth and technology diffusion. Compared to portfolio investments and international loans, FDI projects involve long term commitments and represent less volatile and safer forms of financing (Baharumshah and al., 2006). In host economies, FDI and trade are expected to create employment opportunities and enhance capital formation. In addition, advanced technologies possessed by multi-national companies (MNCs) are expected to leak to host economies through various channels such as imitation-demonstration and contagion effects, competition of foreign firms, training of local employees, backward and forward linkages. Thus, since the last decades, in an increasingly competitive environment, developing countries have been racing with each other through incentive policies to attract FDI flows to their territory.

Despite the general belief in the benefits of openness, in developing countries, recent empirical literature generates mixed evidence on the existence of positive spillovers from FDI and foreign trade (Aitken and Harrison, 1999; Haddad and Harrison, 1993; Kokko, 1996). These studies emphasise that such spillovers are not automatic and their existence depend substantially on the characteristics of the host country such as competitiveness and technological absorption capabilities.

The empirical analysis conducted in this study covers 30 Chinese provinces over the period 1979-2006. Prior to 1979, foreign trade and FDI were virtually inexistent in China. In 1979, the country has moved away from an autarchic economy towards market oriented reform policies. Besides that, China's opening up to the world came along with an impressive economic development and technological upgrade. On that account, we consider that China provides capital statistical information and portrays a unique observation field to explore the long-term relationship between openness to the world and productivity growth.

China is a huge country marked by heterogeneous space. Moreover, opening up pace and economic performances in China show important disparities among regions. Though, previous studies based on regional data generally fails to consider distinctive characteristics of geographical data. By considering each region as an isolated and independent identity, they overlook regional dynamics, agglomeration and proximity effects. Moreover, ignoring spatial effects in empirical analysis could bring about serious misspecification problems and might lead to dubious measures of parameter estimates and statistical inferences (Abreu and al., 2005).

Since the last few decades, the explicit consideration of spatial dependence[2] raised increasing interest in applied econometrics. To date, explanatory spatial data analysis methods have been widely used in "convergence club" studies between regions or countries (e.g. Baumont and al., 2000; Badinger and al., 2004 ; Lall and Yilmaz, 2000). The application of exploratory spatial data analysis (ESDA) methods has been recently extended to various research fields. For instance, studies on geographical targeting of foreign direct investment have started to rely on spatial data analysis. To name only a few, Coughlin and Segev (2000), Blonigen and al. (2004) all conduct spatial econometric analysis on the importance of agglomerations economies in FDI location decisions respectively in China and in OECD countries. Keller and Shuie (2007) analyse the expansion of interregional trade networks in China trough spatial explanatory data. Madariaga and Poncet (2007) utilise spatial regression methods to inquire into the impact of FDI on per capita income growth in Chinese cities. Fingleton (1999) explore productivity spillovers in manufacturing sector among 178 E.U. regions while Conley and Ligon (2002) study cross-country economic growth spillovers through the world. Ying (2003) also conducts an analysis on Chinese output growth and reveals that previous studies which ignore spatial dependence suffer from serious misspecification issues and yield unreliable results. Up to now, certainly due to software limitations, existing empirical studies are mostly confined to cross-sectional analysis. In the sprouting spatial panel data literature, Madariga and Poncet (2007) could be viewed as one of the most comprehensive empirical analysis.

To our best knowledge, this study represents the first attempt to explore the effect of the open door policy on regional productivity performances from a spatial econometric perspective. The theoretical model we use is mainly linked to the "endogenous growth" framework (Lucas, 1988; Grossman and Helpman, 1991) and "economic geography" literature (Krugman and Venables, 1995). The objectives of the study are threefold: The first objective is to examine the main determinants of regional labour productivity performances in Chinese provinces. The second objective is to explore spillover effects through the ERSA and spatial regression methods and to address specification problems arising from spatial effects. The third objective is to inquire into interregional productivity spillovers triggered by opening up policies in China.

The remainder of the paper proceeds as follows. The second section provides a brief overview of China's opening up process and of the literature on openness and spillovers. Section 3 discusses the underlying data and presents the empirical model. Section 4 introduces a methodological discussion on the ERSA methods. The empirical findings are presented and interpreted in Section 5.

II. Openness and Productivity Spillovers in China: Theoretical and Historical Background

2.1. Main characteristics of China's opening up to the world

China started to receive foreign capital in 1979 along with the implementation of economic reform policies. The economic transition of China has been a gradual and spatially uneven process (Table 1). During the early stage of the economic reform, inward FDI amounts to China remained fairly low and the opening up policies were only confined to a few selected regions. Then, in the early 80's, the bulk of the FDI projects were highly concentrated in the southern

[2] Spatial dependence refers to the correlation of observations across space.

provinces of Guangdong and Fujian where four Special Economic Zones (SEZ) has been established[3] to offer preferential treatments to foreign investors. In 1984, the SEZ had been extended to further 14 coastal cities[4] and Hainan Island.

Table 1: FDI flows to China by province (1990 constant USD10000)

Province	1980	1985	1990	1995	2000	2005
*Beijing	0	10404	276955	124304	137398	320084
*Tianjin	410	5165	8315	134749	95153	290470
*Hebei	0	460	3935	69172	55429	141340
Shanxi	0	50	340	5656	18339	33190
Inner Mongolia	0	0	13	9397	8624	N/A
*Liaoning	0	1838	24831	124417	166840	421208
Jilin	0	295	1694	35335	27502	53512
Heilongjiang	0	265	2534	39759	24552	120105
*Shanghai	0	7312	17719	287989	257886	499754
*Jiangsu	0	1395	14110	423623	524359	1225751
*Zhejiang	0	1914	4844	111453	131603	625086
Anhui	0	191	961	42761	25989	97992
*Fujian	549	13801	29002	357892	280064	226459
Jiangxi	0	606	621	25537	18544	197354
*Shandong	0	655	15084	231031	242467	703234
Henan	0	662	1049	42518	46028	129738
Hubei	0	0	2900	55164	77010	172210
Hunan	0	2063	1116	43245	55641	182336
*Guangdong	18619	60360	145984	902107	920590	1020392
*Guangxi	0	1465	3025	59328	42815	31432
*Hainan	15	2454	10055	93488	35156	52669
Chonqing	0	500	332	33607	19941	48942
Sichuan	0	0	1029	25038	35657	N/A
Guizhou	0	173	468	5054	2041	6599
Yunnan	0	183	260	19938	10455	21236
Shaanxi	0	1609	4191	28717	23537	N/A
Gansu	234	346	472	5664	5088	2077
Qinghai	0	0	0	6129	8993	19338
Ningxia	0	29	103	2840	1421	N/A
Xinjiang	0	184	713	5918	1559	7289

Source: Various Issues of China Statistical Yearbook, * denotes coastal regions.

In 1992, the historic tour of the Chinese leader Deng Xiaoping to coastal southern cities had emphasised the commitment to open door policy and started a new era for China's integration into the world economy. Since 1992, a progressive switch from special regimes to nationwide opening up policies had been implemented. New policies to ensure a more even distribution of foreign capital among Chinese provinces had been introduced. FDI flows to China reached the peak in the mid 1990's. Since then China had become the world's largest host of FDI among developing countries. In 1999, due to the Asian Financial crises, FDI flows to China had slowed down but they picked up their rapid growing trend since the last few years.

[3] Shenzhen, Zhguhai, Shantou in Guandong province and Xiamen in Fujian province.
[4] Dalian, Qinhuangdao, Tianjin, Yantai, Qingdao, Lianyungang, Nantong, Shanghai, Ningbo, Wenzhou, Fuzhou, Guangzhou, Zhanjiang and Baihai.

Along with the market oriented economic reforms, Chinese government had also implemented a series of preferential policies to encourage foreign trade (e.g. duty exemptions for intermediate goods used in export-oriented production). Thereby, since the 1980's, China's foreign trade had expanded rapidly. In 2006, China outpaced major trading countries and became the world's 3rd largest trading partner (Table 2). China's accession to the WTO on the 1st January 2001 had also reduced trade distortions and started a new era in its integration into the world economy.

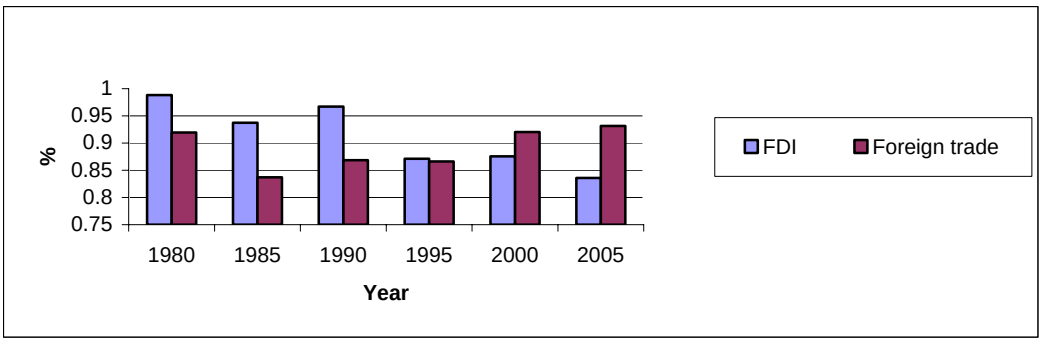
Table 2: World's top 10 trade partners in 2006.

