PRODUCTIVITY SPILLOVERS AND MULTINATIONAL ENTERPRISES: IN SEARCH OF A SPATIAL DIMENSION

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Abstract

In this paper we analyse whether and to what extent MNEs can generate positive externalities for the host economies by allowing for spatial dependence patterns in TFP growth rates at sectoral and regional level. In order to achieve this research objective we use spatial econometric techniques, which allow us to identify not only the type of spatial dependence governing this phenomenon and to estimate it consistently, but also clusters and other "anomalies" in the patterns of productivity spillovers. There has been, at least in our knowledge, no spatial econometric study on the impact of MNEs on aggregate TFP; therefore, we aim at filling this gap. We found evidence of positive spillovers from MNEs operating in the region, and negative spillovers from MNEs outside the region. The latter are however limited to specific groups of regions, such as the capital regions and regions bordering with former EU-15 countries. Therefore, we can conclude that there seems to be a regional channel for FDI spillovers.

Key words: foreign direct investment, productivity growth, spatial spillovers
JEL codes: F23, O40, R11.

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1. Introduction

There seems to be a widely held assumption that multinational enterprises generate benefits that spill over to the host economy, resulting in productivity growth through several channels. The latter includes, backward and forward linkages with local firms – through which multinational firms may foster the entry and development of local suppliers and final goods producing firms (Markusen and Venables, 1999) – competition and demonstration effects (Wang and Blomstrom, 1992; Glass and Saggi, 2001), as well as movements of labour force from multinationals to local firms (Fosfuri, Motta and Ronde, 2001).

The transmission of spillovers from MNEs to domestic firms, however, is not automatic; rather, it is affected by several factors, the most important of which is distance broadly defined in order to encompass both the economic and the geographical dimension. Economic distance concerns relative backwardness and absorptive capacity and determines whether and to what extent local firms eventually benefit from FDI-induced spillovers (Findlay, 1978; Glass and Saggi, 1998). Geographical distance, instead, affects the transmission costs, thus reducing the possibilities for indigenous firms located far from multinational enterprises to reap such benefits. While the former explains *spatial heterogeneity* in FDI spillovers, the latter may generate *spatial dependence*.[1] The existing empirical literature usually accounts for spatial heterogeneity, both across and within countries, while has barely explored and properly discussed the issue of spatial dependence.[2]

In this paper we combine the two approaches. In particular, we analyse whether and to what extent MNEs can generate positive externalities for the host economies by allowing for spatial dependence patterns in TFP growth rates at sectoral and regional level. In order to achieve this research objective we use spatial econometric techniques, which allow us to identify not only the type of spatial dependence governing this

[1] Spatial heterogeneity refers to the impact of being located in one specific point in space, i.e. a country or a region, while spatial dependence refers to the effects of being located closer or further away from other locations. This technical distinction corresponds to the more traditional distinction between absolute and relative location (Abreu, de Groot, and Florax, 2004).

[2] To this respect, Keller (2002), Helpman and Coe (1995) and Abreu, de Groot and Florax (2005) are exceptions.

phenomenon and to estimate it consistently, but also clusters and other "anomalies" in the patterns of productivity spillovers. There has been, at least in our knowledge, no spatial econometric study on the impact of MNEs on aggregate TFP; therefore, we aim at filling this gap.[3]

Several reasons support our approach. First, the non-automaticness of the transmission of FDI spillovers at firm level, due to the existence of several conditionalities (Nicolini and Resmini, 2006), raise doubts on the fact that FDI spillovers may overcome local firms' boundaries and enhance growth at more aggregate levels. Second, the consideration of spatial dependence does not only provide additional insights on the geographical pattern of distribution of FDI spillovers, but it even changes the quantitative estimates of the marginal effect exerted by MNEs. Positive (negative) spatial spillovers induce dissemination and feedback effects that magnify (reduce) the direct impact of MNEs on TFP growth rates. Therefore, disregarding spatial dependence may lead to an omitted variable bias and potentially misleading inference on the role played by MNEs in enhancing growth. Third, spatial autocorrelation allows accounting for variation in the dependent variable arising from latent and unobservable variables. Indeed in the case of TFP models, the appropriate choice of explanatory variables may be problematic, not only conceptually, but also empirically given that data on these variables are not always accessible and/or reliable. Spatial autocorrelation may thus act as a proxy to all these omitted variables and catch their effect. This is particularly useful in case of transition countries, where explanatory variables at regional and sectoral level are quite scarce. Fourth, in presence of positive spatial spillovers, the location of foreign firms within a country may no longer matter. Consequently, the public good nature of such benefits would raise the question on how to insure that FDI promotion policies will be at the efficient level, given the incentive of all to free ride on the efforts of others in attracting MNEs.

The remainder of the paper is organized as follows. Section 2 describes our data set and the method we used to construct our measure of aggregate TFP and its corresponding growth rate. In section 3 we apply spatial data analysis techniques to investigate overall spatial patterns in the data and the presence of clusters and outliers. Section 4 discusses

[3] Very recently, it has been recognized that spatial dependence may play a role as a determinant of MNEs location patterns (Bloningen et al. 2004; Coughlin et al. 2000; Baltagi et al. 2006).

the estimated model and the econometric issues related to it. Section 5 presents our empirical results and section 6 concludes.

2. Data and Methods

The data used in this study constitute an unbalanced panel with annual information on more than 40,000 domestic manufacturing firms and about 10,000 foreign owned firms located in three transition countries, namely Bulgaria, Poland, and Romania. Although these countries started with very similar technological levels and managerial skills, their transitions to a market economy have followed very different paths whereby Poland became a member of the European Union in 2004, while Bulgaria and Romania had to wait other three years before joining the EU. The development of the transition phase has affected the inflows of FDI (Resmini, 2000), which have responded positively to the structural reforms undertaken in Poland and negatively to stagnation of the reform process in Bulgaria and Romania. Consequently, Poland has rapidly become one of the most important FDI recipients in the area, while Bulgaria and Romania fail to attract a substantial stock of foreign capitals, at least till the end of the 1990s. Given our research objectives, these and other socio-economic characteristics make comparison among these three countries of considerable interest.

The data are taken from the Amadeus database published by Bureau Van Djik, which besides standard financial information gives details on several qualitative variables, such as ownership characteristics, industry classification, and geographical location within countries. Firms with a share of foreign ownership greater than 10 per cent have been classified as foreign affiliates, using the definition provided by the OECD and the IMF. All other firms with a percentage of foreign ownership below 10 per cent have been classified as domestic. Although it seems common practice to classify a firm as domestic even in the absence of any information on the nationality of the ownership (Peri and Urban, 2004), we prefer to adopt a more restrictive strategy in order to avoid overestimating the possible impact of foreign firms on domestic firm performance. We consequently excluded from the sample all firms whose ownership could not be properly identified. Despite this and other limitations, our sample is able to reproducing region and sectoral dynamics without large biases, as it is shown in Table 1.[4]

[insert Table 1 about here]

Our analysis considers the period from 1998 to 2003 and focuses on manufacturing firms only. According to the recent studies on productivity growth using longitudinal research data, a large proportion of aggregate productivity growth is attributable to resource allocation, which mainly occurs within manufacturing sectors (Bartelsman and Doms, 2000). Moreover, the latter have been attracting a large number of MNEs since the early of transition, while FDI flows in either primary or tertiary sectors have been quite scarce because of strict regulations, and other impediments removed very recently.

