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The FDI location decision: Distance and the effects of spatial dependence

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ABSTRACT

We investigate how different conceptions of distance impact upon one of the fundamental decisions made by foreign investors, the choice of foreign direct investment (FDI) location within the selected host country. We argue that the attractiveness of host country locations to foreign investors depends not only upon location-specific attributes such as labor costs, but also upon the location's proximity to alternative locations. We provide theoretical rationales for how and why alternative concepts of distance might impact upon firms' FDI location decisions, and explicitly model different measures of geographic, economic and administrative distance. Empirically we illustrate the use of a number of spatial regression models with a new dataset on FDI in Chinese prefecture-cities, and have shown, in this context, that geographic distance is not the 'best' measure of distance to use. We find clear evidence of spatial dependence between the cities based upon economic distance, with weaker evidence related to administrative distance. The distinctive contribution of this paper is to emphasize that city-level policy to attract FDI is more likely to succeed if the prefecture-city is economically (and administratively) close to alternative city locations, while any policy expenditure may fail to attract FDI inflows if the prefecture-city is distant from other city locations.

1. Introduction

Tobler's (1970: 7) first law of geography states that "*everything is related to everything else, but near things are more related than distant things*". But how should *near* and *distant* be conceptualized? In geography, distance is most often equated to physical distance, contiguity, or travel time. In international business (IB), alternative conceptions of distance (for example, cultural, psychic, institutional) are often more pertinent, and have been put forward as explanations for various aspects (*e.g.* international market selection, choice of entry mode) of multinational enterprise (MNE) behavior. The concept of distance is particularly important in understanding the spatial dimensions of international business activity. Various studies have demonstrated that the distance between countries is a major determinant of bilateral international trade (*e.g.* Frankel & Rose, 2002) and international investment flows (*e.g.* Baltagi, Song, & Koh, 2003; Blonigen, Davies, Waddell, & Naughton, 2007; Hall & Petroulas, 2008) but there has been little work (see Coughlin & Segev, 2000; Ledyaeva, 2009) on how the distance between locations at the sub-national level impacts upon MNEs' decision-making.

In this paper, we draw upon economic geography and institutional theory to investigate how different conceptions of distance impact upon one of the fundamental decisions made by foreign investors, namely the choice of foreign direct investment (FDI) location within the selected host country. There is a large literature on FDI location but, with a couple of exceptions (*e.g.* Coughlin & Segev, 2000; Ledyaeva, 2009), all the empirical studies treat alternative locations as distinct places, and implicitly assume that the distances between these have no impact upon the likelihood of FDI location. Yet the boundaries between the alternative locations are often quite arbitrary and defined by administrative fiat rather than political-economic reality, and proximate locations may well impact significantly upon the attractiveness to foreign investors. This results in a situation of *spatial dependence* which, if ignored, can give rise to various estimation and inference problems. The theoretical contribution of this paper is to explain why the attractiveness of host country

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locations to foreign investors depends not only upon location-specific attributes such as labor costs, but also upon the location's proximity to alternative locations. Following Ghemawat (2001), we consider proximity in the context of geographic, administrative and economic distance, and provide rationales for how and why these different concepts of distance should have an impact upon the FDI choice.

Furthermore our paper also makes an empirical contribution in that we model these different specifications of distance, using a panel dataset for 224 prefecture-cities in China over the period 2004–2007. We first estimate a standard 'non-spatial' model of sub-national FDI location, incorporating an array of well-established determinants such as local market attractiveness, wage costs, transport infrastructure, agglomeration economies and trade openness. Our statistical tests show that the data exhibit spatial dependence, which undermines the reliability of the parameter estimates. We then re-estimate the model using several spatial econometric models and different specifications of distance, and thus both control for the spatial dependence and significantly improve the explanatory power of the model. Our empirical evidence thus provides robust support for our theoretical position.

Our analysis has important policy implications for government authorities wishing to promote inward FDI to their prefecture-cities, or more generally to their provinces, states or countries. Neighboring locations are not just rivals for inward investment flows, but may also impact positively upon the likelihood of FDI in a particular location. Furthermore the size of the impact is likely to depend upon how proximate are the neighboring locations. This has important implications for the effectiveness of expenditure to promote inward FDI.

The paper is structured as follows. The first section briefly reviews the literature on FDI location choice. In the next section, we provide details of the dataset and some comments on the pattern of development of FDI in China, describe how the dependent and explanatory variables are defined, provide a short intuitive explanation of the estimation methodology for the spatial effects model, and outline the alternative measures of distance that we intend to test. This is followed by the results and a discussion of the findings and, in particular, contrasts the different measures of distance used to model the spatial dependence. The final section concludes, and offers suggestions for future research on the conceptualization of space and the importance of sub-national location decisions of FDI firms.

2. Literature review

The issue of FDI location choice has generated a large and growing literature. Some studies – see Table 1 – have focused on the choice between alternative country locations within broad geographic regions, others have concentrated on the choice of sub-national location within selected host countries, while a few have attempted to model location choice as a two-stage process involving both the country selected and the sub-national location.

Despite not all studies reporting consistent findings, this literature has established that the choice of FDI location is determined by such location-specific attributes as local market attractiveness, agglomeration economies, labor costs, quality of human capital, transportation infrastructure and trade openness. Foreign firms are typically attracted ceteris paribus to richer local markets because a more affluent customer base means greater potential demand for the firms' output. There are many potential economies arising from industry agglomeration: better infrastructure, better trained workers, a finer division of labor, the provision of more specialized support services and, in general, lower production costs. Furthermore, agglomerations of foreign investment lead to additional benefits such as the creation of expatriate networks with knowledge of the local institutional environment, easier recruitment of local managers who are familiar with the workings of international firms, and reduced liabilities of foreignness (Zaheer, 1995). Labor costs are clearly important, particularly for foreign firms looking to export labor-intensive goods. But so too is the quality of the human capital as this is a key determinant of productivity. Another factor that is generally considered important in attracting FDI is the quality of the transportation infrastructure, as this has a direct impact both on the costs of obtaining supplies of raw materials and intermediate goods, and on the costs of moving the final goods to market. In addition, several studies (*e.g.* Filatotchev, Strange, Piesse, & Lien, 2007; Strange, Filatotchev, Lien, & Piesse, 2009) have pointed to the influence of firm-specific characteristics such as firm size, industry and ownership structure.

The majority of these studies consider only a relatively small number of alternative locations and these locations generally cover large geographic areas, even in studies with a sub-national focus. For instance, those studies that focus on FDI within the United States generally use the state as the unit of analysis, while studies of FDI within Eastern and Western European countries and within China all use broad geographical regions such as provinces, with only a few studies (*e.g.* Head & Ries, 1996) focussing on cities.[1] Many of these provinces, particularly in large countries like the United States or China, are the size of nation-states in terms of population, geographic area and economic activity, and many exhibit substantial intra-province variability in location-specific attributes. For instance, labor costs vary widely within provinces, reflecting urban and rural employment opportunities, yet such differences are lost in the calculation of provincial means. Furthermore, provinces are administrative units and boundaries are often quite arbitrary, hence provincial data may or may not reflect the true nature of the underlying data generation process. Proximate cities in different provinces may have more interaction than distant regions within the same province. Many provinces contain several major urban conurbations, each of which may be considered as a separate location, and such cities often have considerable decision-making authority to attract FDI. Some cities within the same province may have better transport infrastructure (*e.g.* a major port) than others, and such cities will be relatively more attractive as a result. We would thus argue that the city is the most appropriate unit of analysis for studies of FDI location.

Of more importance, however, is the fact that almost all of the cited studies treat the alternative locations as distinct places, isolated in space, and implicitly assume that the distances between one location and another have no impact upon the likelihood of FDI location. Yet there are many reasons to suspect spatial dependence in FDI data, that is, where the value of FDI in one location depends in part upon the attributes of neighboring locations[2],[3]. This spatial dependence could be the result of positive spillover effects. For instance, agglomerations of FDI may lead to higher FDI levels in neighboring or proximate cities. Another cause of positive spatial dependence may be that FDI raises a city's resource costs (*e.g.* the average wage), and therefore makes neighboring cities relatively more desirable. Alternatively, there may be negative spatial dependence if FDI agglomerations deter FDI in proximate cities. Such spillover effects can be captured by incorporating a spatially lagged FDI variable among the regressors. Alternatively spatial

[1] We use provinces in the rest of the paper to refer to these broad geographical regions although clearly in some cases these are states, counties, etc.

[2] Strictly speaking, spatial dependence is a characteristic of the joint probability density function and, as such, it is only verifiable under simplifying conditions such as normality. Spatial autocorrelation is a moment of that joint distribution and it is usual to model this instead and to use the terms spatial dependence and spatial autocorrelation interchangeably. This practice is continued here.

[3] Tobler's first law is fundamental to such spatial analysis (Miller, 2004).

Table 1
Empirical studies of FDI location choice.