Rank	Exporters	Value	Share	Rank	Importers	Value	Share
1	Germany	1112	9.2	1	United States	1920	15.5
2	United States	1037	8.6	2	Germany	910	7.4
3	China	969	8.0	3	China	792	6.4
4	Japan	647	5.4	4	United Kingdom	601	4.9
5	France	490	4.1	5	Japan	577	4.7
6	Netherlands	462	3.8	6	France	533	4.3
7	United Kingdom	443	3.7	7	Italy	436	3.5
8	Italy	410	3.4	8	Netherlands	416	3.4
9	Canada	388	3.2	9	Canada	357	2.9
10	Belgium	372	3.1	10	Belgium	356	2.9

Source: WTO.

In China, FDI patterns show a great disparity as for distribution between regions and sectors. Until recently, economic reforms and open door policy focused on the development of coastal regions. That is to say, preferential treatment of coastal regions brought about an uneven opening up path and serious economic disparities among Chinese regions. Aside from preferential policies, coastal regions in China also enjoy various advantages such as geographical proximity to international markets, low information costs, better infrastructure development, superior access to sea-routes and a relatively well educated human capital stock. Accordingly, today, (despite the growing share of inland regions) the bulk of inward FDI flows are still directed to coastal regions (Figure 1).

Figure 1: The share of inward FDI and foreign trade in coastal regions in China : 1979-2005 (%)



Source: China Statistical Yearbook (2006).

FDI flows to China are largely dominated by overseas Chinese firms from Hong Kong, Taiwan and Macao. Nevertheless, an appropriate estimation of the overstatement of FDI flows due to

"round-tripping[5]" is very hard. According to the World Bank, the scale of the round tripping could be estimated to about one quarter of total inward FDI to China.

As for the sectorial distribution, in China, the major part of onward FDI is drawn to labour-intensive manufacturing industries. Next fallows the real estate sector, during the last few years, the share of service sector has also been increasing considerably[6]. Besides, sectorial distribution of inward FDI to China exhibits different patterns regarding source countries. On one hand, FDI from developed source countries is generally concentrated in capital-intensive and high-technology industries (e.g. electronic industry, automobile, construction, raw-chemical materials, machinery industry etc.) and is mainly oriented towards Chinese local market. Therefore, FDI decisions from those countries are, above all, motivated by the large size of population (around 1.2 billion) and rapid economic growth of Chinese economy (at an official annual average rate of 10 percent). On the other hand, the major part of FDI from overseas China is attracted by cheap labour costs and directed towards labour-intensive and export-oriented manufacturing industries. In the literature, it is generally asserted that, FDI from the Greater China Area does not necessarily represent a genuine source of advanced technology (Hu and Tong, 2003; Lemoine, 2000). Even so, one can not disregard that overseas inward FDI has considerably expanded China's foreign trade through processing trade. Today, labour-intensive processing activities of foreign affiliates still represent by far the most dynamic component of China's foreign trade.

2.2. Theoretical framework on openness spillovers

Along with the progressive expansion of FDI flows and foreign trade throughout developing countries, the nexus between openness to the world and the host country's economic development became a popular subject of interest. The existence of spillovers from foreign trade and FDI has been debated extensively by scholars and policy makers. In time, general belief on the positive effect of openness on developing countries has been established.

In developing countries, which are generally scarce in capital, FDI and foreign trade represent an effective way to alleviate capital shortage and create employment opportunities. Furthermore, multinational companies (MNC) in developing countries enjoy in general higher productivity rates than domestic counterparts. Thereby, when MNCs invest in a foreign country, they transfer to the subsidiaries a "package" composed of capital, advanced technologies and managerial-organisational skills (Hymer,1960; Balasubramanyam and al. , 1996[7]). The "firm-specific assets" of the MNCs enable them to compete with their local counterparts who benefit from a superior knowledge of consumer preferences and business practices on local market (Blomström and Sjöholm, 1999). The advanced technologies brought by MNCs might later leak out to local firms through various channels outlined below.

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[5] Round-tripping designates reinvestment of Chinese capital from abroad due to some bureaucratic and political barriers (e.g. issues between Taiwan and China) or in order to benefit from preferential regimes.

[6] Providing a detailed discussion on the determinants of inward FDI to China is clearly beyond the scope of this paper. For an extensive discussion about the FDI patterns in China, interested reader should refer to Lemoine (2000), Liu (2002).

[7] Mansfeld and Romeo (1980) reveal that in developing countries, technologies transferred from parent firms to their subsidiaries are newer than those sold by licensing agreements.

Imitation-demonstration and contagion effects: (Findlay, 1978; Caves, 1974). Foreign invested firms enjoy a better technological intensity and are expected to bring in new products and technologies into host developing economies. Geographic proximity to foreign firms is prone to stimulate close observation and imitation of high technology products (Blomström et Wang, 1992). That is to say, in host countries, local firms could upgrade technologically by observing (learning by watching) and by imitating (learning by doing) MNCs. In the literature, it has been argued that transmission of technical innovations would be more effective between agents located in the same area (Arrow, 1971; Findlay, 1978). In others words, face-to-face contacts and personal relationships ease diffusion of advanced technologies. Thereby, in the literature, FDI is recognised as a major source of technological upgrade for host countries.

Competition: In host countries, the presence of foreign owned enterprises (FOEs) could exert a competitive pressure and push local indigenous firms to improve their technologic and allocative efficiency (Kokko, 1996). In addition, in host countries where the competition is fierce MNCs would be more inclined to transfer their most advanced technologies to their subsidiary companies.

Labour turnover: In developing countries, MNCs carry most of R&D and training activities. Knowledge created in MNCs is prone to diffuse to local economy through labour turnover while skilled workforce trained by the MNCs move to local firms or establish businesses of their own (Blomström and Sjöholm, 1999).

Backward and forward linkages: Vertical spillovers could arise from foreign-owned firms through supplier-customer relationships. In the presence of quality linkages between foreign and local firms, spillovers can take place in the form of labour training and technological know-how transfer through joint-ventures and licensing to local firms (Blomström and Kokko, 2001).

Trade: The expansion of foreign trade could increase technical efficiency in various ways: First, development of export activities give access to larger markets and allows for scale economies. Generally speaking, in host countries, MNCs tend to be more export oriented than local counterparts. The export activity of MNCs could stimulate the integration of local firms into international markets in various ways. First of all, MNCs's export activities could also reduce information costs in foreign markets and establish adequate transport infrastructure for local counterparts. Secondly, the competition on foreign markets and integration into the international production networks could bring about efficiency gains to local firms (Blomström et Kokko, 2001). Foreign currency brought by exportation activities could finance importation of sophisticated equipments, machinery or products and give rise to technological upgrade.

Despite little theoretical controversy on the subject, empirical studies generate rather conflicting evidence on the extent of spillovers from openness to the world. Some recent studies, Aitken and Harrison (1999) for Venezuela, Haddad and Harrison (1993) for Morocco; and Aslanoglu (2000) for Turkey reveal negative impacts of FDI on host countries' economic performances. These studies mention that host economies are likely to suffer from fierce competition following the entry of MNCs into the local-market (Kokko and al., 1996). In that case, the presence of foreign firms might draw demand from local firms and "crowd out" less competitive local firms (especially in large-scale industries). Moreover, purchasing advanced technology from abroad,

setting up joint-ventures or buying licences might also represent a substitute for local innovation activities (Aitken et Harrison, 1999).

Aforementioned empirical studies emphasise on the fact that spillovers from openness to FDI do not arise automatically. Their existence and strength are strongly conditioned to the host country's innovation absorption capabilities as well as to the level of interaction between foreign and domestic firms. Cohen and Levinthal (1989) define "absorptive capacity" as the ability of a region or an organisation to identify, assimilate and exploit the knowledge from the environment. In the same way, Abramovitz (1986) infer that the ability to absorb more advanced technologies depend on the « social capabilities » of host countries. The notion of social capability refers to number of factors such as technical and organisational competence, human capital, infrastructure development, stability of macroeconomic climate and quality of institutions.

In the empirical literature, absorption capabilities are generally proxied by technology gap between foreign investors and host country. True, a large technology gap between local and foreign firms could hint at a big "catch-up" potential; however, it can also indicate poor absorption capabilities of host economies (Blomström and Sjöholm, 1999). Thereby, technology diffusion is expected to be more efficient when the technology gap is small and host and home countries compete directly in comparable activities (Kokko, 1992). Haddad and Harrison (1992) reveal that there is more scope for technology diffusion in low-tech sectors where the gap between local and foreign firms is small. Besides, Xu (2000), Borensztein and al. (1998) stress the role of human capital development in spillovers process through FDI. Both studies infer that host countries should reach a minimum human capital threshold level in order to benefit from technology spillovers from foreign firms. In the same way, Blomström and Wolff (1994) conclude that in host countries, basic infrastructure has to be in place in order to let technology transfer to take place.