Given the nature of our data, in order to obtain an aggregate measure for TFP, we have to solve two methodological issues: how to recover plant level TFP, and how to aggregate them. We discuss each in turn.

Typically, plant level TFP is measured using the TFP residual ($Ln\omega$) computed as the difference between the log of output (*lnQ*) and the contribution of inputs ($\beta' \ln X$):

$$\ln \omega = \ln Q - \beta' \ln X \quad (1)$$

where (1) represents either the gross output or the value-added production function.

The standard procedure for estimating eq. (1) is to deflate the output or the value-added variable by replacing the unknown firm price index with the price index of the industry each firm belongs to (Aitken and Harrison, 1999; Olley and Pakes, 1996; Levinsohn and Petrin, 2003). However, this solution has been considered not only imperfect, but mainly inappropriate, since the resulting measures are "*contaminated by variation in factor prices and demand shocks*" (Katayama et al. 2006, pag. 2). Although "*differentiating between productivity differences and differences in markups is difficult, if not impossible*" (Bartelsman and Doms, 2000, p. 578), some (partial) and not always viable solutions have been recently proposed. Klette and Griliches (1996) and De Loecker (2005) demonstrate that the omitted variable bias can be eliminated by including among the regressors of eq. (1) a proxy for industry output growth. Katayama et al. (2006) develop an alternative strategy based on Berry's (1994) representation of

[4] Other limitations concern, first, the fact that ownership information is provided for one year only, therefore we have to assume that ownership did not change in the considered period, and, secondly, that only medium sized and large firms are surveyed by Amadeus.

market equilibrium with McFadden (1994) nested-logit demand functions which allows deriving the missing information on price, quality of output and demand elasticities under very specific hypotheses and conditions.[5] Taking advantages of two unique panel-data samples which include information on firm price indexes, Mairesse and Jaumandreu (2005) demonstrate that the elasticities of factors of production included in a simple Cobb-Douglass production function vary more with the estimation procedures than with the particular specification of the production function equation, being the latter a real output function, a revenue function deflated either by individual prices or industry price, and a not deflated revenue function. Therefore, the omitted variable bias claimed by other scholars seems to be negligible.

This result, together with the observation that estimating a production function in "physical" terms may be meaningless, unless firms produce a unique homogenous good, yields us to assume eq. (1) is a two factor Cobb-Douglas (not deflated) revenue function. Following the approach most commonly used in the recent literature on the topic, we estimate it by applying the semi parametric estimation technique developed by Olley and Pakes (1996). This technique takes into account the simultaneity bias due to the endogeneity of the firm's input selection, which may arise if a firm responds to unobservable productivity shocks by adjusting its input choice. This would imply a correlation between the inputs and the error term which biases traditional OLS coefficient estimates. Olley and Pakes suggest as a solution to this problem the use of firm's investment decisions as a proxy for unobserved productivity shock.[6] By applying this two step procedure on a sectoral base, we obtained sector-specific labour and capital intensities.[7] We then fitted eq. (1) and constructed the individual error terms,

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[5] These hypotheses and conditions include the following: *i)* each firm produces a distinctive product; *ii)* each firm faces different demand elasticities; *iii)* product varieties can be grouped in different geographical nests with products belonging to the same nest presumed to be less poorer substitute than products belonging to different nests; *iv)* the production function exhibits constant return to scale and no adjustment costs; *v)* entrant and exiting firms are not considered in constructing performance measures; etc.

[6] This implied that all firms with zero or negative investment could not be included in the sample. Alternatively, Levinsohn and Petrin (2003) suggest that material inputs can be used as a proxy for the firm's reaction to productivity shocks.

[7] Two sectors, namely manufacturing of refined petroleum products (NACE 23) and recycling (NACE 37), were excluded because the small number of firms operating in these sectors made it impossible to apply the Olley and Pakes procedure.

which were the logs of our estimated plant TFP.[8] Discrete changes in (1) have been computed as log changes over the period (Levinsohn and Petrin, 2005), i.e.:

$$ln\,\omega_t - ln\omega_{t-1} \tag{2}$$

Starting from (2) an aggregate measure of TFP changes may be obtained. In so doing, a weight α_i is applied in order to take into account firm heterogeneity, thus yielding to the following approximation:

$$\sum_i \alpha_i (ln\,\omega_{it} - ln\omega_{it-1}) \tag{3}$$

where i denotes the N plants in the sector/economy. For α_i, Tornqvist (1936) suggests averaging beginning and ending period shares in total output: $\alpha_i = \frac{s_{it} + s_{it-1}}{2}$.[9] A principle feature of this approximation is that it allows to group plants in any subaggregates without affecting the measures of aggregate TFP growth. Given the structure of our databases, we consider three subgroups of firms, i.e., continuing firms, exiting firms and entrant firms. The former are active all over the period, therefore TFP changes and shares can be observed both in t and *t-1*. Exiting (entrant) firms, instead, contribute to aggregate TFP from *t-1* to the time they exit (from the time they enter to *t*). Therefore, we can not observe either shares or TFP levels in *t* and *t-1*, respectively. As suggested by Levinsohn and Petrin (2005), averaging shares maintain a good way to minimize potential errors, while missing information on TFP levels can be forecasted using values of $ln\,\omega$ observed immediately after (before) the entry (exit). Therefore, our measure for aggregate TFP changes assumes the following form:

$$\begin{aligned}\Omega_{t-1,t} &= \sum_{i\in C} \frac{s_{it} - s_{it-1}}{2}(ln\,\omega_{it} - ln\,\omega_{it-t}) + \\ &+ \sum_{i\in E} \frac{s_{it}}{2}(ln\,\hat{\omega}_{it} - ln\,\omega_{it-t}) + \sum_{i\in X} \frac{s_{it-1}}{2}(ln\,\omega_{it} - ln\,\hat{\omega}_{it-t})\end{aligned} \tag{4}$$

where C indicates continuing firms, E entrant firms and X exiting firms.

[8] The advantage of this strategy is that it allowed us to consider also information on productivity of firms active in period *t* but with zero investments. In fact, omitting plants with zero investment would have meant omitting plants with low or declining productivities, thus introducing a sample bias in the next steps, i.e. the construction of an aggregate TFP measure and the analysis of the impact of FDI spillovers on it.

[9] This approximation is preferred by a number of scholars. See Levinsohn and Petrin (2005) for an in-depth discussion of the advantages of this approximation with respect to other possible aggregations available in the literature.

We use eq. (4) to retrieve TFP changes in 21 manufacturing sectors in 30 NUTS II regions[10] belonging to Bulgaria, Poland and Romania over the period 1998-2003. Eventually we end up with 630 observations. In the econometric section we explore the role MNEs can play as a determinant of these changes.