Nature of location choice	Country/regional context	Empirical studies
Between countries in a region	European Union	Scaperlanda and Balough (1983), Yamawaki (1991), Mayer and Mucchielli (1998), Ford and Strange (1999), and Crozet, Mayer, and Mucchielli (2004), Basile, Castellani and Zanfei (2008, 2009), Head and Mayer (2004)
	Eastern Europe	Lansbury, Pain, and Smidkova (1996), Holland and Pain (1998), Resmini (2000), Woodward, Rolfe, Guimarães, and Doupnik (2000), Campos and Kinoshita (2003), Bevan, Estrin, and Meyer (2004), Bevan and Estrin (2004), Disdier and Mayer (2004), Grosse and Trevino (2005), and Majocchi and Strange (2007)
	Caribbean Basin	Woodward and Rolfe (1992)
	Gulf Cooperation Council	Mina (2007)
Sub-national location	United States	Carlton (1983), Bartik (1985), Luger and Shetty (1985), Glickman and Woodward (1988), Coughlin, Terza, and Arromdee (1991), Friedman, Gerlowski, and Silberman (1992), Friedman, Fung, Gerlowski, and Silberman (1996), Woodward (1992), Head, Ries, and Swenson (1996), Head, Ries, and Swenson (1999), Shaver (1998), Shaver and Flyer (2000), Chung and Alcácer (2002a, 2002b), Bobonis and Shatz (2007), and Lee, Hwang, and Lee (2012)
	China	Head and Ries (1996), Chen (1997), Wei, Liu, Parker, and Vaidya (1999), Cheng and Kwan (2000), Coughlin and Segev (2000), Belderbos and Carree (2002), Sun, Tong, and Yu (2002), Zhou, Delios, and Yang (2002), He (2002, 2003), Chadee, Qiu, and Rose (2003), Ng and Tuan (2003), Chang and Park (2005), Fung, Garcia-Herrero, Iizaki, and Siu (2005), Wakasugi (2005), Cassidy and Andreosso-O'Callaghan (2006), Cheng and Stough (2006), Kang and Lee (2007), Amiti and Javorcik (2008), Du, Lu, & Tao (2008a, 2008b), and Hong (2009)
	France	Crozet et al. (2005)
	Germany	Spies (2010)
	Hungary	Boudier-Bensebaa (2005)
	India	Mukim and Nunnenkamp (2010)
	Ireland	Barrios, Gorg, and Strobl (2006)
	Italy	Mariotti and Piscitello (1995), Basile (2004), De Propris, Driffield, and Menghinello (2005), and Bronzini (2007)
	Mexico	Mollick, Ramos-Duran, and Silva-Ochia (2006), and Jordaan (2008)
	Poland	Cieslik (2005), Cieślik and Ryan (2005), Chidlow, Salciuviene, and Young (2008)
	Portugal	Guimarães, Figueiredo, and Woodward (2000)
	Romania	Hilber and Voicu (2010)
	Russia	Ledyaeva (2009)
	Turkey	Tatoglu and Glaister (1998)
	Vietnam	Meyer and Nguyen (2005)
Two-stage process	Asia-Pacific	Mataloni (2011)

dependence may be generated by the exclusion from the regression model of FDI determinants which are correlated across space. For example, in countries as large and diverse as China or the United States, physical geographical characteristics (*e.g.* mountain ranges and rivers) may affect the desirability of locating FDI in a particular city. These omitted geographically-correlated variables could be captured through a spatial error term.

The extant international business and management literature on FDI location determinants ignores these spatial dependence effects, with the result that the resulting parameter estimates and statistical inferences are questionable. Doh and Hahn (2008) surveyed 29 papers published in the *Strategic Management Journal* that explicitly addressed spatial or geographic issues, and found that none adopted a formal spatial analysis. There are a few relevant papers in the economics literature. Baltagi et al. (2003), Blonigen et al. (2007) and Hall and Petroulas (2008) all focused on the choice of FDI locations at the country level, and all found evidence of significant spatial dependence between proximate countries. A key step in estimating models with spatial dependence is the definition of the neighborhood structure: *i.e.* what locations can be considered neighbors and how strong is the relationship between them. These two critical factors are captured by a researcher-defined spatial weights matrix. All three studies used similar measures of geographical distance between the alternative host countries as the elements in the spatial weights matrix. Only two papers have considered the choice of FDI locations at the sub-national level. Coughlin and Segev (2000) estimated a model with spatially correlated errors (a spatial error model) using data on mean US FDI inflows to 29 Chinese provinces over the period 1990–1997. They used a very simple definition of neighbor, whether or not two provinces shared a common border (contiguity), and gave every neighbor equal weighting. They found evidence of weak though significant spatial dependence, suggesting that FDI in one province had positive effects on FDI in contiguous provinces. Ledyaeva (2009) looked at FDI location across 74 Russian regions, but found only weak evidence of spatial dependence despite trying two alternative specifications of the spatial weights matrix: the first based on a simple inverse distance function between the capital cities of the regions, while the second took account of the presence of a sea port in adjacent regions.

Building on this literature, this study draws upon economic geography (EG) and institutional theory to consider how neighboring locations may impact upon the FDI location choices of MNEs. As Beugelsdijk and Mudambi (2013: 413) argue 'international business (IB) research examining the spatial dimension has serious weaknesses, stemming from its traditional assumption of the country as the location unit of analysis.' Furthermore they (Beugelsdijk & Mudambi, 2013: 414) stress that 'incorporating spatial variation from EG into the modern theory of the MNE will bring us closer to . . . "a general theory of the enterprise in space". In our view, such a general theory centers on recognizing the distinction between *spatial heterogeneity in the subnational context* and spatial discontinuities that arise at national borders' [emphasis added]. Here we start from the premise that alternative subnational locations are not isolated in space, and that some locations are more proximate than others. As Tobler's law suggests, near locations will have more impact than distant ones. The issue then is to establish how to conceptualize and measure near and distant. Near and distant are relatively easy to define in geographical terms and, in the context of the FDI location decisions of profit-maximising MNEs, geographical distances may be interpreted as proxies for transport costs and/or travel time. All of the four studies cited above have used simple measures of geographic distance, either the distance between capital cities

(Baltagi et al., 2003; Blonigen et al., 2007; Hall & Petroulas, 2008; Ledyaeva, 2009) or a dummy variable to capture a common border (Coughlin & Segev, 2000). But institutional theory suggests that foreign firms may well consider near and distant in more nuanced terms, and that a variety of economic and political factors may also impact upon firms' perceptions of the distances between alternative locations – particularly in an emerging economy context. As Peng, Wang, and Jiang (2008: 923) suggest, "strategic choices are not only driven by industry conditions and firm capabilities, but are also a reflection of the formal and informal constraints of a particular institutional framework that managers confront." We thus wish to consider here alternative conceptions of distance and, drawing upon Ghemawat (2001), we suggest that the administrative and/or economic distances from neighboring locations may well affect the likelihood of FDI location. The Ghemawat (2001) framework includes cultural, administrative, geographic and economic measures of distance but here cultural distance is not appropriate as the Chinese population is largely ethnically and culturally homogeneous across prefecture-cities.

As noted above, the rationale for using a measure of *geographic distance* is that spatial dependence may depend upon transport costs and/or travel time. If the FDI is motivated by market-seeking considerations, then the nearby presence of urban concentrations of consumers will enhance the desirability of potential city locations, while more remote cities will be less desirable. Proximate cities should also enhance the availability and cost of skilled labor, facilitate knowledge spillovers and provide improved access to specialized inputs and services. Our first hypothesis is thus:

H1. The attractiveness of a particular sub-national location for inward FDI depends *inter alia* on the geographical distance between the location and alternative neighboring locations.

One possible measure of geographical distance is the great circle distance (d_{ij}) between cities.[4] The Haversine formula is used to calculate the great circle distance between two cities based upon their latitude and longitude. The great circle distance is preferred because it captures the effect of the spherical Earth on distance and is therefore preferred to the Euclidean (crow-flies) distance. A second simple measure is contiguity, in that the spillover effects between prefecture-cities that share a common border are likely to be larger than those between prefecture-cities that do not. Other alternative measures might reflect the shortest travel time between cities, or the availability of a direct air route – such measures might be more pertinent if natural features such as mountains and rivers impede direct communication.

The rationale for using a measure of *administrative distance* is that many of the effects cited above may be hindered or impeded by official regulations at the city and/or provincial level, and this is especially relevant to studies of China. For instance, labor mobility and access to state-sponsored benefits in China were for years restricted by the *hukou* system (Chan & Buckingham, 2008; Wang & Piesse, 2013). Furthermore, provincial protectionism has long been a feature of many former centrally-planned economies and even supposed free trade areas between developed economies. Such protectionism impedes the free flow of goods and services, acts as a barrier to the realization of the benefits from specialization and trade, and thus has an impact upon industrial location (Amiti & Javorcik, 2008; Bai, Du, Tao, & Tong, 2003; Bai, Tao, & Tong, 2008; Batisse & Poncet, 2004; Huang & Li, 2006; Lee, 1998). We thus expect administrative distance to be more important than geographic distance, and our second hypothesis is:

H2. The attractiveness of a particular sub-national location for inward FDI *depends inter alia* on the administrative distance between the location and alternative neighboring locations.