III. Data Description and Theoretical Model

3.1. Data

In this study, we explore labour productivity in 30 Chinese provinces over the period 1979-2006. Tibet is excluded from the panel dataset due to data unavailability. The data is originated from various issues of China Statistical Yearbook. All nominal values are deflated by region-specific retail price indexes and expressed in 1978 constant RMB. Missing observations have been completed by linear interpolation.

3.2. Description of main variables

A detailed description of the main variables used in the empirical analyses is provided below:

Dependent Variable: ***Labour Productivity****:* We proxy technological efficiency of a region by its labour productivity, which is a partial measure of productive efficiency (OECD, 2001). Due to the scarcity of data, average value added per employee (instead of hours worked) has been used to construct labour productivity series.

Control Variables: ***FDI*** is measured in terms of flows instead of stock. In the literature, it is generally asserted that positive effects of inward FDI on host economy could take some time to be observed. Thus, in this study, one-year lagged value of FDI is used in order to detect any delayed effects[8]. ***International trade*** is measured through the sum of exports and imports. Given the mixed empirical literature outlined in section 2, we remain *a priori* agnostic on the expected signs of coefficients associated with those variables. ***Capital intensity*** refers to average capital assets per employee. In accordance with neoclassical framework, we consider that workers equipped with better equipment are expected to exhibit higher productivity. ***Human capital*** proxies host region's absorptive capabilities. Given that data on the composition of employed persons by educational level are not available, human capital is measured by the share of the population studying at the institutions of higher education. We expect that a well-trained and more qualified workforce is likely to achieve higher productivity. ***Infrastructure adequacy*** of the host region could be measured in various ways alternatively. In this study, we rely on infrastructure development in transportation services. For this purpose, we compute a measure of "combined length of highways and railways[9]". Number of phones would also be a good measure of infrastructure development, but data are unavailable over our study period. We also built an alternative measure of infrastructure adequacy which is the interaction term of FDI per habitant and combined length of railways and highways. We consider that a better infrastructure development would lead to higher labour productivity. Descriptive statistics and expected signs of model variables are outlined respectively in Table 3 and Table 4.

Table 3: Descriptive statistics

Variable	Labour Productivity	One-year-lagged FDI	Trade	Education	Capital Intensity	Infrastruc-Ture
Mean	-1.66	-1.63	3.93	-5.21	-0.57	1.24
Median	-1.69	0.65	4.53	-5.43	-0.51	1.36
Maximum	0.71	5.15	10.65	-2.56	2.15	3.18
Minimum	-5.04	-13.82	-13.82	-6.88	-13.82	-1.47
Std. Deviation	0.94	6.05	3.70	0.90	1.48	0.78

Notes: All of the variables are explained in log linear form.

Table 4: Summary of expected signs

Variable	Expected Sign
FDI	+/-
Education	+
Trade	+
Capital Intensity	+
Infrastructure	+
Wages	+

[8] The amount of FDI to a province is directly affected by the size of the province. Thus, in order to control for 'size' effect we also tested alternative measures of FDI such as FDI per capita and ratio of FDI over GDP. Nevertheless, these variables turn insignificant and the models exhibit a very bad fit. As a consequence we take into account of heterogeneity across regions through cross-section dummies.

[9] We consider that if those two measures are not combined, they are likely to represent biases against regions where railway or road transportation dominates.

3.3. Model

In the empirical model, the log-linear functional form is adopted to reduce a likely heteroscedasticity. Thereby, the estimated coefficients could be interpreted as elasticities. The model is set as follows:

$$\ln LP_{i,t} = \alpha_0 \ln FDI_{i,t-1} + \alpha_1 \ln Trade_{i,t} + \alpha_2 \ln Edu_{i,t} + \alpha_3 \ln K / L_{i,t} + \alpha_4 Infra_{i,t} + \eta_i + \gamma_t + \varepsilon_{i,t} \quad (1)$$

In Equation 1 the index i denotes cross-sectional dimension while the index t indicates time dimension. The disturbance term is composed as fallows: η_i corresponds to unobservable time variant province specific fixed effect, γ_t designates unobserved period specific effect that is constant across regions and ε_{it} is the error term which is assumed to be i.d.d. Region specific effects allow to deal with biases as well as with omitted-variable and misspecification issues. Differences in opening up paces across regions are expected to be captured by time specific fixed effects.

IV. Spatial Effects: Model Background

The origins of spatial econometrics are expressed in Tobler's first law of geography (1970) as follows: « Everything is related to everything else, but near things are more related than distant things ». Thereby, spatial econometrics is dedicated to the study of spatial structure and spatial interactions between observations. It is mainly inspired from the research issues of economic geography and regional science (Anselin, 2001).

The pioneering work of Moran (1948), Hordijik and Paelinck (1976), Paelinck and Klaassen (1979), Cliff and Ord (1973), Anselin (1988) introduced an empirical framework and made considerable methodological progress in spatial modelling. Since the last decade, with a better availability of geo-coded socioeconomic data sets, spatial econometrics has received an increasing attention from mainstream econometrics from both theoretical and applied point of view. To date, the usual approach in spatial explanatory data analysis has consisted on leaving out the time dimension and focusing on a single cross-section interaction equation (Fingleton, 2001). Since the last decade, the field of spatial econometrics has been extended to space-time data specifications. To name only a few, Elhorst (2001, 2003); Anselin (2001); Anselin and LeGallo (2008) provide comprehensive discussion and theoretical framework on spatial panel econometrics. However, for the time being, the growing literature on spatial panel econometrics is in particular confined to theoretical framework (due to software limitations). Today, developing alternative approaches and adequate spatial econometrics softwares for panel data remain a challenge for ongoing research.

4.1. Main econometric issues introduced by spatial data

The use of spatial data in empirical analysis could bring about two major econometric problems: Spatial dependence and spatial heterogeneity[10]. Living out these two issues could lead to serious misspecification problems and unreliable results (Abreu and al., 2005).

[10] Going into an excessive discussion on spatial econometrics methods is behind the scope of this paper. For a complete discussion on spatial regression models see Anselin (1988), Anselin and Bera (1998), Baumont and al. (2000).

Spatial Dependence

Spatial dependence refers to absence of independence between geographic observations. In other words, spatial autocorrelation is the coincidence of value similarity and location similarity (Anselin, 2001). In some way, spatial autocorrelation could be viewed as analogous to serial correlation in time series models. Hence, models using geographical data need to be tested systematically for spatial autocorrelation (Cliff and Ord, 1981)[11].

Spatial dependence could arise from some theoretical or statistical issues. On one hand, it could be the outcome of the integration of geographical units due to labour migration, capital mobility and inter-regional trade. It can also arise from some institutional and political factors and externalities such as technology and knowledge spillovers (Buettner, 1999, Ying, 2003). On the other hand, spatial dependence could be related to some statistical issues such as measurement errors, varying aggregation rules, different sample designs and omission of some variables with spatial dimension (e.g. climate, topology and latitude) (Anselin and Florax, 1995).

Figures below display the choropleth maps on spatial correlation in labour productivity and FDI for the years 1995 and 2005. In the maps, Chinese provinces are divided into quartiles based on the amount of FDI flows they have received. It is obvious from Figures 2 and 3 that in China, the regional distribution of labour productivity, FDI and trade exhibit a clear positive spatial dependence in 1995 and 2005. In other words, we can clearly observe from the maps that regions with high or low values of FDI, trade and labour productivity are strongly clustered.

[11] Unlike time dependence, dependence in space implies feedback effects and simultaneity due to the two-directionality of neighbourhood relation in space: "I am my neighbours' neighbour" (Anselin and Bera, 1998; Anselin and Rey, 1991).

Figure 2: Spatial dispersion of labour productivity in China: 1995, 2005.

