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Who Learns More from Afar?

Spatial Empirical Evidence on Manufacturing and Services

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Abstract

This paper investigates spatial dependence of FDI knowledge spillovers in manufacturing and services using spatial panel techniques applied to the 2006-2014 Bureau Van Dijk's Amadeus firm-level dataset for Croatia and Slovenia. The paper finds diverse results across the two sectors. The distance between regions does not hinder the absorption of foreign knowledge in manufacturing despite the strong market-stealing effects operating within regions as well as spatially. On the other hand, FDI knowledge spillovers decrease service productivity within regions, because of market-stealing effects operating strongly across a smaller geographical scale. However, its impact is lost as knowledge spillovers from more distant neighbours are accounted for, because the poaching of local labour is impeded by distance due to rising costs of labour mobility. The research indicates that for knowledge absorption, geographic distance plays differing roles in manufacturing and services, due to the different nature of the production process.

Keywords: knowledge spillovers, FDI, spatial econometrics, manufacturing, services

JEL classification: F23, L6, L8, L2, O3, O4

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1. Introduction

Many countries, especially developing ones and those in transition, try to attract foreign direct investment (FDI) to boost their growth potential. This is because local firms can learn from foreign (investor) firms and thereby improve their knowledge bases and, eventually, their productivity and innovation (Vujanovic et al., 2022, 2021; Orlic et al., 2018; Javorcik, 2004). The mechanism through which local firms learn from foreign firms is known as FDI spillover. The speed of technological catch-up of emerging economies depends on how firms absorb foreign sources of technology, which is the biggest part of productivity growth (Bekkers et al., 2021).

An important mechanism of FDI spillover transmission is the physical distance to the source of knowledge, particularly because of its tacit nature (Boschma, 2005). Despite the fourth industrial revolution, whereby digital technologies became an important facilitator of knowledge transmission, in many industries personal contact is pivotal for knowledge transmission (Gertler, 2003). Current research has investigated mostly how spillovers vary with respect to local firms' potential to learn, i.e. their absorptive capacity (Kosova, 2010; Ferragina and Mazzotta, 2014; Seyoum et al., 2015), technological gaps (Ferragina and Mazzotta, 2014; Seyman et al., 2015), level of industry competition, but also the adverse effects of economic events such as financial crises (Vujanovic et al., 2022), among many other factors. However, very little is known about how the geographical distance between local and foreign firms affects learning. Bekkers et al. (2021) explore this matter empirically and find that some industries, like services, due to the intangible nature of knowledge that is difficult to transmit without close personal contact, are less likely to catch up technologically.

This paper aims to fill this gap by investigating how geographical proximity to the source of foreign knowledge affects FDI horizontal spillovers at the regional (NUTS 3) level in Croatia and Slovenia. This is an important empirical question, in particular for FDI horizontal spillovers, because foreign competitors may be very possessive of their knowledge and close proximity facilitates knowledge spillovers by inducing interaction between employees of domestic and foreign firms. As these countries are rather small, geographical proximity to the source of knowledge becomes crucial as a channel of FDI spillover transmission. If this is ignored, our understanding of the full range of mechanisms of foreign knowledge transmission will be significantly reduced. Hence this paper aims to provide further evidence of the spatial effects of FDI horizontal spillovers and their contribution to regional total factor productivity. The geographical (spatial) dependence of FDI horizontal spillovers will be investigated using spatial econometric techniques. These techniques have only recently, and to a limited extent, been applied in this field of study.

The similarities between the two countries make the case additionally interesting, as knowledge could spill over even across the countries' borders (LeSage et al., 2007). From 1918 to 1991 Croatia and Slovenia shared the same institutional, political and socio-economic background. They are both in the EU, and speak similar languages. Generations of Slovenians educated prior to the break-up of former Yugoslavia also speak Croatian. They are both in the euro area and Schengen area, following Croatian entry at the beginning of 2023. This implies that both countries now use the same currency and have free mobility of their citizens across borders.

Hence, spatial dependence will be investigated across the regions of Croatia and Slovenia combined. However, the analysis will be performed separately for manufacturing and services because knowledge is acquired in different forms, depending on whether the final product is a good or service (Ibert, 2007; Schmidt, 2015). Consumption of physical products does not require close physical proximity to the production place, while services are consumed as they are produced. Thus, we can “observe” services only during their production time, but manufacturing products can be observed beyond the production process. This is the first study to investigate spatial aspects of FDI spillover effects in services and to compare them with those for manufacturing, thus accounting for the different natures of the production process.

The paper is organised as follows. Section 2 discusses the theoretical framework of the spatial aspect of knowledge spillovers, with a greater focus on geographical dependence. Section 3 introduces empirical evidence accounting for the geographical dimension of FDI spillovers, Section 4 introduces the method of investigation. Section 5 discusses data. Section 6 presents results and a robustness check. Section 7 concludes.

2. Theoretical background

Multinational enterprises (MNEs) are more innovative and possess superior technologies compared to local firms (Vujanovic et al., 2022). Once MNEs enter a foreign market, their knowledge can spill onto local firms via knowledge spillovers, whereby local firms can use foreign firms' knowledge to increase their technological efficiency. This is especially true for emerging markets that are still catching up technologically with their developed peers. These spillovers occur horizontally and vertically. Horizontal spillover effects occur through labour mobility and reverse engineering (Dasgupta, 2012) between foreign and local firms operating in the same industry. Vertical spillover effects occur between firms operating in different industries and could be forward or backward depending on whether a foreign firm is a customer or a supplier. Backward spillover occurs when a local firm supplies inputs to a foreign firm, thereby being prompted to technologically upgrade to meet foreign customers' standards (Newman et al., 2015). Forward spillovers occur when local firms buy from foreign customers; through better quality inputs, they improve their production processes.

However, knowledge spillovers are contingent on many factors, one of which is the physical distance to the source of knowledge. Two actors can exchange knowledge more efficiently when they are in close physical proximity to one another (Boschma, 2005). Firms located further away from multinational corporations (MNCs) absorb fewer knowledge spillovers, as "*everything is related to everything else, but near things are more related than distant things*" (Tobler, 1970, p.236). Knowledge is intangible and some knowledge externalities are local by nature. Hence being in close proximity to the source of knowledge matters (Fujita and Thise, 2002; Balland et al., 2013). It is also more difficult to transmit knowledge as the distance to its source increases, even if knowledge is codified (Boschma, 2005; Howells, 2002) and seemingly public by nature (Döring and Schnellenbach, 2006). This is especially the case for 'technical' knowledge, which is complex and, unlike 'simple' knowledge, requires informal interactions for knowledge transmission between firms (Iammarino and McCann, 2006). Communicating knowledge across geographical distances incurs costs and is prone to error, while face-to-face interaction drives these transfer costs to zero (Keller and Yeapple, 2013). Besides this, foreign knowledge could be complex for less developed market and physical proximity could, thus, be particularly relevant in this case.

Effective knowledge transmission, especially in services, often requires face-to-face interactions and mutual trust (Bekkers et al., 2017; 2021; Eggert et al., 2015). Storper and Venables (2004) argue that face-to-face interaction facilitates efficient communication, socialisation and learning, helps solve incentive problems, and prompts psychological motivation. Indeed, an important channel of knowledge transmission is communication between employees. Employees are mobile and might cross regions for better opportunities. However, this labour mobility is expected to occur mostly at the local level (Boschma, 2005) which is why it may exhibit spatial (geographical) dependence. In close proximity, spillovers acquired through inter-firm linkages, imitation and workers' mobility additionally increase (Autant-Bernard and LeSage, 2011). Besides labour, knowledge acquired through demonstration of other firms' production processes could be local in nature too (Wen, 2014), although the geographical dimension of this mechanism of knowledge transmission is less discussed in the literature.

The geographical area in which knowledge spillover effects operate varies. Knowledge spillovers via labour mobility operate at a more local level, while knowledge spillovers via networks (i.e. co-inventor networks, members of a group, etc.) operate in a larger geographical area. In addition, close physical distance between the two economic agents facilitates increasing returns to learning. Balland et al. (2013) explain that this happens because it takes time to be acquainted with the technology of other firms, implying that learning due to close proximity to the source of knowledge is a dynamic process. Future collaboration is more easily established as communication costs decrease with shorter geographical distances.

Geographical distance may not be equally important for all industries when it comes to knowledge spillovers. It may play a greater role in services than in manufacturing, due to the nature of the production processes and knowledge. Manufacturing is characterised by 'codified' knowledge that is less tacit in nature, as products can be observed regardless of distance. ICT also facilitates the transmission of this 'codified' knowledge across various distances (Morgan, 2004). On the other hand, services are more tacit and challenging to 'copy'. Bekkers et al. (2021) find that knowledge-intensive services in developing economies have not been catching up technologically with their advanced peers as absorbing knowledge in these economies is contingent on personal contact. The opposite holds for knowledge-intensive manufacturing where observation of knowledge is not constrained by physical distance. The authors explain that the catch-up through knowledge transfers especially in advanced services is more challenging, as the services are accustomed to customer needs.

Physical distance between economic actors might also be harmful for learning. Close geographical proximity could lead to spatial 'lock-in' – an outcome occurring when firms within a region specialise in certain skills while becoming incapable of absorbing different knowledge from outside their location of operation (Boschma, 2005). This phenomenon, referred to as the proximity paradox (Boschma and Franken, 2010), could adversely affect learning among firms.