3. Exploratory analysis

In Figure 1 we have plotted the growth rates of TFP over the period 1998-2003 against the level of TFP in 1998. We observed a negative correlation in Romania, indicating a slight tendency to convergence, and a positive but very small correlation in Poland and Bulgaria, indicating an even slighter tendency to divergence. These opposite tendencies cancel each other out when we consider the whole sample.[11] Figure 2 is a scatterplot of the growth rates of TFP against a measure of MNEs in the 1998.[12] In this case the correlation is more pronounced and always positive, consistent with the hypothesis that higher MNEs is associated with more technological transfer. As before, this relationship varies across countries, being more pronounced in Poland and Romania than in Bulgaria. Overall, this indicates that spatial heterogeneity does occur.

[insert Figure1 and Figure 2 about here]

The spatial distribution of TFP growth at regional level can be seen in figure 3.[13] Regions with high growth rates over this period are Sofia region in Bulgaria (BG04), Timis region in Romania (RO05), the three Polish regions bordering with German (Dolnoslaskie (PL01), Lubiskie (PL04), and Zachodniopomorskie (PL16)), and the Wielkopolskie (PL15) and Slaskie region (PL12). Note that these regions are not among those which lag behind in term of TFP in 1998. Therefore, divergence seems to characterize growth patterns in our sample. Country differences still occur: Romania is

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[10] Several studies have emphasized that the transition process yield to both regional and sectoral changes. These studies belong to an emerging body of literature focusing on regional performance following transition, i.e. detecting loosing and winning regions (Traistaru, Njikamp and Resmini, 2003, Resmini, 2003; Petrakos, 2000).

[11] An explanation for this unusual result might be the fact the level of TFP in 1998 may not adequately reflect the level of development available over the period 1998-2003, since Bulgaria and Romania experienced rapid changes in the early 2000s. If we plot the average of TFP over the period, patterns of convergence and divergence persist and become clearer.

[12] How we construct MNE measures is explained in the next section.

[13] Changes in (and levels of) TFP in region *r* have been constructed as an output share weighted average of the productivity changes (levels) of all sectors active in that region.

characterized by a convergence growth process, while Poland and Bulgaria show very weak patterns of divergence.[14]

[insert Figure 3 about here]

Spatial autocorrelation can be defined as the coincidence of value similarities in locational similarity (Anselin, 2001). There is positive spatial autocorrelation when high or low values of a variable tend to cluster together in space, and negative spatial autocorrelation when high values of a variable are surround by low value and vice versa. In order to display visually spatial autocorrelation, the Moran scatterplot can be used (Anselin, 1996), which plots the spatial lag Wx over x, where x is either the TFP level or the TFP growth rate and W is a row standardized spatial weights matrix.[15] As Figures 4 and 5 shows, both levels and growth rates of TFP are spatially correlated. The positive correlation is stronger in levels than in growth rates and tends to be stable over time.

To summarize, our explanatory analysis suggests the data are not randomly distributed, but follow a systematic spatial pattern. This feature is taken into account in our econometric estimations that are presented next.

[insert Figures 4 and 5 about here]

4. Model specification

This section discusses the empirical specification used in this study. We specify a regression equation (log form) as follows:

$$\begin{aligned}\Delta TFP_{sr}^{03,98} &= \alpha_0 + \beta_1 TFP_{sr}^{98} + \beta_2 LQ_{sr}^{98} + \beta_3 size_{sr}^{98} + \beta_4 MNE_{sr}^{98} + \\ &+ \beta_5 (TRADE_s^{98} * LQ_{sr}^{98}) + \beta_6 \Delta \mathrm{PPI}_s^{03,98} + \beta_7 HR_r^{98} + \varepsilon_{sr}\end{aligned} \tag{5}$$

according to which the growth rate of TFP of sector s in region r over the 1998-2003 period ($\Delta TFP_{sr}^{03,98}$) is expressed as a function of a number of sectoral and regional characteristics measured at the beginning of the period in order to minimize possible endogeneity problems. Sectoral characteristics, always measured at regional level, include the initial level of TFP (TFP_{sr}^{98}), the relative concentration of the sector,

[14] It is worth noticing that in Bulgaria divergence patterns are driven by the exceptional performance of the Sofia region, which is on a growth trajectory completely different from the rest of the country. When Sofia region is not considered, patterns of convergence clearly emerge.

[15] A detailed description of the spatial weight matrix W is given in section 4.

measured by the traditional location quotient (LQ_{sr}^{98}), the average size of firms ($size_{sr}^{98}$), a measure of MNE activity (MNE_{sr}^{98}), whose construction will be discussed below, a measure of trade openness $(TRADE_{s}^{98})$, obtained as the ratio of export and import over the output of the sector. This measure has been interacted with the location quotient in order to give it a regional dimension, otherwise impossible to obtain. Finally, we consider the variation of the production price index ($\Delta PPI_{s}^{03,98}$) in order to understand the role played by the price component in TFP changes, thus (partially) correcting for possible measurement errors in the construction of the dependent variable. Regional characteristics concern mainly the human capital endowment, proxied by the human resources devoted to science and technology activities (HR_{r}^{98}) while α_0 is the constant and ε_{sr} the error term, whose specification will be explained below.

We used existing literature to justify eq. (5). Technology diffusion models emphasize the importance of either absorptive capacity, that is, the ability of a country/region to adopt foreign technology for use in the domestic markets (Findlay, 1978), or human capital in productivity growth (Nelson and Phelps, 1966; Benhabib and Spiegel, 1994). We use the initial level of TFP and the human resource variable to capture these effects. New technologies are diffused through a variety of channels, the most important of which are international trade and MNEs (Coe and Helpman, 1995; Xu, 2000; Xu and Wang, 1999; Keller, 2002). Finally, the findings that firms geographically clustered are more productive because of agglomeration economies (Henderson, 2001) justify the inclusion in the set of the explanatory variables of the location quotient, a traditional measure of industry concentration.

In order to capture the effects of FDI on growth, we measure the presence of foreign firms with their shares in sector *s* and region *r*'s total employment ($E_{sr}^{f} \big/ \sum_{s} E_{sr}$). This rough measure of FDI density has then been interacted with factors able to explain both the degree of interdependence of manufacturing sectors and the nature – i.e. source for inputs or destination for output – of such interdependence. Both these characteristics can be inferred from input-output tables, which suggest that each manufacturing sector is at the same time both a supplier and a customer of several manufacturing sectors, itself included.[16] We thus ended up with the following four measures for MNEs:

$$MNE\_for_{sr}^{98} = \alpha_{ss} * \frac{E_{sr}^{f}}{\sum_s E_{sr}} \quad (6)$$

$$MNE\_for_{k\neq s,r}^{98} = \sum_{k\neq s} \alpha_{sk} * \frac{E_{kr}^{f}}{\sum_k E_{kr}} \quad (7)$$

$$MNE\_back_{k\neq s,r}^{98} = \sum_{k\neq s} \omega_{sk} * \frac{E_{kr}^{f}}{\sum_k E_{kr}} \quad (8)$$

$$MNE\_back_{sr}^{98} = \omega_{ss} * \frac{E_{sr}^{f}}{\sum_s E_{sr}} \quad (9)$$

Eq. (7) and (8) measure foreign firm penetration in upstream and downstream industries, thus accounting for forward and backward linkages, respectively. α_{sk} (ω_{sk}) is the share of sector *k* output (input) that is supplied (sold) to sector *s*, as indicated by the input-output tables. Eqs. (6) and (9) have the same meaning as eq. (7) and (8) respectively, but refer to foreign firms operating in the same sector (and region).

