CENTRE D'ETUDES
ET DE RECHERCHES
SUR LE DEVELOPPEMENT
INTERNATIONAL

SERIE ETUDES ET DOCUMENTS DU CERDI

Foreign Direct Investment across China: what should we learn from spatial dependences?

Nasser Ary Tanimoune, Cécile Batisse and Mary-Françoise Renard

Etudes et Documents n° 12

Juin 2013

CERDI
65 BD. F. MITTERRAND
63000 CLERMONT FERRAND - FRANCE
TEL. 04 73 17 74 00
FAX 04 73 17 74 28
www.cerdi.org

The authors

Nasser ARY TANIMOUNE
School of International Development and Global Studies, University of Ottawa (Canada)

Cécile BATISSE
Associate Professor, Clermont Université, Université d'Auvergne, CNRS, UMR 6587, CERDI-IDREC, F-63009 Clermont Fd

Mary-Françoise RENARD
Professor, Clermont Université, Université d'Auvergne, CNRS, UMR 6587, CERDI-IDREC, F-63009 Clermont Fd

Corresponding author : cecile.batisse@udamail.fr

La série des *Etudes et Documents* du CERDI est consultable sur le site :

http://www.cerdi.org/ed

Directeur de la publication : Patrick Plane

Directeur de la rédaction : Catherine Araujo Bonjean

Responsable d'édition : Annie Cohade

ISSN : 2114 - 7957

Abstract

The paper investigates the importance of spatial dependences on Foreign Direct Investment (FDI) localization across Chinese provinces over the 1992-2009. Based on exploratory spatial data analysis, spatial sigma-convergence and spatial Durbin specifications, we present a much clearer picture of FDI dispersion and spatial convergence across China by highlighting the spillover effects of FDI localization in Chinese provinces and regions. Our results are threefold. First, FDI convergence is more pronounced compared to the Central region, whereas the dispersion is greater when the Coastal and the Western regions are taken as reference points. Second, at the province level, FDI localization seems to present a substitutable configuration. Third, when controlling for the spatial distribution of FDI at the level of regions, it seems, conversely, that the FDI localization presents a complementary configuration. The finding resulting from the opposing configurations of the FDI localizations observed at the region and province levels seems to argue in favor of promoting FDI attractiveness policies based on regional complementarities.

Mots clés / Key Words: FDI, Convergence, China, Spatial panel data, Spatial Durbin model

Codes JEL / JEL classification: C33, O53, R12

This paper has been presented at CES Conference in Changsha, in june 2012

Foreign Direct Investment across China: what should we learn from spatial dependences?

1 Introduction

The success of China's opening to the international economic community is widely acknowledged (Sumei et al., 2012). Foreign Direct Investment (FDI) in China has grown as it has collapsed in developed countries, making China the largest FDI host country in the world (Whalley and Xin, 2008). As a consequence, numerous studies have focused on FDI in China, as pointed out recently by Fetscherin et al. (2010). For instance, literature on FDI localization choice has addressed several themes, such as the effects of agglomeration (Chang and Park, 2005; Amiti and Javorcki, 2005), the host of FDI (Fung et al., 2003) and the role of institutions (Du et al., 2012). On the effects of FDI localization, FDI generates positive horizontal spillovers for firms that receive foreign investment in China, except in Hong Kong, Macao and Taiwan, according to Lin et al. (2009).

Du et al. (2011) find that the effects of FDI stock on risk sharing across the country (as well as in coastal and inland regions) has changed over time. For the country as a whole and in the inland provinces, FDI stock's effects on risk sharing were not significant from 1990 to 1999, whereas they were from 1998 to 2007. The uneven FDI distribution across Chinese provinces is cited among the reasons for the failure in risk sharing. Moreover, it has been shown that FDI concentration, taking part in investment and/or consumption within each province, influences economic growth in China (Mah, 2010). Consequently, the provinces' growth can be unbalanced, or inequality can be amplified across provinces (Zhang and Zhang, 2003, Ng and Tuan, 2006). Particularly, based on empirical evidence from 277 Chinese cities from 1996 to 2004, Ouyang and Fu (2012) find that FDI in China's coastal cities has had a positive effect on the economic growth of inland cities. In addition, other micro-level studies (Tong and Hu, 2003; Hu and Jefferson, 2001) on intra- and inter-industry productivity spillovers within regions in the Chinese manufacturing sector (Wei and Liu, 2006) have shown positive FDI spillovers. More recently, using firm-level census data for the Chinese manufacturing industry over 2000-2003, Xu and Sheng (2012b) find that the FDI spillovers seem to be positive within the same industry in the same region.

What most studies evaluating FDI spillovers have in common (even the recent ones) (Lin et al., 2009; Du et al., 2011; Ouyang and Fu, 2012; Su and Jefferson, 2012, Sumei et al., 2012) is that they do not include explicitly spatial disturbances in their empirical approaches. However, according to Blonigen et al. (2007) and Fetscherin et al. (2010), the FDI stock in one province is not independent of the FDI stock in its neighbors.[1] Nevertheless, a large number of empirical studies consider provinces as isolated units. In other words, the role of interactions across spatial units (regions or provinces) was for the most part neglected, even though it seems to be an important force in the process of convergence (Rey and Montouri, 1999). Moreover, endogenous growth theories and new economic geography models stress the role of interactions across spatial units and suggest that they are not independent (Ertur and Le Gallo, 2006). Spatial units are supposed to interact strongly with each other through channels such as trade, knowledge diffusion, capital inflows, and similar institutions and policies. In such cases, feedback effects can contribute to the explanation of growth and/or convergence between certain spatial units (Fingleton and Lopez-Bazo, 2006).

After all, focusing on the effects of spatial dependences on FDI localization has broad policy implications. For example, in cases of substantial spatial dependences between provinces, the best policy practice may be to not try systematically appealing for FDI. It could be more efficient to set up attractive policies that allow complementary development between these spatial units.

Different empirical methods allow one to account for spatial dependences. A large majority of such studies have either used a spatial lag model to include endogenous interaction effects or a spatial error model to consider unobserved spatial spillover effects. Kelejian and Prucha (1999) have discussed the estimation of a more general model including both a spatially lagged dependent variable and spatially lagged explanatory variables. Indeed, this type of specification, known as a spatial Durbin model, allows one to control for endogeneity, omitted variables, and spatial (endogenous and exogenous) interaction effects. Moreover, according to Elhorst (2010a), spatial Durbin model estimations produce unbiased coefficient estimates and do not impose restrictions on the magnitudes of potential spatial interaction effects, which can be either global or local and can be different for various explanatory variables.

We present a much clearer picture of FDI dispersion and spatial convergence across Chinese provinces by highlighting the spillover effects of FDI localization in China. To the best of our knowledge, this is the first study that systematically investigates the feedback and indirect spillover effects of FDI localization. We focus on China for several reasons. First, China provides the opportunity to explore the spatial distribution of FDI within a single country. Compared to cross-national studies, spatial study within the same country may have an advantage because legal systems (and other institutions) all change at the same pace. Second, in addition to the fact that China is the largest FDI host country in the world, FDI has been a crucial factor in the process of intense growth that has been enjoyed by the Chinese economy since the

[1] Such remarks are not limited to FDI analysis. Indeed, it is only recently that more interest has been shown in spatial effects on economic fundamentals (Corrado and Fingleton, 2011).

beginning of the 1990s. Third, Chinese policy makers have regularly expressed concern about the adverse implications of regional disparities for national cohesion and stability[2] (Yu et al., 2008).