2.1. SPATIAL EFFECTS OF COMPETITION

In the context of spatial spillover effects it is important to understand the impact of competition effects in terms of distance. Foreign rival firms can prompt better use of resources (and hence productivity), but also hinder learning from foreign firms. Regarding the latter, negative competition effects may affect learning in two ways. First, foreign firms can take away significant market share from domestic firms, decreasing their production and possibly crowding out spillovers. Second, foreign rival firms can poach skilled labour away from domestic firms, hampering their ability to absorb knowledge spillovers. Halpern and Muraközy (2007) explain that market-stealing effects may be stronger than spillover effects with greater distance between firms, as increased labour mobility costs may impede learning between firms. On the contrary, Autant-Bernard and LeSage (2011) argue that competition effects could be local in nature due to clusters evolving via firms' collocation, characterised by intense labour market competition and thus, increased labour (production) costs. Further away from a cluster, firms have access to cheaper labour and increased mark-ups. Accordingly, poaching of local employees away from domestic firms is more likely to operate in close proximity. Lin and Kwan (2016) argue that the poaching of local labour should decrease with distance, while knowledge spillovers could still transmit across greater geographic distances. This is because the cost of labour reallocation increases with distance while technology facilitates communication when agents are further away. The authors further explain that market stealing effects operate at the country level, through the integrated market, and are not local in nature.

Overall, both competition and knowledge spillovers transmit different effects and may vary over geographical distances, but their spatial effects are not clear, while the nature of knowledge in manufacturing and services can affect to different extents how geographic distance facilitates learning.

3. Empirical evidence and conceptual framework

The evidence on the dependence of FDI spillovers on geographical proximity to the source of knowledge is fairly recent, sparse, and mostly refers to China (Madariagi and Poncet, 2007; Lin and Kwan, 2017; 2016; Wen, 2014; Lu et al., 2017), and to a lesser extent transition (Resmini and Nicolini 2007; Halpern and Muraközy, 2007) and developed economies (Girma and Wakelin, 2002; Bode et al., 2012). These studies are also focussed on manufacturing, but not on services. No study investigates these effects in selected Southeast European (SEE) economies.

Girma and Wakelin (2002) were the first to investigate the geographical dimension of FDI horizontal spillovers in the UK context during the 1988-1996 period. They find that horizontal spillovers have a positive effect only if domestic and foreign firms are located within the same region, while foreign firms transmit negative spillovers to firms outside their region. Bode et al. (2012) find positive Marshallian (horizontal) spillover effects from foreign firms in the USA, but negative effects from domestic firms during the 1977-2003 period. These externalities operate in narrow geographical areas – at the local (metropolitan) rather than the state level. Positive foreign spillover effects are explained with foreign firms' superiorities which benefit other firms while the negative effects from domestic firms are explained with market-stealing effects.

Jordaan (2008) suggests that the geographical concentration of firms in Mexico in 1993 stimulates negative backward spillovers due to a negative competition effect arising among agglomerated suppliers. Resmini and Nicolini (2007) indicate that foreign firms' presence in neighbouring regions exerted negative effects on the productivity growth of domestic firms in Bulgaria, Romania and Poland during 1997-2003. These negative effects are present only in the capital regions with more qualified labour and productive firms, and partially in regions bordering the EU where firms are more likely to cooperate with EU suppliers rather than local ones.

Other studies are based on China. The most recent study by Liu et al (2022), using city level data, shows that FDI in China prompted regional innovation in the 2003-2017 period. They reveal that FDI spatial spillovers in China depend on the level of urbanisation, which also to a large extent determines the sophistication of human capital and thus the ability to absorb foreign firms' knowledge. Wen (2014) investigates the spatial spillover effects of FDI inflow on per capita GDP at the city level in the two largest recipient regions in China: the Yangtze River Delta (YRD) and the Pearl River Delta (PRD) regions. The author finds positive FDI spatial spillover effects on city growth in the YRD region, but negative ones on city growth in the PRD region as a result of the differing spatial distribution of FDI in the two regions. Madariagi and Poncet (2007), studying a comparable issue, find that Chinese regional growth benefits from regional FDI and FDI in neighbouring regions. Lin and Kwan (2016, 2017) find strong evidence of negative intra-regional and inter-regional FDI spillovers. Inter-regional spillovers in China turn from insignificant to positive as the distance increases. The authors explain these negative effects with the mobility of talented local labour from domestic to foreign firms, a mechanism that operates more efficiently when domestic and foreign firms are located close to one another. Lu et al. (2017) find that domestic firms in China benefit from foreign firms' knowledge only if foreign and domestic firms are located within the same city.

3.1. CONCEPTUAL FRAMEWORK

The abovementioned studies have mostly focused on China and to a lesser extent transition and developed economies. This paper contributes to the current empirical literature by investigating the geographical dimension of FDI horizontal spillovers effects in two SEE countries, Croatia and Slovenia, both relatively new members of the EU that share many historical and cultural similarities, and economically largely depend on one another.

While all the previous evidence is based on the manufacturing sector, this paper will investigate both manufacturing and service sectors. The production and consumption process in manufacturing is differentiated in time and space, and its output is tangible in nature, allowing easier observation and possible better knowledge transmission. The opposite holds for services, which despite digitalisation, are still usually confined to the geographical space in which they are consumed and produced simultaneously. Thus, horizontal spillovers may be negative for services. We develop several hypotheses.

In this paper we hypothesise that FDI spillover effects in manufacturing and services, two important sectors of economic growth in Croatia and Slovenia, have differing spatial effects due to the differing nature of their knowledge. The paper hypothesises that in manufacturing FDI spillovers can be transmitted irrespective of the location of a foreign firm. This is because manufacturing products are tangible in nature and can be observed outside the production process. On the contrary, services are consumed when they are produced, thereby limiting this scope for horizontal spillover via reverse engineering, even in close proximity. Thus, horizontal spillovers may be negative in services. We develop two hypotheses:

H1: FDI horizontal spillover effects in manufacturing are positive, locally and spatially
H2: FDI horizontal spillover effects in services are negative, locally and spatially

In addition, this paper will account for the geographical dimension of competition effects as negative competition effects (i.e. market-stealing effects and the poaching of the local labour away from domestic firms) may counteract the process of learning. The literature points out that when firms are close to one another these negative competition effects may be stronger. However, some evidence shows that competition effects could be global in nature. This research will unravel which effects, operating horizontally, dominate: negative competition effects or knowledge spillover effects. Our hypothesis is that competition operates differently in manufacturing and services. In manufacturing it is more global, as consumers can be geographically more distant from the place where a product is manufactured. That is, production and consumption of manufactured products are distant in geographical space and time. For services, competition may operate more locally, as service providers serve consumers mostly within a limited geographical area. It is also likely that due to digitalisation, services are consumed across regions' borders. We hypothesis the following:

H3: Competition effects in manufacturing operate locally and spatially.
H4: Competition effects in services operate only locally, but not spatially.

Besides the importance of distance for knowledge spillovers between rival firms (horizontal), distance is important for inter-industry (vertical) spillovers too. Greater distance impedes firms from having close personal contacts with suppliers and customers (Girma and Wakelin, 2002; Jordaan, 2008; Bode et al., 2012). Firms also tend to choose their suppliers so as to minimise transportation costs (Dunning, 1993; Halpern and Muraközy, 2007; Jordaan, 2008). However, Halpern and Muraközy (2007) show that in the period 1996-2003 vertical spillovers show no spatial effects in Hungary. It is also well established that business entities from Croatia and Slovenia operate in price - competitive segments of the market and in segments of value-added chains where costs are the decisive comparative advantage (Stojčić et al., 2013; Bartlett, 2014). In such a context it can be expected that MNCs establish vertical links with firms in their proximity in order to maintain cost efficiency. For these reasons the spatial effects of vertical spillovers are not investigated. It should be noted, however, that this does not imply the absence of spatial effects of vertical spillovers. Rather, our modelling approach assumes that these take place through total factor productivity (TFP) channels, and this mechanism will be clarified further.

4. Method of investigation

The geographical dependence of FDI knowledge spillovers on productivity is accounted for in two different ways in the empirical research – via standard econometric techniques or via spatial econometric techniques. Few studies account for the spatial dependence in knowledge spillovers via augmentation of FDI spillover measures while using standard panel and cross-section econometric techniques. This is usually done by constructing a spillover measure separately for different groups of regions (Aiken and Harrison, 1999; Girma and Wakelin, 2002) or by augmenting the spillover measures with a simple function decreasing the distance (1/d) between firms located in different regions (Jordaan, 2004; Halpern and Marukozy, 2007; Lu et al, 2017; Lui et al, 2022).

The multidirectional nature of spatial dependence cannot be accounted for appropriately by these techniques and demands a spatial econometrics approach (Anselin, 1988). The spatial (regional) structure of the data is better tested with spatial econometric techniques which model spatial dependence explicitly (Anselin, 1988; Anselin and Bera, 1998) using the spatial weight matrix that defines relations among the regions. These models are also applied to some extent in the literature (Resmini and Nicolini, 2007; Tanaka and Hashiguchi, 2015; Bode et al., 2012; Lin and Kwan, 2017, 2016; Wen, 2014; Madariagi and Poncet, 2007).

This paper applies static spatial panel models, thereby accounting for time and spatial dynamics. These models are estimated with a maximum likelihood estimator (MLE), which is used for derivation of various Lagrange multiplier (LM) tests allowing for justification of the modelling strategy.[1]

$$TFP_{R(t)} = \alpha_{R(t)} + \beta Hor_{R(t)} + \delta W_R Hor_{R(t)} + \omega HH_{R(t)} + \tau W_R HH_{R(t)} + \\ + \gamma Backward_{R(t)} + \varphi Forward_{R(t)} + \mu_R + \varepsilon_{Rt} \quad (1)$$

$TFP_{R(t)}$ is the vector of regional observations of the dependent variable in year *t*. $Hor_{R(t)}$ is the vector of foreign horizontal spillovers with its corresponding vector of coefficients β. This variable is spatially lagged ($W_R Hor_{R(t)}$) and δ is the vector of parameters on spatially lagged FDI horizontal spillovers which accounts for the effects of horizontal spillovers in neighbouring regions on regional productivity $TFP_{R(t)}$. FDI horizontal spillovers from closer regions have greater weight (importance) than FDI horizontal spillovers from farther regions in the calculation of the spatial lag of FDI horizontal spillovers.