Given the high level of aggregation implied in our model specification, eq. (6)-(9) can not be included directly in eq. (4), at least for two reasons. First backward and forward measures are correlated each other, since manufacturing sectors are highly interrelated, as indicated by the input-output table.[17] Therefore, we estimate the effects of downstream MNEs on TFP changes separately from those of upstream MNEs. Secondly, MNEs might be very sensitive to a number of variables included in the right hand side of eq. (4), namely the initial level of TFP, the degree of relative concentration and openness of the manufacturing sector they belong to, and the human resource endowment of a region, as suggested by previous empirical studies on FDI location in transition countries (Campos and Kinoshita 2003, Resmini, 2000; Pusterla and Resmini,

[16] We used the latest available national Input Output tables at two digit level for each country. This strategy implies that supplier and client relationships occur within sectors as well. This is not too unrealistic, given the level of aggregation we work with. This concept can be clarified if we consider two firms, one producing cotton fibres and the other producing cotton fabrics. Both firms belong to the same manufacturing sector, i.e. textiles (Nace 17), although they produce at different stages of the production chain. We are aware that this specification did not allow us fully to capture intra-sectoral spillovers, which also stem from foreign activity taking place at the same production stage as domestic firms. These spillovers derive from imitation and or demonstration effects, as well as from personnel training and mobility. However, it is likely that multinational firms try to minimize them, because they involve the transmission of specific knowledge to their local competitors (Haskel et al., 2002).

[17] See Nicolini and Resmini (2006) for an in depth discussion of correlations among different measures of MNE variables.

2007). In order to avoid severe multicollinearity problems, we first regressed the MNE variables on the other explanatory variables and then used the residuals of these regressions as a proxy for MNEs in eq. (4).[18]

A final consideration concerns the error term, because it captures spatial correlation. The latter can be accounted for different models, whose choice is not arbitrary but driven by specific tests. In our case, it is restricted to the error term.[19] This implies that spatial dependence works through omitted variables with a spatial dimension, i.e. climate, common rules and institutions, exogenous shocks. Therefore, the error term in eq. (4) has the following form:

$$\begin{aligned} \varepsilon_{sr} &= \lambda W \varepsilon_{sr} + \mu_{sr} \\ \varepsilon_{sr} &= (I - \lambda W)^{-1} \mu_{sr} \end{aligned} \qquad (10)$$

where λ is the parameter indicating the extent of the spatial correlation between the errors, *W* is the squared matrix defining the interaction among regions and μ is an *i.i.d.* error component. The spatial weights, i.e. the elements of the matrix are proportional to the size of the economies – proxied either by the GDP or the population of the neighbouring regions – and the inverse of their bilateral great circle distance. By convention, the matrix has zero on the main diagonal and it is row standardized, so that it is relative and not absolute distance that matters. In formulas:

$$\begin{aligned} w^*_{ij} &= POP_j * d_{ij}^{-1} \\ w^*_{ii} &= 0 \\ w_{ij} &= w^*_{ij} \big/ \textstyle\sum_j w^*_{ij} \end{aligned} \qquad (11)$$

5. Empirical findings

Table 2 shows the results for various specifications used in order to explore the existence and the nature of spatial dependence. Column (1) reports the results of the OLS estimation, while column (2) and (3) the results of spatial lag and spatial error model, respectively. Column (4) and (5) present the results of the spatial error model

[18] Residuals, by definition, are the portion of the variation of the dependent variable not explained by the explanatory variables. Thus, in our case, they pick up the effects of FDI not related to the other explanatory variables on changes in TFP proxy.
[19] Spatial dependence may also be directly modelled by including the spatial lag of the dependent variable among the explanatory variables. See Anselin (2003), Le Sage (1998) and Elhorst (2003) for a formal discussion on specification and estimation of spatial models.

estimates with spatial fixed effects and sectoral fixed effects. The upper part of the table shows estimates with a measure of MNEs in upstream manufacturing sectors, while the impact of MNEs in downstream sectors is shown in the lower part of the table.

Spatial diagnostics are provided at the end columns (1) and (2). In the first column, we report two tests for spatial dependence: the Moran's *I* test, and the Lagrange multiplier tests for spatial error dependence in OLS residuals. The Moran's *I* statistic for regression residuals is a general test for detecting spatial dependence, but it does not allow to discriminate between spatial dependence and spatial error models. The statistics is significant at the 1% level in both specifications, indicating that the residuals from OLS regressions are spatially autocorrelated and that the standard model is miss-specified. Therefore, we estimate eq. (4) by using either spatial lag model (column 2) or spatial error model (column 3). The Lagrange Multiplier tests confirm that the errors are spatially autocorrelated, and that accounting for the spatial lag of the dependent variable is not appropriate. On the base of these results, the spatial error model seems to be the most appropriate, as confirmed by the R^2 and the log likelihood, which are better in the SEM than in the SAR specification.

Our results indicate that changes in aggregate TFP are positively affected by the human resources devoted to science and technology activities, the relative concentration of the sector, and the average size of firms belonging to the sector. As expected, variation in production prices does affect TFP, while the initial level of TFP and the degree of openness do not seem to be able to exert any impact on TFP changes.[20] The technology superiority of MNEs spreads to local economy only within the same manufacturing sector, as indicating by the positive coefficients of the variables measuring the importance of foreign firms in each manufacturing sectors. Also the coefficients of the variables for MNEs operating in upstream and downstream sectors enter positively, yet they are not significant. This result changes when we control for spatial heterogeneity by introducing regional specific dummies (column 4). To test the validity of these restrictions (i.e. if dummy variables should be introduced into the model) the F test has been performed. It allows us to reject the null hypothesis that the restricted and unrestricted specifications are the same, use regional dummy variables in the regression estimations. In so doing, both MNE variables become significant at the conventional

[20] While the latter result is quite surprisingly, the former confirms what we have already uncovered with the exploratory analysis (see. Section 3 and figure 4).

levels. The magnitude of intra and inter-sectoral spillovers is the same, regardless of the position of the MNEs in the production value chain (i.e. upstream or downstream). Then the restrictions are relaxed for sectoral dummies too, and the complete unrestricted model is estimated (last column of table 2). In this case, however, the test F is not significant, therefore the constraint of not including sectoral dummies is valid.[21]

[insert Table 2 about here]

In table 3, we further refine our model by controlling for two specific geographical patterns detected in the exploratory analysis (section 3). In particular, we specify a country pattern in the TFP initial level, and control for spatial dependence. This implies, first, interacting the TFP level variables with country dummy variables, and, secondly, introducing these variables spatially lagged among the regressors. The results do not change substantially. However, we found a slight evidence for convergence patterns in Romania, and a strong evidence of spatial spillovers exerted by Polish regions, as indicated by the coefficients of the spatially lag TFP variable interacted with a dummy for Poland, which is positive and statistically significant in all specifications. It is also worth noticing that the coefficient of spatial autocorrelation becomes less significant, indicating that by introducing country patterns and controlling for spatial spillovers in TFP levels we reduce the omitted variable bias responsible for spatial dependence. As before, sectoral fixed effects are not supported by data.

