

Regional Assessment of FDI and International Trade Spillovers in China from 1979 to 2006: A space-time model

Selin Ozyurt¹

Department of Economics, University of Paris-Dauphine

First draft; no citation please

Abstract. This study empirically 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 and foreign trade and other traditional variables such as capital intensity, infrastructure development, human capital and average wages. 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, (whether 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 allows us to draw reliable statistical inferences and coefficients.

Our preliminary results give strong evidence of positive spatial autocorrelation in labour productivity between Chinese provinces. 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, FDI and trade exhibit a positive spatial pattern and give rise to interregional productivity spillovers among Chinese provinces. These findings are robust to a number of alternative spatial weighting matrix specifications.

Key words: FDI, China, spatial autocorrelation, labour productivity.

JEL classification: O11, O18, P27.

¹ EURISCO, University of Paris-Dauphine; LAMETA, University of Montpellier 1. E-mail address: ozyurt@lameta.univ-montpl.fr

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 started to attract increasing amounts of foreign capital and its foreign trade recorded a rapid expansion. Thereby, since the last decade, China became the second largest recipient of foreign direct investment (FDI) 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 into the world's 3rd largest trading country 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, recent empirical literature generates mixed evidence on the existence of positive spillovers from FDI and foreign trade in developing countries (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, namely to its 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. In addition, opening up pace and economic performances show important disparities among regions. In spite of this, previous research 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 lead to dubious measures of parameter estimates and statistical inferences (Abreu and al., 2005).

Taking into account spatial dimension provides additional information on regional dynamics and spillovers. Since the last few decades, the explicit consideration of spatial dependence² 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 spatial econometrics has been recently extended to various research fields. For instance, studies on geographical targeting of foreign direct investment have started to on spatial data analysis. To name only a few, Coughlin and Segev (2000) and Blonigen and al. (2004) all conduct a 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 analysis. Madariaga and Poncet (2007) utilise appropriate spatial explanatory data analysis tools to explore 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 growth spillovers in the world. Ying (2003) conduct an analysis on Chinese output growth and reveal that previous studies that ignore spatial dependence suffer from serious misspecification.

Up to now, certainly due to software limitation, existing empirical studies are in particular confined to cross-sectional analysis. In the sprouting spatial panel data literature, Madariga and Poncet (2007) constitutes undoubtedly 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. In this study, a balanced spatial panel data set is used to analyse labour productivity performances in Chinese provinces. The theoretical model we use is mainly linked to the “endogenous growth” framework (Lucas, 1988; Grossman and Helpman, 1991) and “economic geography” (Krugman and Venables, 1995). The objectives of the study are threefold: First, to examine the main determinants of regional labour productivity performances in Chinese provinces. The second objective is to explore diffusion of technology across space through spatial econometrics tools and to address specification problems arising from spatial effects. The third objective is to inquire into the interregional productivity spillovers arising from FDI and foreign trade.

The remainder of the paper proceeds as follows. The second section provides a brief overview of main features of Chinese opening up and the literature on the relationship between openness and spillovers. Section 3 discusses the underlying data and presents the empirical model. Section 4 introduces a methodological discussion on explanatory spatial data analysis. The empirical results are presented and interpreted in Section 5.

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

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

A) Main characteristics of China's opening up to the world

China started receiving foreign capital in 1979 along with the implementation of economic reform policies. China has followed a gradualist development path of inward FDI: During the early stage of the economic reform, inward FDI amounts remained fairly low and the opening up policies were only confined to a few selected regions. Then, in the early 80's, FDI in China was highly concentrated in the southern provinces of Guangdong and Fujian, where four Special Economic Zones (SEZ) has been established³ to offer preferential treatments to foreign investors. In 1984, the SEZ had been extended to further 14 coastal cities⁴ 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
InnerMong	0	0	13	9397	8624	0
*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
Chongqing	0	500	332	33607	19941	48942
Sichuan	0	0	1029	25038	35657	0
Guizhou	0	173	468	5054	2041	6599
Yunnan	0	183	260	19938	10455	21236
Shaanxi	0	1609	4191	28717	23537	0
Gansu	234	346	472	5664	5088	2077
Qinghai	0	0	0	6129	8993	19338
Ningxia	0	29	103	2840	1421	0
Xinjiang	0	184	713	5918	1559	7289

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

³ Shenzhen, Zhuhai, Shantou in Guangdong province and Xiamen in Fujian province.

⁴ Dalian, Qinhuangdao, Tianjin, Yantai, Qingdao, Lianyungang, Nantong, Shanghai, Ningbo, Wenzhou, Fuzhou, Guangzhou, Zhanjiang and Baihai.

In 1992, the historic tour of 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 (Lemoine, 2000). 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, FDI flows to China had slowed down owing to the Asian Financial crises but they picked up their rapid growing trend since the last few years (Table 1).

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 products 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 country (Table 2). China's accession to the WTO on 1st January 2001 had also reduced trade distortions and started a new era in its integration into the world economy.

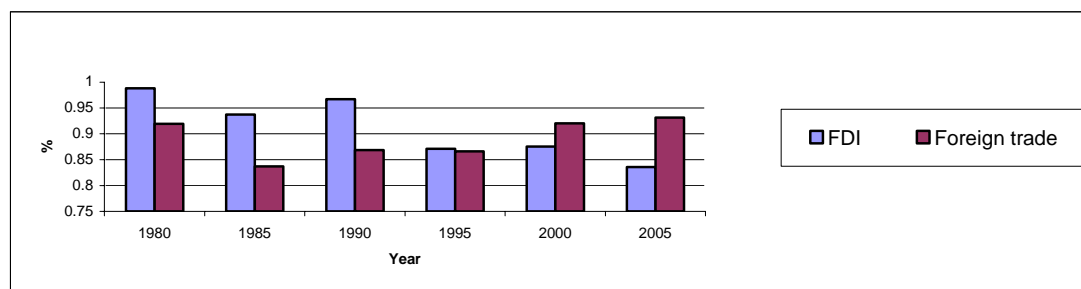
Table 2: World's top 10 exporter and importer countries in 2006.

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 economic disparities among Chinese regions. Aside from preferential policies, coastal regions in China enjoy various advantages such as geographical proximity to international markets, low information costs, better infrastructure development, superior access to sea-routes and relatively well educated human capital. Accordingly, today, despite increasing 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

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 follows the real estate sector, the share of service sector has also been increasing considerably during the last few years⁶. Sectorial distribution of inward FDI 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 oriented towards Chinese local market. Therefore, FDI decisions from those countries are mainly motivated by the large size of population (around 1.2 billion) and rapid economic growth (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 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, overseas inward FDI has considerably triggered the expansion of China’s foreign trade through processing trade. Labour-intensive processing activities of foreign affiliates still represent by far the most dynamic component of China’s foreign trade.