$HH_{R(t)}$ is the vector of region-specific competition controls (Hirshman-Herfindahl index) with its corresponding coefficients ω. The spatial effects of competition on TFP are accounted for via $W_R HH_{R(t)}$, where τ represent the parameter vector on vertical spillovers. $Backward_{R(t)}$ is the vector of backward

1 An alternative approach would be using dynamic spatio-temporal panel models, in line with Madariagi and Poncet (2007), Bode et al., (2012), Lin and Kwan (2017, 2016) and Wen (2014). Spatial-temporal models account for time-dependence and for the endogeneity of spatial lags and spillovers. However, the dataset contains a limited number of cross-sectional units. Furthermore, as in the previous two chapters the endogeneity of the spillovers is accounted for via time-lagging of spillovers, in which case the effective period of study amounts to eight years (2007-2014). Considering the number of cross-sectional units and that the endogeneity of spillovers is already addressed, the chapter employs static spatial panel techniques.

spillovers; γ is its parameter vector. $Forward_{R(t)}$ is the vector of forward spillovers; φ is its parameter vector. $\alpha_{R(t)}$ is the vector of region-specific intercepts. ε_{Rt} is the vector of idiosyncratic errors. μ_R is the time invariant region-specific component that could be random or fixed. The composite error term is hence the sum of the two components and has the form: $u_R = \mu_R + \varepsilon_{Rt}$.

To address the endogeneity of FDI being attracted by more productive regions, all the spillover variables are time-lagged once. Spatial lagging of an independent variable accounts for the spatial effects of that independent variable in neighbouring regions (defined by the matrix) on the dependent variable. However, the spatial models imply spatial dependence of the dependent variable with or without spatial dependence of the error term. Spatial lagging of the dependent variable (productivity) accounts for the fact that regional domestic productivity is being influenced by productivity in other proximate regions. Spatial lagging of the error term allows for the unobservable shocks among neighbouring regions to be correlated.

4.1. MATRIX DEFINITION

It is important to impose some constraints when modelling the spatial structure of the data consisting of an *RxR* spatial relation (*R* refers to the number of NUTS 2 regions). For each unit in R a 'neighbourhood set' S is defined (Anselin and Bera, 1998). The spatial relation among neighbours in this set could be specified via the spatial weight matrix W, which is symmetric with size *RxR*. These neighbouring relations are defined by the matrix elements w_{rg} where r stands for region r (row *r* of matrix *W*) and *g* stands for potential neighbour of region *r* (column *g* of matrix *W*). There could be (R^2 – *R*) potential relationships between regions, *R* being the number of regions (subtraction accounts for the exclusion of *R* diagonal elements) (LeSage and Pace, 2009, p.9).

The matrix is symmetric and its elements w_{rg} have positive values if two regions are neighbouring and at zero value otherwise. The diagonal terms of the matrix are set to zero, as a region is not a neighbour to itself. Thereby, the *W* matrix accounts for the total effects of all the specified neighbours. It is common to row-standardise matrix elements for computational purposes (LeSage, 1999), in such a way that each row-sum is equal to one.[2]

The spatial weight matrix allows for spatial 'lagging' of the variables - by multiplying the *W* matrix with the variable of interest. The spatial lag operator shifts over space and produces a weighted average of the neighbouring observations (LeSage, 1999). To create a neighbourhood set (that is a non-zero element of the matrix) we calculate the maximum (bilateral cut-off) distance between the centroids of regions that allows each region within Croatia and Slovenia to have at least one neighbour, which is in line with studies in this area (Madariagi and Poncet, 2007; Bode et al., 2012; Wen, 2014; Lin and Kwan, 2017; 2016). This amounts to 126.6km distance between thirty-three regions in Croatia and Slovenia. In other words, if the distance between centroids is over 126.6km the spatial weight elements have zero value (suggesting no relations). If the distance between regions' centroids is up to 126.6km the matrix elements are equal to the inverse squared bilateral great distance between centroids of two regions.

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[2] Row-standardisation implies dividing each matrix element by the total sum of the positive matrix elements in that row. New matrix elements then have the value: $w^*_{rg} = \frac{w_{rg}}{\sum_g w_{rg}}$ (*g* being row) so that $\sum_g w^*_{rg} = 1$.

Acknowledging the discussion in the spatial econometrics literature on the sensitivity of results to different weight matrix specifications, four different model estimations, differing in weight matrices, are considered. In other words, each model employs a spatial weight matrix that differs with respect to the definition of neighbourhood. Via the inclusion of more distant neighbours in the neighbourhood set, the geographical variation of FDI knowledge spillovers across space will be better accounted for. To see how the relationships among regions change, the threshold distance is arbitrarily (hence, exogenously) increased to allow for more links among neighbours. The maximum bilateral great circle distance between regions is increased to 226km, 326km and 492.6km, the latter being the largest distance between two regions. The matrix constructed using the 492.6km distance in defining matrix elements has only zero values for diagonal terms (as all the regions are proclaimed as neighbours) while other elements have positive values. Hence, this matrix accounts for the maximum number of possible links between regions. In the appendix, we show how the number of links increases as we changed the definition of the matrix, that is – as we include a greater number of regions in the neighbour set.

The matrices decrease in the level of sparseness by accounting for more distant regions as neighbours. The first (*W_126*), second (*W_226*), third (*W_326*) and fourth (*W_493*) matrix have inverse-squared distance value elements if region *r* and *g* are up to 126km, 226km, 326km and 492.6km apart, respectively.[3] These matrices are row-standardised in line with the current literature (Resmini and Nicolini, 2007, Bode et al, 2012, Lin and Kwan, 2016, 2017; Lui et al, 2020) and have elements that are decreasing in between-regions distance. Since the distances between regions do not change over time and the panel of regions is constant, so is the definition of matrices across years.

3 Kopczewska et al. (2015) explain that the inverse-squared distance matrix allows non-linear relationships among regions that decline more quickly than proportionally to distance while allowing for local clusters (nearer neighbours transmitting greater effects).

5. Data

The paper uses Bureau van Dijk's Amadeus firm level dataset for Croatia and Slovenia for the 2006-2014 period. This dataset contains balance sheet financial information as well as non-financial data on location of a firm at the NUTS2 regional level, firm industry (NACE 4), and number of employees among other factors. After eliminating missing observations, the firm level data count 2,273 and 1,558 manufacturing firms in Croatia and Slovenia respectively, and 3,855 and 2,171 firms in services in Croatia and Slovenia, respectively.[4]

All firm variables are aggregated at the NUTS2 regional level for manufacturing and services separately, which is an approach also taken by Lin and Kwan (2017, 2016) and Tanaka and Hashiguchi (2015). Five regional variables are calculated: regional TFP (dependent variable), three spillover variables and competition control.

The aggregation process takes place in several steps to account for industry and regional heterogeneity across years. First, data are aggregated across firms in each industry and region, leading to the new 2006-2014 dataset on industry-level observations varying across regions. Second, these industry level observations within each region are aggregated further over industries for each year, thereby forming the final dataset containing thirty-three cross-sectional observations for all regions in Croatia and Slovenia over the 2006-2014 period. TFP is aggregated based on the sample of domestic firms only, while horizontal spillovers and competition variables are based on the entire population of firms (local and foreign ones). This is because TFP should reflect the regional productivity of domestic firms, as productivity effects on local firms are the focus of the study, while spillovers and competition control are calculated from the samples that contain *all* firms, irrespective of ownership structure. Hence, their aggregation of spillovers is conducted and explained separately.

5.1. TFP CALCULATION AND AGGREGATION

The outcome variable is total factor productivity, which measures the level of efficient use of capital and labour in production process (Barnett et al., 2014). However, this measure is more manufacturing- rather than service-specific. This is because in manufacturing, output depends directly on capital and labour, while in services productivity also depends on external factors like consumers' perception of service quality, in addition to (internal) efficiency (Calabrese, 2012). This concept is not accounted by the production function, used for the estimation of TFP. However, in the wake of digitisation, technological capabilities started to play an important role and TFP is argued to be able to explain a large part of productivity in services (Wang et al, 2016).

TFP is first estimated for individual domestic firms using the Cobb-Douglass production function, and then it is aggregated at the regional level. Thus, we will first explain the process of calculating TFP and then proceed with the explanation of the aggregation of firm data to regional data. Firm-level TFP is

[4] After dropping firms with missing employment figures, the samples amount to 62% (46,530) and 76.2% (88,325) of the corresponding population of firms for Slovenia and Croatia, respectively.

estimated separately for each two-digit industry within the manufacturing sector to account for price, demand, technology and other industry-specificities (Gal, 2013) expected to be homogeneous within an industry but not across industries. However, the Cobb-Douglas production function estimation is impeded by the fact that firms' choices on labour are affected by the productivity shock unobserved in the data, causing endogeneity (simultaneity bias). To circumvent this issue the paper relies on the use of the Wooldridge (2009) technique has been demonstrated to be superior to other techniques (Olley and Pakes, 1996 - OP, Levinsohn and Petrin, 2003 – LP, and Ackerberg et al., 2006),[5] in estimating firm productivity. Wooldridge (2009) is a one-step generalised method of moments (GMM) estimation, that estimates capital and labour simultaneously (unlike other techniques that do it separately, in two steps), with the use of robust standard errors. In addition, this technique has the advantage of Sargan-Hansen test use for the validity of internal instruments for labour, that causes endogeneity in the Cobb-Douglass setting. Once firm productivity is calculated, we proceed with the aggregation to the regional level.