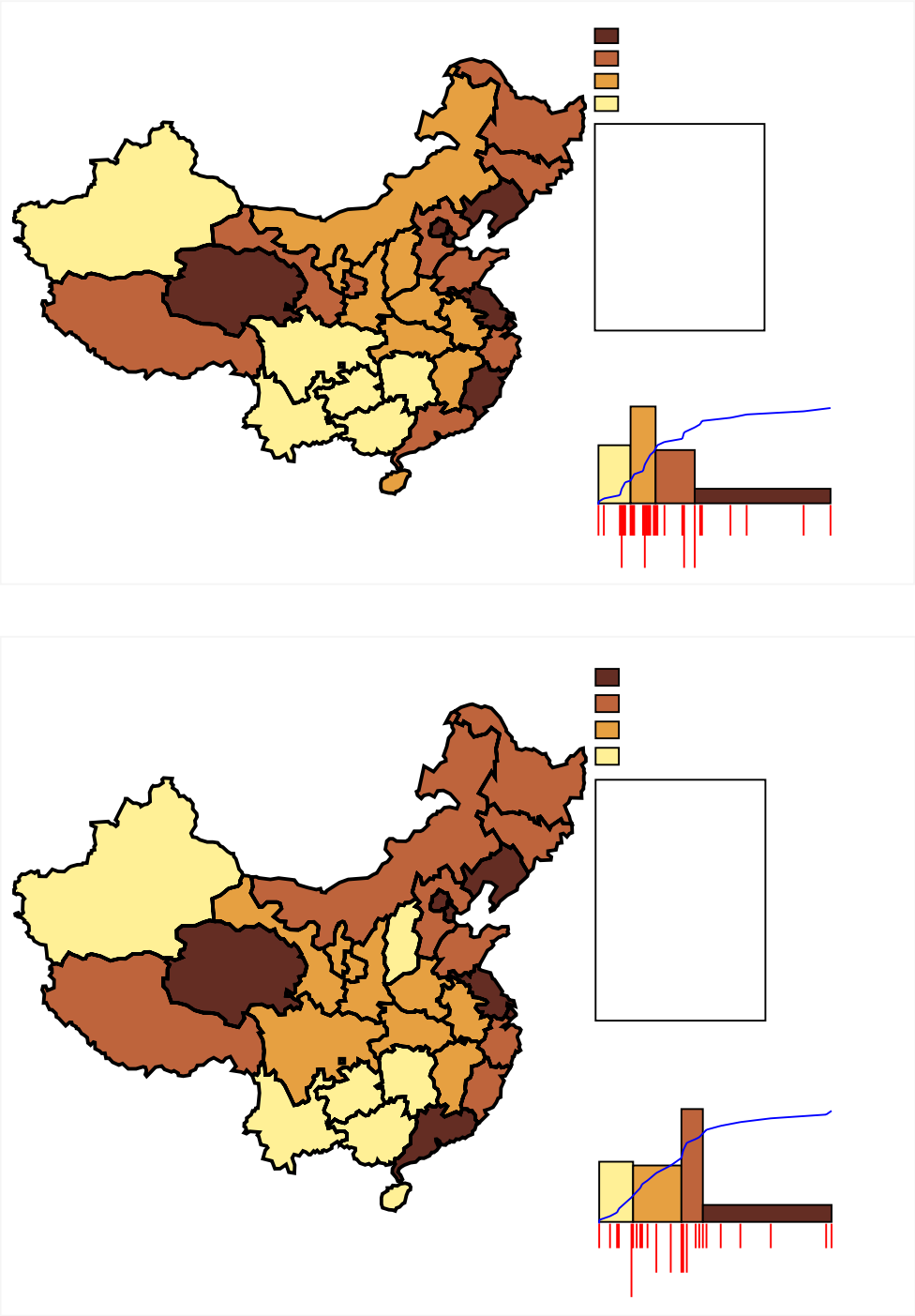
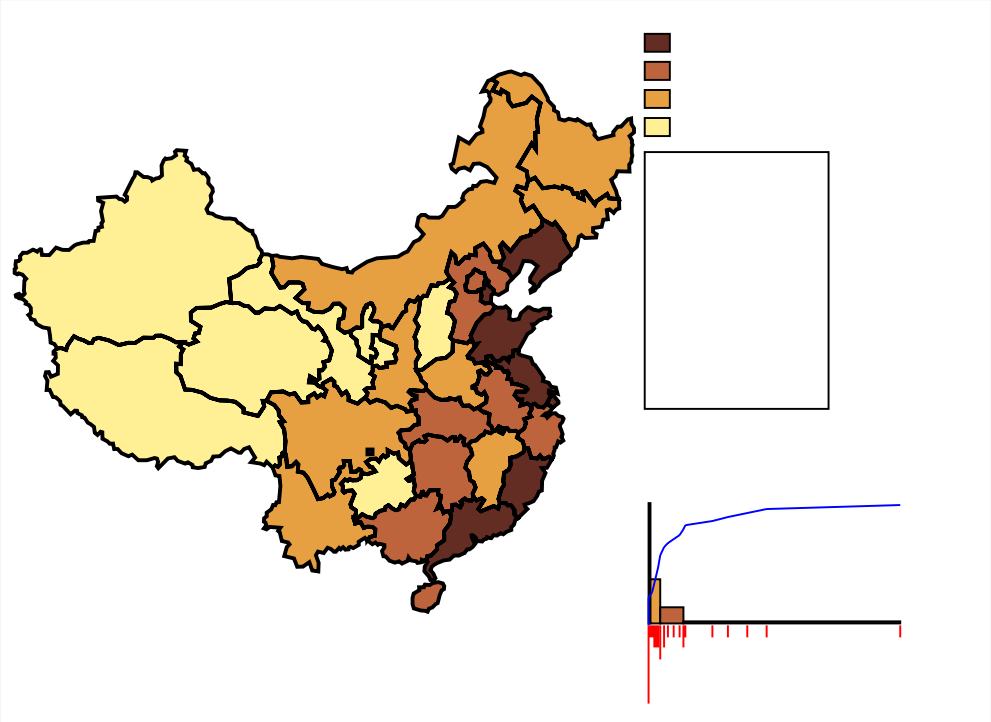


Figure 3: Regional distribution of FDI in China: 1995, 2005.



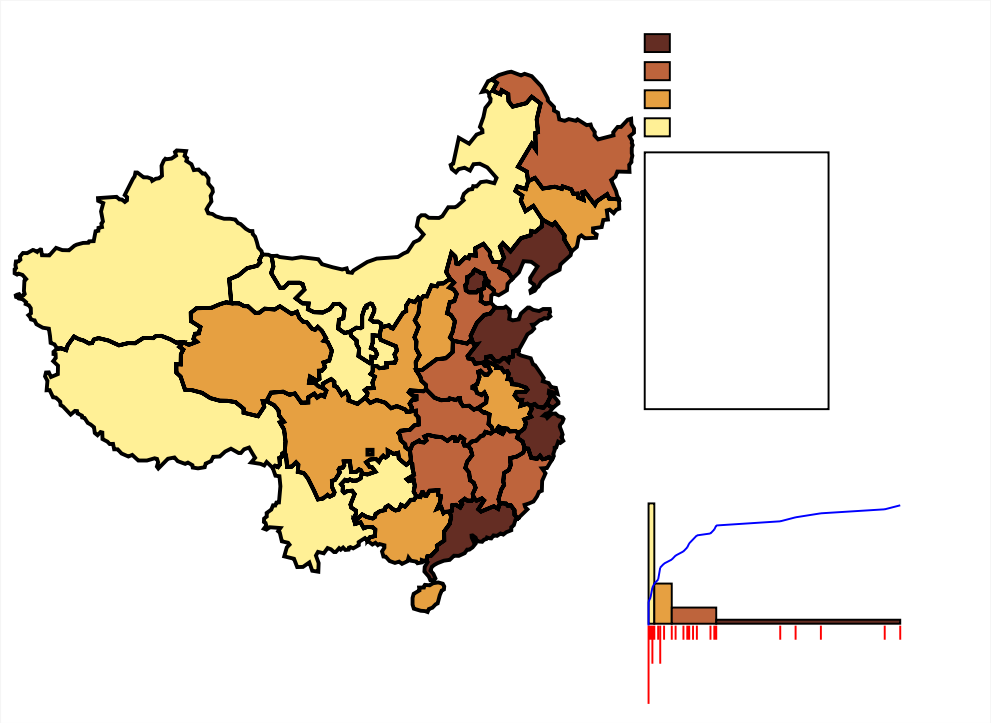
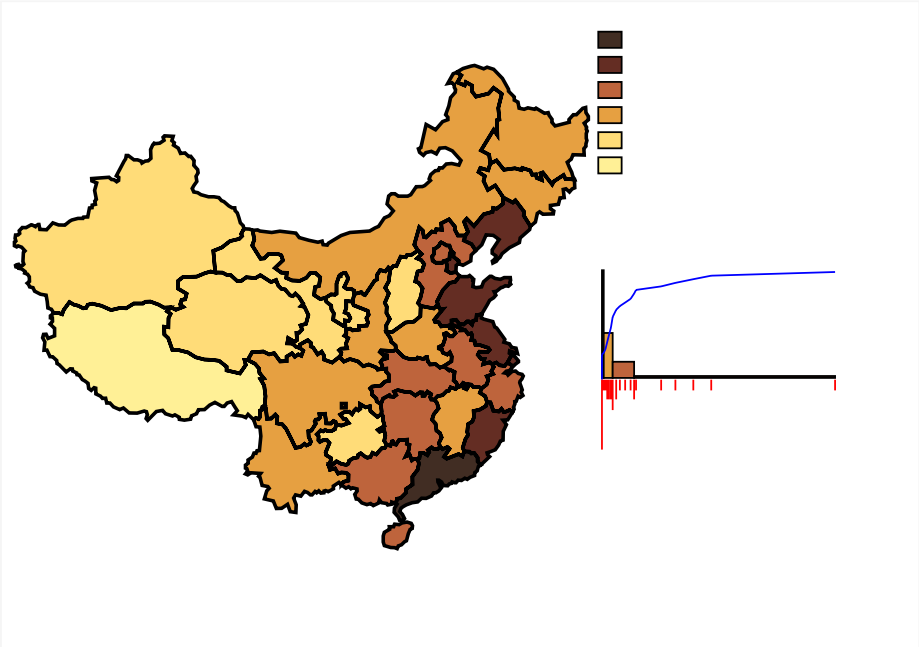
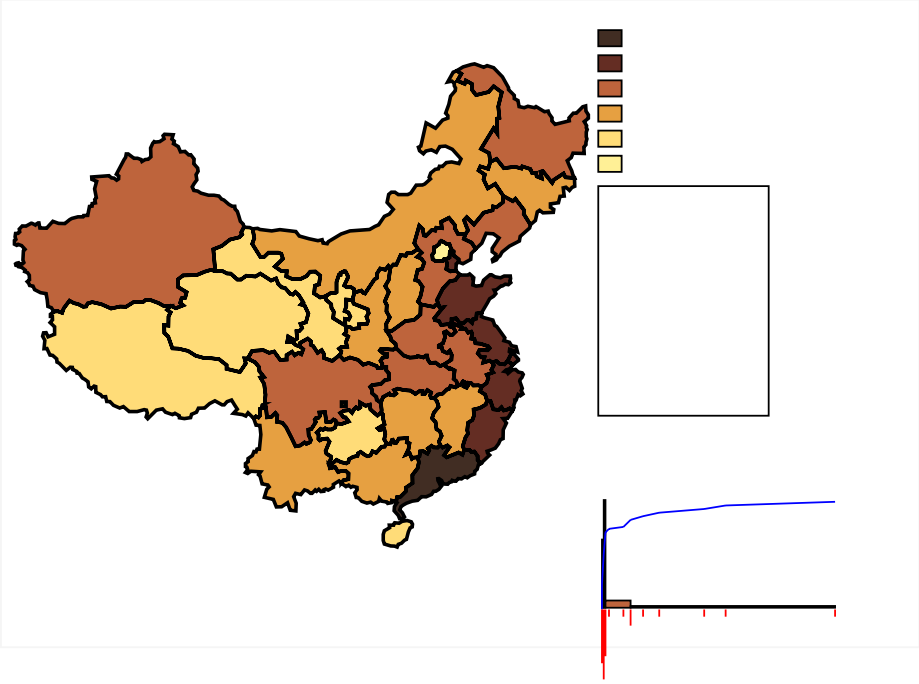