The operationalization of the administrative distance concept is not obvious. One possibility is to distinguish between cities that are in the same province and those that are not, with the spillover effects likely to be larger in the former than the latter irrespective of the geographical distance between them. An alternative possibility is to weight the geographical distances (d_{ij}) between cities by a measure of their relative bureaucratic burdens. The underlying theory is that cities with greater administrative autonomy from central government are more attractive to foreign investors than those under close control. A proxy for administrative autonomy is the level of expenditure on the "administrative" function at the city level; bigger expenditures indicate that cities have retained greater surpluses from their revenues and therefore have more autonomy. Administrative distance between cities therefore relates to the similarity or difference in the level of administrative autonomy between cities.

Economic distance may be a more important determinant of the spillover effects of FDI than simple geography. Large cities may be less remote than their geographical isolation implies, yet smaller cities or towns may be more insular and isolated. Fingleton and Le Gallo (2008) argue that, if prices are high in one large city, some demand tends to be displaced to a similar place (perhaps another remote city) rather than spill over to somewhere on the city periphery. Likewise displaced supply may not be totally constrained by spatial proximity, but be attracted to locations closer in terms of economic distance. Hence economic distance reflects the reduced transaction costs associated with flows between geographically remote cities, which have better communications infrastructure, lower costs of information gathering and uncertainty, and similar economic and employment structures. Thus we hypothesize that cities with similar levels of average income are more attractive than dissimilar cities at the same geographic distance. Firms undertaking FDI projects in their preferred locations will not only be cognizant of the proximity of neighboring cities, but also of their market characteristics. We thus hypothesize that firms will be drawn to locations in which the neighboring cities have similar levels of gross product per capita (Tsang & Yip, 2007). Firms engaging in market-seeking FDI will thus favor locations with similar, rather than richer, markets nearby, while firms investing for efficiency considerations will favor locations with similar low-cost cities nearby. We therefore expect economic distance to be more important than geographic distance (though it is not clear *a priori* whether or not it will be more or less important than administrative distance), and our third hypothesis is:

H3. The attractiveness of a particular sub-national location for inward FDI *depends inter alia* on the economic distance between the location and alternative neighboring locations.

Once again, we consider alternative specifications for the economic distance construct. The first simply focuses on the differences in gross product per capita, while the second weights these differences by the great circle distances (d_{ij}).

3. Data and methodology

In this section, we outline the basic characteristics of the data, describe how the variables have been measured, explain the methodology for the estimation of the spatial panel model, and

[4] The Haversine formula is used to calculate the great circle distance between two cities based upon their latitude and longitude. The great circle distance is preferred because it captures the effect of the spherical Earth on distance and is therefore preferred to the Euclidean (crow-flies) distance.

Table 2
Prefecture-cities in China by province.

Province	Prefecture-cities
Anhwei	Anqing, Bengbu, Bozhou, Chaohu, Chizhou, Chuzhou, Fuyang, Hefei, Huaibei, Huainan, Huangshan, Liuan, Maanshan, Suzhou, Tongling, Wuhu, Xuancheng
Fujian	Fuzhou, Longyan, Nanping, Ningde, Putian, Quanzhou, Sanming, Xiamen, Zhangzhou
Gansu	Baiyin, Dingxi, Jiayuguan, Jinchang, Jiuquan, Lanzhou, Longnan, Pingliang, Qingyang, Tianshui, Wuwei, Zhangye
Guangdong	Chaozhou, Dongguan, Foshan, Guangzhou, Heyuan, Huizhou, Jiangmen, Jieyang, Maoming, Meizhou, Qingyuan, Shantou, Shanwei, Shaoguan, Shenzhen, Yangjiang, Yunfu, Zhanjiang, Zhaoqing, Zhongshan, Zhuhai
Guangxi	Baise, Beihai, Chongzuo, Fangchenggang, Guigang, Guilin, Hechi, Hezhou, Laibin, Liuzhou, Nanning, Qinzhou, Wuzhou, Yulin
Guizhou	Anshun, Guiyang, Liupanshui, Zunyi
Hainan	Haikou, Sanya
Hebei	Baoding, Cangzhou, Chengde, Handan, Hengshui, Langfang, Qinhuangdao, Shijiazhuang, Tangshan, Xingtai, Zhangjiakou
Heilongjiang	Daqing, Harbin, Hegang, Heihe, Jiamusi, Jixi, Mudanjiang, Qiqihar, Qitaihe, Shuangyashan, Suihua, Yichun
Henan	Anyang, Hebi, Jiaozuo, Kaifeng, Luohe, Luoyang, Nanyang, Pingdingshan, Puyang, Sanmenxia, Shangqiu, Xinxiang, Xinyang, Xuchang, Zhengzhou, Zhoukou, Zhumadian
Hubei	Ezhou, Huanggang, Huangshi, Jingmen, Jingzhou, Shiyan, Suizhou, Wuhan, Xiangfan, Xianning, Xiaogan Yichang
Hunan	Changde, Changsha, Chenzhou, Hengyang, Huaihua, Loudi, Shaoyang, Xiangtan, Yiyang, Yongzhou, Yueyang, Zhangjiajie, Zhuzhou
Inner Mongolia	Baotou, Bayannaoer, Chifeng, Erdos, Hohhot, Hulunbeier, Tongliao, Wuhai, Wulanchabu
Jiangsu	Changzhou, Huaian, Lianyungang, Nanjing, Nantong, Suqian, Suzhou, Taizhou1, Wuxi, Xuzhou, Yancheng, Yangzhou, Zhenjiang
Jiangxi	Fuzhou, Ganzhou, Jian, Jingdezhen, Jiujiang, Nanchang, Pingxiang, Shangrao, Xinyu, Yichun, Yingtan
Jilin	Baicheng, Baishan, Changchun, Jilin, Liaoyuan, Siping, Songyuan, Tonghua
Liaoning	Anshan, Benxi, Chaoyang, Dalian, Dandong, Fushun, Fuxin, Huludao, Jinzhou, Liaoyang, Panjin, Shenyang, Tieling, Yingkou
Ningxia	Guyuan, Shizuishan, Wuzhong, Yinchuan, Zhongwei
Qinghai	Xining
Shaanxi	Ankang, Baoji, Hanzhong, Shangluo, Tongchuan, Weinan, Xian, Xianyang, Yanan, Yulin
Shandong	Binzhou, Dezhou, Dongying, Heze, Jinan, Jining, Laiwu, Liaocheng, Linyi, Qingdao, Rizhao, Taian, Weifang, Weihai, Yantai, Zaozhuang, Zibo
Shanxi	Changzhi, Datong, Jincheng, Jinzhong, Linfen, Luliang, Shuozhou, Taiyuan, Xinzhou, Yangquan, Yuncheng
Sichuan	Bazhong, Chengdu, Dazhou, Deyang, Guangan, Guangyuan, Leshan, Luzhou, Meishan, Mianyang, Nanchong, Neijiang, Panzhihua, Suining, Yaan, Yibin, Zigong, Ziyang
Xinjiang	Karamay, Urumqi
Yunnan	Baoshan, Kunming, Lijiang, Linzang, Qujing, Simao, Yuxi, Zhaotong
Zhejiang	Hangzhou, Huzhou, Jiaxing, Jinhua, Lishui, Ningbo, Quzhou, Shaoxing, Taizhou, Wenzhou, Zhoushan
Plus: Beijing, Chongqing, Shanghai and Tianjin	

Notes: (1) Province is used to describe the 22 provinces, 4 autonomous regions (excluding Tibet), and four municipalities.

consider alternative specifications for the elements to be used in the spatial weights matrix.

3.1. The sample

The People's Republic of China (PRC) is the empirical setting for this study. China is an appropriate context for several reasons. First, China covers a huge geographical area and has substantial regional variations with respect to economic activity, income distribution, industry concentration, infrastructure, political autonomy and engagement in foreign trade and investment. Second, China has been a major recipient of FDI inflows for many years and the FDI is spread over many locations. Third, the data on FDI inflows into China are available at the highly disaggregated prefecture-city level, and it is likely that the spatial effects will be more apparent than at lower levels of disaggregation. China is composed of thirty three provincial-level administrative units: 22 provinces (Anwei, Fujian, Gansu, Guangdong, Guizhou, Hainan, Hebei, Heilongjiang, Henan, Hubei, Hunan, Jiangsu, Jiangxi, Jilin, Liaoning, Qinghai, Shaanxi, Shandong, Shanxi, Sichuan, Yunnan, Zhejiang); five autonomous regions (Guangxi Huang, Inner Mongolia, Ningxia, Tibet, Xinjiang); four large municipalities (Beijing, Chongqing, Shanghai and Tianjin); and two special regions (Hong Kong and Macau). In principle, the provinces[5] are subservient to the PRC central government but, in practice, provincial officials have considerable discretion with regard to policy. We omit three of these administrative units; Hong Kong and Macau because of their special circumstances and Tibet because of a lack of data. The thirty remaining units contain 268 prefecture-cities, and these constitute the individual locations in this study – see Table 2. The prefecture-cities form the second level of the administrative structure, ranking below the provinces. Such prefecture-cities typically comprise both a main urban area and a surrounding rural area, plus smaller towns and villages. Most of these cities are in the eastern and southern parts of the country.