[insert Table 3 about here]

5.1 Spatial spillovers and MNEs

The previous discussion has suggested that MNEs located in the region can exert, on average, a positive effect on changes in sectoral TFP. The evidence, however, is stronger for MNEs operating in the same sector than for MNEs operating in other sectors. This result is not new in the literature, and support the idea that local firms, as a whole, can take advantages from proximity with MNEs. However, recent developments in economics of agglomeration have shown that some externalities are not necessarily localized. This is the realm of pecuniary externalities that arise from imperfect competition in presence of market-mediated linkages among firms (Fujita and Thisse,

[21] The poor explanatory power of specification (4) may be explained by the fact that sectoral heterogeneity is already captured by explanatory variables; therefore, adding sectoral fixed effects may generate multicollinearity problems that worsen the goodness of fit of the mode.

2002). Therefore, it is not unrealistic to assume that spillovers generated by MNEs can overcome regions' boundaries to the extent foreign firms interact with indigenous firms, consumers and workers located in other regions.

In order to control for this hypothesis, we create a spatial lag variable for MNEs operating either in the same or in other manufacturing sectors, which should take into account the effect of MNE in neighbouring regions on changes in TFP.[22] In table 4 we present results from the estimation of the unrestricted specification with spatial lag variables of MNEs and TFP initial levels. Two features are worth noticing. First, the coefficients of the spatial lag variable of MNEs enter negatively, though they are significant only for MNEs operating downstream in the production value chain but within the same manufacturing sector. Second, the coefficients of the proxies for MNEs located in the same region maintain their positive sign, though one of them turn on be insignificant in the case of MNEs in downstream sectors.

Summarizing our result, we do find evidence that positive spillovers from FDI occur, but only in the same sector and region. We also find some evidence on negative effects from MNEs located outside the region.[23]

[insert Table 4 about here]

Finally, we investigate whether and to what extent the negative impact of MNEs located outside the region is generalized or driven by particular groups of regions. To accomplish this task we interact the spatially lagged MNE variables with different regional dummy variables. In particular we explore the following spatial regimes: *i)* capital regions vs all other regions; *ii)* regions bordering with the former EU-15; *iii)* most dynamic regions, i.e. regions with the highest TFP level in 1998 and with the highest TFP growth rates over the period; *iv)* less dynamic regions, i.e. regions with the lowest TFP level in 1998 and the lowest TFP growth rate over the period;[24] *v)* northern regions vs southern regions, i.e. Poland vs. Bulgaria and Romania. Results for the cross regressive model in pool and with spatial fixed effects are shown in table 5, which reports the coefficients for the MNE variables, only. This new set of estimates indicates that the negative impact exerted by MNEs is confined to a specific group of regions,

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[22] When adding spatially lagged variables, the matrix of exogenous variable can suffer from multicollinearity problems. In order to identify possible collinear relationships in this matrix, we applied the method set forth in Belsey, Kull and Welsch (1980). Exogenous variables are not collinear.

[23] A similar result was obtained by Girma and Wakelin (2000) though with a different methodology.

[24] These regions are, respectively, those in the upper-right and bottom-left quadrants of figure 3.

which includes the capital regions and, though to a lesser extent, the regions bordering with the former EU-15 countries, as indicated by the negative and significant sign of the coefficients of the spatially lagged MNE variables interacted with the dummy variable in specification (1) and (2) of table 5.

There are at least to possible explanations for these results, which do not necessarily mutually exclude. The first is that MNEs located along the former EU-15 borders are likely to have more strict relationships with firms operating in the EU-15 regions than in other regions of transition countries, which, therefore, do not reap any externalities and suffer from the lack of potential business with technologically advanced partners. Secondly, in transition countries, the capital regions usually catalyze most of the economic activity of their own countries, either because of legacy from the past or because the lack of other important industrial poles. This suggests that capital regions, in order to sustain their development, may draw resources - both in terms of qualified labour and productive firms – from neighbouring regions. This effect may be further exacerbated by MNEs enterprises. Therefore, being located close to the capital regions, which usually host most of foreign firms located in their own country does not help in enhancing TFP growth rates.

[insert Table 5 about here]

6. Summary and conclusions

This paper investigated the hypothesis that MNEs are important channels for technology diffusion and, consequently, important determinants of TFP growth rates. Our investigation used data on foreign manufacturing firms operating in Bulgaria, Poland and Romania covering the period 1998-2003. Distinctive features of our work were, on the one hand, the consideration of TFP at aggregate level, and, on the other hand, the inclusion of spatial effects, and, therefore, the explicit consideration of both spatial dependence and spatial heterogeneity. This is the first time this methodology is proposed and applied to the analysis of FDI induced spillovers. It allows us to reject previous methodologies that are considering only one aspect, but not both, because results may be biased and inefficient.

Our results, based on panel data estimation, indicate that spillovers from MNEs occur both within and across complementary manufacturing sectors at regional level. The latter, however, are less significant than the former in almost all specification, indicating that intra-sectoral spillovers are more robust than inter-sectoral spillovers. We also find some evidence of negative spillovers outside the region, though limited to specific groups of regions, such as the capital regions and regions bordering with former EU-15 countries. Therefore, we can conclude that there seems to be a regional channel for FDI spillovers.

Besides MNEs, there are other characteristics of sectors and regions able to affect changes in aggregate TFP. In particular, we found that relatively concentrated sectors with large firms in regions well endowed with human capital enjoy high TFP growth rates. The latter are also positively affected by neighbouring regions' TFP levels, but only in Poland. Bulgaria and Romania do not show any significant spatial autocorrelation pattern working through TFP levels. Spatial autocorrelation, however, do exist in all countries, but it works through omitted variables with a spatial dimension, as indicated by diagnostics tests on spatial autocorrelation in the error term.

These results open interesting perspectives on the policy side. The expectation of regional spillovers from MNEs supports the existence of FDI promotion policies implemented at regional level. However, the existence of possible negative spillovers from MNEs located in some neighbouring regions suggests that MNEs location should be carefully planned in order to avoid regional policies to attract FDI may generate opposite results, thus vanishing the objectives they wish to obtain.