B) Theoretical framework on Openness and spillovers

Along with the rapid expansion of FDI flows and foreign trade throughout developing countries, the nexus between openness to the world and the host county’s economic development became a popular subject of interest. Spillovers from foreign trade and FDI have been debated extensively in the literature. A general belief on the positive effect of openness on developing countries has been progressively established among scholars and policy makers.

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. In addition, it has been generally asserted that, multinational companies (MNC) enjoy higher productivity rates than domestic counterparts owing to their technological advantage. Thereby, when MNCs invest in a foreign country, they transfer to the subsidiaries a “package” of capital, advanced technologies and managerial-organisational skills (Hymer,1960; Balasubramanyam and al. , 1996⁷). In this way, the “firm-specific assets” they hold enable them to compete with their local counterparts in foreign markets who benefit from a superior knowledge of consumer preferences

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.

and business practices on the local market (Blomström and Sjöholm, 1999). The advanced technologies brought by MNCs may later leak out to local firms through various channels outlined below:

Imitation-Demonstration and contagion effects: (Findlay, 1978; Caves, 1974). Foreign invested firms enjoy some technological advantages 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). Hence, in host countries, FDI could promote technological innovations through “learning by doing” and “learning by watching. In the literature, it is 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 between those who already have the knowledge of the innovation and those who eventually adopt it. 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 (Blömstrom and Persson, 1983; Kokko, 1996).

Labour turnover: In developing countries, MNCs carry most of R&D and training activities. Knowledge created in MNCs could later diffuse to local economy through labour turnover while skilled workers 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 licensing to local firms (Blomström et 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, local firms could benefit from the superior marketing knowledge and business experience of FMN on foreign markets. Secondly, MNCs’s export activities could also reduce information costs in foreign markets and establish adequate transport infrastructure for local counterparts. In addition, the competition on foreign markets and integration into the international production networks could bring about efficiency gains to local firms (Blomström et Kokko, 2001). Besides, importation of sophisticated equipments, machinery or products could give rise to technological upgrade through imitation and retro-engineering activities.

Despite little theoretical controversy on the subject, empirical studies generate rather conflicting evidence on the extent of spillovers from the openness of local economy. Some recent studies reveal negative impacts of FDI on host countries’ economic performances (Aitken and Harrison, 1999) for Venezuela; Haddad and Harrison (1993) for Morocco; and Aslanoglu (2000) for

Turkey. These studies mention that host economies could suffer from fierce competition following the entry of MNCs into the local-market. For instance, the presence of foreign firms could draw demand from local firms. Especially in large scale activities, MNC's could "crowd out" less competitive local firms (Kokko and al., 1996). Moreover, purchasing advanced technology from abroad, setting up joint-ventures or buying licences could 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 and 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 and 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 low absorption capabilities of host economy (Blomström and Sjöholm, 1999). Thereby, technology diffusion would be more efficient when the 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) found 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

a) Data

In this study we explore labour productivity in 30 Chinese provinces from 1979 through 2006. Tibet is excluded from the panel dataset because of data unavailability. The data 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.

b) Description of Main Variables

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

a. 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.

b. 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 effects⁸. **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 absorptive capabilities of the host region. Over the study period, data on the composition of employed persons by educational level are not available. Thereby, we use the share of the population studying at the institutions of higher education to measure human capital. **Average-wages** rate is used to proxy for labour quality. 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 railways⁹”. 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.

⁸ The amount of FDI to a province is 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, heterogeneity across regions due to scale effects is captured by 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.

Table 3: Descriptive statistics

Variable	Labour Productivity	One-year-lagged FDI	Trade	Education	Wages	Capital Intensity	Infrastructure	FDI per habitant* Infrastructure
Mean	-1.66	-1.63	3.93	-5.21	7.23	-0.57	1.24	0.20
Median	-1.69	0.65	4.53	-5.43	7.027	-0.51	1.36	2.21
Maximum	0.71	5.15	10.65	-2.56	9.28	2.15	3.18	7,90
Minimum	-5.04	-13.82	-13.82	-6.88	6.32	-13.82	-1.47	-15.29
Std. Deviation	0.94	6.05	3.70	0.90	0.64	1.48	0.78	5.74

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	+

c) 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:

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

In Equation 1 the index i denotes cross-sectional dimension while the index t indicates time dimension. The disturbance term is composed as follows: 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.i.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).

Pioneering work of Moran (1948), Hordijk 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 socio economic 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 time-space 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 mainly confined to theoretical framework. Developing alternative approaches for panel data is a subject for ongoing research. Software limitations still stand against the explicit introduction of spatial heterogeneity and dependence into panel data models (Anselin and LeGallo, 2008).

a) *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 heterogeneity¹⁰. Living out these two issues could lead to serious misspecification (Abreu and al. 2005).

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 applied econometrics, spatial autocorrelation could be viewed as analogous to serial correlation in time series models. In this way, 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, 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,

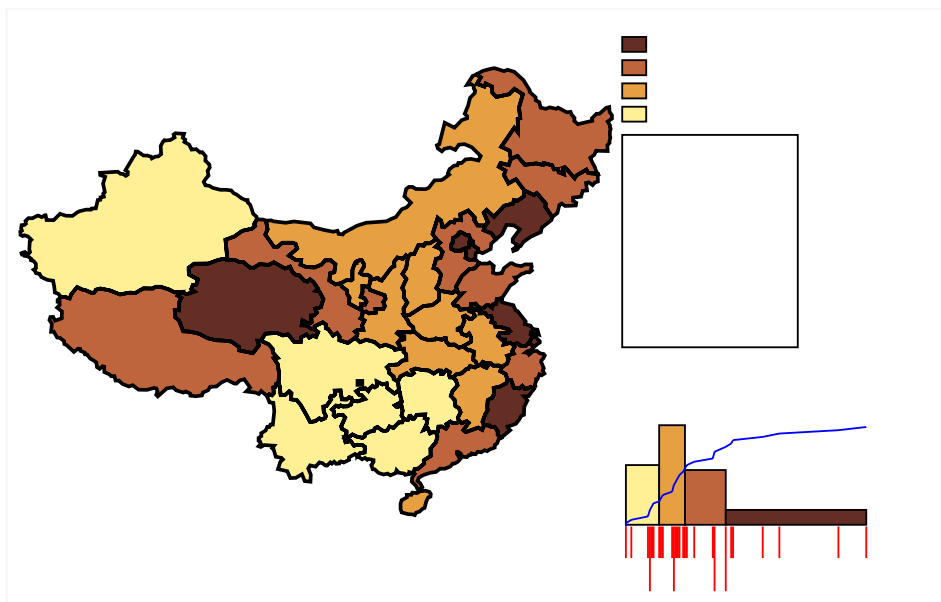
¹⁰ Going into an excessive discussion on spatial econometrics methods is behind the scope of this paper. For a complete discussion on spatial regression models see Anselin (1988), Anselin and Bera (1998), Baumont and al. (2000).