The paper is presented as follows. Section 2 analyzes the location of FDI in Chinese provinces. The econometric framework for FDI spatial dependence considerations is presented in section 3. The results and discussion are presented in the section 4. Finally, section 5 concludes.

2 FDI localization in Chinese provinces

China has different levels of spatial organization. Our analysis considers the 26 provinces (excluding Tibet) plus the three province-status "super-cities"—Beijing, Shanghai and Tianjin—over the 1992-2009 period.[3] We check for relevant spatial dispersion of FDI at the level of the main three regions, Coastal, Center and Western, all of which are composed of provinces[4].

An important feature of China's FDI inflow is that it is mostly concentrated in the eastern coastal regions. Some regions of China are, in fact, even more open to FDI than a "typical" Southeast Asian nation (Naughton, 2007). The uneven regional distribution of FDI in China is a result of a variety of factors, including FDI policies and regional disparities in investment. This distribution is in line with China's gradual reform policy that has favored coastal provinces by establishing special economic zones and offering preferential tax treatment (Démurger et al., 2002). Moreover, coastal provinces have geographical advantages for export-oriented FDI and offer larger domestic markets for foreign firms serving local customers (Ouyang and Fu, 2012). The coastal provinces have experienced greater profits and more rapid growth of light industries, while heavy industries are heavily concentrated in inland provinces. Two main reasons help explain this location pattern. First, during the centrally planned economy, Mao feared potential foreign military attacks and hence allocated heavy industries in remote inland provinces. Second, inland provinces are endowed with abundant natural resources.

Moreover, because of their geographic isolation, inland provinces have limited access to outside markets, both national and international. The effect of geographic isolation is even more apparent for the western provinces. Western investors concern themselves primarily with market access; therefore, metropolitan cities (such as Beijing, Shanghai and Shenzhen) and coastal areas would inevitably be heavily favored by investors relative to inland regions. In reaction to the widening regional gap, more broadly based economic reforms and open-door policies were promoted in the 1990s. As the authorities introduced new policies aimed at easing foreign investment restrictions and attracting foreign investment to more parts

[2] This is evidenced by a number of special policies: the Great Western Experiment (announced in 1999 during the Ninth Five-Year Plan), the Resurgence of Northeastern Old Industry Base and the Stimulation of the Central region (during the Tenth Five-Year Plan), and the Eleventh Five-Year Plan, in which there has been a major push to redress the growing regional disparities.

[3] Without specific mention, we adopt such spatial organization. Data are collected from various issues of *China Statistical Yearbooks* edited by the National Statistical Bureau.

[4] Details are given in appendix, Table 5.

of the country, FDI began to spread to new provinces. In the spring of 1992, Chinese leader Deng Xiaoping announced that the economic success of the southern provinces should be a model for the rest of the country. This spatial concentration raises the concern that FDI inflows lead to unbalanced regional growth and widen income inequality across regions within China (Yu et al., 2011). However, FDI concentrated in coastal provinces may have boosted economic growth and/or the growth of FDI in inland provinces in China.

A relevant (static) spatial dispersion can usually be detected by using Exploratory Spatial Data Analysis.[5] In this case, we refer to spatial autocorrelation indicators, or the correlation between observations at different points in space, to assess the province-level FDI spatial dependences. Each Chinese province is described by FDI variables and its proximity to other provinces, or the way by which each province is connected to the neighboring provinces. Standard approaches define proximity in terms of contiguity (areas are designated as neighbors if they share a common boundary) or by considering the geographical distance between two relevant points (Anselin, 1988). Given the fact that the Chinese provinces are defined by administrative boundaries and considering that FDI is generally localized within the principal city of a province, we have chosen a proximity specification based a queen contiguity built matrix for FDI spatial dispersion analysis.[6] Such proximity relations between provinces are represented through a spatial weight matrix W of N x N dimensions with N number of provinces.

Global and local spatial autocorrelation tests are conducted to determine whether the presence of FDI in one province is more or less likely to favor FDI in nearby provinces. The former test is based on Moran's (1950) I spatial autocorrelation statistic, which determines whether FDI, globally observed, depends on geographical distribution. The latter test, known as the Local Indicator of Spatial Association (LISA), is based on a specific Moran's statistic, which identifies local "hot spots," or in other words, the provinces where strong spatial correlations exist. The statistical relevance of these tests is measured with a pseudo p-value that is determined by methods that generate spatially random simulated data sets (Anselin, 1996). Under the null hypothesis, the FDI localization in different provinces is considered to be spatially independent.

Figure 1 presents the univariate Global Moran's I statistic calculated from the average of the logarithm of FDI in Yuan at constant 1992 prices over the 1992-2009 period for each province ($MLFDI$). We can see from the Moran's I, which has a value equal to 0.06 and a pseudo-p value of 0.00, that the location of FDI

[5] Exploratory Spatial Data Analysis (ESDA) is a set of techniques aimed at describing and visualizing spatial distributions, detecting patterns of global and local spatial association and suggesting spatial regimes or other forms of spatial heterogeneity (Anselin, 1988).

[6] With queen contiguity arrangements, the spatial data observations are specified as polygonal and include boundaries and vertices, which allows for more neighbors based on the latitude and longitude of each province. All calculations have been performed with GeoDa software (ESDA & spatial regression software: http://geodacenter.asu.edu/projects/opengeoda).

by provinces exhibits positive and significant spatial autocorrelation. In other words, the province-based FDI dispersion exhibits relevant spatial resemblances in China on average.

Figure 1: Global Moran's I spatial autocorrelation statistic

(FDI, in logarithm, average over 1992-2009)