Regional TFP is obtained in two steps. First, firm level productivity is aggregated at the industry (*j*) and regional (*r*) level for year (*t*), using weights. The following formula has been applied:

$$TFP_{jrt} = \sum_{j=1}^{N} weight_{ijrt} * TFP_{ijrt} \tag{2}$$

i - firm, *j* – industry, *r* – region and *t* – time

where *N* is the number of firms within industry *j* and region *r* in year *t*. *weight* represents the share of firm *i*'s employment in the total employment of industry *j* in region *r* in year *t*. These industry variables are then aggregated at the regional level, separately for manufacturing and services using the following formula:

$$TFP_{rt} = \sum_{j\ within\ region\ r}^{M} weight_{jrt} * TFP_{jrt} \tag{3}$$

M is 1 for manufacturing and 2 for services

TFP_{rt} is the productivity of region *r* in year *t* for manufacturing (services). $weight_{jrt}$ represents the share of industry *j* employment in total manufacturing (or services) employment of region *r* in year *t* and thus these weights assign higher importance to bigger industries within the region, as measured by relative employment. The resulting aggregation leads to regional TFP, the dependent variable varying across thirty-three regions and over the years of investigation.

5.2. SPILLOVERS

Four aspects are important to consider when calculating FDI spillovers and industry competition at the regional level. First, both domestic and foreign firms need to be included in the calculation. Second, vertical spillovers account for inter-sectoral spillovers and hence encompass all sectors (not only manufacturing and services). Third, IO tables vary across industries, countries and years, requiring the calculation of spillovers for Croatia and Slovenia separately. Fourth, for the calculation of regional

5 Wooldridge (2009) develops from the inferiority of previous methods. The previous methods ignore the correlation between the two steps, as well as heteroscedasticity and serial correlation which are not adequately addressed with bootstrapped standard errors in the OP and LP methods.

spillovers, there must be at least two firms in an industry within a region, as learning occurs *among* firms. To fulfil the fourth criterion, a higher level of NACE industry aggregation is used (2-digit) and micro firms are included in the calculation of spillover measures.

Horizontal spillovers in industry *j*, in region *r* in year *t* are calculated as following:

$$Horizontal_{jrt} = \frac{\sum_{i\ for\ all\ i\ \in j\ and\ r} Foreign\ share_{ijrt} * Y_{ijrt}}{\sum_{i\ for\ all\ i\ \in j\ and\ r} Y_{ijrt}} \quad (4)$$

Where *Y* represents the number of employees of firm *i,* in (2-digit) industry *j* in region *r* in year *t*. Horizontal spillovers reflect how much domestic firms learn from their foreign rivals within industry *j* located in region *r* in year *t*. $Foreign\ share_{ijrt}$ represents the share of foreign equity of firm *i* in industry *j* in region *r,* at time *t,* taking values 0 to 1.[6] For the purpose of calculating vertical spillovers at this level of aggregation, horizontal spillovers are aggregated at two and three-digit industries for Croatia and Slovenia, which corresponds to the level of industry aggregation of the IO tables in the two countries.[7] The following formulas are applied:

$$Backward_{jrt} = \sum_{k\ in\ region\ r\ if\ k \neq j} \alpha_{jkt} * Horizontal_{krt} \quad (5)$$

$$Forward_{jrt} = \sum_{k\ in\ region\ r\ if\ k \neq j} \alpha_{kjt} * Horizontal_{krt} \quad (6)$$

j represents industry and *r* region. These backward (forward) spillover measures proxy for the knowledge domestic suppliers (customers) in sector *j* in region *r* gain via supplying (buying) inputs to (from) sector *k* in region *r* with some share of foreign firms. α_{jkt} calculated using 2006-2013 IO tables, represents the share of sector *j*'s output supplied to downstream industry *k* in year *t*. α_{kjt} is the share of sector *j* inputs, purchased from upstream industry *k* in year *t*.

Once the spillovers (varying over industry, region and time) are calculated, two separate datasets are formed – one containing spillover measures for manufacturing in Croatia and Slovenia and the other containing spillover measures for services in the two countries. The calculated spillover measures are aggregated further across all industries in each region for each year. This results in a final measure of spillovers in region *r* in year *t* - $spillover_{jrt}$ calculated as a weighted average (horizontal, backward and forward) of spillover measures for manufacturing (or services) in region *r* in year *t*. The following equation is used:

$$spillover_{rt} = \sum_{j\ within\ region\ r} weight_{jrt} * spillover_{jrt} \quad (7)$$

$weight_{jrt}$ is the share of industry *j*'s employment in region *r*'s manufacturing (or services) employment in year *t*.

6 $Foreign\ Share_{ijrt}$ takes the value zero if the firm is domestic (sum of shares of foreign investors < 10%). It takes the values in a range of between 0.1 to 1 if the sum of shares of the foreign investor is between a range of 10%-100%.

7 The IO tables differ for each year during 2006-2014 period and are sourced from Eora multi-region input-output (MRIO) database. The IO tables have industries aggregated at one (two)-digit industry level for Croatia and two (three)-digit industry level for Slovenia.

In a similar fashion the competition measure (Hirshman-Herfindahl index – HH) is aggregated at the regional level. Its aggregation requires summing the squared market shares of firm *i* in each (2-digit) industry *j* and region *r* in year *t*. These regional and industry level competition measures for each year HH_{jrt} are further aggregated (using exactly the same weights used for TFP and spillover aggregation in equations 2 and 6, respectively) into the average regional competition measure according to equation (7)

$$HH_{rt} = \sum\nolimits_{j\ within\ region\ r} weight_{jrt} * HH_{jrt} \tag{8}$$

Since the purpose of this study is to analyse FDI spatial spillover effects across the regions of two neighbouring countries in manufacturing and services, the resulting datasets containing regional spillovers and competition control are merged across Croatia and Slovenia. This leads to the two final regional datasets for manufacturing and services, containing thirty-three different regional spillovers and competition variables, varying over the 2006-2014 period.

6. Results

The results are presented separately for manufacturing (Table 1) and for services (Table 2). Four different columns represent four different equations that differ with respect to the spatial lag operator, that is, the matrix used to define the number of neighbours. So, Columns I, II, III and IV represent the regression that uses 126.6km (*W_126*, Column I), 226km (*W_226*, Column II), 326km (*W_326*, Column III) and finally 493km (*W_493*, Column IV) as a maximum threshold level defining the neighbours.

The table results contain various tests defining modelling strategy. In the first place, the two Anselin Lagrange Multiplier (LM) tests, respectively, test spatial error dependence (conditional on the spatial dependence in TFP) and spatial dependence in TFP (conditional on spatial error dependence). The spatial Hausman test reveals whether region-specific components are correlated with the independent variables, in which case spatial fixed effects (FE) is a more appropriate strategy. The Baltagi et al. (2007b) LM test follows and tests spatial dependence in the error term (C.1 - conditional on the presence of serial correlation and random effects), serial correlation (C.2 - conditional on the presence of spatial dependence in the error term and random effects) and random effects (C.3 – conditional on the presence of serial correlation and spatial dependence in the error term).

Model selection tests showed different modelling strategies for manufacturing and services. The Spatial Housman tests suggest that spatial FEs should be applied to manufacturing while spatial random effects (RE) in services. Furthermore, the Baltagi LM tests suggest that the externality effects of productivity across regions (suggested by Ciccone and Hall, 1996) are also industry-specific. The tests suggest spatial dependence in TFP in manufacturing regardless of how many regions are included in the neighbourhood set. However, this dependence is not revealed in services within a small geographical area stretching to only first-order neighbours. The results suggest that productivity spatial spillovers are local in nature in services as they operate in small geographical areas. This is mainly because of the simultaneity of production and consumption in services (Bishop, 2009). The externality effects from such ‘closed’ production processes may be observed only at a close distance. On the other hand, these externality effects in manufacturing may transmit across a greater geographical space.

To sum up, the preferred modelling strategy for all estimations in manufacturing is Spatial FE – Manski type:

$$TFP_{R(t)} = \lambda W_R TFP_{R(t)} + \beta Hor_{R(t)} + \delta W_R Hor_{R(t)} + \omega HH_{R(t)} + \tau W_R HH_{R(t)} + \gamma Backward_{R(t)} + \varphi Forward_{R(t)} + \rho W_R \varepsilon_{R(t)} \quad (9)$$

λ is the parameter vector of coefficients on the spatially lagged TFP. Within transformation, wiped out region-specific effects μ_R and the remaining idiosyncratic part of the error $\varepsilon_{R(t)}$ is spatially lagged. The spatial dependence in the error is captured by parameter ρ.

The Spatial Hausman test reveals that region-specific time-invariants are not fixed over time for services, but rather random. The modelling strategy in services is the Spatial RE - Durbin error model implying spatial lag in the explanatory variables and in the error. Modelling spatial error dependencies is more challenging if μ_R is random, in which case the error term has a more complex structure as it consists of both random effects and an idiosyncratic part $\varepsilon_{R(t)}$ having the form u_{Rt} = μ_R+ $\varepsilon_{R(t)}$. This poses an issue on how to model spatial dependence in the error u_{Rt}. Two approaches are offered - by Baltagi et al. (2007) and Kapoor et al. (2007), and the higher maximum likelihood helps to decide which of the two models is more applicable. Baltagi et al. (2003) claim that spatial dependence in the error term occurs via time and the spatially-variant idiosyncratic (innovation) component of the error term $\varepsilon_{R(t)}$. According to Kapoor et al. (2007) spatial dependence applies to both components of the error term (u_{Rt}).[8] The likelihood ratio tests support that most of the models should be estimated with the KKP approach of estimating the spatial dependence in the error term.