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).

spatial dependence could stem from 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 received. It is obvious from Figures 2 and 3 that in China, the distribution of labour productivity, FDI and trade among provinces exhibit a clear positive spatial dependence in 1995 and 2005. We can clearly observe from the maps that regions with high or low FDI, trade and labour productivity values are strongly clustered.

Figure 2: Spatial dispersion of labour productivity in China: 1985,2005.



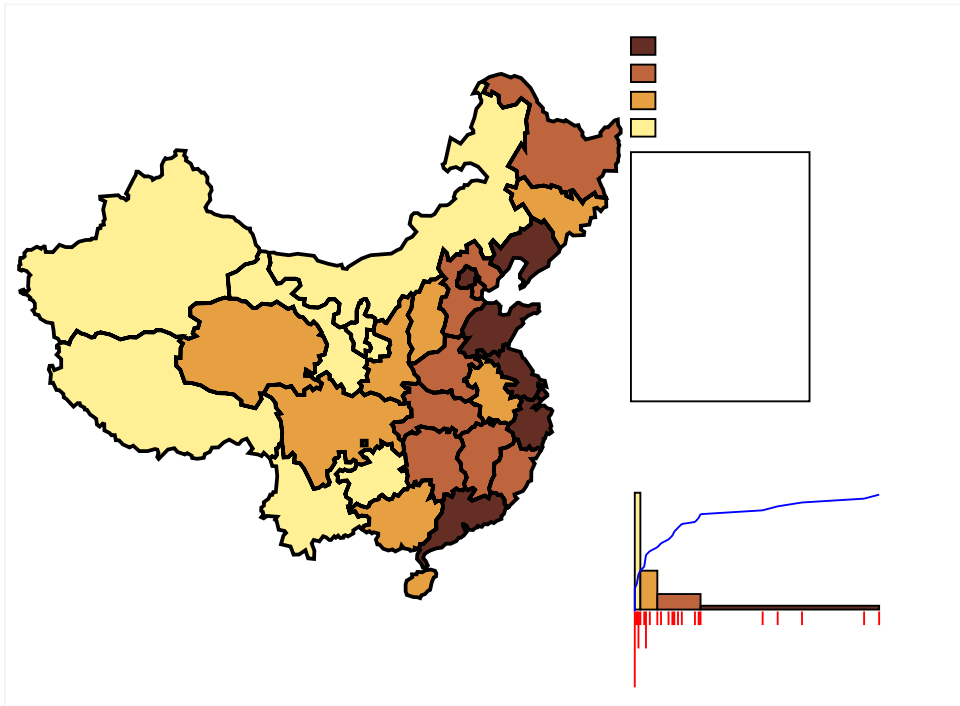
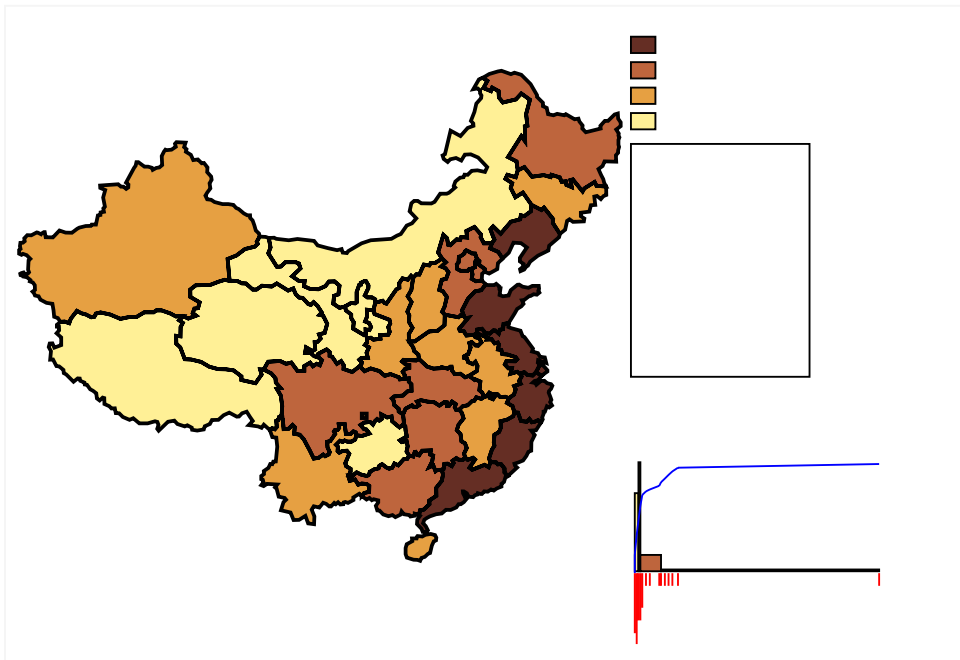
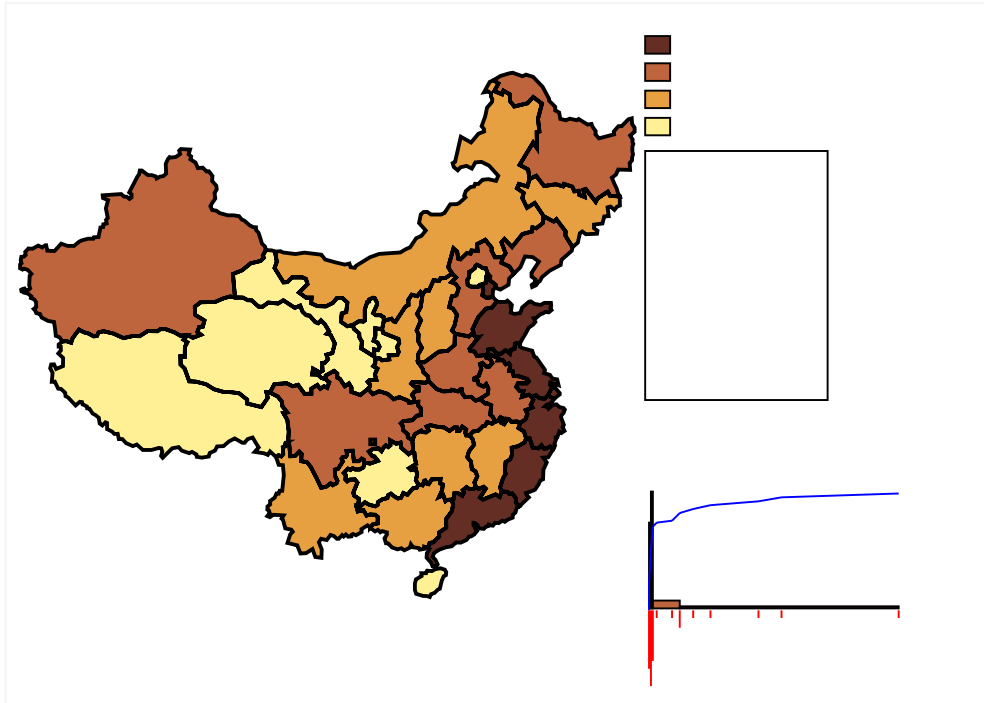