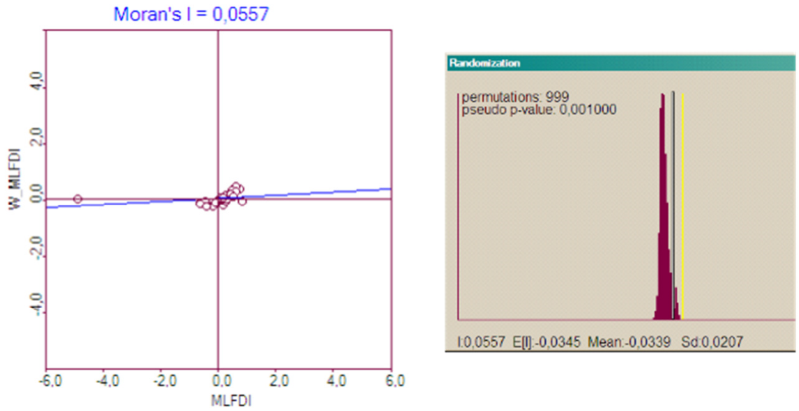
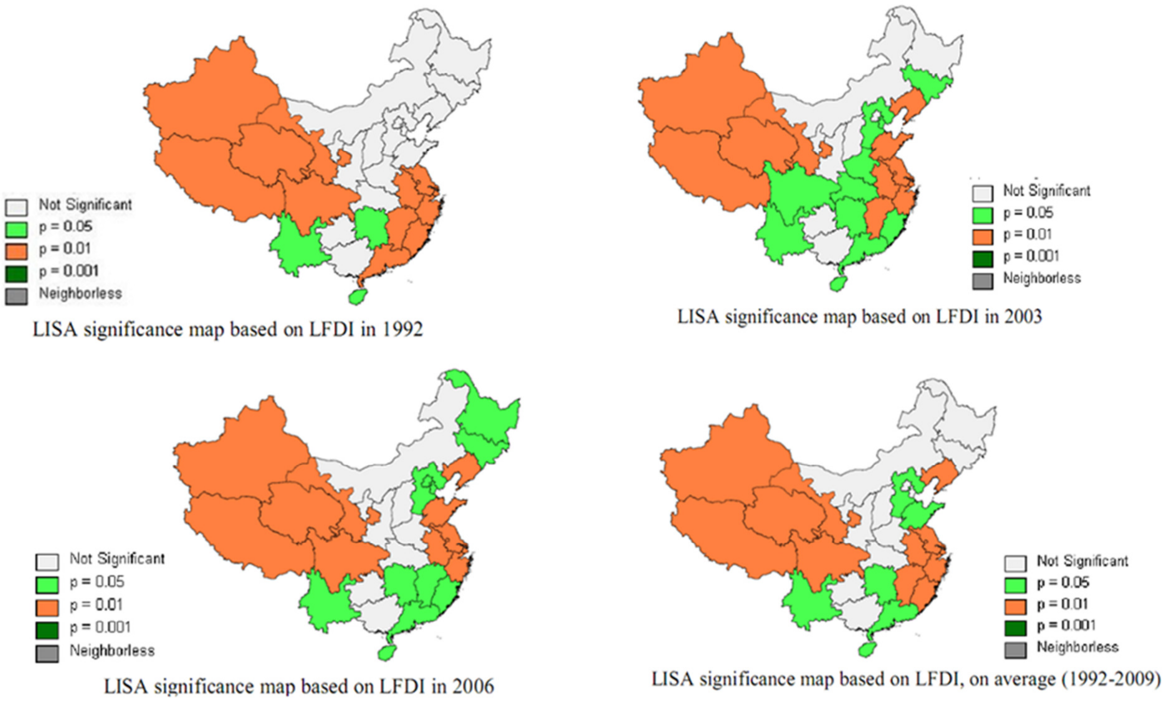


Figure 2 presents a different univariate LISA significance map of FDI by provinces over different years (1992, 2006 and 2009), as well for the average of the logarithm of FDI. For those selected years, it appears that, based on the univariate LISA, the spatial localization of FDI between provinces are relevant. Thus, we can deduce that it there is a positive spatial dependence regarding FDI across Chinese provinces from 1992 to 2009.

Figure 2: FDI local spatial mapping



LISA significance map based on LFDI in 1992

LISA significance map based on LFDI in 2003

LISA significance map based on LFDI in 2006

LISA significance map based on LFDI, on average (1992-2009)

The significant regional localization of FDI indicates the importance of examining the spatial structures of FDI across the Chinese provinces.

3 FDI spatial convergences modeling

The empirical strategy adopted to assess FDI spatial distribution in China is twofold. The first method refers to sigma-convergence analysis. We seek to determine for a given region (Coastal, Center and Western) whether there is a convergence of FDI over time. The second method, based on a conditional beta-convergence framework, allows us to analyze FDI convergence in China. More specifically, we attempt to identify spatial dependence and its magnitude among Chinese provinces.

3.1 FDI Spatial sigma-convergence

To determine whether FDI changes over time are significantly different when using each of the three main Chinese regions as a reference, we use a referential sigma-convergence indicator (RSC). This indicator reports the FDI harmonization relative to a specific region (Coastal, Central or Western). Thus, for RSC calculation, the dispersion is appreciated around the central value, (the average of FDI in the given region).

Let denote the logarithm of FDI in Yuan at constant 1992 prices at time t in province i and denote the simple average of LFDI of region k

Coastal region, Central region, Western region). The referential sigma-convergence RSC, related to the k^{th} region, is given as:

$$\sigma\left[LFDIR_{k,t}\right] = \sqrt{\sum_{i=1}^{N} \frac{\left(LFDI_{i,t} - MLFDI_{k,t}\right)^2}{N}} \ .$$

For a given k^{th} region, a downward trend of RSC suggests FDI sigma-convergence, or a FDI harmonization compared with the given region.

3.2 FDI Spatial beta-convergence framework

Our empirical strategy relies on conditional beta-convergence modeling in which the FDI growth depends on the initial FDI and a set of variables capturing the structural characteristics of each province (Barro and Sala-i-Martin, 1995).

We innovate by using spatial panel data models to look for evidence that values of FDI growth in Chinese provinces are more spatially clustered than they would be under random assignment. The rationale for using spatial econometric models is twofold. First, considering that both of our results above highlighted static and temporal spatial dependences of FDI in Chinese provinces, it is reasonable to investigate FDI convergence, as it seems to be a matter of contemporary importance in China (Ito et al. 2012). Second, there is empirical evidence suggesting that the productivity of technological spillovers declines as the geographical distance between regions increases (Keller, 2002). Moreover, various convergence studies have found evidence for model misspecifications if the spatial interdependencies of regional growth are ignored (Arbia et al., 2008). In general, ignoring relevant spatial dependence effects leads to two types of consequences. When the model specification suffers from endogenous and exogenous spatial dependences, the estimated coefficients will be biased and inconsistent. Furthermore, the estimators will be affected by a loss of efficiency in the case of correlated spatial effects (Greene, 2005).

There are typically three different types of correlations that explain why selected observations may be associated with spatial considerations (Manski, 1993). Applied to the FDI location in Chinese provinces, one can identify endogenous correlation effects, in which an economic decision in the i^{th} province depends upon the location of FDI in the other provinces; exogenous correlation effects, in which the location of FDI in the i^{th} province depends upon independent explanatory variables of the decisions made by the different provinces; and correlated effects, in which the FDI location decisions are affected by similar unobserved spatial characteristics. Following Elhorst (2010b) and Corrado and Fingleton (2011), we test for these three types of correlation.