The data are sourced from the Chinese National Bureau of Statistics.[6] We have no way of independently checking the reliability of this data, but there seems to be no reason to believe that there is any particular bias across the prefecture-cities. FDI data for each of these 268 cities are available for the period from 1996 to 2008, but some data for the explanatory variables are missing for some cities and this has reduced the size of the sample. The estimation of the spatial panel model requires a balanced panel, hence we have had to weigh up the relative merits of using a bigger cross-section over fewer years against a smaller cross-section over more years. Given that the focus of the paper is on the distance between cities, we chose to sacrifice the time dimension to increase the number of cities in the cross-section. The final dataset is thus a panel of four years (2004–2007) for 224 cities.

The 44 prefecture-cities excluded from the dataset share very similar characteristics on average to the 214 cities that are included, hence we are confident that their omission will not have biased our empirical results. For instance, the average values of the dependent variable (FDI/GDP) are 0.0226 for the 44 excluded cities and 0.0241 for the 214 included cities. The average values of all the explanatory variables are also similar across the two sub-samples.

3.2. The development of FDI in china

China has become the first emerging market with annual FDI inflows of more than USD100 billion. Inward FDI is the main source of foreign capital in China and is mostly concentrated on manufacturing. Sixty percent of China's inbound FDI originates,

[5] We use the term province for each of the 33 provinces, municipalities, and autonomous regions.

[6] The data were downloaded from www.ceicdata.com in January 2010.

at least nominally, from Taiwan, Hong Kong, South Korea and tax havens such as the Cayman Islands, while the combined share of US, EU and Japanese investment is 25% (whereas US, EU and Japanese FDI accounts for 92% of total worldwide FDI flows). The amount of FDI in the Chinese economy has declined from 6% of gross domestic product (GDP) in the mid 1990s to about 3% in 2010, as the share of domestic investment in GDP has increased.

Until relatively recently, FDI in China was almost entirely driven by export processing; that is importing parts into China and then re-exporting the assembled products. Prompted by Hong Kong firms looking for low-cost labor, officials in the province of Guangdong were already lobbying the central government for the creation of special economic zones (SEZs) to attract FDI in the late 1970s. In the early 1980s, two SEZs were created in the city of Xiamen, the capital prefecture of the province of Fujian, which faces Taipei across the Taiwan Straits, and in Guangdong within easy reach of Hong Kong. The central government legalized export processing, which was the objective of the city officials and the Taiwanese and Hong Kong firms, and the SEZs were established to serve as an experiment to open the Chinese economy to FDI. While SEZs had a slow start because of the cost of building the required infrastructure and several cases of corruption, FDI quickly leaked out of the designated zones as cities and villages competed to attract investment and jobs. In 1984, 14 new Economic and Technological Development Zones were created in coastal cities, and within a few years most of the Chinese coast line was accessible to FDI (Naughton, 2007). In 1992, the first High-Tech Development Zone in Shanghai Pudong also marked the opening of new sectors to FDI beyond merely export processing. In particular, the possibility to invest in land use rights and real estate attracted large inflows of capital from Hong Kong and beyond. By 2003, there were more than 100 national level economic development zones (EDZs) that benefitted from the direct support of the central government, and hundreds of other EDZs at the provincial, prefecture and county level, all with the sole purpose of attracting FDI.

The combination of central government policy to develop the coastal areas and their cities with the objective of re-exporting the output of foreign-invested firms partly explains why most FDI has taken place in areas with direct access to the sea. Prefectures and provinces compete intensely to develop the infrastructure necessary to attract this investment. In 2008, for example, the city of Shanghai finished building the first phase of an artificial deep-water port (Yangshan), while similar infrastructure is already offered in two neighboring provinces: Ningbo (Zhejiang province, South of Shanghai) and Nanjing (Jiangsu province, North of Shanghai). But FDI has also been spreading to neighboring provinces and cities: wage increases due to competition for local labor have pushed the low added-value, high labor-intensive FDI further inland. Moreover, in recent years the central government has encouraged the development of the country's more underdeveloped regions with its 'Go West' policy (2000–2010) and this has created opportunities for FDI aimed at serving China's internal market, especially for consumer products. Thus the pattern of inbound FDI in China has been heavily influenced by the reform policy and the decision to open export-driven sectors first in certain coastal cities. Fig. 1 depicts the geographical distribution of FDI across the 268 prefecture-cities in 2007.

3.3. The dependent and explanatory variables

Two quite different approaches are commonly used in the literature to model FDI location choice. One approach uses data on individual FDI projects, and uses a discrete choice modeling technique such as conditional, multinomial or nested logit with the sample size equal to the number of projects. The rationale for this is that FDI projects are the result of firms' strategic decisions, and hence the focus is on the decision-making processes of the individual firms. Such discrete choice models allow for potential interdependencies between locations, but impose major restrictions on the data (*e.g.* the assumption of the independence of

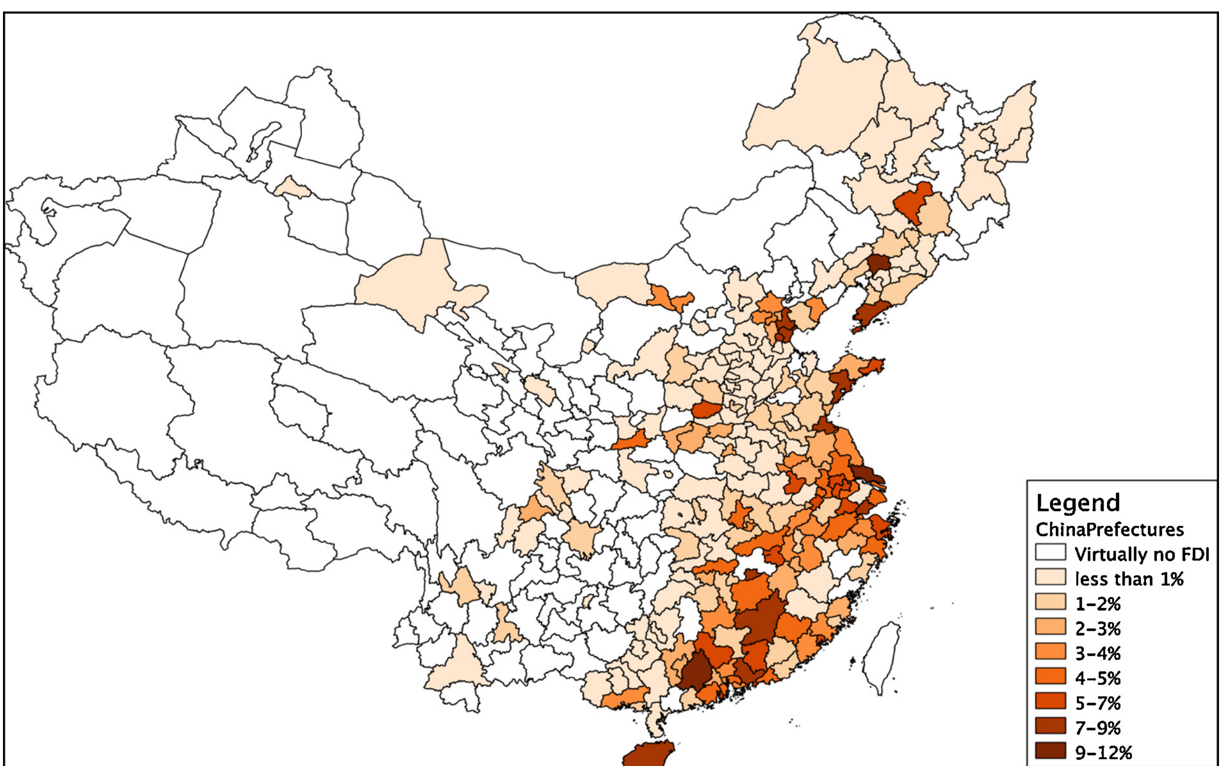

Fig. 1. The distribution of FDI across prefecture-cities in China, 2007.