Figure 4 : Regional distribution of FDI in China: 1985, 2005.





Spatial Heterogeneity

The second issue introduced by the use of geographical data is spatial heterogeneity in the econometric relationship. Spatial heterogeneity corresponds 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 appropriately model this variation and draw reliable inferences. In the literature, spatial variability in the regression coefficients is modelised in various ways such as 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, spatial heterogeneity issue is tackled by means of standard spatial panel methods, namely through a fixed effect model where time invariant cross-sectional and time period dummy variables capture unobserved heterogeneity.

b) 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).

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 contiguity¹² (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 $w_{ij}=0$ if they do not.

Distance based contiguity: In distance based contiguity matrices, spatial weights attributed to observations depend on geographical distance d_{ij} between locations i and j . Distance matrices differ in functional form used, such as simple distance function [$w_{ij} = d_{ij}$], inverse function of distance [$w_{ij} = 1/d_{ij}$], squared inverse distance [$w_{ij} = 1/d_{ij}^2$] and negative exponential function [$w_{ij} = \exp(-\theta d_{ij})$] etc. In distance decay functions, the strength of 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 criteria such as 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 $w_{ij} / \sum_j w_{ij}$. In this way, the elements of each row sum to unity¹³ and each weight w_{ij} ¹⁴ corresponds to 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.

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 literature to construct weighting matrices (Conley and Ligon, 2002). However, this could imply serious identification problems since the weights are not exogenous to the model (Manski, 1993).

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 than *vice-versa*.

¹⁴ We extend the use of weights for cross-sectional dimension to panel data by assuming that weights are time-invariant, so in our sample, $w_{ij,1979} = w_{ij,1980} = \dots = w_{ij,2006}$. 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).

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

Table 5: Characteristics of distance 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

c) *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), 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-stationary¹⁵. Spatial diagnostic tests are conducted under the null hypothesis of lack of model misspecification 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 displays the results of Moran's I and Geary's c statistics and related p-values¹⁶ for labour productivity, FDI and trade¹⁷. We can observe from table 6 that Moran's I and Geary's c statistics

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 : $i \neq j$

$$I_y = \frac{N}{S_0} \frac{\sum_{i=1}^N \sum_{j=1}^N w_{ij}^{(y)} z_i z_j}{\sum_{i=1}^N z_i^2}, \quad \forall \text{ all } t=1,2,\dots,T \quad \text{Where, } n \text{ is number of regions, } z_i \text{ and } z_i \text{ are normalised vectors of}$$

observed values of the variable at locations i and j , w_{ij} is the element of spatially weighting matrix $W(N \times N)$ 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

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 exhibit strikingly increasing positive spatial dependence since 1990.

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

Variable	Moran's I statistic	Moran's I p-values	Grey's c statistic	Grey'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.

d) 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 LeGallo 2008, Anselin 2006).

random variable tends to cluster in space. $I < 0$ with $(p < 0.05)$ reveals dissimilar values of proximate regions. The expected value of Grey's c is 1. So, $c = 0$ indicates absence of spatial dependence between observations, $c < 1$ with $(p < 0.05)$ 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 spatial correlation. The results are not reported due to lack of space but available upon request from the author.

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 operators¹⁸ imply a shift over space and they are analogous to the back shift operator in the first order autoregressive time series models. In this way, spatial autocorrelation could be eliminated by applying a spatial autoregressive filter. Spatial lag model could be expressed as follows:

$$y = \rho Wy + X\beta + \varepsilon \quad (\text{II})$$

Using traditional notation, y is a $(N \times 1)$ vector of observations of dependent variable, X , a $(N \times K)$ matrix of K exogenous variables, β , a $(K \times 1)$ vector of explanatory variable coefficients and ε , a $(N \times 1)$ vector of stochastic disturbance terms. W corresponds to a $(N \times N)$ spatial weighting matrix which identifies the geographic relationship among spatial units. ρ refers to spatial autoregressive parameter that captures spatial interactions between observation. 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 estimating a reduced form of the model by means of maximum likelihood (ML) estimator, by instrumenting the spatial lag or else, by generalised method of moments (GMM) estimator as suggested by Kelejian and Prucha (1999).

In spatial lag models, additional informational derived from explicit consideration of spatial effect improves the explanatory power of the model in several respects. On one hand, adding a spatially lagged variable to the model enables to asses the pattern and the extent of spatial effect. On the other hand, controlling for spatial dependence allows to isolate the significance of other explanatory variables (Anselin, 1996).

Spatial Error Model

In spatial error model, spatial autoregressive process is confined to the error term. So, it is considered that spatial dependence works through omitted variables (Baumont and al., 2000) and spatial autocorrelation affects the covariance structure of disturbances. Spatial error models can be represented in the following form:

$$y = X\beta + \varepsilon \quad (3)$$

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

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

Where ε , a (N×1) 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. In other words, it measures the extent a random shock to neighbouring provinces affect a given province through inverse spatial transformation (Equation 4)

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 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 the endogenous variable which would otherwise be captured by the traditional error term. Those three spatial structures can also be combined in order to obtain higher order spatial models (Anselin, LeGallo, 2008). In this study we extend usual spatial specifications to panel data.