To specify a process that better explains the FDI spatial dispersion in Chinese provinces, we follow the estimation strategy proposed by Elhorst (2010b) and based on the Manski (1993) general specification:[7]

$$Y_{i,t} = \beta_0 LFDI_{i,0} + \beta X_{i,t} + \rho \sum_{j=1}^{N} W_{ij} Y_{i,t} + \theta \sum_{j=1}^{N} W_{ij} \left(X_{i,t} \sim LFDI_{i,0}\right) + \alpha_t + \mu_i + \left(\lambda \sum_{j=1}^{N} W_{i,j} \vartheta_{it} + \varepsilon_{i,t}\right) \qquad \text{(eq. 1)}$$

with $Y_{i,t}$ denoting the FDI growth rate of the i[th] province at t[th] period, $LFDI_{i,0}$ denoting the logarithm of the initial level of FDI of the i[th] province, $X_{i,t}$ denoting a set of explanatory variables, ε_{it} representing the error-term (which is assumed to be normally distributed with zero mean ($E(\varepsilon_{i,t}) = 0$) and constant variance ($E(\varepsilon_{it}^2) = \sigma^2 I_N$)), α_t denoting the time-period fixed effects and μ_i denoting the spatial (individual) effects. $\rho \sum_{j=1}^{N} W_{ij} Y_{i,t}$ is set to capture spatial endogenous interaction effects with ρ denoting a spatially lagged dependent coefficient, $\theta \sum_{j=1}^{N} W_{ij} \left(X_{i,t} \sim LFDI_{i,0}\right)$ denoting exogenous interaction effects with θ the spatially lagged independent coefficient and $\left(\lambda \sum_{j=1}^{N} W_{ij} \vartheta_{i,t} + \varepsilon_{i,t}\right)$ denoting the disturbance terms with λ representing the spatial errors' interaction effects.[8]

Elhorst's strategy first consists of estimating the model (eq. 1) with OLS and then testing for spatial lag dependence ($H_0: \theta = 0$) spatial error auto-correlation ($H_0: \theta + \rho\beta = 0$). If both hypotheses are rejected, then a spatial Durbin model can be estimated. If the spatial lag hypothesis (the spatial error hypothesis) is only rejected, then a spatial auto-regressive model (a spatial error model) is suitable for specification. However, if both hypotheses cannot be rejected, then Elhorst suggests estimating an OLS model with spatially lagged independent variables and then testing for $H_0: \theta = 0$. If that hypothesis cannot be rejected, then one must consider estimating an OLS model; otherwise, one can estimate a spatial Durbin model and test for spatial lag dependence ($H_0: \rho = 0$). Finally, if the latter hypothesis is rejected, then a model with spatially lagged independent variables would seem to be better. However, if $H_0: \theta = 0$ is not rejected, a spatial Durbin model specification must be adopted.[9] We then turn to the variables description.

3.3 Variables and data

Hereafter, for all spatial considerations, tests and regressions, we use the simple distance between the largest cities in two provinces to emphasize the spatial arrangement characterizing China's provinces; each of these cities is supposed to be a decision-making center. Thus, the spatial arrangement based on the

---

[7] From Manski's general specification, different spatial dependence models are deduced. For instance, for $\lambda = 0$, equation 1 becomes a spatial Durbin (SD) model, whereas for $\rho = 0$, it becomes a spatial Durbin error model, and for $\theta = 0$, it becomes a Kelejian-Prucha (1999) model. Moreover, for $\theta = \lambda = 0$, the specification is called a spatial lag model (SAR), and for $\theta = \rho = 0$, it is called a spatial error model (SEM).

[8] Recall that with $\theta = \lambda = \rho = 0$, eq. 1 yields the basic convergence form, which is to say: $Y_{i,t} = \beta_0 LFDI_{i,0} + \beta X_{i,t} + \alpha_t + \mu_i + \varepsilon_{it}$

[9] The test for spatial lag or spatial error dependences on the OLS model are based on classic LM-tests proposed by Anselin (1988) and robust LM-tests proposed by Anselin et al. (1996); the statistic of these tests follows a chi-squared distribution with one degree of freedom. The related tests conducted on spatial Durbin models also follow a chi-squared distribution but with K degrees of freedom. The spatial models are estimated by maximum likelihood methods. For an extended technical discussion on these tests, see Elhorst (2010a).

inter-city bilateral distances of all provinces is defined by an $N*N$ spatial weight matrix W,[10] with N representing the 29 provinces.

To highlight the importance of FDI convergence among provinces, we define two dependent variables. The first dependent variable refers to the nationwide FDI growth rate $\left(NWFDI_{i,t} = \frac{LFDI_{i,t}}{LFDI_{i,0}}\right)$, given by the ratio between $LDFI_{i,t}$, the logarithm of FDI of the ith province at tth period, and $LDFI_{i,0}$, the logarithm of FDI of the ith province at the initial level $(t_0 = 1992)$. The second measure of the dependent variable pertains to a region-wide FDI growth rate of the ith province related to the region to which it belongs at the tth period $\left(RWFDI_{i,t} = \frac{LFDI_{i,t}}{MLFDI_{k(i\in k),0}}\right)$. $RWFDI_{i,t}$ is given by the ratio between $LDFI_{i,t}$ and $MLFDI_{k(i\in k),0}$, the simple average of the logarithm of FDI at the initial level $(t_0 = 1992)$ of provinces that composed the k^{th} region (k= Coastal, Central and Western). Thus, equation 1 presents two specifications:

$$NWFDI_{i,t} = \beta_0 LFDI_{i,0} + \beta X_{i,t} + \rho \sum_{j=1}^{N} W_{ij} NWFDI_{i,t} + \theta \sum_{j=1}^{N} W_{ij} \left(X_{i,t} \sim LFDI_{i,0}\right) + \alpha_t + \mu_i + \left(\lambda \sum_{j=1}^{N} W_{ij} \vartheta_{i,t} + \varepsilon_{i,t}\right) \quad \text{(eq. 2)}$$

$$RWFDI_{i,t} = \beta_0' MLFDI_{k(i\in k),0} + \beta' X_{i,t} + \rho' \sum_{j=1}^{N} W_{ij} RWFDI_{i,0} + \theta' \sum_{j=1}^{N} W_{ij} \left(X_{i,t} \sim MLFDI_{k(i\in k),0}\right) + \alpha'_t + \mu'_i + \left(\lambda' \sum_{j=1}^{N} W_{ij} \vartheta'_{i,t} + \varepsilon'_{i,t}\right) \quad \text{(eq. 3)}$$

In both cases, we expected a negative sign from β_0 and β_0', the coefficients of the initial FDI variables $\left(LDFI_{i,0} \text{ and } MLDFI_{i,0}\right)$, which would reflect a conditional convergence of FDI regarding all Chinese provinces (eq. 2) or regarding a given region (eq. 3).

The common factors that may contribute to explaining the localization patterns of FDI, as identified by a substantial volume of literature, include factors such as market size, international economic opening, infrastructure stock, inputs costs, and institutional changes (Xu and Sheng, 2012a). Our study controls for these factors and pays attention to their effects on FDI convergence after correcting for spatial dependences.

In the literature, market size appears to be one of the main characteristics attracting FDI. Indeed, FDI inflows are associated with potential market activities. Moreover, market demand and market size have positive effects on FDI because they are supposed to affect the expected revenues of investments. Several studies have found support for market-seeking FDI motives in China (Cheng and Kwan, 2000; Coughlin and Segev, 2000; Gong, 1995; Sun et al., 2002; Wei and Liu, 2001; Zhang, 2001a, 2001b). We retain $LRGPC$, the logarithm of the gross domestic product of province i (in constant 1992 prices), as a proxy of market size and expect it to have a positive sign.

The degree of openness, measured by the logarithm of trade to GDP ratio ($LOUV$), is also considered. Sun et al. (2002) state that the impact of this factor is ambiguous, because a more open economy attracts FDI as a result of foreign investors already being familiar with the host economy, but it also increases

[10] The spatial weight matrix is available on request.

competition. However, most study finds that the first effect is stronger (Sun et al., 2002; Zhang, 2001a; Berthélemy and Démurger, 2000; Wei and Liu, 2001).