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irrelevant alternatives). A further disadvantage is that every project, regardless of size, is given equal weighting. The alternative approach uses an aggregate measure of FDI (annual flows or stocks) as the dependent variable – the sample size is then equal to the number of alternative locations considered multiplied by the number of years under consideration. An advantage of this approach is that the data reflect the totality of the FDI in the alternative locations rather than the number of projects. Here we follow the second approach and use the annual inflow of FDI in each of the prefecture-cities as the dependent variable (FDI). Real, gross FDI flows are expressed as a percentage of GDP to avoid bias due to differences in scale across the prefecture-cities and thus heteroskedastic errors.

We expect several explanatory variables to have a positive impact upon the inflows of FDI: the attractiveness of the local market (MKT), as measured by GDP per capita; agglomeration economies, as measured by the industrial output of foreign-invested enterprises as a percentage of total industrial output (AGG); the quality of human capital, as measured by government expenditure on science (HUM); the transportation infrastructure, as proxied by the shortest distance to the coast (COAST); and the extent of trade openness, as measured by exports (OPEN). In contrast, labor costs, as measured by the mean wage level (WAGE) are expected to have a negative impact upon FDI inflows. We also include two further variables that we believe may be important in the Chinese context. The government still plays a substantial and influential role in many areas of the Chinese economy, and accounts for a major proportion of aggregate demand. Hence we include government spending, as measured by the proportion of total government revenue as a share of GDP (GOVT), and expect this to have a positive impact upon FDI inflows. Second, as noted above, the prefecture-cities typically encompass both urban and rural populations, and it is the former that will be most attractive to foreign investors. We thus include the proportion of the population in the rural areas (RURAL), and expect this to have a negative impact upon FDI inflows. See Table 3 for detailed definitions of the explanatory variables.

We have checked for potential multicollinearity problems by computing the Variance Inflation Factors (VIF) for each of the explanatory variables in the regression model. These were all well below the commonly used critical value of five, *viz.*: MKT (3.91), AGG (1.63), HUM (1.57), COAST (1.21), OPEN (1.78), GOVT (1.84), WAGE (3.59), and RURAL (1.49). We thus do not anticipate any multicollinearity issues.

Table 3
Variable definitions.

Variable	Variable definition	Expected sign
Dependent variable		
FDI	Annual FDI inflow as % of GDP	
Explanatory variables		
MKT	ln (GDP per capita) (2008 RMB)	+
AGG	Industrial output from foreign-invested enterprises as % of total industrial output	+
HUM	ln (government expenditure on science) (2008 RMB millions)	+
COAST	ln (shortest distance from city to the nearest coast) (m)	–
OPEN	ln (exports) (2008 USD millions)	+
WAGE	ln (mean wage) (2008 RMB)	–
GOVT	Government revenue as % of GDP	+
RURAL	The % of the city population that lives in rural areas	–
Measures of distance		
G1	The squared inverse of the great circle distances (km) between the cities	
G2	=1 if two cities share a border; =0 otherwise	
E1	The inverse of the squared difference in GDP per capita between the cities	
E2	The squared differences in GDP per capita weighted by the squared inverse of the great circle distances between the cities	
A1	=1 if two cities are in the same province; =0 otherwise	
A2	The squared difference in government spending on city administration weighted by the squared inverse of the great circle distances between cities in the same province	

3.4. Methodology

We initially estimated the following non-spatial model of FDI location in city i at time t (a) using OLS and a pooled dataset, (b) a fixed effects panel model, and (c) a random effects panel model:

$$\begin{aligned}\mathrm{FDI}_{it} = {} & \beta_1 + \beta_2\mathrm{MKT}_{it} + \beta_3\mathrm{AGG}_{it} + \beta_4\mathrm{HUM}_{it} + \beta_5\mathrm{COAST}_{it} \\ & + \beta_6\mathrm{OPEN}_{it} + \beta_7\mathrm{WAGE}_{it} + \beta_8\mathrm{GOVT}_{it} + \beta_9\mathrm{RURAL}_{it} \\ & + u_{it}\end{aligned} \tag{1}$$

However, as discussed in the literature review, there are many reasons to suspect spatial dependence in FDI location data. Spatial dependence may take several forms (see Appendix A for a more detailed discussion), and we only provide a brief explanation here. The random effects (or fixed effects) panel model is extended by the introduction of the user-defined spatial weights matrix (W) composed of elements (w_{ij}) linking city i and city j. The matrix has as many rows and columns as there are cities in the dataset, and the elements reflect the strength of the dependence between the cities. Spatial dependence may be captured by incorporating a spatially lagged (*i.e.* autoregressive) dependent variable (SAR), a spatially correlated error term (SEM), or both (SEM-SAR). The spatial autoregressive parameter (ρ) in the SAR model captures the strength of the effect of neighboring cities' FDI on the FDI of city i. Spatial autocorrelation in the SEM model is captured by the spatially-correlated error term (λ), the value of which highlights possible measurement errors when the units of analysis (cities) do not reflect the underlying data generation process. An additional level of flexibility can be achieved by allowing for serial correlation in the time-series errors. This is possible by simply including a serial correlation parameter (φ). There are thus a variety of potential spatial regression models as summarized in Table 4. The most general model (SEM-SAR-SR) includes a spatially lagged dependent variable, and a spatially correlated error term which allows for the possibility of serial correlation. The other spatial models – *i.e.* the spatial lag model (SAR), the spatial error model (SEM), and the combination model (SEM-SAR) – are restricted versions nested within the general model. Both the standard random effects model and the pooled OLS model are also restricted versions of the general model.

3.5. Measures of distance

At the center of all spatial regression models is the spatial weights matrix (W), where the elements (w_{ij}) are user-defined to reflect the assumed nature of the spatial relationship between the cities. In this paper, we are interested in exploring the effects of modeling alternative measures of distance.

As noted above, most prior studies have focused on *geographic distance*, and we estimate the model using two alternative

Table 4
Comparison of the spatial models.

	$\lambda \neq 0, \rho \neq 0$	$\lambda \neq 0, \rho = 0$	$\lambda = 0, \rho \neq 0$	$\lambda = 0, \rho = 0$
$\varphi \neq 0$	SEM-SAR-SR	SEM-SR	SAR-RE	Random effects
$\varphi = 0$	SEM-SAR	SEM	SAR	OLS

specifications – see Appendix A for more detailed definitions. In the first specification (G1), the elements of the matrix W are initially defined by the great circle distance in kilometers (d_{ij}) between cities i and j. The second specification (G2) uses contiguity as the measure of geographical distance, hence the distance is zero if two prefecture-cities share a common border but one otherwise. The first specification of *economic distance* (E1) uses the inverse of the (squared) differences in GDP per capita as the basis for the spatial weights matrix. The second (E2) weights these (squared) differences in GDP per capita by the inverse of the great circle distances (d_{ij}). We also put forward two alternative specifications to capture the effects of *administrative distance*. The first specification (A1) distinguishes between cities that are in the same province and those that are not, and defines the spatial weights matrix accordingly. The second specification (A2) hypothesizes that cities with similar administrative sizes are more attractive than dissimilar cities at the same geographic distance. We thus base the spatial weights matrix on the inverse of the (squared) differences in government spending on city administration. Alternative measures of administrative distance could use some measure of market, trade, or financial liberalization.

To summarize, we consider three alternative forms of the spatial weights matrix (W) where the elements (w_{ij}) are defined in terms of *geographic distance*, *economic distance*, or *administrative distance*. Furthermore, we estimate two alternative specifications of the model using each of these different dimensions of distance. In two of the specifications (G1 and E2), the inverse-squared great circle distance is used to capture the decaying effect of distance (cities further and further away have less and less effect on each other).

4. Empirical results and discussion

Our starting point was a consideration of 'non-spatial' pooled, fixed and random effects models. We estimated OLS regressions using the pooled sample, a balanced fixed effects panel, and a balanced random effects panel.[7] Unsurprisingly given that there are only four years of data but 224 cities, the fixed effect model performed poorly with very low explanatory power ($\bar{R}^2 = 0.129$). In comparison, the pooled model had much higher explanatory power ($\bar{R}^2 = 0.473$) and more variables were significant predictors. The random effects model also fitted the data well ($\bar{R}^2 = 0.441$) with all of the variables statistically significant. Moreover, the Honda (1985) test rejects the pooled model ($p < 0.001$) and, given that the sample comprises a subset of China's prefecture-cities, the random effects specification is preferable theoretically to the fixed effects specification – this is also supported by the Hausman test ($p = 0.997$) which shows that the random effects results are not only more efficient but are also consistent. At this point, traditional (non-spatial) studies would stop and interpret the regression coefficients in the light of their theory.