V. MODEL ESTIMATION and RESULTS

a) 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. Furthermore, the introduction of spatially lagged control variables implies that they can also exert an influence on labour productivity in the reference region due to spatial interactions. The spatial model we estimate takes the following form:

$$\ln LP_{i,t} = \alpha_0 \ln LP_{i,t-T} + \alpha_1 \ln WLP_{i,t} + \alpha_2 \ln WFDI_{i,t-1} + \alpha_3 \ln WTrade_{i,t} + \alpha_4 \ln FDI_{i,t-1} + \alpha_5 \ln Trade_{i,t} + \alpha_6 \ln Edu_{i,t} + \alpha_7 \ln K/L_{i,t} + \alpha_8 \ln Infra_{i,t} + \eta_i + \gamma_t + \varepsilon_{i,t} \quad (5)$$

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. A spatially lagged variable for province i in year t ($WLP_{i,t}$) corresponds to the row-sums of spatially weighted values of variable of interest in year t in surrounding provinces.

b) Results

The OLS and ML estimations of Equation V are presented respectively in Tables 7 and 8. The OLS results are only reported as a baseline, given that in the presence of spatial dependence, the OLS estimator no longer achieves consistency.

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

Dependent Variable: LP	(1)	(2)	(3)	(4)
Constant	-3.969 (0.000)	-3.087 (0.000)	-3.086 (0.000)	-3.048 (0.000)
FDI	-0.0047 (0.008)	-0.004 (0.018)	-0.004 (0.017)	-0.004 (0.013)
Edu	0.391 (0.000)	0.381 (0.000)	0.382 (0.000)	0.384 (0.000)
Trade	-0.001 (0.403)	-0.002 (0.165)	-0.002 (0.172)	-0.002 (0.161)
KL	0.020 (0.000)	0.021 (0.000)	0.021 (0.000)	0.022 (0.000)
FDI*Infra	-0.003 (0.086)	-0.0029 (0.104)	-0.002 (0.107)	-0.002 (0.116)
Wages	0.601 (0.000)	0.529 (0.000)	0.529 (0.000)	0.527 (0.000)
Spatially Lagged LP	-	0.234 (0.000)	0.231 (0.000)	0.226 (0.000)
Spatially Lagged FDI	-	-	-0.001 (0.470)	0,001 (0.558)
Spatially Lagged Trade	-	-	-	-0.004 (0.053)
Adjusted R ²	0,98	0,98	0,98	0,98
Log Likelihood	743	753	753	755
AIC	-1,62	-1,64	-1,64	-1,64
Log Ratio Test		20.330 (0.000)	20.896 (0.000)	24.370 (0.000)

Notes: p -probabilities in parentheses. Spatially weighting matrix we use is a binary contiguity matrix computed by MATLAB program spatial econometrics toolbox of Lesage (www.spatial-econometrics.com).

We can observe from Table 7 that, as expected, spatial autocorrelation variable ρ has a positive sign and it is always significant at the 1 percent confidence level. This outcome indicates that in China, labour productivity spills over province borders. Besides, the LR tests¹⁹ display that incorporating spatially lagged variables improves the overall explanatory power of the model. Table 7 show that FDI has a very low but negatively significant effect on labour productivity. In

¹⁹ 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).

addition, in the OLS estimates, human capital turns to be significant but unexpectedly with a negative sign. Furthermore, other variables such as trade and infrastructure²⁰ show a lack of significance. Due to spatial autocorrelation, we strongly suspect the OLS results to be fallacious.

From the ML²¹ estimations (Table 8) we can observe that the coefficients associated with spatially dependent labour productivity are positive and significant at the 1% level. This confirms the positive pattern of spatial clustering for labour productivity among Chinese regions. The value of ρ lies around 4.5. Thereby, the elasticity estimates suggest that a 1 percent increase in average productivity in surrounding regions lead to a 4.5 percent increase in labour productivity of reference region.

Table 8: ML estimates with time specific and cross-section fixed effects

Dependent Variable: LP	(1)	(2)	(3)	(4)
FDI	0.003 (0.039)	-0.004 (0.036)	-0.004 (0.011)	-0.003 (0.011)
Education	0.077 (0.000)	0.091 (0.000)	0.086 (0.000)	0.036 (0.006)
Trade	0.009 (0.000)	0.005 (0.011)	0.003 (0.11)	0.004 (0.001)
KL	0.031 (0.000)	0.023 (0.000)	0.028 (0.000)	0.017 (0.000)
FDI*Infra	0.003 (0.041)	-0.000 (0.670)	-0.001 (0.552)	0.001 (0.476)
Wages	0.611 (0.000)	0.596 (0.000)	0.554 (0.000)	0.304 (0.000)
Spatially Lagged LP	0.047 (0.000)	0.045 (0.000)	0.040 (0.000)	0.043 (0.000)
Spatially Lagged FDI	-	0.016 (0.000)	0.006 (0.002)	0.000 (0.647)
Spatially Lagged Trade	-	-	0.035 (0.000)	0.019 (0.000)
LP serially lagged (one year)	-	-	-	0.466 (0.000)
Adjusted R ²	0,98	0,98	0,98	0,99
Log Likelihood	534	574	601	614

Notes: z-probabilities in parentheses. Spatially weighting matrix used is a binary contiguity matrix computed by MATLAB using spatial econometrics toolbox of Lesage (www.spatial-econometrics.com).

²⁰ We only report the interaction term between FDI per capita and combined length of highways and railways. We also run the regressions with alternative infrastructure measures but they all turned to be insignificant.

²¹ Maximum Likelihood Estimation (MLE) consists of applying a non-linear optimisation to a log-linear function. It should be heard 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).

Column 1 displays that all of the explanatory variables exhibit a significant effect on the dependent variable at the 5 percent level with expected signs. Consistent with the theory, one can observe that the traditional variables such as labour quality, human capital and capital intensity exert the greatest impact on labour productivity. In addition, the results reveal positive impacts of FDI and trade on labour productivity, although the magnitudes remain low. It is striking that, in terms of magnitude, trade has a greater impact (about three times) on labour productivity than FDI. It should be outlined that, 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 belief that in China, openness leads to productivity gains in host regions.

In Column 2 we introduce spatially lagged FDI variable in order to capture possible spatial spillovers associated. Surprisingly, after including spatially lagged FDI, FDI variable itself turns to negative however significant at the 5 percent level. 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 hint at a complementarity pattern (instead of crowding-out) among Chinese regions regarding FDI.

After including spatial effects, the negative sign of FDI is fairly deceptive but not inconsistent with previous literature. Accordingly, productivity spillovers arising from FDI are only of inter-regional nature. In other words, Chinese regions do not take advantage from their own inward FDI but from those going to surrounding regions. This finding remains quite puzzling to us and motivates our sensitivity analysis with respect to various distance weighting matrixes.