In terms of input costs, we use a wages variable. Higher wages are supposed to deter foreign investment. However, some previous studies of FDI have found somewhat conflicting results regarding wages. For instance, no statistically significant relationships were found by Head and Ries (1996). Conversely, Cheng and Kwan (2000), Coughlin and Segev (2000), Sun et al. (2002) and Wei and Liu (2001) find that higher real average wages have a negative impact on FDI flow. We use the logarithm of the ratio of wage over provincial GDP $(LRAW)$ to take into account the effect of labor costs on FDI inflows to China's provinces. The expected sign of $LRAW$ is negative.

In addition, the coast/interior dichotomy of Chinese provinces highlights the importance of transportation costs in determining a province's participation in the international division of labor (Démurger et al., 2002). Particularly, research by Head and Ries (1996) and Li and Park (2006) indicates that investments in physical and transportation infrastructures are important factors when analyzing FDI location choices in an emerging market like China. To measure this impact, following Sun et al. (2002), Berthélemy and Démurger (2000), Zhang (2001b), Cheng and Kwan (2000), we include a variable measuring the number of railways and roads per km2 ($LVFR2$), expecting to find a positive effect on FDI location.

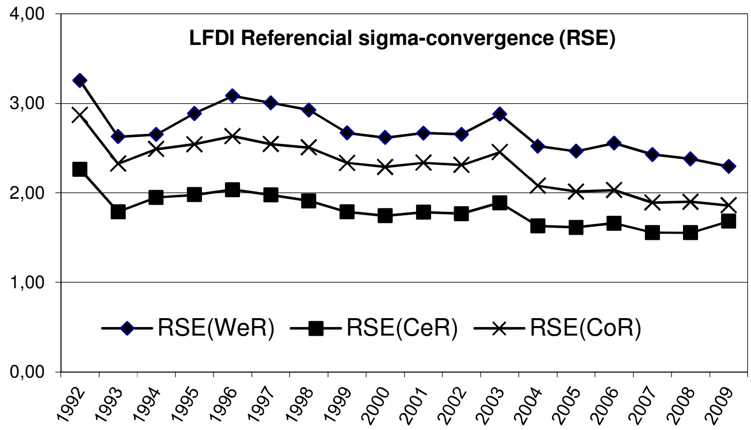
Finally, we pay attention to the estimated spatial dependences coefficients $(\rho, \theta, \lambda \; and \; \rho', \theta', \lambda')$. In absolute terms, a positive sign indicates that the neighborhood generated positive externalities in a considered province or region, whereas a negative sign indicated negative externalities. Whereas a positive sign might indicate some degree of complementarity, a negative sign should be considered a situation of substitutability. However, it is necessary to interpret these effects in light of the expected sign of the variable of interest. For example, if the FDI between the provinces are substitutable, then as market size in a province increases, other provinces should attract less FDI. Conversely, if the FDI between the provinces is complementary, then as market size in a province increases, other provinces should attract more FDI. The opposite analysis stands for wages. Thus, the expected sign of that potential spatial exogenous variable can be negative or positive. We now turn to the results.[11]

4 Results and discussion

Let us first analyze the FDI convergence across Chinese provinces. The referential sigma-convergence indicators (RSC) trends are presented in Figure 3.

[11] All tests and regressions have been performed on Matlab programs originally drafted by Elhorst (http://www.regroningen.nl/elhorst/software.shtml) and Lacombe D. (http://community.wvu.edu/~djl041/matlab.html).

Figure 3: Referential Sigma-convergence of FDI (Yuan 92)



Our calculations. WeR: Western region; CeR: Central Region; CoR: Coastal region

Recalling that a downward RSC, for a k^{th} region, suggests a FDI harmonization compared to the considered region, the trends suggest two main results. On one hand, the downward trend of each referential sigma-convergence indicator suggests a convergence of FDI in China for 1996-2009, although this convergence is not very pronounced. On the other hand, the convergence of FDI is proportionally more important when considering the Central region (CeR), and the dispersion is greater when the Coastal and the Western regions (CoR and WeR, respectively) are taken as reference points. Thus, our findings suggest a dividing line between coastal provinces and inland provinces in attracting foreign capital. As in many recipient countries, FDI is geographically concentrated in a few regions in China (Ouyang and Fu, 2012). Despite a set of preferential policies to attract FDI to western provinces, more than 85% of FDI inflows consistently cluster in the coastal regions. According to China's statistics, four provinces (Guangdong, Jiangsu, Shanghai and Zhejiang) have been receiving more than half of China's FDI inflow.

Second, we turn to the FDI spatial sigma-convergence analysis. First, unit root tests are conducted on each variable. They are all integrated of order 0, which is to say that each variable is stationary (see appendix, Table 6). Table 1 gives a summary of spatial dependence identification tests conducted based on (robust) LM tests for a missing spatially lagged dependent variable and (robust) LM tests for spatial errors dependence. All the tests are significant and reject the hypothesis of no spatial, lag and error dependences. Thus, regarding the (robust) LM tests results, a spatial Durbin model specification seems better adapted to analyze the FDI dispersion between Chinese provinces or regions.

Table 1: (Robust) LM Spatial dependences tests

Time-period fixed effects + (robust) LM tests for spatial lag and spatial error model Ordinary Least-squares Estimates			
		Dependent Variable	
		NWFDI (eq. 2)	RWFDI (eq. 3)
Nobs		522	522
LM test no spatial lag		2.78*	15.69***
	probability	[0.10]	[0.00]
Robust LM test no spatial lag		3.84**	19.71***
	probability	[0.05]	[0.00]
LM test no spatial error		8.09***	10.11***
	probability	[0.00]	[0.00]
Robust LM test no spatial error		9.15***	14.12***
	probability	[0.00]	[0.00]

In brackets is the t of Student. *. **. ***: respectively significant at 10%. 5% and 1%.

Table 2: Spatial Durbin models estimations

	Dependant variable	
	NWFDI (province-based)	RWLDI (level-based)
$LFDI_O$	-0.56***	
	(-17.57)	
$MFDI_O$		-0.60***
		(-9.02)
LRGPC	1.18***	0.91***
	(7.16)	(4.38)
LRAW	0.09	-0.82**
	(0.31)	(-2.28)
LOUV	-0.34***	-0.02
	(-3.45)	(-0.19)
LVFR2	0.44***	0.74***
	(6.81)	(10.52)
$W*LFDI_O$	-1.56**	
	(-2.39)	
$W*MLFDI_O$		2.51
		(1.59)
W*LRGPC	9.10**	-10.76**
	(2.49)	(-2.22)
W*LRAW	-1.42	9.96
	(-0.20)	(1.16)
W*LOUV	-2.98***	-1.72
	(-2.67)	(-1.19)
W*LVFR2	0.19	-0.90
	(0.18)	(-0.60)
W*dep. var.	-0.72***	-1.00***
	(-3.45)	(-4.42)
R-squared	0.73	0.61
corr-squared	0.58	0.38
Nobs	522	522

Maximum Likelihood estimation method. Time-fixed effects. In brackets is the t of Student. *. **. ***: respectively significant at 10%. 5% and 1%.