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Figure 1. TFP patterns of growth by country (1998-2003)

Figure 2. TFP growth and MNEs

Figure 3. The distribution of TFP changes by country and region

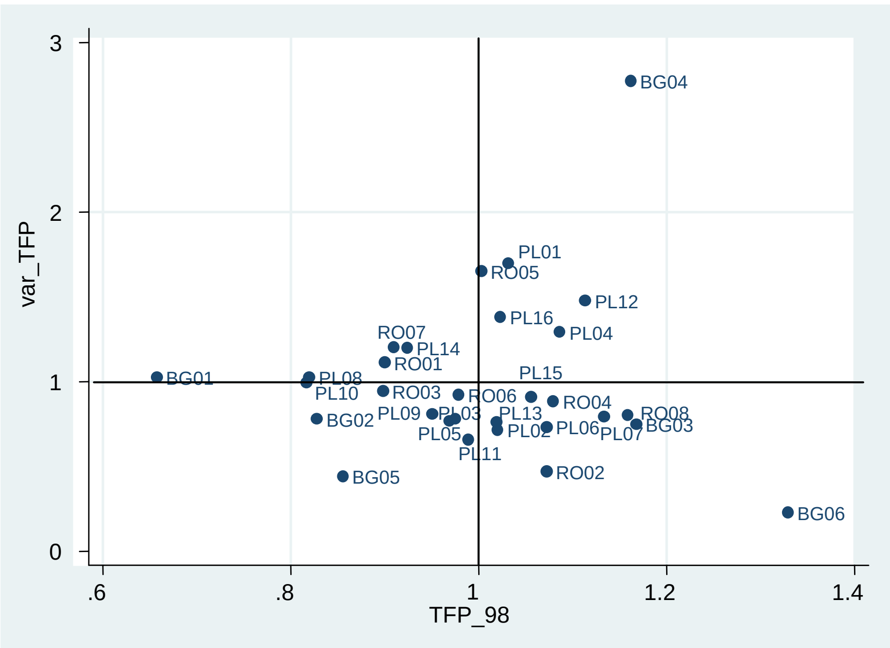

Figure 4. Moran I scatterplot of TFP levels (1998 and 2003)

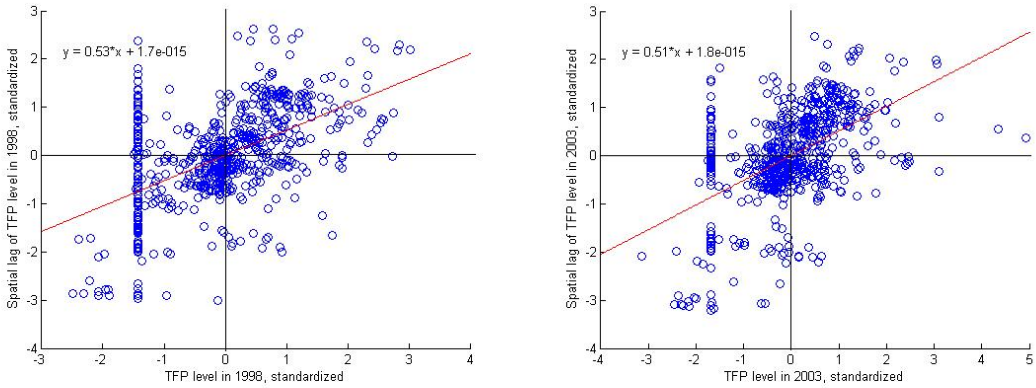

Figure 5. Moran I scatterplot of TFP growth rates over the period

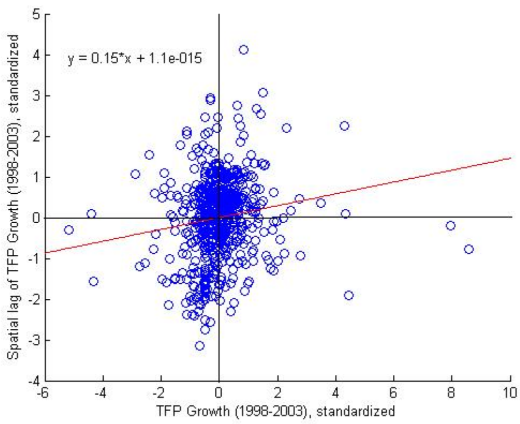

Table 1. Representativeness of the sample: distribution of manufacturing employment

	By region	By sector
1998	0.89 (p>0.000)	0.89 (p>0.000)
2003	0.97 (p>0.000)	0.72 (p>0.000)

Correlation with official data (EUROSTAT)

Table 2 Estimation results: OLS vs. spatial models

	OLS		SAR - Pool		SEM - Pool		SEM spatial FE		SEM all FE	
	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat
costant	**-0.77****	-2.544	**-0.80*****	-2.671	**-0.71****	-2.383	-	-	-	-
TFP level	-0.00	-0.122	-0.372	-0.122	-0.01	-0.705	0.00	0.372	0.00	0.288
HRST	**0.25*****	2.90	**0.25*****	2.866	**0.24*****	2.833	-	-	-	-
LQ	**0.05*****	2.72	**0.05*****	2.687	**0.05*****	2.722	**0.05*****	2.643	**0.06*****	2.996
avg size	**0.03****	2.37	**0.03****	2.247	**0.03****	2.197	**0.03*****	2.595	**0.03****	2.468
openness*LQ	0.00	0.00	0.00	0.026	0.00	0.044	-0.01	-0.201	0.04	1.084
Var PPI	**0.14****	2.45	**0.13****	2.258	**0.14****	2.197	**0.60*****	3.905	**0.55*****	3.859
MNE_forw same sect	**0.03***	1.88	**0.03***	1.897	**0.03****	1.958	**0.05*****	2.722	0.01	0.843
MNE_forw other sect	0.01	1.10	0.02	1.255	0.02	1.233	**0.05****	2.378	0.03	1.521
spat. Autocorr coeff.	-	-	**0.23****	2.415	**0.26*****	2.675	**0.25*****	2.619	**0.23****	2.463
n. obs	630		630		630		630		630	
R squared	0.0415		0.0407		0.0500		0.1368		0.0744	
adj. R suqared	0.0292		0.0283		0.0428		0.0844		-0.0161	
log likelihood			-322.35		-322.16		-511.848		-533.728	
Moran I	3.047***									
LM (error)	6.79***		12.11***							
test F on fixed effects							F[29,593]=1.94***		F[50,573]=0.61	
costant	**-0.77****	-2.567	**-0.79*****	-2.674	**-0.70****	-2.358	-	-	-	-
TFP level	-0.00	-0.275	-0.00	-0.502	-0.01	-0.838	0.00	0.088	-0.00	-0.089
HRST	**0.25*****	2.89	**0.25*****	2.85	**0.24*****	2.800	-	-	-	-
LQ	**0.05*****	2.65	**0.05*****	2.60	**0.05*****	2.67	**0.05*****	2.480	**0.05*****	2.702
avg size	**0.03*****	2.39	**0.03****	2.58	**0.03****	2.22	**0.03*****	2.675	**0.03*****	2.602
openness*LQ	-0.00	-0.000	0.00	0.038	0.00	0.08	-0.00	0.056	0.04	0.960
Var PPI	**0.14****	2.458	**0.13****	2.302	**0.14****	2.24	**0.63*****	4.035	**0.57*****	4.007
MNE_back same sect	**0.02***	1.90	**0.03****	2.00	**0.03****	2.15	**0.05*****	2.826	0.01	0.548
MNE_back other sect	0.02	1.44	0.02	1.43	0.02	1.28	**0.05****	2.298	**0.04****	2.21
spat. Autocorr coeff.	-	-	**0.23*****	4.144	**0.26*****	2.636	**0.26*****	2.779	**0.24****	2.463
n. obs	630		630		630		630		630	
R squared	0.0424		0.041		0.0563		0.1377		0.0789	
adj. R suqared	0.0301		0.0287		0.0442		0.0854		-0.0111	
log likelihood			-322.05		-321.70		-511.65		-532.15	
Moran I	3.121***									
LM (error)	7.050***		2947.88***							
test F on fixed effects							F[29,593]=1.94***		F[50,573]=0.29	

*, **, *** indicates significance level at 10, 5, and 1 per cent respectively.