Figure 4 : Regional distribution of trade in China: 1995, 2005.





Spatial Heterogeneity

The second issue introduced by the use of geographical data is spatial heterogeneity in the econometric relationship. Spatial heterogeneity refers to the situation where the estimated parameters vary across regions depending on their location (Baumont and al., 2000). The presence of spatial heterogeneity violates the Gauss-Markov assumption of existence of a single linear relationship with constant variance across the entire data sample. In the case of structural instability, alternative estimation procedures are needed to model appropriately this variation and draw reliable inferences. In the literature, spatial variability in the regression coefficients is modelised in various ways through spatial regimes (Anselin, 1988), spatial expansion (Casetti, 1997), geographically weighted regressions (Fotheringham and al., 1998) and Bayesian hierarchical models (Anselin and Florax, 1995). However, neither of these specifications has seen application in panel data contexts (Anselin and Le Gallo, 2008). Therefore, in this study, we limit our attention to unobserved heterogeneity and tackle it by standard panel econometrics methods such as time invariant cross-sectional and time period dummy variables.

4.2. Properties of spatial weighting matrix

The spatial weighting matrix provides the structure of assumed spatial relationships and captures the strength of potential spatial interactions between observations. Determination of an accurate spatial weights matrix is one of the fundamental steps in spatial data analysis. In fact, over-specification or under-specification of the spatial weights matrix can affect the performance of spatial dependence diagnostic tests as well as the reliability of spatial lag coefficients and statistical inferences (Florax and Rey, 1995).

The spatial weighting matrix is a square matrix of dimension equal to the number of cross sectional units (NxN). Given the elements of the spatial weights matrix are to be non-stochastic and exogenous to the model (otherwise the model would be highly non linear), spatial matrices are generally geography based on distance or contiguity[12] (Anselin and Bera, 1998). In the literature, spatial connectedness between regions is defined in various ways:

Simple contiguity: The contiguity weighting binary matrix is widely used in the literature due to its simplicity of construction. The binary contiguity matrix is based on adjacency of locations of observations. Put w_{ij} to express the magnitude of the interaction between province i and j. Then, if two provinces share a common boundary $w_{ij}=1$ and $w_{ij}=0$ otherwise.

Distance based contiguity: In distance based contiguity matrices, spatial weights attributed to observations depend on geographic or Euclidean distance d_{ij} between locations *i* an *j*. Distance matrices differ in functional form used, distance function [$w_{ij}=d_{ij}$], inverse function of distance [$w_{ij}=1/d_{ij}$], inverse distance raised to some power [$w_{ij}=1/d_{ij}^{N}$] and negative exponential function [$w_{ij}=\exp(-\theta d_{ij})$] are mostly used in the literature. In distance decay functions, the strength of

[12] Interdependence between observations could be a function of other factors than geographic distance (e.g. differences in factor prices between countries, cultural distance, travel time, similarities in per capita income etc.). Economic distance has also been increasingly in use in recent studies to construct weighting matrixes (e.g.Conley and Ligon , 2002). However, given that the weights are not exogenous to the model, the use of economic distance to compute distance weighting matrix could imply serious identification problems (Manski, 1993).

spatial dependence declines with distance. In addition, it is generally assumed that beyond a certain critical bilateral geographic distance, interactions between provinces become negligible (Abreu et al., 2005). In the literature, cut-off points are generally set up following some statistical or arbitrary criterions based on the minimum or median distance between regions, the significance of spatial diagnostic statistics or goodness of fit of the regression etc.

Usually, the weighting matrix is row standardised by dividing each weight of an observation by the corresponding row sum $w_{ij} / \Sigma_j w_{ij}$. In this way, the elements of each row sum to unity[13] and each weight w_{ij}[14] could be interpreted as the province's share in the weighted average of neighbouring observations. $w_{ij}=0$ indicates lack of spatial interactions between observations. By convention, distance matrix has zeros on the main diagonal, thus no observation predicts itself.

In this study, in order to capture different spatial structures, a row-standardised simple binary contiguity and five inverse distance matrices are computed. The characteristics of the great circle distance matrix (based on coordinates of centroids of Chinese provinces) are listed below in Table 5.

Table 5: Characteristics of great circle distance matrix for capital cities of Chinese provinces.

Distance matrix arc	
Dimension:	30
Average distance between points:	603.208
Distance range:	1714.61
Minimum distance between points:	21.0473
Quartiles:	
First:	329.798
Median:	535.332
Third:	823.098
Maximum distance between points:	1735.66
Min. allowable distance cut-off:	201.639

4.3. Diagnostic tests for spatial dependence

The most widely used diagnostic tests for spatial association among observations are based on the research of Moran (1948), Geary (1954) and Cliff and Ord (1973). In short, spatial autocorrelation diagnostic tests capture whether the value of an observation in one location is similar to those of observations in proximate regions. Moran's I is by far the most used test to determine whether a process is spatially non-stationary[15]. Spatial diagnostic tests are conducted

[13] Whereas the original spatial weighting matrix is usually symmetric, the row-standardised one is not (Anselin and LeGallo, 2008). An asymmetric spatial weighting matrix implies that, region *i* could have a larger influence on the random variable of interest in region *j* and *vice-versa*.

[14] We extent the use of weights for cross-sectional dimension to panel data by assuming that weights are time-invariant, so in our sample, $w_{ij,1979}=w_{ij,1980}=\ldots= w_{ij,2006}$. With W_N as the matrix dimension of weights for cross-sectional dimension, for panel data, we obtain the weight matrix $W_{NT}=I_T \otimes W_N$, where I_T is an identity matrix of dimension T (Anselin and LeGallo, 2008).

[15] Moran's I statistic gives evidence about the spatial autocorrelation on the sample data as a whole for a given year t and spatial lag y: $i \neq j$

under the null hypothesis of lack of model misspesification due to spatial dependency (in the form of an omitted spatially lagged dependent variable) and uncorrelated homoscedastic error terms. The significance of the coefficient is based on z-values. Anselin (1995) has also developed local indicator of spatial correlation (LISA) which provides a spatial association measure for a particular locality and identifies local clusters. Cliff and Ord (1988) adopted Moran's I test to spatial autocorrelation in regression residuals.

Table 6: Moran's I and Geary's c test results for labour productivity, trade and FDI in China, 1979-2006.

Variable	Moran's I statistic	Moran's I p-values	Geary's c statistic	Geary's c p-values
Labour Productivity				
1979-1985	0.041	0.22	0.875	0.07
1986-1990	0.062	0.12	0.864	0.05
1991-1996	0.074	0.08	0.869	0.05
1997-2001	0.106	0.02	0.854	0.03
2002-2006	0.144	0.00	0.840	0.02
FDI				
1979-1985	0.009	0.47	0.866	0.05
1986-1990	0.031	0.28	0.861	0.04
1991-1996	0.098	0.03	0.803	0.00
1997-2001	0.069	0.09	0.841	0.02
2002-2006	0.131	0.00	0.824	0.01
Trade				
1979-1985	0.087	0.03	0.833	0.01
1986-1990	-0.004	0.29	0.883	0.09
1991-1996	0.009	0.07	0.868	0.05
1997-2001	0.022	0.10	0.863	0.04
2002-2006	0.055	0.06	0.856	0.03

Notes: Results are based on arc distance matrix with a critical band of 0-800 km.