On one hand, Table 2 presents the beta-convergence based on spatial estimation results of FDI across Chinese provinces. On the other hand, Table 3 shows the results derived from spatial Durbin model estimations, or the direct, indirect and total spatial effects.

While Table 2's results are informative, our analyses are conducted mainly based on the direct and indirect spatial spillover effects. Indeed, as pointed out by LeSage and Pace (2009), several empirical studies that use simply spatial regression estimated coefficients—as in Table 2—to assess spatial spillovers in a way that may lead to erroneous conclusions. The estimated parameters in spatial models do not represent the marginal effect of a change in an independent variable because they include direct and indirect effects. At the very least, one cannot infer whether these spillover effects are significant solely by using the estimated parameters in spatial models (Elhorst, 2010b). On one hand, direct effects measure the impact of changing an independent variable (such as $LFDI_0$, $MLFDI_0$, LRGPC, LRAW, LOUV or LVFR2) on the dependent variable of a province (or region). However, this measure includes feedback effects or the effects passing through neighboring provinces and back to the province (or region) from which the change occurred.[12] On the other hand, indirect effects measure the effect of changing an independent variable in a particular province (or region) on the dependent variables of all other provinces (or regions). The statistical significance of the direct and indirect effects is determined by simulating the distribution using the variance-covariance matrix implied by the maximum likelihood estimated coefficients.

Table 3: Direct and indirect spillover effects on FDI

	Dependant variable	
	NWFDI (province-based)	RWFDI (region-based)
	Direct effects	
$LFDI_O$	-0.54***	
	(-20.28)	
$MFDI_O$		-0.67***
		(-11.69)
LRGPC	1.03***	1.19***
	(6.51)	(5.67)
LRAW	0.11	-1.07***
	(0.38)	(-3.16)
LOUV	-0.28***	0.02
	(-3.21)	(0.15)
LVFR2	0.44***	0.78***
	(7.22)	(11.19)
	Indirect effects	
$LFDI_O$	-0.72*	
	(-1.77)	
$MLFDI_O$		1.6385*

[12] It is noteworthy that due to the feedback impacts, the direct effect of an explanatory variable is different from its estimated coefficient. Indeed, the feedback effects depend partly on the effect of the spatially lagged dependent variable and partly on the effect of the coefficient of the spatially lagged value of the explanatory variable itself. This is a consequence of effects passing through neighboring provinces and back to the provinces themselves (Elhorst, 2010a and b).

		(1.89)
LRGPC	5.08**	-6.1697**
	(2.15)	(-2.25)
LRAW	-0.91	5.8126
	(-0.21)	(1.29)
LOUV	-1.66**	-0.9195
	(-2.25)	(-1.23)
LVFR2	-0.05	-0.8784
	(-0.08)	(-1.10)
	Total effects	
$LFDI_O$	-1.26***	
	(-3.02)	
$MLFDI_O$		0.9692
		(1.12)
LRGPC	6.10***	-4.9795*
	(2.57)	(-1.82)
LRAW	-0.80	4.7402
	(-0.19)	(1.06)
LOUV	-1.95**	-0.904
	(-2.51)	(-1.16)
LVFR2	0.39	-0.1009
	(0.59)	(-0.13)

Maximum Likelihood estimation method. Time-fixed effects. In brackets is the t of Student. *, **, ***: respectively significant at 10%, 5% and 1%. t-statistics are calculated from a set of 1,000 simulated parameter values.

Nevertheless, our results regarding direct and indirect spillover effects are relevant both in terms of FDI convergence and in terms of our model's explanatory variables.

In regard to the first point, it seems that there is an important FDI convergence in China either across all provinces (Table 3, column 1: NWFDI) or at the level of the three regions (Table 3, column 2: RWFDI). Indeed, the estimated coefficients of the direct spillover effects of the initial value of FDI at the province ($LFDI_0$) and region ($MLFDI_0$) levels are negative and bounded between 0 and 1. Moreover, the direct spillover effects of the market size—considered through LRGPC, the logarithm of real gross domestic product of province i (in constant 1992 prices)—appear with positive and statistically significant estimates in province-based and region-based regressions. In other words, the increase of LRGPC in a particular province (or region) will result in an increase of FDI in that province (region) as a result of positive effects passing through neighboring provinces (regions) and back to the provinces (regions) themselves. As expected, the direct spillover effects of investments in physical and transportation infrastructures (LVFR2) appear with significant positive coefficients in both spatial regressions (NWFDI and RWFDI). Contrary to Berthélemy and Démurger (2000) and Wei and Liu (2001), our results show that the logarithm of trade to GDP ratio (LOUV), used as a proxy for the degree of openness, appears to have negative effects on FDI convergence. In particular, the negative effects of the degree of openness are statistically significant for direct spillover effects in region-based regression and for the total spillover impacts at the province-based level. These findings indicate that the negative effects resulting from competition following an increase in the degree of openness have surpassed the positive effects expected from attracting FDI due to the degree of openness of China economy, as pointed out by Sun et al. (2002). Furthermore, our proxy of labor costs on FDI (LRAW) yields ambiguous results depending on the level of administrative organization. Indeed, the direct spillover effects appear to be insignificant at the province-based level, which is a result similar to Head and Ries' (1996) conclusion. However, at the region-based level, the direct spillover effects resulting from the labor costs are negative and significant.

In addition, the spatial dependence analysis of FDI distribution across China focuses attention particularly on the feedback effects, or the relative importance and nature of the effects passing through neighborhoods and shifting back to the spatial units, (regions or provinces) themselves (Table 4). From region-based regression, it is interesting to observe that the statistically significant feedback effects are positive and relatively important. For instance, the feedback impacts account for +11.53% in the process of FDI convergence across regions when considering the initial average regional FDI ($MFDI_O$). Conversely, such feedback impacts seem to slow down the FDI convergence process across provinces, because its value is negative (-3.89%) for $LFDI_O$. At the level of provinces, it is as if the neighboring provinces are creating an inertial effect on the FDI convergence process, probably because the absorption capacity of FDI is not so different at the level of provinces. Indeed, that aspect seems to be confirmed by the fact that in province-based regression, the feedback effects of all independent variables have negative signs, as reported in Table 4.

Table 4: FDI in China: speed of convergence, half-life and feedback spillover effects

	NWFDI (province-based)	RWFDI (region-based)
Speed of convergence	4.29%	6.15%
Half-life period (years)	23	18
	Feedback effects	
LFDIO	-3.89%	---
MFDIO	---	11.53%
LRGPC	-12.86%	30.78%
LRAW	---	30.78%
LOUV	-16.24%	---
LVFR2	---	5.07%

Source: Authors. Calculations are based on estimated direct spillover effects that are statistically significant.

Finally, on the indirect spillover effects side, whereas the effects of the market size remain positive in province-based regressions, they appear to be negative in region-based regressions (NWFDI). In other words, if the market size for a particular region increases in its neighboring regions, the shifted impact will decrease FDI in the region itself. It is interesting to note that at the region level, the negative indirect spillover effects of LRGPC are so important that they outstrip the positive direct spillover effects of FDI. Indeed, the total spillover effect of the market size through Chinese regions is somewhat negative. These findings add nuance to the common conclusion reached by scholars such as Wei and Liu (2001) or Zhang (2001a). Although the indirect spillover effects of transport infrastructure (LVFR2) are not statistically significant, it is interesting to observe that the estimated coefficients are negative. In other words, a particular province or region would not benefit in terms of FDI from an increase of investments in physical and transportation infrastructure in neighboring provinces or regions. Thus, our results suggest conclusions that are complementary to those of previous studies such as in Zhang (2001a) and Sun et al. (2002) or in Li and Park (2006). Labor costs also stand out, with statistically insignificant estimated coefficients, both at the province and region levels.