However, as outlined in the previous sections, there are a number of reasons to suspect the presence of spatial dependence in models of FDI, especially at the city-level. Previous studies, most notably Coughlin and Segev (2000), found evidence of mild positive spatial autoregression in the disturbances ($\lambda = 0.12$), which they attributed to an omitted spatially varying regressor. There are a number of ways to detect spatial dependence in the regression analyses, and the most common test is Moran's I-statistic. The values of Moran's I-statistic for 2004–2007 are 0.310, 0.293, 0.286 and 0.242 respectively and all have p-values smaller than 0.001. These figures demonstrate consistent evidence of positive spatial dependence at a high level of statistical significance. The pattern is broadly similar for all four years. In addition, Fig. 1 shows a clear pattern of positive spatial autocorrelation with cities with high (low) levels of FDI/GDP being clustered together. While this points toward spatial dependence it is not clear whether there is a spillover effect from the dependent variable or just spatial correlation in the disturbances.

Given the likely presence of spatial dependence, four spatial panel regression models were run: a spatial error model (SEM), a spatial autoregressive model with spatially lagged dependent variable (SAR), a model with both a spatially lagged dependent variable and spatially correlated errors (SEM-SAR), and a SEM-SAR model allowing for serial correlation (SEM-SAR-SR). These are reported as models 1–4 in Table 5. Each of these models used a random effects specification as this was indicated by the non-spatial panel results. In these initial spatial regression models, neighboring cities are defined using geographical proximity as measured by the great circle distance between them and this is weighted using the inverse-square formula to capture distance decay.

As discussed above, R^2 measures of fit are not applicable to spatial dependence models (see Anselin, 1988) but the AIC and associated statistics are reported in Table 5. All four spatial random effects models are supported over the non-spatial random effects model by likelihood-ratio tests ($p < 0.01$) – hypothesis H1 is thus supported.

The spatial error model (Model 1) is clearly the best of the four spatial specifications, with a relative likelihood (Akaike weight) of 99.8%. Our preference for the SEM model is further supported by an examination of the regression coefficients in Table 5. The coefficients are largely stable across all specifications, indicating that there is no omitted variable bias caused by the exclusion of the spatially lagged dependent variable under the SEM specification (Model 1). The coefficient of the labor costs variable (WAGE) becomes larger and statistically significant in Models 2–4, indicating there may be a slight correlation between high wages in neighboring cities and high values of FDI. The spatial autocorrelation coefficient (λ) in Model 1 is strong (0.414). Coughlin and Segev (2000) also found evidence in favor of the SEM model, but their spatial autocorrelation coefficient was smaller (0.12). They had a small dataset comprised of a cross-section of 29 provinces, and it is likely that the spatial spillover effects are stronger at prefecture-city level than across (geographically) large provinces, providing support for the higher level of disaggregation used here.

One unusual and potentially interesting result is the relationship between the spatial lag and spatial error terms. When both coefficients are estimated (Model 3) the spatial autocorrelation coefficient (λ) becomes negative (-0.299) while the spatial autoregressive coefficient (ρ) remains positive but becomes stronger than in Model 2 when it is estimated in isolation. This suggests that the spatial autoregressive parameter coefficient (λ) is capturing the effect of an omitted spatially correlated variable which appears to be negatively correlated with the lagged value of the dependent variable (FDI). Furthermore, this variable appears to be correlated geographically because the effect disappears in later models that use alternative spatial weights matrices. Of all the models reported in Table 4, Model 3 (allowing for serial correlation in the errors) is least supported by the AIC.

Having selected the spatial error model (SEM) as the preferred model to describe the spatial relationships present in the FDI data, alternative definitions of distance were considered by running the SEM model using the six alternative specifications of (geographic, economic and administrative) distance. The results for the alternative specifications are presented as Models 1 and 5–9 in Table 6.

[7] We have not included these regression results in the paper, but the results are available on request from the authors.

Table 5
Regression results with allowance for spatial dependence.

Variable	Model 1	Model 2	Model 3	Model 4
	SEM	SAR	SEM-SAR	SEM-SAR-SR
Constant	+0.036 (0.025)	+0.043** (0.022)	+0.038** (0.019)	+0.021 (0.018)
MKT	+0.006** (0.003)	+0.006** (0.003)	+0.006** (0.003)	+0.006*** (0.002)
AGG	+0.014*** (0.004)	+0.014*** (0.004)	+0.013*** (0.004)	+0.008** (0.003)
HUM	+0.031*** (0.010)	+0.024*** (0.009)	+0.019** (0.009)	+0.003*** (0.001)
COAST	−0.003*** (0.001)	−0.002* (0.001)	−0.001 (0.001)	−0.001 (0.001)
OPEN	+0.002** (0.000)	+0.002** (0.001)	+0.002** (0.001)	+0.001** (0.000)
WAGE	−0.005 (0.004)	−0.008** (0.003)	−0.009*** (0.003)	−0.008** (0.003)
GOVT	+0.108*** (0.039)	+0.097** (0.038)	+0.086** (0.037)	+0.086** (0.034)
RURAL	−0.011* (0.006)	−0.012** (0.005)	−0.013** (0.005)	−0.007* (0.004)
P		0.378*** (0.053)	0.552*** (0.084)	0.674*** (0.059)
Λ	0.414*** (0.070)		−0.299** (0.135)	−0.492*** (0.009)
φ				0.810*** (0.074)
AIC	5155.88	5168.66	5174.38	5339.86
Delta AIC	0.000	12.780	18.500	183.980
Akaike weights	0.998	0.002	0.000	0.000

Notes: (1) Geographic distances (based on the inverse squared great circle distances) were used to specify the spatial weights matrices for models 1–4. (2) The dataset consisted of four years' data (2004–2007) for 224 prefecture-cities. (3) All four models are estimated using a random effects specification.
*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.

The coefficient estimates for the explanatory variables are very similar across the six different specifications, and close to the results for the non-spatial random effects model indicating a lack of omitted variable bias in the original specifications. Local market attractiveness (MKT), aggregation economies (AGG), human capital (HUM), trade openness (OPEN), and government spending (GOVT) generally show significant positive effects upon FDI location, while the distance from the coast (COAST) and the percentage population in rural areas both show significant negative effects. The coefficients of the labor cost variable are sometimes weakly significant but often not, though the coefficient always carries the expected negative sign. However, while these findings imply that the original (non-spatial) specifications were simply inefficient rather than biased and inconsistent, the findings of the spatial models themselves are both empirically and theoretically interesting.

Model 1 uses the G1 specification of the spatial weights matrix: *i.e.* it focuses on geographic distance, and assumes that the spatial dependence may be captured by using weights linked to the great circle distances between cities. The log-likelihood for this model is −2566.94, while the spatial error term (λ) takes the value of 0.414 and is highly significant. In contrast, the alternative G2 specification of geographic distance (Model 5) based on contiguity has a significantly lower log-likelihood (−2589.50) and a correspondingly higher AIC statistic. The next two models (Models 6 and 7) consider the effects of economic distance. Both show significantly improved fit compared to Model 1, with the reported log-likelihoods equal to −2554.91 (LR = 24.06; $p < 0.01$) for the E1 specification, and −2554.73 (LR = 24.24; $p < 0.01$) for the E2 specification respectively – hypothesis H3 is thus strongly supported. The spatial error terms are much smaller that for the G1/G2 specifications, but are still statistically significant. The final two models (Models 8 and 9) both focus on administrative distance. The spatial weights matrix based on provincial membership (A1) has the poorest fit (log-likelihood = −2575.78) of the six alternative specifications. However, the alternative specification based upon the cities' administrative budgets (A2) performs significantly better than Model 1 (LR = 13.70; $p < 0.01$) – hypothesis H2 is thus weakly supported.

The 'best' model is thus Model 7, using spatial weights (specification E2) based upon the (squared) differences in GDP per capita divided by the great circle distances (d_{ij}). It has a relative likelihood of 0.544 given the data and other models. However, the

Table 6
Regression results using alternative spatial weights.