Table 6 displays the results of Moran's I and Geary's c statistics and related p-values[16] for labour productivity, FDI and trade[17]. We can observe from table 6 that Moran's I and Geary's c statistics

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$$I_y = \frac{N}{S_0} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij}^{(y)} z_i z_j}{\sum_{i=1}^{N} z_i^2}, \quad \forall \text{ all } t=1,2,...,T$$

Where, n is number of regions, z_i, and z_i, are normalised vectors of observed values of the variable at locations *i* and *j*, w_{ij} is the element of spatially weighting matrix W(N x N) corresponding to the observation pair *i* and *j* and S_0 is a scaling constant. Moran's I statistic could be interpreted as the statistic measure of covariance of observations in nearby provinces relative to the variance of the observations across regions. Given that variables are standardised, Moran's I values range from -1 to 1.

[16] The expected value of Moran's I statistic is zero in case of the absence of spatial autocorrelation. So, if I=0 we consider that observed values are randomly and independently distributed over space (Goodchild, 1986). Moran's I statistic could be interpreted in the following way: If I>0 with (p<0.05) nearby regions have similar values, the random variable tends to cluster in space. I<0 with (p<0.05) reveals dissimilar values of proximate regions. Besides, the expected value of Grey's c is 1. So, c=0 indicates absence of spatial dependence between observations, c<1 with

hint at positive and mostly significant autocorrelation between 1979 and 2006. In addition, it is obvious from Table 6 that labour productivity, FDI and trade in China have been exhibiting an increasing trend of positive spatial dependence since 1990.

4.4. Spatial model specifications

In the empirical literature, spatial dependence is generally incorporated into the regressive structure in three major ways: In the form of a lag operator to the dependent variables, to the explanatory variables or to the error term (Anselin and LeGallo 2008, Anselin 2006).

Spatial Lag Model: The spatial lag model combines the standard regression model with a spatially lagged dependent variable introduced as an explanatory variable. Spatial lag operators[18] imply a shift over space and could be viewed as analogous to the back shift operator in the first order autoregressive time series models. Spatial lag model could be expressed as follows:

$$y = \rho Wy + X\beta + \varepsilon \qquad (2)$$

Using traditional notation, y is a (N x 1) vector of observations of dependent variable, X, a (N x K) matrix of K exogenous variables, β, a (K x 1) vector of explanatory variable coefficients and ε, a (N x 1) vector of stochastic disturbance terms. W corresponds to a (N x N) spatial weighting matrix which identifies the geographic relationship among spatial units. ρ refers to spatial autoregressive parameter that captures spatial interactions between observations. It measures the impact of surrounding regions (positive or negative) on the dependent variable in a reference region *i*. ρ is assumed to lie between -1 and 1. If $\rho \neq 0$, ignoring ρ have similar consequences to omitting a significant independent variable in the regression model.

In spatial lag model, including a spatially lagged dependent variable in the right hand side introduce a simultaneity problem. By construction, the lagged dependent variable is correlated with the individual fixed effects in the error term. Consequently, the OLS estimator is inconsistent and biased. In spatial models, endogeneity problem is usually solved by applying instrumental variables approach, maximum likelihood (ML) estimator or generalised method of moments (GMM) estimator recently suggested by Kelej ian and Prucha (1999).

It should be outlined that in spatial lag models, additional information derived from the explicit incorporation of spatial effect improves the explanatory power of the model. On one hand, adding a spatially lagged depending variable enables to asses the pattern and the extent of spatial effect. On the other hand, controlling for spatial dependence allows to isolate the effect of other explanatory variables (Anselin, 1996).

Spatial Error Model: In spatial error model, spatial autoregressive process is confined to the error term. Thereby, spatial dependence works through omitted variables and spatial

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($p<0.05$) indicates positive autocorrelation whereas $c>1$ with ($p<0.05$) indicates negative autocorrelation (Anselin, 1992).

[17] We also performed spatial correlation tests for other explanatory variables but we didn't detect any significant spatial correlation. The results are not reported due to lack of space but available upon request from the author.

[18] Spatial lag operator corresponds to a weighted average of random observations in nearby regions.

autocorrelation affects the covariance structure of disturbances (Baumont and al., 2000). Spatial error models can be represented in the following form:

$$y = X\beta + \varepsilon \tag{3}$$

$$\varepsilon = \lambda W\varepsilon + \mu \text{ then } \varepsilon = (I - \lambda W)^{-1} \tag{4}$$

Where ε, a (Nx1) element vector of error terms and λ the spatial autocorrelation coefficient which is assumed to lie between -1 and 1. The parameter λ captures how a random shock in a specific region is propagated to surrounding regions. By definition, the spatial lag term $W\varepsilon$ is clearly endogenous and correlated with the error term. Living out spatial correlation between error terms has similar consequences to ignoring heteroscedasticity. That is to say, the OLS estimator remains consistent but no longer efficient (it leads to biased and inconsistent statistical inferences).

Spatial Cross-Regressive Model: In cross-regressive models, spatial correlation is included in the form of one or more spatially lagged explanatory variables on the right hand side. This type of spatial specification does not require special estimation methods (Anselin, 1999; Baumont and al., 2000; Lall and Yilmaz, 2002).

The spatial model specifications presented above place additional structure on the unobserved determinants of the endogenous variable which would otherwise be captured by the traditional error term. The spatial lag and error structures can also be combined in order to obtain higher order spatial models (Anselin and LeGallo, 2008). In this study, the traditional cross-section spatial models are extended to panel data specification[19].

V. Model Estimation and Results

5.1. Model with spatial effects

In this section, we augment Equation 1 by allowing for spatial interactions through spatially lagged endogenous and exogenous variables. Thereby, by including a spatially lagged dependent variable, we consider that labour productivity of a given region could be affected by labour productivity of surrounding regions owing to spatial interactions. Furthermore, the introduction of spatially lagged control variables implies that the values of observations in nearby regions can also exert an influence on labour productivity in the reference region. The spatial model we estimate takes the following form:

$$\begin{aligned}\ln LP_{i,t} &= \alpha_0 \ln LP_{i,t-T} + \alpha_1 W \ln LP_{i,t} + \alpha_2 W \ln FDI_{i,t-1} + \alpha_3 W \ln Trade_{i,t} + \alpha_4 \ln FDI_{i,t-1} \\ &+ \alpha_5 \ln Trade_{i,t} + \alpha_6 \ln Edu_{i,t} + \alpha_7 \ln K/L_{i,t} + \alpha_8 Infra_{i,t} + \eta_i + \gamma_t + \varepsilon_{i,t}\end{aligned} \tag{5}$$

The other notation is as before, $WLP_{i,t}$, $WFDI_{i,t-1}$ and $WTrade_{i,t}$ designate respectively spatially lagged labour productivity, FDI and trade. $LP_{i,t-T}$ corresponds to one-year serially lagged dependent variable. To be more precise, a spatially lagged variable for province i in year t

[19] We therefore consider that the equilibrium process is stable over time with constant spatial lag parameter ρ.

corresponds to the row-sums of spatially weighted values of variable of interest in year *t* in surrounding provinces.

5.2. Results

The OLS and ML estimations of Equation V are presented respectively in Tables 7 and 8. As mentioned above, in the presence of spatial autocorrelation the OLS estimator is no longer expected to achieve consistency, therefore, we only report OLS estimates here as a baseline.

Table 7: OLS estimations with time and cross-section fixed effects

Dependent Variable: LP	(1)	(2)	(3)	(4)	(5)
Constant	-2.420	-1.284	-1.281	-1.287	-0.903
	(-29.072)***	(-9.819)***	(-9.735)***	(-9.869)***	(-7.653)***
FDI	-0.008	-0.006	-0.006	-0.005	-0.004
	(-4.347)***	(-3.481)***	(-3.485)***	(-3.255)***	(-3.227)***
Education	0.309	0.303	0.304	0.286	0.189
	(8.700)***	(9.138)***	(9.083)***	(8.549)***	(6.581)***
Trade	-0.003	-0.001	-0.001	0.022	0.017
	(-1.995)**	(-0.903)	(-0.912)	(3.966)***	(3.434)***
KL	0.022	0.023	0.023	0.025	0.019
	(4.596)***	(5.326)***	(5.253)***	(5.768)***	(4.880)***
Infrastructure	0.108	0.054	0.054	0.059	0.022
	(3.443)***	(1.821)*	(1.829)*	(1.994)**	(0.881)
Spatially Lagged		0.613	0.615	0.650	0.411
LP	-	(10.782)***	(10.606)***	(11.270)***	(7.701)***
Spatially Lagged			0.000	-0.001	-0.006
FDI	-	-	(0.219)	(-0.394)	(-1.499)
Spatially	-		-	0.001	0.002
Lagged Trade				(0.411)	(0.881)
LP serially	-	-	-	-	0.311
lagged (one year)					(17.050)***
Adjusted R^2	0.98	0.98	0.98	0.98	0.98
Log Likelihood	561	619	619	628	762
AIC	-1.18	-1.32	-1.32	-1.34	-1.70
Log Ratio Test		116***	116***	134***	402***
Number of observations	840	840	840	840	840

Notes: The numbers in parentheses are t-statistics. (*), (**), (***) denote respectively significance at the 10%, 5% and 1% levels. Spatially weighting matrix used is a binary contiguity matrix computed by MATLAB program spatial econometrics toolbox of Lesage (www.spatial-econometrics.com).