Column 3 introduces spatially lagged trade. We observe that the associated coefficient is positive and highly significant. Whereas, after including spatially lagged trade, trade variable itself loses its significance. This outcome points out that in China, inter-regional trade spillovers prevail over intra-regional trade spillovers. Besides, column 4 reveals that while we introduce one-year serially lagged dependent variable, spatially lagged FDI loses its significance. This could certainly stem from some collinearity problems.

Regional Breakdown: Coastal and Inland

China is a country characterised by heterogeneous economic space and differentiated pattern of regional development (Ying, 1999). In order to capture regional differences in labour productivity patterns we split our sample into two sub-groups based on geographical position: Coastal and inland regions; we estimate Equation 4 for each of the two sub-samples. The results are presented in Table 9.

The first three columns of Table 9 reveal that in inland regions, labour productivity is mainly determined by capital intensity, labour quality and infrastructure development. However, FDI and trade do not appear to exert any significant impact on labour productivity. A positive and highly significant ρ (at the 1 percent level) give strong evidence on the existence of spatial dependence. Thereby, labour productivity of inland regions is strongly determined by the level of productivity in neighbouring regions.

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

Dependent Variable: LP	Inland			Coastal		
	(1)	(2)	(3)	(4)	(5)	(6)
FDI	0.002 (0.198)	-0.002 (0.317)	0.003 (0.126)	-0.002 (0.412)	-0.007 (0.006)	-0.002 (0.450)
Education	0.032 (0.268)	0.044 (0.11)	0.036 (0.202)	0.013 (0.570)	0.022 (0.317)	0.017 (0.446)
Trade	0.004 (0.088)	0.000 (0.762)	0.003 (0.129)	0.014 (0.000)	0.012 (0.000)	0.015 (0.000)
KL	0.029 (0.000)	0.025 (0.000)	0.029 (0.000)	0.289 (0.000)	0.254 (0.000)	0.276 (0.000)
FDI*Infra	0.004 (0.044)	0.000 (0.801)	0.002 (0.335)	-0.004 (0.082)	-0.006 (0.022)	-0.004 (0.131)
Wages	0.805 (0.000)	0.790 (0.000)	0.802 (0.000)	0.604 (0.000)	0.621 (0.000)	0.615 (0.000)
Spatially Lagged LP	0.038 (0.004)	0.035 (0.007)	0.039 (0.003)	0.056 (0.000)	0.056 (0.000)	0.053 (0.000)
Spatially Lagged FDI	-	0.012 (0.000)	0.002 (0.207)	-	0.010 (0.000)	0.003 (0.187)
Spatially Lagged XM	-	-	0.007 (0.326)	-	-	0.025 (0.002)
Adjusted R ²	0.984	0.985	0.984	0.981	0.982	0.981
Log Likelihood	363	376	366	254	263	260

Notes: z-probabilities in parentheses. Spatially weighting matrix used is a binary contiguity matrix computed by MATLAB using spatial econometrics toolbox of Lesage (www.spatial-econometrics.com).

In coastal regions (Columns 4-6) we observe that labour productivity is mainly determined by labour quality, capital deepening and trade. Unexpectedly, the results reveal a significant but negative influence of FDI on labour productivity in coastal regions. This outcome is quite puzzling and may stem from some negative competition effects of foreign presence. Besides, in coastal provinces, spatially lagged dependent variable show a higher magnitude than in inland regions. This finding indicates that productivity interactions are greater within coastal regions.

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 function have been constructed with the upper distance bands ranging from 600 to 1000 km. In addition, given the theoretical framework, it could be considered that a distance-based matrix is more appropriate for spillover and technology diffusion analysis (Abreu and al., 2005).

Table 10: ML estimates with time specific and cross-section fixed effects (1/2)

	Distance band (0,6]	Distance band (0,6]	Distance band (0,6]	Distance band (0,7]	Distance band (0,7]	Distance band (0,7]	Distance band (0,8]	Distance band (0,8]
FDI	0.003 (0.040)	-0.004 (0.032)	-0.004 (0.010)	0.003 (0.042)	-0.004 (0.032)	-0.004 (0.010)	0.003 (0.043)	-0.004 (0.032)
Education	0.077 (0.000)	0.093 (0.000)	0.088 (0.000)	0.076 (0.000)	0.092 (0.000)	0.087 (0.000)	0.076 (0.000)	0.092 (0.000)
Trade	0.010 (0.000)	0.005 (0.006)	0.003 (0.077)	0.010 (0.000)	0.005 (0.006)	0.003 (0.078)	0.010 (0.000)	0.005 (0.006)
KL	0.032 (0.000)	0.0247 (0.000)	0.029 (0.000)	0.033 (0.000)	0.024 (0.000)	0.029 (0.000)	0.032 (0.000)	0.024 (0.000)
FDI*Infra	0.004 (0.039)	-0.000 (0.678)	-0.001 (0.58)	0.003 (0.041)	-0.000 (0.676)	-0.001 (0.574)	0.003 (0.044)	0.003 (0.66)
Wages	0.630 (0.000)	0.616 (0.000)	0.571 (0.000)	0.628 (0.000)	0.615 (0.000)	0.573 (0.000)	0.623 (0.000)	0.613 (0.000)
Spatially Lagged LP	0.019 (0.039)	0.014 (0.105)	0.007 (0.375)	0.023 (0.016)	0.017 (0.059)	0.010 (0.233)	0.031 (0.001)	0.021 (0.025)
Spatially Lagged FDI	-	0.017 (0.000)	0.006 (0.002)	-	0.017 (0.000)	0.006 (0.002)	-	0.168 (0.000)
Spatially Lagged XM	-	-	0.035 (0.000)	-	-	0.035 (0.000)	-	-
Adjusted R ²	0.980	0.981	0.984	0.980	0.981	0.982	0.980	0.981
Log Likelihood	534	576	605	533	575	604	530	574

Notes: z-probabilities in parentheses. Weights are defined as $w_{ij} = 1/d_{ij} \forall i \neq j$. The distance band of 0-600 km is denoted by $d=(0,6]$ and so on. All of the inverse distance matrices are computed by using Anselin's SpaceStat – 1.91 version software package (2001).