Table 3. Estimation results: cross regressive models with spatially lagged TFP levels

	spatial FE		**all FE**		**spatial FE**		**all FE**	
	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat
TFP level*BG	-0.00	0.035	-0.02	-0.702	-0.00	-0.152	-0.02	-0.713
TFP level*PL	0.01	0.897	0.01	1.298	-0.00	-0.270	-0.01	-0.506
TFP level*RO	-0.06	-1.332	**-0.08***	-1.870	-0.06	-1.251	-0.08	-1.555
W-TFP level*BG	-	-	-	-	-0.02	-0.250	-0.06	-0.741
W-TFP level*PL	-	-	-	-	**0.07****	2.38	**0.06****	2.539
W-TFP level*RO	-	-	-	-	0.01	0.056	0.00	0.006
HRST	-	-	-	-				
LQ	**0.05*****	2.593	**0.06*****	2.963	**0.06*****	2.846	**0.06*****	3.322
avg size	**0.03****	2.484	**0.03****	2.296	**0.03****	2.39	**0.02****	2.022
openness*LQ	-0.00	-0.135	0.04	1.120	-0.00	-0.149	0.04	1.093
Var PPI	**0.53*****	3.349	**0.44*****	3.010	**0.51*****	3.188	**0.39****	2.548
MNE_forw same sect	**0.05*****	2.794	0.01	0.871	**0.05****	2.547	0.01	0.76
MNE_forw other sect	**0.05****	2.387	0.03	1.576	**0.05****	2.455	**0.03***	1.736
spat. Autocorr coeff.	**0.23****	2.463	**0.22****	2.249	**0.20****	2.065	**0.18***	1.782
n. obs	630		630		630		630	
R squared	0.140		0.082		0.146		0.09	
adj. R suqared	0.084		-0.0116		0.0871		-0.0077	
log likelihood	-510.68		-531.01		-507.83		-527.83	
test F on fixed effects	F[29,591]=1.58**		F[50,571]=0.108		F[29,588]=1.76***		F[50,568]=0.22	
TFP level*BG	-0.00	0.035	-0.02	-0.811	-0.00	-0.142	-0.02	-0.666
TFP level*PL	0.01	0.592	0.01	0.944	-0.01	-0.521	-0.01	-0.590
TFP level*RO	-0.06	-1.364	**-0.08****	-1.998	-0.06	-1.267	-0.07	-1.472
W-TFP level*BG	-	-	-	-	-0.02	-0.171	-0.08	-1.066
W-TFP level*PL	-	-	-	-	**0.07****	2.321	**0.06****	2.403
W-TFP level*RO	-	-	-	-	-0.00	-0.000	-0.030	0.307
HRST	-	-	-	-				
LQ	**0.05****	2.418	**0.05*****	2.658	**0.05****	2.668	**0.06*****	2.937
avg size	**0.03****	2.571	**0.03****	2.428	**0.03****	2.478	**0.02****	2.160
openness*LQ	0.00	0.005	0.04	0.998	-0.00	-0.000	0.04	0.996
Var PPI	**0.56*****	3.498	**0.46*****	3.144	**0.53*****	3.317	**0.39****	2.563
MNE_back same sect	**0.05*****	2.836	0.01	0.513	**0.04*****	2.690	0.01	0.459
MNE_back other sect	**0.05****	2.312	**0.04****	2.225	**0.04****	2.193	**0.04****	2.215
spat. Autocorr coeff.	**0.23****	2.489	**0.22****	2.273	**0.21****	2.174	**0.18***	1.771
n. obs	630		630		630		630	
R squared	0.140		0.086		0.1467		0.0937	
adj. R suqared	0.085		-0.065		0.0872		-0.0037	
log likelihood	-510.57		-529.41		-507.83		-526.54	
test F on fixed effects	F[29,591]=1.55**		F[50,571]=0.15		F[29,588]=1.70***		F[50,568]=0.23	

*, **, *** indicates significance level at 10, 5, and 1 per cent respectively.

Table 4. Cross-regressive models with spatially lagged MNEs.

	spatial FE		all FE	
	coeff.	t-stat	coeff.	t-stat
TFP level*BG	-0.00	0.100	-0.01	-0.573
TFP level*PL	-0.00	0.171	-0.00	-0.115
TFP level*RO	-0.06	-1.307	**-0.08***	-1.662
W-TFP level*BG	-0.03	-0.292	-0.05	-0.677
W-TFP level*PL	**0.06****	2.219	**0.05****	2.084
W-TFP level*RO	0.01	0.099	0.00	0.053
HRST	-	-	-	-
LQ	**0.06*****	2.948	**0.07*****	3.492
avg size	**0.03****	2.493	**0.02****	2.174
openness*LQ	-0.00	-0.076	0.05	1.149
Var PPI	**0.50*****	3.135	**0.38****	2.482
MNE_forw same sect	**0.05*****	2.625	**0.04***	1.922
MNE_forw other sect	**0.05****	2.428	**0.05****	2.032
W-MNE_forw same sect	-0.05	-1.194	**-0.08****	-2.326
W-MNE_forw other sect	-0.05	-1.104	**-0.06***	-1.706
spat. Autocorr coeff.	**0.18***	1.794	**0.20****	2.005
n. obs	630		630	
R squared	0.148		0.099	
adj. R suqared	0.086		-0.018	
log likelihood	-507.02		-525.02	
test F on fixed effects	F[29,586]=1.49**		F[50,566]=0.17	
TFP level*BG	-0.00	-0.040	-0.01	-0.451
TFP level*PL	-0.01	-0.400	-0.00	-0.298
TFP level*RO	-0.07	-1.349	-0.08*	-1.630
W-TFP level*BG	-0.04	-0.400	-0.10	-1.291
W-TFP level*PL	**0.06****	2.275	**0.05****	2.182
W-TFP level*RO	-0.00	-0.033	-0.04	-0.412
HRST	-	-	-	-
LQ	**0.06*****	2.829	**0.06*****	3.217
avg size	**0.03****	2.517	**0.02****	2.077
openness*LQ	-0.00	0.043	0.03	0.667
Var PPI	**0.52*****	3.278	**0.39*****	2.592
MNE_back same sect	**0.06*****	3.222	**0.05*****	2.681
MNE_back other sect	0.04	1.478	0.03	0.977
W-MNE_back same sect	**-0.06***	-0.817	**-0.09*****	-3.322
W-MNE_back other sect	-0.02	-0.544	-0.01	-0.371
spat. Autocorr coeff.	**0.16***	1.633	**0.18***	1.851
n. obs	630		630	
R squared	0.150		0.111	
adj. R suqared	0.088		0.012	
log likelihood	-506.20		-520.42	
test F on fixed effects	F[29,586]=1.44*		F[50,566]=0.27	