Table 7 outlines that in China over the period 1979-2006, human capital and infrastructure[20] development as well as capital deepening have been the main determinants of labour productivity. Besides, according to the OLS results, FDI and trade have exerted a slightly negative effect on labour productivity. We can also observe that, as expected, the coefficients associated with the spatial autocorrelation variable ρ have a positive sign and are always significant at the 1 percent confidence level. This outcome indicates that in China, labour productivity spills over province borders. In addition, the LR [21] test results reveal that incorporating spatially lagged variables improves the overall explanatory power of the model. The auto-regressive form of the model is presented in Column 5. Accordingly, *one-year-lagged labour productivity* variable turns to be significant at the 1 percent level. However, given the presence of the spatial autocorrelation issue, we strongly suspect the OLS results to be fallacious.

The ML[22] estimations of the model are presented in Table 8. We can Column 1 displays that all of the explanatory variables exhibit a positive and significant effect on the dependent variable at the 1 percent confidence level. Consistent with the theory, one can observe that traditional variables such as human capital, capital intensity and infrastructure development exert the greatest impact on labour productivity performances in China. In addition, Table 8 reveals positive effects of FDI and trade on labour productivity. The coefficients associated with *FDI* and *trade* variables exhibit similar values and are positively significant at the 1% level. Accordingly, in a given region, a 10 percent increase in either FDI or trade leads to an increase of labour productivity about 1.2%.

From Table 8 we can observe that the coefficients associated with spatially lagged labour productivity are positive and significant at the 1% level. This confirms the positive pattern of spatial clustering of labour productivity among Chinese regions. The value of ρ lies around 0.1. On that account the elasticity estimates suggest that a 10 percent increase in average productivity in surrounding regions lead to a 1 percent increase in labour productivity of reference region. It should be outlined that, even after allowing for spatially lagged dependent variables, we are still able to identify productivity spillovers from inward FDI and trade. This outcome strongly supports the argument that openness improves the productivity level of Chinese regions.

[20] As *infrastructure* variable, we refer to the combined length of highways and railways. We also ran regressions with alternative infrastructure measures such as the interaction term between combined length of highways and railways and various measures of FDI. However, those variables have all turned to be insignificant or introduced serious multicollinearity issues.

[21] LR test corresponds to twice the difference between the log likelihood in the spatial lag model and the log likelihood in a standard regression model with the same set of explanatory variables (Anselin, 1996).

[22] Maximum Likelihood Estimation (MLE) consists of applying a non-linear optimisation to a log-linear function. It should be beard in mind that MLE relies on normally distributed variables with constant variance assumptions. The term *quasi* ML estimator is used in the specifications where actual distribution differs from the normal distribution of error terms (Anselin and LeGallo, 2008).

Table 8: ML estimates with time specific and cross-section fixed effects, 1979-2006.

Dependent Variable: LP	(1)	(2)	(3)	(4)
FDI	0.012***	-0.001	-0.003	-0.001
	(9.668)	(-0.916)	(-2.857)***	(-1.438)
Education	0.444	0.448	0.158	0.155
	(29.018)***	(30.563)***	(13.663)***	(12.914)***
Trade	0.012	0.007	0.004	0.004
	(4.813)***	(2.653)***	(2.600)***	(2.771)***
KL	0.036	0.0263	0.016	0.017
	(6.306)***	(4.595)***	(4.596)***	(4.837)***
Infrastructure	0.198	0.186	0.003	0.017
	(6.619)***	(6.521)***	(0.182)	(4.837)***
Spatially Lagged LP	0.103 (6.474)***	0.106 (6.932)***	0.104 (10.462)***	0.101 (10.140)***
Spatially Lagged FDI	-	0.019 (8.536)***	-	-0.002 (-1.539)
Spatially Lagged Trade	-	-	0.021 (6.632)***	0.025 (6.336)***
LP serially lagged (one year)		-	0.598 (31.268)***	0.601 (31.313)***
Adjusted R^2	0.967	0.969	0.98	0.98
Log Likelihood	301	337	662	666
Number of observations	840	840	840	840

Notes: The numbers in parentheses are asymptot *t*-statistics. (*), (**), (***) denote respectively significance at the 10%, 5% and 1% levels. Spatially weighting matrix used is a binary contiguity matrix computed by MATLAB program spatial econometrics toolbox of Lesage (www.spatial-econometrics.com).

In order to capture possible openness spillovers, in Column 2 we introduce spatially lagged FDI variable. Unexpectedly, after including spatially lagged FDI, *FDI* variable itself looses its significance. Besides, spatially lagged FDI appears to be positive and significant at the 1 percent level supporting the hypothesis of interregional FDI spillovers and agglomeration effects. These results point out a complementary pattern of FDI distribution (instead of crowding-out) between Chinese regions. After including spatial effects, the loose of significance of *FDI* variable is fairly deceptive but not inconsistent with previous literature. Accordingly, productivity spillovers arising from FDI turn to be essentially of inter-regional nature. In other words, Chinese regions reap more benefit from FDI directed to surrounded regions rather than their own inward FDI. However, this finding remains quite puzzling to us and motivates our sensitivity analysis with respect to various specifications of the distance weighting matrix.

Column 3 introduces spatially lagged *trade* variable. We can observe that the associated coefficients to spatially lagged *trade* are positive and highly significant. This outcome points at

the existence of positive trade spillovers between Chinese regions. Whereas, after including spatially lagged trade, FDI variable turn to be negative but significant at the 1 percent level.

The auto-regressive form of the model is presented in Column 4. The coefficient associated with the auto-regressive term is positive and significant at the 1 percent level. However, while we introduce one-year serially lagged dependent variable in the model, spatially lagged FDI loses its significance. This outcome could be suspected to stem from some multicollinearity problems.

5.3. Robustness Check

In this section, we explore the robustness of the empirical results to alternative specifications of distance weighting matrix. For this purpose, five simple inverse distance matrixes have been computed with the upper distance bands ranging from 500 to 1000 km. In fact, given the theoretical framework of spillovers, one could consider that a distance-based matrix could be more appropriate to spillover and technology diffusion analysis (Abreu and al., 2005).

Table 9: ML estimates with time specific and cross-section fixed effects

	Distance band (0,5)	Distance band (0,6)	Distance band (0,7)	Distance band (0,8)	Distance band (0,9)	Distance band (0,10)
FDI	0.012	0.011	0.011	0.010	0.010	0.010
	(9.447)***	(9.069)***	(8.843)***	(8.600)***	(8.444)***	(8.399)***
Education	0.465	0.446	0.435	0.421	0.410	0.406
	(30.663)***	(29.862)***	(29.075)***	(28.561)***	(28.061)***	(27.892)***
Trade	0.0144	0.014	0.013	0.013	0.013	0.012
	(5.171)***	(5.138)***	(5.050)***	(4.969)***	(4.923)***	(4.830)***
KL	0.041	0.042	0.049	0.041	0.040	0.012
	(6.738)***	(7.044)***	(7.200)***	(7.067)***	(6.929)***	(4.830)***
Infra	0.209	0.204	0.205	0.200	0.200	0.198
	(6.724)***	(6.679)***	(6.774)***	(6.687)***	(6.773)***	(6.707)***
Spatially Lagged LP	0.054	0.089	0.106	0.134	0.154	0.164
	(4.460)***	(7.030)***	(8.134)***	(10.079)***	(11.402)***	(12.103)***
Spatially Lagged FDI	-	-	-	-	-	-
Spatially Lagged XM	-	-	-	-	-	-
Adjusted R^2	0.964	0.965	0.966	0.966	0.969	0.967
Log Likelihood	273	260	247	222	199	184
Number of observations	840	840	840	840	840	184

Notes: The numbers in parentheses are asymptot *t*-statistics. (*), (**), (***) denote respectively significance at the 10%, 5% and 1% levels. All of the inverse distance matrices are computed by using Anselin's SpaceStat 1.91 version software package (2001). In the distance matrixes weights are defined as $w_{i,j} = 1/d_{i,j}$ $i \neq j$. The distance band of 0-600 km is denoted by d= (0,6] and so on.

Table 9 displays the estimation results of the basic spatial lag model (Table 8 Column 1) with respect to various spatial weighting matrices. We can observe from Table 9 that all of the

coefficients have expected signs and are highly significant at the 1% confidence level. In terms of likelihood, those models exhibit slightly lower performances than the models based on simple binary contiguity matrix (Table 8). In table 9, the magnitude of spatial lagged dependent variable ρ ranges from 0.05 to 0.16 with respect to different cut-off points. This finding is fairly in line with our previous results.