Table 10: ML estimates with time specific and cross-section fixed effects (2/2)

	Distance band (0,8]	Distance band (0,9]	Distance band (0,9]	Distance band (0,9]	Distance band (0,10]	Distance band (0,10]	Distance band (0,10]
FDI	-0.004 (0.009)	0.003 (0.049)	-0.004 (0.030)	-0.004 (0.009)	0.003 (0.050)	-0.004 (0.031)	-0.004 (0.009)
Education	0.087 (0.000)	0.072 (0.000)	0.088 (0.000)	0.084 (0.000)	0.071 (0.050)	0.087 (0.000)	0.083 (0.000)
Trade	0.003 (0.080)	0.009 (0.000)	0.005 (0.007)	0.003 (0.083)	0.009 (0.000)	0.005 (0.007)	0.003 (0.089)
KL	0.029 (0.000)	0.032 (0.000)	0.024 (0.000)	0.029 (0.000)	0.032 (0.000)	0.024 (0.000)	0.029 (0.000)
FDI*Infra	-0.001 (0.563)	0.003 (0.053)	-0.000 (0.618)	-0.001 (0.531)	0.003 (0.057)	-0.000 (0.617)	-0.001 (0.517)
Wages	0.571 (0.000)	0.616 (0.000)	0.604 (0.000)	0.565 (0.000)	0.612 (0.000)	0.603 (0.000)	0.562 (0.000)

Spatially	0.014	0.047	0.039	0.027	0.054	0.041	0.033
Lagged LP	(0.011)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)
Spatially	0.006		-0.000	0.006		0.016	0.006
Lagged FDI	(0.002)	-	(0.618)	(0.002)	-	(0.000)	(0.002)
Spatially	0.035			0.035			0.035
Lagged XM	(0.000)	-	-	(0.000)	-	-	(0.000)
Adjusted R ²	0.983	0.980	0.981	0.984	0.980	0.981	0.983
Log							
Likelihood	604	522	567	601	517	566	598

Notes: z-probabilities in parentheses. Weights are defined as $w_{ij} = 1/d_{ij} \forall i \neq j$. The distance band of 0-600 km is denoted by $d = (0,6]$ and so on. All of the inverse distance matrixes are computed by using Anselin's SpaceStat – 1.91 version software package (2001).

In accordance with our previous results Table 10 shows that all of the coefficients have expected signs, and are highly significant (mostly at 1% confidence level). In terms of likelihood, those models have similar performances as those based on simple binary contiguity matrix (Table 8). In sum, from the Table 10 we observe that the estimates of Equation 4 are not really sensitive to various specifications of W . We still detect a significant but negative effect of FDI on labour productivity while we include spatially lagged FDI. This outcome supports that in China, the benefits of FDI are confined to inter-regional level.

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, labour quality, human capital and capital intensity determines 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. Besides, our results reveal that in China, trade and FDI spillovers are mainly of inter-regional nature. This finding has serious policy implications: Policies that solely consist of attracting FDI do not seem to be enough to improve productivity in China. Thereby, in order to reap more benefits from foreign presence, industrial policies should particularly focus on reinforcing complementarities across regions.

REFERENCES

- Abreu, M., H. L. F. De Groot and R. J. G. M. Florax (2005) Space and Growth: A Survey of Empirical Evidence and Methods. *Région et Développement* 21: 13–44.
- Abramovitz M. (1986) Catching Up, Forgoing Ahead, and Falling Behind. *Journal of Economic History* 46 (2): 385-406.
- Aitken B., Harrison A.(1999) Do Domestic Firms Benefit from Direct Foreign Investment Evidence from Venezuela? *American Economic Review* 89(3): 605-18.
- Anselin, L., (1988) *Spatial Econometrics: Methods and Models*, Kluwer Academic Publishers. Dordrecht et al. loc.
- Anselin, L. (1995) Local Indicators of Spatial Association: LISA. *Geographical Analysis* 27 (2): 93–115.
- Anselin, L. (2001) *Spatial Econometrics*. in B. Baltagi (ed.), *A Companion to Theoretical Econometrics* (Oxford: Basil Blackwell).
- Anselin L. (1996) *SpaceStat tutorial* :West Virginia University, Regional Research Institute, Morgan-town.
- Anselin, L. (2006) *Spatial econometrics*. In Mills, T. and Patterson, K., editors, *Palgrave Handbook of Econometrics: Volume 1, Econometric Theory*, pages 901–969. Palgrave Macmillan, Basingstoke.
- Anselin L., Bera A., (1998) *Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics*”, in *Handbook of Applied Economic*.
- Anselin, L. and Florax, R.J.G.M. (eds) (1995) *New Directions in Spatial Econometrics*, Springer, Berlin et al. loc.
- L. Anselin, J. Le Gallo and H. Jayet. (2008) *Spatial Panel Econometrics* In L. Matyas and P. Sevestre (Eds.), *The Econometrics of Panel Data, Fundamentals and Recent Developments in Theory and Practice* (3rd Edition). Dordrecht, Kluwer.
- Arrow K. J. (1971) *Essays in the Theory of Risk-Bearing*, Amsterdam: North-Holland.
- Aslanoglu E. (2000) Spillover Effect of Foreign Direct Investments on Turkish Manufacturing Industry, *Journal of International Development* 12: 1111-1130.
- Badinger, H., W. Müller and G. Tondl (2004) Regional Convergence in the European Union (1985–1999): A Spatial Dynamic Panel Analysis, *Regional Studies*, 38(3): 241–53.
- Baumont, C., C. Ertur and J. Le Gallo (2000) *Geographic Spillover and Growth: A Spatial*

Econometric Analysis for European Regions', LATEC – Document de travail (Economie 1333-07).

Baharumshah A. Z., Thanoon A.M. (2006) Foreign Capital Flows and Economic Growth in east Asian Countries, *China Economix Review* 17: 70-83.

Balasubramanyam V.N., Salisu M.A. (1991) Export Promotion, Import Substitution and Direct Foreign Investment in Less Developed Countries. in KOEKKOEK A. and MENNES L.B.M. (eds.), *International Trade and Global Development, Essays on Honor of Jagdish Bhagwati*, London, Routledge.

Blomström, M., Sjöholm, F (1999) Technology transfer and spillovers: Does local participation with multinationals matter? *European Economic Review* 43: 915-923.

Blomström, M., A. Kokko, and S. Globerman (2001) The Determinants of Host Country Spillovers from Foreign Direct Investment: A Review and Synthesis of the Literature', in N. Pain (ed.), *Inward Investment, Technological Change and Growth* (London: NIESR): 34–65.

Blomström M., Wang J.Y. (1992) Foreign Investment and Technology Transfer : A Simple Model. *European Economic Review* 36: 137-155.

Blomström M., Wolff E. N (1994) Multinational Corporations and Productive Convergence in Mexico. In Baumol, William J., Richard R. Nelson and Edward N. Wolff (eds.): *Convergence of Productivity: Cross National Studies and Historical Evidence*. Oxford: Oxford University Press: 263-283.