Overall, at the level of provinces, the spatial distribution of FDI across China over the 1992-2009 period suggests that FDI localization would be considered as substitutable for at least three reasons. First, the speed of convergence based on direct spillover effects is relatively low compared to that of region-based estimations. Second, feedback effects passing through neighborhood mitigates effects in the provinces themselves. Finally, due to indirect spillover effects, an increase in market size (LRGPC) in neighboring provinces gives a boost to FDI in a given province. Moreover, as the openness (LOUV) of a province increases, the effects on FDI decrease because of effects from neighboring provinces.

By contrast, at the region level, the spatial dependences allow us to consider FDI localization to be complementary in China. Feedback effects greatly condition the effects of our explanatory variables on FDI (LRGPC, LRAW and LVFR2). Only the market side has yielded statistically significant indirect spillover effects, indicating that an increase of LRGPC in neighboring regions seems to result in a negative effect on FDI in a given region. Ultimately, a speed of convergence of about 6.15% and a half-life period[13] of 18 years related to the direct spillover effects based on $MFDI_0$, (compared to the province-level estimates of 4.29% and 23 years, respectively) resulted in a complementary distribution of FDI at the subdivision of China in terms of regions (Table 4).

5 Conclusion

This study reconsiders the question of FDI localization across China in the perspective of spatial dependences. After having confirmed, based on sigma-convergence analysis, that FDI spatial dependences matter among provinces and regions, we have tried to identify the nature and the amplitude of these spatial correlations through a beta-convergence spatial Durbin modeling. Two types of spatial correlations have been considered with this type of econometric specification: an endogenous interaction effect in which the

[13] The speed of convergence (s) measures how fast FDI converge towards the steady state and the related indicator is calculate it using the following formula: $s = -\ln(1 + \beta_0)/T$. The half-life measures the time necessary for the FDI to fill half of the initial gap of FDI inequalities and the indicator is calculate as follows: $\tau = -\ln(2)/\ln(1 + \beta_0/T)$.

localization of the FDI in a province depends in some way upon the localization of FDI observed in other provinces and an exogenous interaction effect in which decisions observed in a given province depend upon independent explanatory variables regarding the decisions taken by other provinces.

Our results yield three main findings. First, FDI convergence is more pronounced compared to the Central region, whereas the dispersion is greater when the Coastal and the Western regions are taken as reference points. Second, at the province level, FDI localization seems to present a substitutable configuration as a result of the relatively low speed of FDI convergence and the deterring spatial feedback effects of independent explanatory variables of the neighboring provinces on FDI, such the market size or the openness of the province. Third, when controlling for the spatial distribution of FDI at the level of regions, it seems, conversely, that the FDI localization presents a complementary configuration. Indeed, the region-level FDI localization is characterized not only by a relatively high speed of FDI convergence but also by important positive feedback effects arising from neighboring regions.

The main finding resulting from the opposing configurations of the FDI localizations observed at the region and province levels is probably that China seems to not completely exploit the efficiency of FDI because of fragmentation and decentralization. In addition, the competition between local governments to attract FDI may limit the positive effects of the diffusion and exploitation of comparative advantage. In particular, positive effects might be mitigated because it seems very difficult and costly to implement attractive policies for FDI (for instance, in the western provinces), even though the spatial dependence analysis suggests that a region can take advantage of its proximity with the other regions.

Appendix

Table 5: Descriptive statistics of FDI distribution in Chinese provinces

	Provinces	Average Real FDI, by region (billion Yuan, 1992)	Standard error, by region (1992-2009)	Average Real FDI, by province (billion Yuan, 1992)	Standard error, by province (1992-2009)	Growth rate, by province (1992-2009)
Coastal Region (CoR)	BEIJING	34.74	35.61	19.97	12.01	0.20
	TIANJIN			21.03	15.37	0.31
	HEBEI			10.39	6.69	0.24
	LIAONING			31.37	27.13	0.24
	SHANGAI			39.09	18.39	0.21
	JIANGSU			82.36	49.44	0.20
	ZHEJIANG			32.32	26.17	0.26
	FUJIAN			30.74	8.77	0.10
	SHANDONG			39.71	23.36	0.14
	GUANGDONG			98.35	29.74	0.12
	GUANGXI			5.02	1.95	0.12
	HAINAN			6.50	2.34	0.06
Central Region (CeR)	SHANXI	7.42	7.63	2.76	2.41	0.16
	INNER MONGOLIA			5.05	6.92	0.47
	JILIN			3.67	1.97	0.19
	HEILONGJIANG			6.72	5.47	0.24
	ANHUI			7.06	7.93	0.30
	JIANGXI			10.05	9.24	0.26
	HENAN			8.95	9.15	0.32
	HUBEI			11.62	6.80	0.20
	HUNAN			10.91	8.78	0.25
Western Region (WeR)	SICHUAN+CHONGQING	2.46	5.95	11.54	12.86	0.30
	GUIZHOU			0.49	0.27	0.13
	YUNNAN			1.62	1.60	0.24
	SHAANXI			4.16	2.83	0.25
	GANSU			0.46	0.28	0.44
	QINGHAI			0.70	0.87	0.42
	NINGXIA			0.26	0.27	0.38
	XINJIANG			0.48	0.39	0.10

Sources: our calculations based on data from various issues of China Statistical Yearbooks (National Statistical Bureau).

Table 6: Panel unit roots tests

		NWFDI	RWFDI	LRAW	LOUV	LVFR2	LRGPC
	Statistic	-5.84	-2.56	-6.52	-3.64	-8.69	-2.19
Levin, Lin & Chu t*	Probability	0.00	0.01	0.00	0.00	0.00	0.01
	Statistic	-4.54	-2.47	0.93	-3.26	156.68	-6.89
Im, Pesaran and Shin W-stat	Probability	0.00	0.01	0.82	0.00	0.00	0.00
	Statistic	183.10	183.10	307.94	56.57	---	68.71
PP - Fisher Chi-square	Probability	0.00	0.00	0.00	0.45	---	0.12

References

Amiti M., Javorcki, B. S., 2005. Trade costs and location of foreign firms in China. IMF working paper, March. WP/05/55.

Anselin L., 1988. Spatial Econometrics: Methods and Models. Dordrech, The Netherland: Kluwer Academic Publisher.

Anselin L., 1995. Local indicators of spatial association — LISA. Geographical Analysis, 27:93–115.

Anselin L., 1996. The Moran scatterplot as an ESDA tool to assess local instability in spatial association. In Fischer, M., Scholten, H., and Unwin, D., editors, Spatial Analytical Perspectives on GIS in Environmental and Socio-Economic Sciences, Taylor and Francis, London, pp.111–125.

Anselin L., Bera A.K., 1998. Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics, in: Ullah and Giles (Eds) Handbook of Applied Economic Statistics, M.Ockker, NY, Chap.7.