The model applied to services hence takes the form:

$$TFP_{R(t)} = \alpha_{R(t)} + \beta Hor_{R(t)} + \delta W_R Hor_{R(t)} + \omega HH_{R(t)} + \tau W_R HH_{R(t)} + \\ + \gamma Backward_{R(t)} + \varphi Forward_{R(t)} + \rho W_R u_{Rt} + \mu_R + v_{Rt} \quad (10)$$

Parameter estimates on spatially lagged TFP (λ) and in the error (ρ) cannot be greater than one in absolute value. Otherwise, the spatial autocorrelation process is explosive.

The results reveal different patterns of spatial effects of FDI spillovers across the two sectors. Table 1 and Table 2 refer to the results for manufacturing and Table 3 to the results for services. These model specifications differ in the spatial lag operator (spatial weight matrix) used as presented by *W_126*,*W_226*,, *W_326,* and *W_493* columns. Moreover, they differ with respect to spatial lag, which is included across all models in manufacturing but not in services. The matrices interlink regions that are at least 126km (*W_126*), 226km (*W_326*) and 493km apart (*W_493*) as measured by bilateral great circle distance on the sphere of the surface. By including more regions in the neighbourhood set (as one moves from the *W_C* to *W_493* definition of a matrix) the author tests the sensitivity of spatial effects from FDI spillovers across greater geographical distances.

[8] Under this approach, the error term has the following form: $u_{Rt} = \rho W_r u_{Rt}$+ $\varepsilon_{R(t)}$, where $\varepsilon_{Rt} = \mu_R + v_{Rt}$.

Table 1 / Spatial FE results for manufacturing in Croatia and Slovenia using different matrices

Matrices	**W_126**	**W_226**	**W_326**	**W_493**
Model applied	**FE**	**FE**	**FE**	**FE**
Dependent Variable: Regional TFP				
Spatially lagged TFP (λ)	0.45*** (0.07)	0.42*** (0.09)	0.36*** (0.10)	0.36*** (0.11)
Spatially lagged error (ρ)	0.19 (0.13)	0.37*** (0.13)	0.47*** (0.13)	0.46*** (0.13)
Horizontal spillovers (β)	1.58*** (0.37)	1.68*** (0.36)	1.67*** (0.37)	1.63*** (0.38)
Spatially Lagged Horizontal spillovers (δ)	1.80*** (0.60)	2.35*** (0.64)	3.72*** (0.76)	3.76*** (0.83)
Backward spillovers	-2.59** (1.28)	-2.39* (1.26)	-2.51* (1.29)	-2.64* (1.32)
Forward spillovers	7.97*** (1.13)	7.85*** (1.12)	8.44** (1.14)	8.81*** (1.17)
HH index (ω)	5.03*** (0.56)	1.48*** (0.27)	7.62*** (0.80)	7.71*** (0.86)
Spatially lagged HH index (τ)	1.61*** (0.27)	6.06*** (0.63)	1.68*** (0.27)	1.77*** (0.28)
Number of regions= 33				
Number of observations= 264				
Tests of model selection (p-values):				
Anselin LM test: Sp. TFP dependence	0.00	0.00	0.00	0.00
Anselin LM test: Sp Error dependence	0.04	0.1	0.05	0.04
Hausman test	0.02	0.00	0.00	0.00
Baltagi C.1spatial error dependence	0.00	0.00	0.00	0.00
Baltagi C.2 serial correlation test	0.00	0.00	0.00	0.00
Baltagi C.3 random effects test	Not applicable			

Note: *10% level significance; ** 5% level significance; *** 1% level significance. C.1 – Baltagi et al. (2007) LM test for spatial dependence in the error term, conditional on random effects and serial correlation. C.2- Baltagi et al. (2007) LM test for serial correlation, conditional on random effects and spatial dependence in the error. C.3 - Baltagi et al. (2007) LM test for random effects conditional on presence of serial correlation and spatial dependence in the error term. W_126, W_226, W_326, W_493- inverse-squared distance matrices accounting for relations with regions that are at most 126km, 226km, 326km and 492.6km apart.

As expected, the coefficient on the spatially lagged TFP is highly significant across all model specifications, suggesting significant interactions across regions through dense economic activities. Spatial error dependence is significant when more distant regions in the neighbourhood set are included (Column II-IV).

Coefficients cannot be directly interpreted in manufacturing as the interpretation of the coefficients in regressions containing spatial lags of the dependent and/or independent variables is more complex (LeSage and Pace, 2009) because changes within regions are no longer independent. Changes in value for an observation in region *r* in year *t* affect not only productivity within that region but also productivity in other regions. Partitioned effects are divided into direct and indirect effects. The effect of changes in observation in region *r* on productivity in region *r* are called direct effects. The effects of changes in observations in other regions on productivity of region *r* are called indirect effects. The sum of the direct and indirect effects gives the *total* effect from change in the explanatory variable on TFP and that effect will be interpreted in this paper. Apart from Lin and Kwan (2016), authors using spatial econometrics to investigate related matters ignored the issue of interpreting these effects.

Considering that $|\lambda|<1$ the magnitude of these effects dissipates from first- to last-order (neighbouring) region with the order of the neighbour. Since these effects are 'neighbour-of-a-neighbour-of-a-neighbour' effects they are not local in nature. In the literature, they are defined as global effects.

These partitioned effects for manufacturing are presented in Table 2.

Table 2 / Partitioned effects for each model specification in manufacturing

	Partitioned effects	Column I W_126	Column II W_226	Column III W_326	Column IV W_493
Horizontal spillover	Direct	1.650***	1.728***	1.693***	1.656***
	Indirect	1.207**	1.181**	0.892*	0.871*
	Total	**2.857*** **	**2.909*** **	**2.586*** **	**2.528*** **
Spatially lagged horizontal spillover	Direct	1.878***	2.413***	3.777***	3.825***
	Indirect	1.374**	1.649**	1.991**	2.012*
	Total	**3.252*** **	**4.062*** **	**5.767*** **	**5.837*** **
Backward spillovers	Direct	-2.711***	-2.462**	-2.556*	-2.683*
	Indirect	-1.983	-1.683*	-1.347*	-1.412
	Total	**-4.694* **	**-4.146** **	**-3.903*** **	**-4.094* **
Forward Spillovers	Direct	8.339***	8.072***	8.575***	8.953***
	Indirect	6.101***	5.518***	4.520**	4.710*
	Total	**14.440*** **	**13.590*** **	**13.095*** **	**13.663*** **
HH index	Direct	1.686***	1.521***	1.703***	1.798***
	Indirect	1.233**	1.039***	0.898**	0.946*
	Total	**2.919*** **	**2.560*** **	**2.601*** **	**2.745*** **
Spatially lagged HH index	Direct	5.266***	6.228***	7.741***	7.834***
	Indirect	3.853***	4.257***	4.080**	4.122*
	Total	**9.119*** **	**10.485*** **	**11.821*** **	**11.956*** **
Number of regions= 33					
Number of observations= 264					
Tests of model selection (p-values):					
Anselin LM test: Sp. TFP dependence		0.00	0.00	0.00	0.00
Anselin LM test: Sp Error dependence		0.04	0.1	0.05	0.04
Hausman test		0.02	0.00	0.00	0.00
Baltagi C.1spatial error dependence		0.00	0.00	0.00	0.00
Baltagi C.2 serial correlation test		0.00	0.00	0.00	0.00
Baltagi C.3 random effects test		Not applicable			

Note: *10% level significance; ** 5% level significance; *** 1% level significance. C.1 – Baltagi et al. (2007) LM test for spatial dependence in the error term, conditional on random effects and serial correlation. C.2- Baltagi et al. (2007) LM test for serial correlation, conditional on random effects and spatial dependence in the error. C.3 - Baltagi et al. (2007) LM test for random effects conditional on presence of serial correlation and spatial dependence in the error term. W_126, W_226, W_326, W_493- inverse-squared distance matrices accounting for relations with regions that are at most 126km, 226km, 326km and 492.6km apart.

FDI horizontal spillovers are positive and significant for manufacturing, both within and across regions (spatially). A one percentage point increase in foreign presence within a region in manufacturing has an average total effect of 2.5% – 2.9% on regional productivity (depending on the model). Spatial effects of FDI spillovers are also positive and significant. A one percentage point increase in foreign firm presence in each neighbouring region (as defined by the matrix) has a total average effect on regional TFP in the range of 3.3-5.8%. Between 57.7%-65.5% of these total within-region and spatial effects, originate from changes in foreign presence within the region and in neighbouring regions, respectively (direct effect). The rest, 34.5% - 42.3%, originate from indirect cross-border effects (through TFP).

The strong indirect effects imply that regions in Croatia and Slovenia are strongly interconnected when it comes to manufacturing. The average total effect rises with the number of regions included in the neighbourhood set (as defined by matrix *W_126* – *W_493*). The impact is the largest when the spatial effects from all the regions (aside from region itself) are accounted for (matrix *W_493*).