Blonigen, B A, Davies, R B., Waddell, Glen R. and Naughton, H (2004) FDI in Space: Spatial Autoregressive Relationships in Foreign Direct Investment. NBER Working Paper 10939

Borensztein E, Gregorio J., LEE J (1998) How Does Foreign Direct Investment Affect Economic Growth? *Journal of International Economics* 45: 115-135.

Buettner, T., 1999, "The effects of unemployment, aggregate wages, and spatial contiguity on local wages: An investigation with German district level data", *Paper in Regional Science* 78, 47 – 67

Casetti E., 1997, The expansion method, mathematical modeling, and spatial econometrics, *International Regional Science Review*, 20, 9-33.

Caves R. (1974) Multinational Firms, Competition and Productivity in Host Country Markets. *Economica* , n°41, p.176-93.

Cliff, A.D. and Ord, J.K (1973) *Spatial Autocorrelation*, Pion Press, London.

Cohen W. M., Levinthal D. A., (1989) Innovation and Learning The Two Faces of R&D. *Economic Journal* 99: 569-596.

Conley, Timothy G. and Ligon, Ethan (2002) Economic distance, spillovers and cross country comparisons. *Journal of Economic Growth*, 7:157–187.

Coughlin, C. C. and E. Segev (2000) Foreign Direct Investment in China: A Spatial Econometric Study. *The World Economy*, 23(1): 1–23.

Elhorst, J. Paul (2001) Dynamic models in space and time. *Geographical Analysis* 33:119–140.

Elhorst, J. Paul (2003) Specification and estimation of spatial panel data models. *International Regional Science Review* 26(3):244–268.

Findlay R. (1978) Relative Backwardness, Direct Foreign Investment, and the Transfer of Technology: A Simple Dynamic Model. *Quarterly Journal of Economics* 92: 1-16.

Fingleton, B. (1999) Estimates of Time to Economic Convergence: An Analysis of Regions of the European Union. *International Regional Science Review* 22(1): 5–34.

Florax R. et Rey S. (1995) The Impacts of Misspecified Spatial Interaction in Linear Regression Models. In Anselin L et Florax R. (eds.), *New Directions in Spatial Econometrics*, Springer: 111-135.

Fotheringham A.S., Charlton M., Brundson C. (1998) Geographically weighted regression : a natural evolution of the expansion method for spatial data analysis, *Environment and Planning A*, 30: 1905-1927.

Geary, R.C. (1954) The Contiguity Ratio and Statistical Mapping, *The Incorporated Statistician*, Vol.5: 115-145.

Goodchild, M. F (1986) *Spatial Autocorrelation*. CATMOG 47, Geo Books. Norwich.

Grossman G. M., Helpman E. (1991) Trade, Knowledge Spillovers, and Growth. *European Economic Review* 35(2-3): 517-526.

Haddad M., Harrison A. (1993) Are there Positive Spillovers from Direct Foreign Investment? Evidence from Panel Data for Morocco. *Journal of Development Economics* 42: 51-74.

Hordijk, L. and J. Paelinck (1976) Some principles and results in spatial econometrics. *Recherches Economiques de Louvain* 42: 175–97.

Hu A. Y., Tong S.Y. (2003) Do Domestic Firms Benefit from Foreign Direct Investment ? Initial Evidence from Chinese Manufacturing. *Conference on China's Economic Geography and Regional Development*.

Hymer S. H (1960) *The International Operations of National Firms : A Study od Direct Investment* . PdH Thesis , MIT : MIT Press.

Kelejian, H. and I. Prucha (1999) A generalized moments estimator for the autoregressive

parameter in a spatial model. *International Economic Review* 40(2): 509-533.

Keller, W and C. H. Shiue (2007) The origin of spatial interaction. *Journal of Econometrics* 140: 304-332.

Kokko A. (1992) Foreign Direct Investment, Host Country Characteristics and Spillovers », Ph.D Thesis, Stocholm Scool of Economics.

Kokko A. (1996) Productivity Spillovers from Competition between Local Firms and Foreign Affiliates. *Journal of International Development* Vol. 8: 517-530.

Kokko, A., Tansini, R. and Zejan, M. (1996) Local Technological Capabilities and Productivity Spillovers from FDI in the Uruguayan Manufacturing Sector. *Journal of Development Studies*, 32: 602-11.

Krugman, P. and A. J. Venables (1995) Globalization and the Inequality of Nations. *Quarterly Journal of Economics* 110(4): 857-880.

Lall, V. and S.Yilmaz (2001) Regional economic convergence: Do policy instruments make a difference ? *The Annals of Regional Science* (35), 153-166.

Le Gallo, J. (2000) Spatial Heterogeneity, Working Paper n° 2001-01.

Lemoine F. (2000) Main determinants and impacts of foreign direct investment on China's economy, OECD, working papers on international investment: 2000/4.

Liu Z. (2002) Foreign Direct Investment and Technology Spillover : Evidence from China. *Journal of Comparative Economics* 30: 579-602.

Lucas R. E. (1988) On the Mechanics of Economic Development. *Journal of Monetary Economics* 22(1): 3-42.

Madariaga, N. and S. Poncet (2007) FDI in Chinese Cities: Spillovers and Impact on Growth, *The World Economy*: 837-862.

Mansfield E., Romeo A. (1980) Technology Transfer to Overseas Subsidiaries by US-based Firms. *Quarterly Journal of Economics* 95(4): 737-750.

Manski, C. F. (1993). Identification of endogenous social effects: the reflection problem. *Review of Economic Studies* 60: 531-542.

Moran, P.A.P. (1948) The Interpretation of Statistical Maps. *Journal of the Royal Statistical Society B*, Vol. 10: 243-251.

OECD (2001) *Measuring Productivity: Measurement of Aggregate and Industry-Level Productivity Growth*. Paris: OECD Publications.

- Paelinck, J. and L. Klaassen (1979) *Spatial Econometrics*. Saxon House, Farnborough.
- Tobler W.R. (1970) "A Computer movie simulating urban growth in the Detroit Region", *Economic Geography* 46: 234-240.
- Ying LG (1999) China's changing regional disparities during the reform period. *Economic Geography* 75:59-70.
- Ying LG (2000) Measuring the spillover effects: Some Chinese evidence. *Papers in Regional Science* 79:75-89.
- Ying LG (1999) China's changing regional disparities during the reform period. *Economic Geography* 75: 59-70.
- Ying, L G (2003) Understanding China's recent growth experience: A spatial econometric perspective. *The Annals of Regional Science* 37(4): 613-628.
- XU B. (2000) Multinational Enterprises, Technology Diffusion and Host Country Productivity Growth. *Journal of Development Economics*. 62: 477-493.