Variable	Model 1	Model 5	Model 6	Model 7	Model 8	Model 9
	Geographic distance		Economic distance		Administrative distance	
Spatial weights	G1	G2	E1	E2	A1	A2
Constant	+0.036 (0.029)	+0.040 (0.028)	+0.066*** (0.024)	+0.008 (0.026)	+0.036 (0.029)	+0.008 (0.026)
MKT	+0.006** (0.003)	+0.007*** (0.003)	+0.007** (0.003)	+0.006** (0.003)	+0.006** (0.003)	+0.006** (0.003)
AGG	+0.014*** (0.004)	+0.016*** (0.004)	+0.015*** (0.005)	+0.014*** (0.005)	+0.015*** (0.004)	+0.015*** (0.005)
HUM	+0.031*** (0.010)	+0.031*** (0.009)	+0.027*** (0.010)	+0.028*** (0.010)	+0.036*** (0.010)	+0.028*** (0.010)
COAST	−0.003*** (0.001)	−0.003*** (0.001)	−0.003*** (0.001)	−0.003*** (0.001)	−0.003*** (0.001)	−0.003*** (0.001)
OPEN	+0.002** (0.000)	+0.002*** (0.000)	+0.002** (0.000)	0.002** (0.000)	+0.002** (0.000)	+0.002** (0.000)
WAGE	−0.005 (0.004)	−0.007* (0.004)	−0.008** (0.001)	−0.002 (0.004)	−0.005 (0.004)	−0.002 (0.004)
GOVT	+0.108*** (0.039)	+0.110*** (0.037)	+0.091** (0.040)	+0.080** (0.039)	+0.111*** (0.038)	+0.008** (0.039)
RURAL	−0.011*** (0.006)	−0.006 (0.006)	−0.014** (0.006)	−0.012** (0.006)	−0.008 (0.006)	−0.012** (0.006)
λ	0.414*** (0.070)	0.397*** (0.043)	0.111*** (0.037)	0.227*** (0.091)	0.434*** (0.052)	0.522*** (0.113)
AIC	5155.88	5201.01	5131.82	5131.45	5173.57	5173.17
Delta AIC	24.426	69.552	0.366	0.000	10.718	42.112
Akaike weights	0.000	0.000	0.453	0.544	0.003	0.000

Notes: (1) The dataset consisted of four years' data (2004–2007) for 224 prefecture-cities.
*** Significance at the 1% level.
** Significance at the 5% level.
* Significance at the 10% level.

other measure of economic distance (specification E1) based upon the inverse (squared) difference in GDP per capita performs almost as well with an AIC within 0.4 of the best model and an associated relative likelihood of 0.453. Statistically speaking these two models are indistinguishable.

The implication is clear. Cities that are economically similar may generate spatial autocorrelation in the data by capturing the effect of omitted variables which correlate with economic distance. For instance, GDP per capita may capture the effects of human capital or city-level infrastructure development, while total product may be capturing market size. In the economic specifications, firms move not to neighboring geographic cities when priced out of their preferred cities but to cities which are economically close to the original. This model of distance using economic measures may help to explain why countries often exhibit clusters of development. Investment clusters in a particular city or area are followed by spillovers to surrounding cities or areas, but there are often several of these clusters in a country each of which will be economically similar. Thus it may be the case that both geographic and economic distance helps explain the patchwork of investment across countries. All the explanatory variables have the expected signs and are statistically significant at the 5% level or better, with the exception of the labor cost variable which is statistically insignificant. This may also help to explain the observed negative correlation between the spatial error term and the spatially lagged dependent variable. There appears to be a complex relationship between human capital, wages and investment decisions which is generating positive spillovers. This is certainly an area for future research.

Two important conclusions emerge from these regression results. The first is that a consideration of the spatial dependence relationships is essential to a full understanding of the determinants of the FDI location decision, and that the explicit modeling of these relationships adds significantly to the explanatory power of the regression model. The second is that the nature of these relationships appears to depend more upon the *economic* (and to a lesser extent the *administrative*) distances between the prefecture-cities than on the simple notions of *geographic* distance that have been used in most of the limited number of prior empirical spatial studies.

A possible explanation for the positive spatial effect when we use weights reflecting administrative distance is that our measure of administrative distance relies upon economic data: *i.e.* the revenues and expenditures of city governments. Larger cities (by total product) will generally spend more on administration and if this proportion if constant across city size then our administrative measure will mimic the underlying economic circumstances of the cities. An improved measure may be the proportion of government revenue spent on administration rather than the absolute value. This is an area for further research. Other areas for further research include expanding the econometric 'toolbox' to include measures of cultural distance. Using data on Chinese cities makes this difficult as there is a high degree of cultural homogeneity as it is commonly defined by nationality, ethnicity or language.

5. Conclusions

This paper has made both a theoretical and an empirical contribution to the IB literature. Our theoretical contribution has been to stress that the attractiveness of a particular location to foreign investors depends not only upon the attributes of the location but also upon the location's proximity to alternative FDI locations. We have addressed the question of how firms define *near* and *distant*, provided rationales for how and why alternative concepts of distance might impact upon firms' FDI decisions, and explicitly modeled different measures of geographic, economic and administrative distance. Furthermore, we have emphasized that the 'non-spatial' models of FDI location used in much of the extant literature are likely to suffer from biased parameter estimates. Empirically we have illustrated the use of a number of spatial regression models with a new dataset on FDI in Chinese prefecture-cities, and have shown, in this context, that geographic distance is not the 'best' measure of distance to use. We find clear evidence of spatial dependence between the cities based upon economic distance, with weaker evidence related to administrative distance: cities that are economically and administratively close are likely to experience positive FDI spillovers from their neighbors. Furthermore, most studies on the determinants of sub-national FDI location are at a high level of aggregation, either by country or region or, in the case of China, by province. City-level data allow a more focused examination on FDI flows and are more useful for directing policy.

The policy implications of our study are twofold. First, we have confirmed the findings of the previous literature that foreign firms, when considering the sub-national location of their investments within a host country, are influenced positively by factors such as local market attractiveness, aggregation economies, human capital, trade openness, and government spending, and negatively by the distance from the coast, the percentage population in rural areas, and (weakly) by labor costs. City governments intent on attracting inward FDI might therefore consider additional expenditure on demand management (to increase market attractiveness), education and training (to improve human capital), industrial subsidies (to attract investment and generate agglomeration economies), trade liberalization, and the promotion of intra-prefecture migration to the urban areas – while giving due consideration to whether or not the likely benefits of such policies outweigh the costs incurred.

The second implication, and the distinctive contribution of this paper, is to emphasize that such expenditure is more likely to attract FDI if the prefecture-city is economically (and administratively) close to alternative city locations. As we noted in the Introduction, the extant literature on FDI location choice (with very few exceptions) treats alternative locations as distinct places, isolated in space, and ignores the spatial configuration of the possible locations for the investment. Furthermore the few exceptions only consider the geographical distances between the alternative locations, whereas we demonstrate that economic and administrative distances are more important. We argue that the proximity of similar investment locations enhances the attractiveness of any particular location, while previous empirical studies have failed to take this into account. Thus any city-level expenditure on improving the 'FDI attractors' may fail to yield additional FDI inflows if the prefecture-city is economically distant from other city locations.

The study inevitably has limitations. First, we would have liked to have obtained data on the explanatory variables for all 268 prefecture-cities for the thirteen-year (1996–2008) period for which FDI data were available. Future studies should try to validate our findings not only using longer datasets but also including up-to-date figures so that the effects of recent developments can be analyzed. Second, some of our proxy measures (notably the proxy for human capital) are not entirely satisfactory. Third, there are many other potential explanatory variables that could be included[8]: alternative measures to capture the complexity of the administrative autonomy within prefecture-cities; measures of effective city governance relating to *inter alia* the control of corruption, the protection of intellectual property, and bureaucra-

[8] We are grateful to one of the anonymous referees for drawing our attention to these possible influences.

cy; measures related to the quality and effectiveness of the prefecture-city institutions.

Notwithstanding these limitations, we feel that this study highlights the need to consider explicitly the effects of spatial dependence on FDI location decisions. At the same time, there is a clear need for further work to refine our understanding of the nature of this spatial dependence. This refinement could involve better specification of the economic and administrative measures of distance so that the separate effects are not confounded. Moreover, consideration should be given to the impact of other possible dimensions (*e.g.* cultural, psychic, institutional) of distance. Another avenue would be to develop spatial versions of the multinomial logit models of firms' investment decisions used elsewhere in the literature, which would then permit the analysis of firm-level data on individual FDI projects. This approach would allow us to consider spatial dependence between firms.

Appendix A

A.1. Methodology

There are many reasons to suspect spatial dependence in FDI location data. If this spatial dependence is ignored it will result in econometric problems because each observation is partly predictable from the observations on neighboring cities, similar to autocorrelation in time series data. The consequences of ignoring spatial dependence depend upon whether the correct model is a spatial lag or a spatial error model (see Anselin, 2003 for details). Excluding a spatially lagged dependent variable is equivalent to an omitted variable error and will lead to biased and inconsistent parameters. Monte Carlo studies have shown that OLS estimates may be biased by up to 35% when a spatially lagged dependent variable is incorrectly excluded from the specification (Darmofal, 2006). Alternatively, ignoring the presence of spatially correlated errors will produce biased standard errors, but the parameters estimates themselves will remain unbiased; it is therefore more a problem of efficiency. Yet this can cause serious type I errors with the biased standard errors being as low as 50% of the true standard errors (Darmofal, 2006). Moreover, to the extent that the spatially correlated errors mask a spatially varying omitted variable, the true consequences of ignoring this problem may be more serious than much of the literature acknowledges (Cookson, 2009). Analogous to the non-spatial setting, if the spatially varying omitted variable is correlated with the independent variables then the errors will also be correlated, generating biased coefficients.

The usual test for spatial autocorrelation in the dependent variable is Moran's *I*-statistic (Moran, 1950). This statistic is a variant of the Pearson moment correlation coefficient for univariate data and a significant value points to the presence of spatial dependence. The *I*-statistic is calculated as:

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i-\bar{y})(y_j-\bar{y})}{\sum_{i=1}^{n}(y_i-\bar{y})^2}$$

where $\bar{y}$ is the mean of the dependent variable (FDI) and w_{ij} is the element of the spatial weights matrix linking city *i* and *j*.