Learning from foreign rivals (horizontally) works across regions possibly because of the nature of knowledge in manufacturing as well as the small geographical area studied in this research. The economic impact is quite strong, but that could be the consequence of the measure of spillovers which account for learning in the manufacturing sector as a whole. The evidence on spatial effects of FDI horizontal spillovers in manufacturing may suggest the weakening importance of geographical proximity in the wake of globalisation, and information and communication technology (ICT) (Morgan, 2004). Manufacturing is characterised by ‘codified’ knowledge that is less tacit in nature, as the products can be observed regardless of distance and with the growth of ICT, this knowledge travels even faster and farther (Morgan, 2004). Technological (cognitive), social and organisational distance, rather than physical distance, could hinder learning. This research evidently lacks the answer as other proximities are not controlled for simultaneously due to data limitations.

The positive horizontal spillovers are not overshadowed by negative market-stealing effects in manufacturing, as implied by the positive coefficient on market concentration variable and its spatial lag. Competition effects operate across regions and within regions, which supports the argument by Lin and Kwan (2016) that market stealing effects operate at the country level (through market integration) rather than locally. A one percentage point increase in within- region competition on average decreases productivity by 2.6% to 2.9%. If competition in each neighbouring region increases by the same amount, the regional TFP decreases by 9.7-12%. Between 57.8% to 65.5% (depending on the model) of these total effects originate solely from the direct effects of competition on TFP. The rest, 34.5% to 42.2% of the total effects originates from indirect cross-border effects.

The spatial effect of competition rises as more distant regions are included in the matrix specification (that is, as we move from Column I to Column IV). The greatest negative spatial competition impact arises when the effects from all the potential neighbours are considered. A large impact may result from the nature of this measure - representing the average competition level within the manufacturing sector as a whole. Again, the effects are mainly driven by changes in regional competition per se (direct effects) rather than consequential induced changes of TFP across regions (indirect effect).

Knowledge sourced through backward linkages on average decreases regional productivity. Increasing the foreign firm presence in the downstream sector within the region by one percentage point, on average decreases the domestic regional productivity of the manufacturing upstream sector by

3.9-4.7%. On the contrary, knowledge sourced through forward linkages within a region is on average productivity enhancing. Increasing foreign firms' presence in the upstream sector within the region by one percentage point increases regional productivity in the downstream manufacturing sector by 12.7%-13.7%. Between 57.8%-65.5% of these total effects through backward and forward linkages originate solely from direct effects of backward and forward spillovers on TFP. The rest, 34.5% to 42.2% of these effects are indirect effects. As noted, the effects of vertical spillovers are quite high and that could be due to the level of aggregation of vertical linkages which incorporate spillovers across various industries, irrespective of how related they are technologically. However, a more likely reason, under this research setting, could be the measure of vertical spillovers within a region which account for combined customer-supplier linkages for the manufacturing sector as a whole. This is an issue raised in other studies too (Vujanovic et al., 2021, 2022; Orlic et al., 2018).

Table 3 / Spatial RE results for services in Croatia and Slovenia using different matrices.

Matrices	**W_126**	**W_226**	**W_326**	**W_493**
Model applied	**RE -KKP**	**RE -KKP**	**RE -KKP**	**RE KKP**
Dependent Variable: Regional TFP				
(intercept)	3.88***	3.86***	3.85***	3.85***
	(0.11)	(0.14)	(0.14)	(0.14)
Spatially lagged error (ρ)	0.21**	0.25**	0.28**	0.28***
	(0.09)	(0.10)	(0.11)	(0.11)
$\phi = \sigma_\mu^2/\sigma_\varepsilon^2$	15.89***	16.16***	16.11***	16.10***
	(4.24)	(4.32)	(4.31)	(4.30)
Horizontal spillovers (β)	-0.59**	-0.58**	-0.58**	-0.58***
	(0.23)	(0.23)	(0.23)	(0.23)
Spatially lagged horizontal spillovers (δ)	0.51	0.57	0.64	0.61
	(0.55)	(0.62)	(0.64)	(0.65)
Backward spillovers	-0.21	-0.11	-0.09	-0.06
	(0.60)	(0.60)	(0.60)	(0.60)
Forward spillovers	1.12**	1.11**	1.09**	1.09**
	(0.44)	(0.44)	(0.44)	(0.44)
HH index (ω)	0.94***	0.91***	0.91***	0.91***
	(0.14)	(0.14)	(0.14)	(0.13)
Spatially lagged HH index(τ)	0.41	0.54	0.56	0.56*
	(0.29)	(0.32)	(0.34)	(0.34)
Number of regions=33				
Number of observations=264				
Tests for model specification (p-value):				
Anselin LM test Sp Error	0.21	0.13	0.19	0.79
Anselin LM test Sp. TFP	0.56	0.38	0.59	0.58
Baltagi et al. (2007) C.1	0.02	0.01	0.01	0.00
Baltagi et al. (2007) C.2	0.00	0.00	0.00	0.00
Baltagi et al. (2007) C.3	0.00	0.00	0.00	0.00
Hausman test	0.9	0.92	0.92	0.36

Note: *10% level significance; ** 5% level significance; *** 1% level significance
C.1 – Baltagi et al. (2007) LM test for spatial dependence in the error term, conditional on random effects and serial correlation. C.2- Baltagi et al. (2007) LM test for serial correlation, conditional on random effects and spatial dependence. C.3 - Baltagi et al. (2007) LM test for random effects conditional on serial correlation and spatial dependence in the error term. W_126, W_226, W_326, W_493- inverse-squared distance matrices accounting for relations with regions that are at least 126km, 226km, 326km and 492.6km apart.

FDI horizontal spillovers show a different spatial nature in services (see Table 3 for the results). Like in the case of manufacturing, the first, second, third and the fourth columns of results refer to results from estimating equation 10 with spatial weight matrices calculated using 126km, 226km, 326km and 493km of inverse-squared-bilateral-distance matrices. The results are uniform across all model specifications.

The negative effects of horizontal spillovers operate locally: they are negative and significant only within a region but the effects from the neighbouring regions (spatially) are insignificant. A one percentage point increase in foreign firm presence within region in services decreases regional TFP by approximately 0.6%.

This result suggests the geographical scope at which negative FDI horizontal spillovers operate is the NUTS 3 region itself but not beyond.

Negative effects within a small geographical area could be due to high market-stealing effects operating locally. The coefficient on the regional industry concentration in services is positive, implying negative effects from market competition on regional productivity. Strong market-stealing effects across the service sector seem to crowd out knowledge spillovers from foreign firms. The negative competition effects in services dissipate with distance. The sign of the coefficient of the spatially lagged regional industry concentration variable is insignificant (no matter the model specification), implying that regional productivity is not affected by competition from neighbouring regions (as defined by matrices *W_126-W_493*), no matter how distant they are. This indicates that competition crowds out learning from foreign firms in services only within a small geographical area. The poaching of local labour in services could be cheaper within a small geographical space and that may harm domestic firms' ability to absorb knowledge because their human capital is weakened.

Competition among firms in close proximity could hinder knowledge spillovers either through market-stealing effects or poaching of the local labour from domestic firms. Kloosterman (2008) finds that firms in the field of architecture do not cooperate even when sharing open-space offices, due to a possessive attitude towards their businesses. Lin and Kwan (2017, 2016) explain the negative within-region and positive spatial horizontal spillovers in China (manufacturing) with market-stealing effects and poaching of local labour dominating in close proximity. Hence, positive horizontal spillovers are overshadowed by negative competition effects. However, poaching of local labour is more expensive when domestic firms are at a greater distance to the foreign firms (Autant-Bernard and LeSage, 2011) and less harmful to the spillover process. The results in services are supportive of this notion.

The difference in (spatial) FDI horizontal spillover effects in manufacturing and services could be because of the nature of knowledge itself in the two sectors. Knowledge in manufacturing is less tacit than knowledge in services. The level of tacitness is reflected in the cost of codification of a particular piece of knowledge (Morgan, 2004). There is a difference between knowledge and knowing, the first more inherent to manufacturing, while the second more to services. Knowledge has a more tangible form - blueprints, texts, patent applications or products (Schmidt, 2015) characterise manufacturing (i.e. high-tech products). Considering that 'knowing' truly presents itself in intangible form, it is tacit in nature, and hence geographically bounded (Howells, 2012; Schmidt, 2015). Ibert (2007, p.106) concludes that "*due to its embeddedness in social practice, knowing cannot simply retain its practical value when 'transferred' across time and space*." Hence, even within a region it may be difficult to acquire service-related knowledge from other rival firms.

Overall, the literature points out that the tacit feature of knowledge is more applicable to services than to manufacturing. Consequently, the demonstration effect of production technology (Blomström and Kokko, 1998; Saggi, 2006) is a viable source of knowledge transmission in manufacturing, in addition to labour mobility. Due to the different nature of knowledge as well as greater embeddedness of production and consumption in services, it is harder to assume that this channel of knowledge absorption is available in services. Not only because knowledge in services is harder to codify but there could be fewer channels of transmissions. The results presented may support this argument and evidently show the sensitivity of knowledge transmission across space in services.

Furthermore, firms in services may be only established in one location but provide their services in other regions. Torre and Rallet (2005) and Morgan (2004) argue that services are increasingly provided to more distant clients, further from a firm's localisation. They explain these effects with the increasing development of transportation, information and communication technology, which decreases the costs of labour mobility. Greater connectivity among regions increases the need for communication, which induces further labour mobility and commuting. Accordingly, it is the temporary geographic proximity that matters, accomplished via occasional meetings and business gatherings, rather than permanent physical distance to a partner. Conti et al. (2014) state that in business services social proximity may matter more than physical proximity when choosing customers. Mariotti et al. (2015) argue that this is particularly true for foreign firms in services. Hence, even when located within the same region foreign firms in services may offer their services elsewhere, thus limiting the spillover effects to nearby rival firms.