Anselin L., Bera A.K., Florax R., Yoon M.J., 1996. Simple diagnostic tests for spatial dependence. Regional Science and Urban Economics 26, 77-104.

Arbia G., Le Gallo J., Piras G., 2008. Does evidence on regional convergence depend on the estimation strategy? Outcomes from analysis of a set of NUTS2 regions. Spatial economic analysis. 3, 209-224.

Barro R.J., Sala-i-Martin X., 1995. Economic Growth. New-York, McGraw-Hill, Inc.

Berthélémy J-C., Démurger S., 2000. Foreign Direct Investment and Economic Growth: Theory and Application to China. Review of Development Economics. 4(2), 140-155.

Blonigen B.A., Davies R.B., Waddell G.R., Naughton H.T., 2007. FDI in space: Spatial autoregressive relationships in foreign direct investment. European Economic Review. 51, 1303-1325.

Chang S.-J., Park S., 2005. Types of firms generating network externalities and MNCs' co-location decisions. Strategic Management Journal, 26, 595–615.

Cheng L. K., Kwan Y. K.. 2000. What Are the Determinants of the Location of Foreign Direct Investment? The China Experience. Journal of International Economics. 51, 379-400.

Corrado L., Fingleton B., 2011. Where is the Economics in Spatial Econometrics? Working Papers 1101, University of Strathclyde Business School, Department of Economics.

Coughlin C.C., Segev E., 2000. Foreign Direct Investment in China: A spatial Econometric Study. World Economy. 21(1), 1-23.

Démurger S., Sachs J.D., Woo W.T., Bao S., Chang G., 2002. Geography, Economic Policy, and Regional Development in China. Asian Economic Papers. 1(1), 146-197.

Du J., He Q., Rui O.M., 2011. Channels of interprovincial risk sharing in China. Journal of Comparative Economics. 39, 383–405.

Du J., Lu Y., Zhigang T., 2012. Institutions and FDI location choice: The role of cultural distances. Journal of Asian Economics. 23, 210–223.

Elhorst J.P., 2010a. Spatial Panel Data Models, in: Fischer MM, Getis A (Eds.) Handbook of Applied Spatial Analysis. Springer: Berlin Heidelberg New York, pp.377-407.

Elhorst J.P., 2010b. Matlab Software for Spatial Panels. Presented at the IVth World Conference of the Spatial Econometrics Association (SEA), Chicago, June 9-12, 2010.

Ertur C., Le Gallo J., 2006. The European regional convergence process, 1980-1995: Do spatial dependence and spatial heterogeneity matter? International Regional Science Review. 29 (1), 2-34.

Fetscherin M., Voss H., Gugler P., 2010. 30 Years of foreign direct investment to China: An interdisciplinary literature review. International Business Review. 19, 235–246.

Fingleton B., López-Bazo E., 2006. Empirical growth models with spatial effects. Papers in Regional Science. 85 (2), 177-219.

Fung K. C., Iizaka, H., Siu, A., 2003. Japanese direct investment in China. China Economic Review, 14, 304–315.

Gong H.M, 1995. Spatial patterns of foreign direct investment in China's Cities, 1980-1989. Urban Geography. 16 (3), 189-209.

Greene, W.H., 2005. Econometric Analysis, Upper Saddle River: Prentice Hall.

Head K., Ries J., 2006. Inter-City Competition for Foreign Investment: Static and Dynamic Effects of China's Incentive Areas. Journal of Urban Economics. 1996, 40(1), 38-60.

Ito B., Yashiro N., Xu Z., Chen X., Wakasugi R., 2012. How do Chinese industries benefit from FDI spillovers? China Economic Review 23 (2012) 342–356.

Kelejian H.H., Prucha I.R., 1999. A generalized moments estimator for the autoregressive parameter in a Spatial model. International Economic Review 40, 509–533.

Keller W., 2002. Geographic localization of international technology diffusion. American Economic Review. 92, 120-142.

Li S., Park S.H., 2006. Determinants of Locations of Foreign Direct Investment in China. Management and Organization Review. 2:1, 95-119.

Lin P., Liu Z., Zhang Y., 2009. Do Chinese domestic firms benefit from FDI inflow? Evidence of horizontal and vertical spillovers. China Economic Review. 20, 677–691.

Mah J.S., 2010. Foreign direct investment inflows and economic growth of China. Journal of Policy Modeling. 32, 155–158.

Manski CF., 1993, Identification of endogenous social effects: The reflection problem. Review of Economic Studies. 60(204), 531-542.

Moran P., 1950. A test for Serial Independence of Residuals. Biometrica. 37, 178-181.

National Bureau of Statistics. China Statistical Yearbooks. People's Republic of China, Beijing: China Statistical Press. Various years.

Naughton B., 2007. The Chinese Economy: Transitions And Growth, MIT Press.

Ng F. L., Tuan C., 2006. Spatial agglomeration, FDI, and regional growth in China: Locality of local and foreign manufacturing investments. Journal of Asian Economics, 17(4), 691–713.

Ouyang P., Fu S., 2012. Economic growth, local industrial development and inter-regional spillovers from foreign direct investment: Evidence from China. China Economic Review. 23, 445-460.

Rey S., Montouri B., 1999. US regional income convergence: a spatial econometric perspective. Regional Studies Association, 33, 146-156.

Su J., Jefferson G. H., 2012. Differences in returns to FDI between China's coast and interior: One country, two economies? Journal of Asian Economics. 23, 259–269.

Sumei T, Selvanathan E. A., Selvanathan S.V., 2012. China's economic miracle: does FDI matter?. Edward Elgar Publishing.

Sun Q., Tong W., Yu Q., 2002. Determinants of foreign direct investment across China. Journal of International Money and Finance. 21, 79-113.

Tong J.Y., Hu A.Y., 2003. Foreign Investment and Technology Transfer: A Simple Model. European Economic Review. 36 (1), 137-155.

Wei Y., Liu X., 2001. Foreign Direct Investment in China: Determinants and Impact, Edward Elgar, UK.

Wei Y., Liu X., 2006. Productivity spillovers from R&D, exports and FDI in China's manufacturing sector. Journal of International Business Studies. 37, 544–557.

Whalley J., Xin, X., 2008. China and foreign direct investment. Brooking Trade Forum. Brookings Institute.

Xu X., Sheng Y., 2012. Determinants of foreign direct investment across China. Journal of Asian Economics. 23, 244-258.

Yu K., Xin X., Guo P., Liu X., 2011. Foreign direct investment and China's regional income inequality. Economic Modelling, 28, 1348–1353.

Y, K., Tan, X.Y., Xin, X., 2008. Have China's FDI policy changes been successful in reducing its FDI regional disparity? Journal of World Trade. 42, 641–653.

Zhang X., Zhang K., 2003. Howdoes globalisation affect regional inequality within a developing country? Evidence fromChina. Journal of Development Studies, 39(4), 47–67.

Zhang K. H., 2001a. What Attracts Foreign Multinational Corporations to China? Contemporary EconomicPolicy. 19, 336-346.

Zhang K.H., 2001b. How does Foreign Direct Investment Affect Economic Growth in China? Economics of Transition. 9(3), 679-693.