Spatial dependence may take several forms. Elhorst (2003) and Anselin (1988) provide complete references for the specification and estimation of spatial panel models, and we only provide a brief explanation here. The random effects (or fixed effects) panel model is extended by the introduction of the user-defined spatial weights matrix (W) composed of elements (w_{ij}) linking city *i* and city *j*. The matrix has as many rows and columns as there are cities in the dataset, and the elements reflect the strength of the dependence between the cities. As a point of departure, consider the traditional one-way error panel regression model (*e.g.* Baltagi, 2001: 11):

$$\mathrm{FDI}_{it} = X_{it}\beta + u_{it} \tag{2a}$$

where i ($i = 1, \ldots, 224$) indexes the cross-sectional units (cities) and t ($t = 1, \ldots, 4$) indexes the years (2004–2007). FDI is the dependent variable, X_{it} is a matrix of observations on the (k) explanatory variables, and β is a matching ($1 \times k$) vector of fixed but unknown parameters. u_{it} is a one-way error term:

$$u_{it} = \mu_i + \epsilon_{it} \tag{2b}$$

where μ_i is an unobserved, time-invariant, city-specific effect, and ε_{it} accounts for the remainder of the disturbance. To avoid the loss of degrees-of-freedom from estimating i fixed effects, the μ_i are assumed to be random with $\mu_i \sim \mathrm{IID}\ N(0, \sigma_u^2)$ and $\epsilon_{it} \sim \mathrm{IID}\ N(0, \sigma_E^2)$.

Spatial dependence may be captured by incorporating a spatially lagged (*i.e.* autoregressive) dependent variable (SAR), a spatially correlated error term (SEM), or both (SEM-SAR). A spatial lag is suggestive of a possible diffusion process. In this study, the spatial lag variable is the weighted average FDI of the neighboring cities as defined by the spatial weights matrix, W. Eq. (3) adds a spatially lagged dependent variable multiplied by the spatial autoregressive parameter (ρ) and the spatial weights matrix (W) that captures the spatial configuration or connectedness of the spatial units. This is also known as the spatial lag model:

$$\mathrm{FDI}_{it} = \rho W(\mathrm{FDI}_{i,t}) + X_{it}\beta + u_{it} \tag{3}$$

In Eq. (3) the spatial autoregressive parameter (ρ) captures the strength of the effect of neighboring cities' FDI on the FDI of city *i*. It captures the strength of the spillover or diffusion process and is commonly forced to be in the range $[-1, +1]$ by row-standardizing the spatial weights matrix (that is, the sum of the weights in each row is one) – see Anselin, 1988 for a discussion. This gives ρ a similar interpretation to the familiar time-series autoregressive coefficient.

Alternatively, spatial dependence may enter the model through the error term, so that Eq. (2a) remains unchanged but Eq. (2b) includes a spatially (auto) correlated error term where the spatial autocorrelation is captured by the parameter (λ). This model is known as the spatial error model (SEM), as Eq. (4) depicts.

$$u_{it} = u_i + \epsilon_{it} \quad \text{where } \epsilon_{it} = \lambda W \epsilon_i + e_{it} \tag{4}$$

As in the case of the SAR, if the weights in the W matrix are row-standardized then λ will fall in the range $[-1, +1]$, measuring the strength of the effect of the neighboring cities' errors on city *i*. The value of this spatially correlated error term highlights possible measurement errors when the units of analysis (cities) do not reflect the underlying data generation process. More frequently, spatially correlated errors may also be induced by spatially correlated omitted variables such as physical characteristics such as rivers or mountain ranges. And, as in this study, where neighbors are defined not merely by geographic distance but also alternative measures (*e.g.* economic distance) the potentially omitted variables relate to factors which are correlated across these alternative dimensions of distance.

An additional level of flexibility can be achieved by allowing for serial correlation in the time-series errors. This is possible by simply including a serial correlation parameter (φ).

$$\epsilon_{it} = \lambda W \epsilon_i + \nu_t \quad \text{where } \nu_t = \varphi \nu_{t-1} + \epsilon_t \tag{5}$$

There are thus a variety of potential spatial regression models, as summarized below. The most general model (SEM-SAR-SR) includes a spatially lagged dependent variable, and a spatially correlated error term which allows for the possibility of serial correlation. The other spatial models – *i.e.* the spatial lag model (SAR), the spatial error model (SEM), and the combination model (SEM-SAR) – are restricted versions nested within the general model. Both the standard random effects model and the pooled OLS model are also restricted versions of the general model – see Table 4.

The traditional R^2 measures of goodness-of-fit are not applicable in spatial models (Anselin, 1988) but, as the models are estimated using maximum likelihood, the Akaike Information Criterion (AIC) may be calculated for each model as the absolute value of twice the log-likelihood plus a penalty of twice the number of model parameters. [In order to compare the spatial regression models with the non-spatial regression models, AIC can also be calculated based upon the residual sum of squares from an OLS regression as $n \times \ln(\text{RSS}/n) + 2k$ where n is the samples size, k is the number of parameters, and RSS is the residual sum of squares.] The AIC does not given an indication of absolute goodness-of-fit, but can be used to assess the relative goodness-of-fit among a set of alternative models. A useful metric is therefore the difference between the best fitting model (that with the lowest AIC) and the rest: this is 'Delta AIC' in the tables of regression results. Another useful statistic is the Akaike weight which gives the relative likelihood of the model given the data and the other candidate models. It provides a probability for each model where the sum for all models under consideration is one.

The spatial models were estimated using Ord's (1975) maximum likelihood method, as extended to panel data by Elhorst (2003). This was implemented in the statistical programming language *R*. There are currently no routines for spatial panel models in commercially-available econometric software, so we extended the routines for spatial cross-sectional models provided in the *spdep* package (Bivand, 2010) and for panel data models in the *plm* package (Croissant and Millo, 2008). Both packages use the statistical programming language *R*. Full details on the estimation process are available from the authors.

A.2. Measures of distance

In the first specification of geographic distance (G1), the elements (wg^*_{ij}) of matrix W are initially defined by the great circle distance in kilometers (d_{ij}) between cities i and j as follows:

$$wg^*_{ij} = 0 \quad \text{if } i = j$$
$$wg^*_{ij} = \frac{1}{d^2_{ij}} \quad \text{if } d_{ij} < 1600\,\text{km}$$
$$wg^*_{ij} = 0 \quad \text{if } d_{if} > 1600\,\text{km}$$
$$w_{ij} = \frac{wg^*_{ij}}{\sum wg^*_{ij}}$$

where (wg^*_{ij}) are the elements of the unstandardized weights matrix, and (wg_{ij}) are the elements of the row-standardized weights matrix (that is, where the sum of each row is 1). This standardization gives the weights an intuitive interpretation as the city's share in the total spatial effect of China. The cut-off parameter of 1600 km was used to ensure that every city had at least one neighbor. The inverse-squared distance is used to reflect a gravity relation and is common in spatial studies.

The first specification of economic distance (E1) uses the inverse of the (squared) differences in GDP per capita as the basis for the spatial weights matrix.

$$we^*_{ij} = \frac{1}{(e_i - e_j)^2}$$

The second (E2) weights these (squared) differences in GDP per capita by the inverse of the great circle distances (d_{ij}). Fingleton and Le Gallo (2008) use a similar measure, but use the negative exponential function of the distances to weight the economic variables. The elements (we^*_{ij}) of matrix W are thus initially defined:

$$we^*_{ij} = 0 \quad \text{if } i = j$$
$$we^*_{ij} = \frac{(e_i - e_j)^2}{d^2_{ij}} \quad \text{if } d_{ij} < 1600\,\text{km}$$
$$we^*_{ij} = 0 \quad \text{if } d_{if} > 1600\,\text{km}$$
$$w_{ij} = \frac{we^*_{ij}}{\sum we^*_{ij}}$$

where e_i is GDP per capita for city i and, as for the matrix with the geographically-defined weights, the matrix is row-standardized.

We also put forward two alternative specifications to capture the effects of *administrative distance*. The first specification (A1) distinguishes between cities that are in the same province and those that are not, and defines the spatial weights matrix accordingly. The second specification (A2) hypothesizes that cities with similar administrative sizes are more attractive than dissimilar cities at the same geographic distance. We thus base the spatial weights matrix on the inverse of the (squared) differences in government spending on city administration. The elements (wa^*_{ij}) of matrix W are thus initially defined:

$$we^*_{ij} = \frac{1}{(a_i - a_j)^2}$$

$$w_{ij} = \frac{wa^*_{ij}}{\sum wa^*_{ij}}$$

where a_i is government spending on administration for city i and, as for the matrix with the geographically-defined weights, the matrix is row-standardized.

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