Table 10: ML estimates with time specific and cross-section fixed effects

	Distance band (0,5)	Distance band (0,6)	Distance band (0,7)	Distance band (0,8)	Distance band (0,9)	Distance band (0,10)
FDI	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(-1.094)	(-1.319)	(-1.315)	(-1.407)	(-1.407)	(-1.429)
Education	0.473	0.450	0.442	0.433	0.420	0.413
	(32.534)***	(31.482)***	(30.753)***	(30.439)***	(29.811)***	(29.477)***
Trade	0.008	0.008	0.007	0.007	0.007	0.007
	(2.993)***	(2.975)***	(2.922)***	(2.858)***	(2.841)***	(2.752)***
KL	0.029	0.031	0.032	0.030	0.029	0.029
	(4.958)***	(5.353)***	(5.483)***	(5.305)***	(5.218)***	(5.172)***
Infra	0.200	0.193	0.195	0.192	0.192	0.188
	(6.691)***	(6.589)***	(6.707)***	(6.651)***	(6.718)***	(6.634)***
Spatially	0.048	0.090	0.102	0.122	0.144	0.159
Lagged LP	(4.139)***	(7.420)***	(8.166)***	(9.545)***	(11.075)***	(12.201)***
Spatially	0.020	0.020	0.019	0.019	0.019	0.018
Lagged FDI	(8.686)***	(8.584)***	(8.459)***	(8.470)***	(8.470)***	(8.248)***
Spatially						
Lagged XM	-	-	-	-	-	-
Adjusted R^2	0.966	0.968	0.968	0.969	0.969	0.970
Log Likelihood						
	313	296	286	270	244	222
Number of observations	840	840	840	840	840	840

Notes: The numbers in parentheses are asymptot *t*-statistics. (*), (**), (***) denote respectively significance at the 10%, 5% and 1% levels. All of the inverse distance matrices are computed by using Anselin's SpaceStat 1.91 version software package (2001). In the distance matrixes weights are defined as $w_{i,j} = 1/d_{i,j}$ $i \neq j$. The distance band of 0-600 km is denoted by d= (0,6] and so on.

In order to test the robustness of our puzzling finding on inter-regional FDI spillovers (Table 8 Column 2), Table 10 introduces a spatially lagged *FDI* variable with respect to various specifications of distance weighting matrix. Consequently, one can observe that sensitivity analysis displayed above also confirms the finding that in China, the benefits of inward FDI are confined to an inter-regional level. In sum, on the outcome of various specifications of W, the overall picture we obtain by various cut-off points is quite similar to those based on simple

contiguity matrix. That is to say, our results are not really sensitive to various specifications of spatial weight matrix[23].

5.4. Time Breakdown

China's integration to the world economy has been a gradual and spatially uneven process. In order to capture different productivity patterns over time, we split our sample into two sub-periods: 1979-1991 and 1992-2006. We, therefore, estimate Equation 5 for each sub-period separately.

Table 11 shows the estimation results for the period 1979-1991. The first stage of China's integration to the world economy is above all characterised by special regimes and large disparities in opening up paces between Chinese regions.

Table 11: ML estimates with time specific and cross-section fixed effects 1979-1991

Dependent Variable: LP	(1)	(2)	(3)	(4)
FDI	0.004	-0.000	-0.005	-0.000
	(3.688)***	(-0.916)	(0.877)	(-0.371)
Education	0.312	0.197	0.176	0.136
	(8.610)***	(5.342)***	(4.744)***	(3.941)***
Trade	-0.000	0.001	-0.003	-0.001
	(-0.001)	(-0.972)	(-0.087)*	(-0.917)
KL	0.016	0.011	0.014	0.012
	(3.784)***	(2.849)***	(3.585)***	(3.331)***
Infrastructure	0.696	0.488	0.421	0.345
	(8.459)***	(5.904)***	(5.119)***	(4.401)***
Spatially Lagged LP	0.228 (6.176)***	0.201 (7.661)***	0.201 (5.782)***	0.203 (6.055)***
Spatially Lagged FDI	-	0.014 (7.661)***	0.009 (4.524)***	0.006 (3.103)***
Spatially Lagged Trade	-	-	1.018 (4.288)***	0.016 (3.838)***
LP serially lagged (one year)		-	-	1.171 (6.669)***
Adjusted R^2	0.983	0.983	0.984	0.985
Log Likelihood	340	340	348	361
Number of observations	390	390	390	390

[23] We also tested the robustness of the models with spatially lagged *trade* variable and the auto-regressive form. We eventually obtained similar results to those in Table 8. In order to save space those results are not reported here but they are available from the author upon request.

Notes: The numbers in parentheses are asymptot *t*-statistics. (*), (**), (***) denote respectively significance at the 10%, 5% and 1% levels. Spatially weighting matrix used is a binary contiguity matrix computed by MATLAB program spatial econometrics toolbox of Lesage (www.spatial-econometrics.com).

From Table 11 we can observe that over the sub-period of 1979-1991 labour productivity in China had been mainly determined by human capital and infrastructure development. In addition, capital deepening had also exerted a positive but relatively low effect on productivity performances. For the first period of China's opening-up, *FDI* variable is significant at the 1 percent level and positive although its magnitude remains very low. However, for this period, we are not able to detect any significant effect of foreign trade on productivity performances.

We observe that the associated coefficients to the spatial autocorrelation variable ρ have a positive sign and are always significant at the 1 percent confidence level. In Table 11, the value of ρ lies around 0.2 which is two times higher than our previous estimations for the whole period of 1979-2006. Accordingly, one can presume that regional labour productivity interactions were stronger during the first stage of China's opening up process.

In addition, Column 2 and Column 3 show that the associated coefficients to spatially lagged *FDI* and *trade* variables are positive and significant at the 1 percent level. In line with our previous outcomes, this confirms that over the period 1979-1991 opening up spillovers in China turn to be of inter-regional nature.

Table 12: ML estimates with time specific and cross-section fixed effects 1992-2006

Dependent Variable: LP	(1)	(2)	(5)	(6)
FDI	-0.006	-0.007	-0.007	-0.008
	(-1.126)	(-1.055)	(-0.999)	(-1.989)**
Education	0.205	0.208	0.210	0.059
	(11.243)***	(11.179)***	(10.730)***	(4.555)***
Trade	0.111	0.111	0.119	0.037
	(10.723)***	(9.441)***	(7.348)***	(3.723)***
KL	0.229	0.230	0.231	0.100
	(9.914)***	(9.868)***	(9.891)***	(6.781)***
Infrastructure	-0.029	0.028	-0.027	-0.065
	(-1.427)	(-1.402)	(-1.334)***	(-5.228)***
Spatially	0.175	0.169	0.175	0.096
Lagged LP	(11.896)***	(11.464)***	(11.884)***	(11.042)***
Spatially		0.001	0.005	0.006
Lagged FDI	-	(0.178)	(0.451)	(0.850)
Spatially		-	-0.017	-0.005
Lagged	-		(-0.740)	(-3.799)***
Trade				
LP serially		-	-	0.761
lagged (one				(29.885)***

year)				
Adjusted R^2	0.988	0.988	0.988	0.995
Log Likelihood	305	313	304	567
Number of observations	450	450	450	450

Notes: The numbers in parentheses are asymptot *t*-statistics. (*), (**), (***) denote respectively significance at the 10%, 5% and 1% levels. Spatially weighting matrix used is a binary contiguity matrix computed by MATLAB program spatial econometrics toolbox of Lesage (www.spatial-econometrics.com).

The second stage of China's integration to the world is especially marked by nation wide opening-up policies aiming at reducing disparities between regions. Table 12 reveals that over the period 1992-2006 human capital, capital deepening and international trade had been the main determinants of labour productivity in China. In addition, Table 12 illustrates that the coefficients associated with *capital intensity* variable are strongly higher than our previous results. This finding outlines the fact that during the second stage of China, capital deepening has been the main determinant of productivity gains in China. Furthermore, we can observe from Table 12 that *FDI* and *infrastructure* variables are not significant in none of the equations. In addition Columns 2 and 3 give no evidence on the existence of inter-regional FDI and trade spillovers.

In Table 12, spatial autocorrelation variable ρ appear with a positive sign and is always significant at the 1 percent confidence level. However the associated coefficients to ρ exhibit lower values than those of the sub-period 1979-1991. That is to say, the second era of China's opening up had been marked by lower inter-regional dynamics than the first era.

VI. Conclusion

In this study, we focus on a panel of Chinese provinces and investigate the influence of several key economic and policy factors on labour productivity. We attempt to draw a clearer picture of regional productivity spillovers and agglomeration effects by introducing spatial effects in the model. Our empirical outcomes show that, consistent with empirical framework, human capital, infrastructure development and capital intensity determine positively labour productivity in a given region. In addition, FDI and trade also exert a positive impact on productivity performances.

Our results show that the geographical environment has a subsequent influence on labour productivity of a given region. The more a region is surrounded by high productivity regions, the more its efficiency is expected to be high. Our results show that productivity interactions between Chinese regions have been stronger during the first stage of China's opening-up (1979-1991).

According to our empirical results, in China, FDI spillovers turn to be particularly of inter-regional nature. This finding has serious policy implications: Policies that solely consist of attracting FDI are not sufficient enough to improve productivity in the host region. Thereby, in

order to reap more benefits from foreign presence, industrial policies should particularly focus on reinforcing complementarities across regions.

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