There are no significant FDI backward spillovers within the region. On the contrary, FDI spillovers through forward linkages are productivity enhancing. If foreign firms' presence in an upstream industry increases by one percentage point, regional TFP increases by 0.8%-1.1%. This could be because inputs in services might not need as much adjustment as those in manufacturing. Because of the simultaneity of production and consumption in services, as opposed to manufacturing, close cooperation with customers is necessary (Spohrer and Kwan, 2009), facilitating knowledge transmission through forward linkages.

6.1. ROBUSTNESS CHECK

A good way to check whether the results are robust is to use different spatial weight matrix specifications (Elhorst, 2010). The results for manufacturing and services are robust across all weight matrix specifications. However, this analysis will go further in checking the robustness of this evidence. The results from these models are presented in the appendix.[9] Considering that Elhorst (2012) suggests that spatial fixed effect models are the justified strategy when the sample represents the population itself, which it does in this case, the models for services are re-estimated with spatial fixed effects. The results remain robust (see Table 5).

9 A robustness check is conducted for one chosen model: one with the *W_126* matrix specification for several reasons mainly related to model estimations for services. First, the results for spatial effects of competition are insignificant across all inverse-squared distance matrices for services. Second, the within-the-region and spatial effects of FDI horizontal spillovers are very similar for model specifications that used *W_126*, *W_226*, *W_326,* and *W_493* matrices in services.

The results showed the clear presence of serial correlation. Lee and Yu (2012) find that the bias in coefficient estimates in the presence of non-modelled serial correlation is not substantial (a slight increase in root-mean square error) if spatial lag and spatial error dependence are accounted for, which is the case for manufacturing. However, the spatial Hausman test is over-rejected under such a setting (p value equal to one). Conversely, if spatial error, serial correlation and spatial dependence in the independent variable are not modelled, there is a bias in coefficient estimates on the spatial lag and independent variable. The authors augment their spatial panel models with the presence of serial correlation. However, their model is not suited for short-panels (small number of regions - *R*). Lee and Yu (2012, p. 1375) state that the *"serial correlation coefficient can be consistently estimated under large R even when T is small*" and that the inference on the parameter of the serial correlation is obtained *"from the cross-sectional variation of the data"*. Considering a very limited number of regions, applying the Lee and Yu (2012) model accounting for serial correlation, is not suitable in this research.

Alternatively, to account for serial correlation in the error term, models 9-10 are augmented with the inclusion of year dummies. Two augmented models are estimated – one with seven-year dummies (see Table 6) and the other with two time dummies indicating accession to the EU (for Croatia) and the period of the financial crisis (for both countries) (Table 7). This is because the inclusion of seven-year dummies gives a high p-value of the Hausman test for services (close to one) which makes the model doubtful considering the discussion of tests with high p-values (Roodman, 2009a), albeit in a different model context.

The results remain robust with respect to the sign and significance of variables of interest (when two year dummies are included), and to a greater extent in manufacturing. However, the tests still show a serial correlation in the error. Interestingly, the inclusion of time dummies takes away the spatial dependence from the error term, as judging by the Baltagi et al. (2007) and Anselin LM tests of spatial error dependence.

Although, the model contains only 33 cross-sectional units, a few more variables are added to the model to check the robustness. Those are: a year dummy indicating the year of the financial crisis (*crisis*), average firm size (*size*), and two measures of absorptive capacity (*lnintang*-average regional intangible assets ratio and *lnhc*-average regional wage).[10] The results reveal that spatially lagged spillovers dissipate once other controls are included for manufacturing (along with forward spillover effects). In services, there is an issue of the Hausman test being equal to one for model specifications (*W_126*), which makes the model's fit doubtful. This point also explains why the inclusion of additional explanatory variables or spatial lags was not feasible in this analysis. The significance and signs of spillovers, however, remain robust.

10 The inclusion of dummy variable for Croatia would be justifiable as well. However, considering that FE methods are used for manufacturing, a country dummy that does not vary over years, cannot be added to the model.

7. Conclusion

This paper investigates spatial dependence in FDI spillovers in manufacturing and services in Croatia and Slovenia using spatial econometric techniques. To investigate these issues, the paper uses the Amadeus firm level database for 2006-2014 and aggregates it to a panel of thirty-three NUTS 33 regions in a manner that accounts for industry and regional heterogeneity. FDI spillover effects across the regions of the two countries make an interesting case-study because these countries shared similar institutional, political and socio-economic backgrounds during most of the 20th century.

The spatial effects of FDI horizontal spillovers on total factor productivity are investigated using five different weight matrices. The first matrix allows for links among a limited number of (geographically) very close neighbours. The other three matrices decrease in the level of sparseness by allowing for relationships and knowledge spillovers from more distant regions.

The models are appropriately chosen on the basis of relevant tests which hypothesise spatial dependence in the error and TFP, as well as the presence of serial correlation and random effects. These tests and the spatial Hausman test point to a different modelling strategy for the two industries. According to the tests, Spatial FE, which models spatial dependence in both TFP and the error term, should be applied in manufacturing, while Spatial RE, which models the structure of spatial dependence in the error term, should be applied in services.

The results reveal evident positive spatial dependence in FDI horizontal spillovers in manufacturing. The spatial effect increases as matrix specification takes into account relations with more distant regions. Knowledge transmission between regions is an important mechanism for regional spillovers, irrespective of the distance between them. The distance between regions does not hinder learning in manufacturing across Croatia and Slovenia and is not prevented by negative competition effects operating within a region as well as across regions. Rising spatial horizontal spillover effects with the inclusion of more distant regions in the neighbourhood set, could also be due to the decreasing value of geographical proximity for the absorption of knowledge in manufacturing.

Horizontal spillovers from foreign firms reveal quite a different pattern in services. FDI knowledge spillovers affect productivity negatively only within a region, likely because market-stealing effects operate strongly locally. However, this effect diminishes as the effects from more distant neighbours are accounted for in the estimation. This could be because the practice of poaching local labour weakens with distance due to rising costs of labour mobility. However, the situation is different in manufacturing, whereby negative effects do not hinder knowledge absorption within a region and across regions.

The difference in the FDI spillover transmission mechanism could reflect the nature of knowledge in the two sectors. Unlike in manufacturing, knowledge in services is less tangible, and hence more challenged in terms of spilling over across a greater geographical space. Its form is represented through practice and actions, which generally require face-to-face interaction and a level of trust. The results in manufacturing and services are also robust across all matrix specifications.

Finally, a limitation of the approach taken in this paper should be taken into account. Due to the lack of data, the model could not account for cognitive, organisational, social and institutional proximities that might intertwine with geographical proximity. The effects of a single proximity measure (geographical) should be interpreted with caution, if other dimensions are not controlled for (Boschma, 2005; Schmitt and Van Biesebroeck, 2013). Modelling a single proximity dimension (geographical) could lead to ignoring the relevance and importance of other dimensions of proximity as highlighted by LeSage and Pace (2009) and Parent and LeSage (2008). The model also suffers from serial correlation. Adding time dummies to account for various macroeconomic shocks, however, has not solved this issue. Instead of taking away serial correlation from the error term, the inclusion of time dummies takes away spatial correlation from the error term. Considering that spatial econometric techniques in the panel data context do not have a long tradition as other econometric techniques, further research in future is needed.

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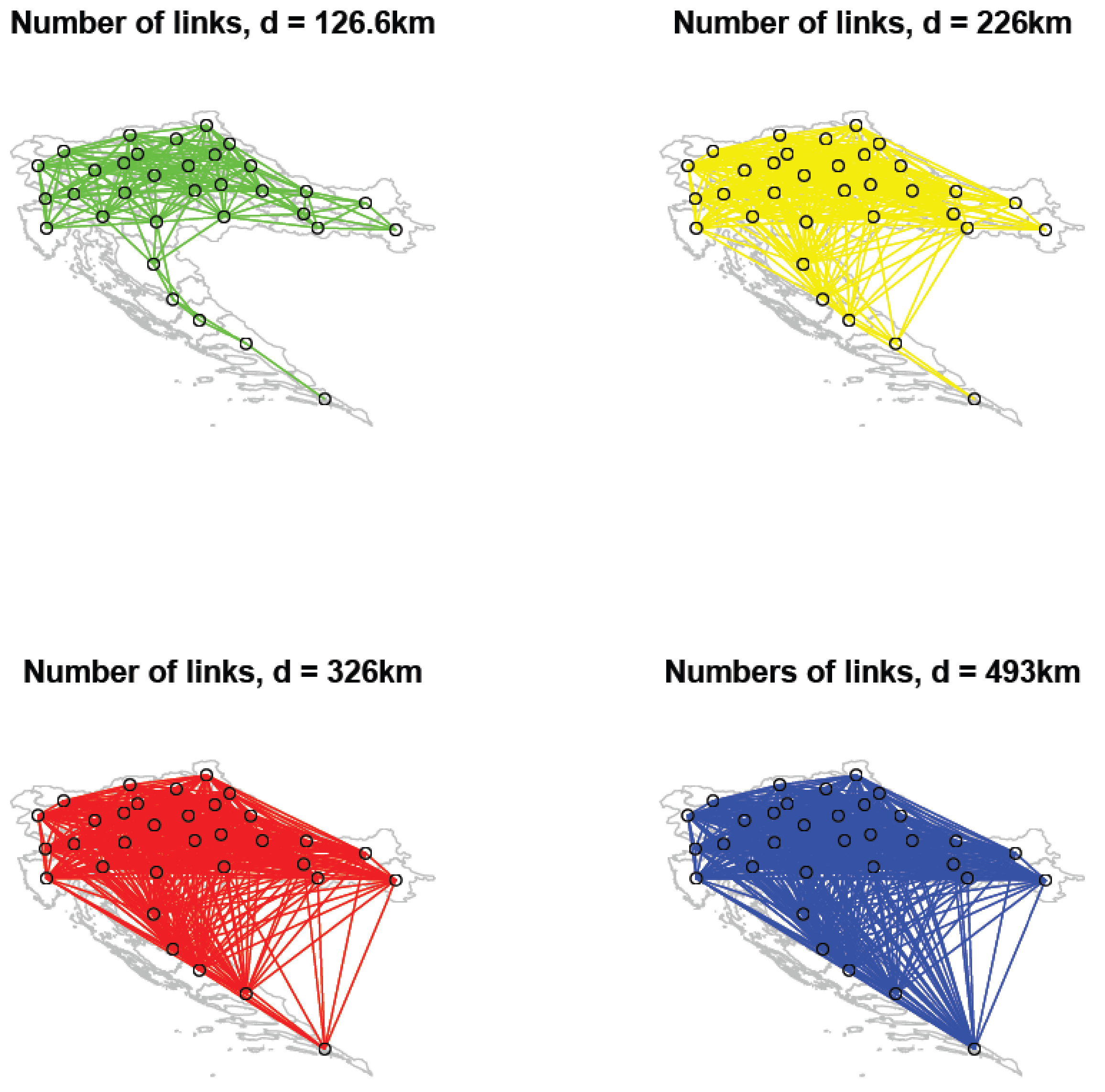
Appendix