Table 5. Cross regressive models with spatial regimes

	pool	spatial FE	pool	spatial FE	pool	spatial FE	pool	spatial FE	pool	spatial FE
	(1)		(2)		(3)		(4)		(5)	
MNE_forw same sect	**0.05****	**0.07*****	**0.04***	**0.07*****	**0.04***	**0.07*****	**0.05****	**0.06*****	**0.04****	**0.06*****
	(2.546)	(3.245)	(1.993)	(3.029)	(1.853)	(3.004)	(2.189)	(2.730)	(1.977)	(2.663)
MNE_forw other sect	**0.03****	**0.07*****	0.01	**0.06****	0.01	**0.06****	**0.03***	**0.06****	**0.03**	**0.06****
	(2.012)	(3.088)	(0.815)	(2.442)	(0.510)	(2.542)	(1.655)	(2.275)	(1.527)	(2.413)
W-MNE_forw same sect	-0.05	-0.06	-0.04	-0.05	-0.04	-0.05	-0.04	-0.05	-0.05	-0.07
	(-1.194)	(-1.330)	(-1.049)	(-1.289)	(-1.062)	(-1.306)	(-1.094)	(-1.168)	(-0.882)	(-1.338)
W-MNE_forw other sect	-0.04	-0.06	-0.02	-0.05	-0.03	-0.05	-0.03	-0.05	-0.02	-0.07
	(-0.988)	(-1.409)	(-0.636)	(-1.190)	(-0.698)	(-1.175)	(-0.809)	(-1.087)	(-0.338)	(-1.222)
W-MNE_forw same sect*DUMMY	**-0.11****	**-0.14****	-0.03	**-0.07***	-0.01	-0.06	-0.03	-0.03	0.00	0.05
	(-2.564)	(-2.537)	(-0.745)	(-1.672)	(-0.425)	(-1.462)	(-1.028)	(-0.854)	(0.080)	(0.672)
W-MNE_forw other sect*DUMMY	**-0.06****	-0.12	**0.04****	-0.02	**0.06*****	-0.03	-0.01	-0.01	-0.03	0.04
	(-2.170)	(-2.383)	(2.002)	(-0.472)	(3.528)	(0.834)	(-0.652)	(-0.137)	(-0.684)	(0.572)
Spat. Aucorrelation coeffificent	**0.17***	**0.20****	**0.17***	**0.19***	**0.17***	**0.19****	**0.17***	**0.19****	**0.17***	**0.18***
	(1.668)	(2.029)	(1.679)	(1.887)	(1.645)	(1.921)	(1.702)	(1.919)	(1.679)	(1.828)
n. obs	*630*	*630*	*630*	*630*	*630*	*630*	*630*	*630*	*630*	*630*
R squared	*0.0979*	*0.158*	*0.0929*	*0.152*	*0.104*	*0.151*	*0.087*	*0.150*	*0.086*	*0.149*
adj. R suqared	*0.0728*	*0.093*	*0.068*	*0.087*	*0.079*	*0.086*	*0.062*	*0.084*	*0.061*	*0.083*
log likelihood	*-525.00*	*-503.40*	*-526.75*	*-505.58*	*-522.90*	*-505.96*	*-528.79*	*-506.56*	*-529.01*	*-506.77*
test F on fixed effects		F[29,584]=1.44*		F[29,584]=1.41*		F[29,584]=1.13		F[29,584]=1.48*		F[29,584]=1.48**
MNE_back same sect	**0.05*****	**0.05*****	**0.04****	**0.06*****	**0.04****	**0.06*****	**0.07*****	**0.07*****	**0.05*****	**0.06*****
	(2.673)	(2.899)	(2.372)	(3.157)	(2.308)	(3.196)	(3.459)	(3.649)	(2.832)	(3.276)
MNE_back other sect	**0.04***	**0.07****	0.01	**0.05***	-0.00	**0.05***	0.02	0.04	0.02	0.04
	(1.856)	(2.228)	(0.507)	(1.803)	(-0.019)	(1.726)	(1.087)	(1.377)	(0.979)	(1.495)
W-MNE_back same sect	**-0.06***	-0.05	**-0.06***	-0.06	-0.05	-0.06	-0.05	**-0.06***	-0.06	-0.09
	(-1.706)	(-1.635)	(-1.728)	(-1.849)	(-1.635)	(-1.817)	(-1.625)	(-1.728)	(-1.516)	(-2.042)
W-MNE_back other sect	-0.02	-0.04	-0.01	-0.03	-0.00	-0.03	-0.01	-0.03	0.01	-0.04
	(-0.612)	(0.824)	(-0.157)	(-0.644)	(-0.002)	(-0.593)	(-0.213)	(-0.597)	(0.185)	(-0.804)
W-MNE_back same sect*DUMMY	-0.01	-0.03	0.03	-0.01	0.02	-0.02	**-0.06****	-0.06	0.01	0.05
	(-0.159)	(-0.409)	(0.842)	(-0.324)	(0.676)	(-0.619)	(-2.147)	(-1.782)	(0.303)	(1.018)
W-MNE_back other sect*DUMMY	-0.07***	**-0.13****	0.03	-0.05	**0.06*****	-0.04	-0.01	0.01	-0.020	0.04
	(-2.619)	(-1.940)	(1.473)	(-1.149)	(3.196)	(-973)	(-0.381)	(0.373)	(-0.589)	(0.667)
Spat. Aucorrelation coeffificent	**0.15**	**0.18***	0.15	0.15	0.16	**0.17***	0.15	**0.17***	0.15	0.16
	(1.511)	(1.770)	(1.500)	(1.467)	(1.544)	(1.657)	(1.483)	(1.747)	(1.467)	(1.611)
n. obs	*630*	*630*	*630*	*630*	*630*	*630*	*630*	*630*	*630*	*630*
R squared	*0.16*	*0.16*	*0.093*	*0.152*	*0.105*	*0.151*	*0.0964*	*0.158*	*0.09*	*0.152*
adj. R suqared	*0.095*	*0.095*	*0.068*	*0.086*	*0.0797*	*0.086*	*0.0713*	*0.093*	*0.065*	*0.086*
log likelihood	*-502.60*	*-502.59*	*-526.43*	*-505.52*	*-522.57*	*-505.71*	*-525.38*	*-503.46*	*-527.29*	*-505.66*
test F on fixed effects		F[29,584]=1.44*		F[29,584]=1.38*		F[29,584]=1.11		F[29,584]=1.46**		F[29,584]=1.44*

DUMMY is defined as follows: (1) capital regions = 1, 0 otherwise; (2) BEU regions=1, 0 otherwise; (3) most dynamic regions=1, 0 otherwise; (4) less dynamic regions =1, 0 otherwise; (5) northern regions (Poland) =1, 0 otherwise. *, **, *** indicates significance level at 10, 5, and 1 per cent respectively.