Figure 1 demonstrates how the number of links between regions increases as we include neighbours that are up to 126.6km (green lines), 226km (yellow lines), 326km (red lines) and 493km (blue lines) apart.

Figure 1 / Number of links accounted for by different inverse-squared distance matrices



Note: d-bilateral great distance expressed in kilometres.

Table 4 below shows how the percentage of links accounted for (hence, positive spatial weight elements) among regions increases as the definition of neighbourhood changes.

Table 4 / Number of links between regions

Matrix	% of positive weights matrix elements	Total number of links between regions	Avg. number of links per region
W_126	35.8%	390	11.8
W_226	68.7%	748	22.7
W_326	89.4%	974	29.6
W_493	99.9%	1056	32

Note: W_126, W_226, W_326, W_493- inverse-squared distance matrices accounting for relations with regions that are at least 126km, 226, 326 and 492.6km apart.

Table 5 / Spatial FE results for services (across all model specifications)

	W_C	W_126	W_226	W_326	W_493
lambda	-0.17				
	(0.23)				
rho	0.47***	0.21**	0.25**	0.28**	0.28**
	(0.17)	(0.09)	(0.10)	(0.11)	(0.11)
lhorizontal	-0.97***	-0.67***	-0.67***	-0.66***	-0.67***
	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)
lbackward	0.21	-0.20	-0.08	-0.06	-0.03
	(0.51)	(0.57)	(0.56)	(0.56)	(0.56)
lforward	1.00**	1.05**	1.04**	1.02**	1.02**
	(0.37)	(0.41)	(0.41)	(0.41)	(0.41)
wlhorizontalc	-2.02***	0.21	0.51	0.56	0.53
	(0.57)	(0.09)	(0.58)	(0.61)	(0.62)
HH	0.80***	0.95***	0.91***	0.92***	0.91***
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
wHHc	0.04	0.34	0.46	0.47	0.48
	(0.32)	(0.28)	(0.31)	(0.32)	(0.33)

Note: the diagnostics is the same as in Table 3

Table 6 / Spatial FE and RE results for services and manufacturing, with year dummies included

	Manufacturing FE	Services RE
WTFP	0.40***	
	(0.08)	
WU	0.28**	-0.26***
	(0.12)	(0.10)
lhorizontal	1.63***	-0.72***
	(0.36)	(0.19)
wlhorizontalc	1.71***	0.26
	(0.84)	(0.45)
lbackward	-2.76**	-0.21
	(1.31)	(0.54)
lforward	8.12***	0.69*
	(1.13)	(0.39)
HH	1.64***	0.87***
	(0.27)	(0.13)
wHHc	5.49***	-0.35
	(0.67)	(0.26)
factor(year)2008	-0.21**	-0.04**
	(0.11)	(0.02)
factor(year)2009	-0.01	-0.07***
	(0.11)	(0.02)
factor(year)2010	-0.01	-0.14***
	(0.13)	(0.02)
factor(year)2011	0.01	-0.16***
	(0.14)	(0.02)
factor(year)2012	0.02	-0.11***
	(0.14)	(0.02)
factor(year)2013	-0.07	-0.10***
	(0.16)	(0.03)
factor(year)2014	0.03	-0.04
	(0.16)	(0.03)
Diagnostics		
Baltagi et al. (2007) C.1 (pvalue)	0.00	0.51
Baltagi et al. (2007) C.2 (pvalue)	0.00	0.00
Baltagi et al. (2007) C.3 (pvalue)	0.00	0.00
Anselin Spatia Error test (pvalue)	0.01	0.16
Anselin Spatial Lag test (pvalue)	0.00	0.37
Hausman test (pvalue)	0.00	1
FE compared with	Baltagi	Baltagi

Note: C.1 – Baltagi et al. (2007) LM test for spatial dependence in the error term, conditional on random effects and serial correlation. C.2- Baltagi et al. (2007) LM test for serial correlation in the error term, conditional on random effects and spatial dependence. C.3 - Baltagi et al. (2007) LM test for random effects conditional on serial correlation and spatial dependence in the error term.

Table 7 / Spatial FE and RE results for services and manufacturing, with few dummies included.

	Manufacturing FE W_126	Services RE W_126
Intercept		
WTFP	0.44*** (0.07)	
WU	0.20 (0.13)	0.06 (0.10)
$\phi = \sigma_\mu^2/\sigma_\varepsilon^2$		
lhorizontal	1.51*** (0.36)	0.68*** (0.21)
wlhorizontal	1.56*** (0.69)	0.44 (0.48)
lbackward	-2.63* (1.27)	0.01 (0.56)
lforward	7.91*** (1.11)	0.70* (0.42)
HH	1.61*** (0.26)	0.86*** (0.13)
WHH	5.03*** 0.62	-0.37 (0.31)
eu	-0.18*** (0.08)	0.05*** (0.02)
crisis	0.12 (0.08)	0.10*** (0.02)
Diagnostics		
Baltagi et al. (2007) C.1 (pvalue)	0.10	0.10
Baltagi et al. (2007) C.2 (pvalue)	0.00	0.00
Baltagi et al. (2007) C.3 (pvalue)	0.00	0.00
Anselin Spatia Error test (pvalue)	0.08	0.07
Anselin Spatial Lag test (pvalue)	0.00	0.21
Hausman (FE vs Baltagi RE) (pvalue)	0.00	0.91
Hausman (FE vs KKP RE) (pvalue)	0.00	0.92
LL Baltagi	-48.77	144.81
LL KKP	-52.99	145.09

Note: C.1 – Baltagi et al. (2007) LM test for spatial dependence in the error term, conditional on random effects and serial correlation. C.2- Baltagi et al. (2007) LM test for serial correlation in the error term, conditional on random effects and spatial dependence. C.3 - Baltagi et al. (2007) LM test for random effects conditional on serial correlation and spatial dependence in the error term.

Table 8 / Spatial FE and RE results for services and manufacturing with additional control variables

	Manufacturing FE W_126	Services RE W_126
phi		11.87***
		(3.51)
lambda	0.08*	-0.41***
	(0.04)	(0.15)
rho	0.48***	0.59***
	(0.08)	(0.09)
(Intercept)		2.97***
		(0.28)
lhorizontal	0.65***	-0.56***
	(0.19)	(0.20)
wlhorizontal	0.23	-0.09
	(0.36)	(0.52)
lbackward	-1.71**	0.09
	(0.66)	(0.46)
lforward	0.86	0.78**
	(0.63)	(0.33)
HH	0.14	0.58***
	(0.15)	(0.12)
wHH	1.60***	-0.187
	(0.34)	(0.36)
size	0.27***	0.128***
	(0.02)	(0.02)
lnintang	-0.06***	-0.00
	(0.02)	(0.01)
lnhc	1.14***	0.64***
	(0.06)	(0.08)
crisis	0.02	-0.13***
	(0.04)	(0.04)
Diagnostics		
Baltagi et al. (2007) C.1 (pvalue)	0.00	0.00
Baltagi et al. (2007) C.2 (pvalue)	0.00	0.00
Baltagi et al. (2007) C.3 (pvalue)	0.00	0.00
Anselin Spatia Error test (pvalue)	0.02	0.00
Anselin Spatial Lag test (pvalue)	0.00	0.00
Hausman test (pvalue)	0.00	1.00
FE compared with	Baltagi	KKP

Note: C.1 – Baltagi et al. (2007) LM test for spatial dependence in the error term, conditional on random effects and serial correlation. C.2- Baltagi et al. (2007) LM test for serial correlation in the error term, conditional on random effects and spatial dependence. C.3 - Baltagi et al. (2007) LM test for random effects conditional on serial correlation and spatial dependence in the error term.

IMPRESSUM

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Offenlegung nach § 25 Mediengesetz: Medieninhaber (Verleger): Verein "Wiener Institut für Internationale Wirtschaftsvergleiche", A 1060 Wien, Rahlgasse 3. Vereinszweck: Analyse der wirtschaftlichen Entwicklung der zentral- und osteuropäischen Länder sowie anderer Transformationswirtschaften sowohl mittels empirischer als auch theoretischer Studien und ihre Veröffentlichung; Erbringung von Beratungsleistungen für Regierungs- und Verwaltungsstellen, Firmen und Institutionen.

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