ECONOMIC DISCUSSION PAPERS

Efficiency Series Paper 6/2019

Spatial Production Economics

Luis Orea, Inmaculada C. Álvarez

Departamento de Economía

Universidad de Oviedo

Available online at: https://www.unioviedo.es/oeg/

Spatial Production Economics [*]

Luis Orea [a]
Oviedo Efficiency Group
Department of Economics
University of Oviedo

Inmaculada C. Álvarez
Oviedo Efficiency Group
Department of Economics
Universidad Autónoma de Madrid

Abstract

This chapter summarizes the empirical literature that uses a spatial analysis framework in production economics. This literature takes advantage of the spatial dimension of the data to capture the spillover effects of neighboring production units. In the first three sections, we outline standard spatial extensions of the neoclassical production models aiming to measure knowledge spillovers, the effect of network inputs and economies of agglomeration. The next three sections outline the literature that on one hand examines returns to scale and productivity growth from both internal and external inputs, and on the other hand summarize the spatial econometric techniques used in frontier analyses of firms' production. The last section includes a set of final remarks regarding the application of spatial econometric techniques in production analyses.

Keywords: Spatial econometrics, stochastic frontier models, production economics

JEL codes: C4, C5, C6, D24.

---

[*] Parts of the manuscript will be published as a chapter in the forthcoming Volume II of the 2-volume *Handbook of Production Economics* that S.C. Ray, R.G. Chambers and S.C. Kumbhakar are currently editing for publication by Springer.

[a] Luis Orea would like to thank the financial support obtained from the Government of the Principality of Asturias and the European Regional Development Fund (ERDF).

1. Introduction

This chapter summarizes the empirical literature that uses a spatial analysis framework in production economics. Overall speaking, this literature incorporates external returns from other (nearby) production units, extending the set of production inputs in neoclassical production models. Most empirical models in this field are estimated using individual (e.g. firms) or aggregate (e.g. regions) production units. In some settings, these production units can be associated with locations and, therefore, can be placed on the map. The spatial dimension of the data is used in this literature to compute overall marginal products, returns to scale or productivity growth measures from both internal and external factors or simply to get better parameter estimates. Other researchers have used the spatial information in frontier production analyses to control for unobserved but spatially correlated variables that or to analyze interesting features of firms' economic performance.

This chapter is organized as follows. Section 2 introduces the so-called 'knowledge production functions' and formalizes the existence of knowledge spillovers in this setting. We take advantage of this discussion to introduce the three most popular production specifications in spatial econometrics: the *spatial lag* of X model (SLX), the *spatial autoregressive* model (SAR) and the *spatial Durbin* model (SDM). As firms' productivity might be spatially correlated due to the existence of knowledge spillovers, the standard neoclassical growth models can also be estimated using some of the above spatial specifications.[1] Section 3 presents several papers that argue that some inputs have network characteristics and generate external effects on neighboring production units (regions). This is the case of transport infrastructure and information and communication technologies (ICT). We introduce in this section a discussion on the selection of local versus global spillovers. Section 4 outlines the empirical literature that examines agglomeration economies, i.e. external returns from the concentration of economic activity, via localization effects or urbanization economies.

The next three sections are more methodological. Section 5 discusses how to measure internal, external and total returns to scale once a spatial specification of production units' technology has been estimated, either using homogeneous or heterogeneous coefficient models. This section also discusses how to compute aggregate or economy-wide returns to scale from a set of observations. Section 6 offers a brief discussion of the small but evolving literature on spatial stochastic frontier modelling. This literature is actually resuscitating the interest in *spatial error* models (SEM) because the stochastic frontier models have two different random terms and controlling for spatial spillovers in both noise and inefficiency terms does matter due to the significant and different economic consequences of such correlations. Section 7 is devoted to the decomposition of spatial measures of firms' total factor productivity (TFP). We outline the main features of two papers that have extended the standard TFP growth decomposition to include both direct (own) and indirect (spillover) components. We conclude this chapter with a set of final remarks in Section 8.

It is worth mentioning that, for notational ease, we have developed this chapter for panel data. We also confine our discussion to the estimation of (frontier) production functions due to other primal and dual representations of the technology deserve similar comments.

[1] Notice that the economic growth models are built from a previously defined production function.

2. Knowledge production function and spatial economic growth models.

As the spatial terms in a standard neoclassical growth model appear due to the existence of knowledge spillovers, we first introduce in this section the concept of 'knowledge production function' (KPF). We next summarize several empirical papers that have estimated neoclassical growth models using spatial econometric techniques.

The knowledge or ideas production is crucial in the theory of innovation and in the definition of optimal public policies. Pakes and Griliches (1984) defined the KPF as a function intended to represent the transformation process leading from innovative inputs (e.g. R&D) to commercially valuable knowledge or innovative output (e.g. patents). Most of the studies aiming to estimate a KPF depart from a Cobb-Douglas functional form where the level of technological knowledge (A_{it}) depends on the amount of physical resources allocated to R&D activities (z_{it}). This function can be enlarged to include learning ideas processes (Jaffe, 1986) that depends on neighbor's knowledge (see e.g. Audretsch and Feldman, 2004):

$$lnA_{it} = \alpha + \beta lnz_{it} + \lambda \sum_{j\neq i}^{N} w_{ij}\, lnA_{jt} + v_{it} \quad (1)$$

where subscript $i(=1, \dots, N)$ stands for regions, $t(=1, \dots, T)$ stands for periods, z_{it} is a vector of knowledge determinants, v_{it} is the traditional noise term, and the weight term w_{ij} formalizes the connectivity between firm i and firm j. According to this, the learning ideas process drives to knowledge spillovers if λ is positive.

Cunha and Neves (2018) review the empirical literature on KPFs, identifying a handful of papers that estimate KPFs using spatial econometric techniques. For instance, Botazzi and Peri (2003) estimate a KPF where the regional (spatial) spillovers decreases with the geographical distances between regions. The spatial specification of this model is justified by theories of localization that argue that geographic proximity reduces the cost of accessing and absorbing knowledge spillovers (Grasjö, 2006, p. 19). This explains why knowledge spillovers and spatial spillovers are different but related concepts.

In the early articles, it was common to find spatial interdependence in the determinants of knowledge, while more recently researchers consider also spatial spillovers in knowledge itself. These considerations result in different spatial specifications of KPF that correspond with different models widely known in the spatial econometric literature (Vega and Elhorst, 2015). On the one hand, the model that incorporates the spatial lag of the dependent variable or the weighted average of neighboring values of the dependent variable is the well-known *spatial autoregressive* model (SAR).[2] Equation (1) is an example of a SAR model. On the other hand, the model that incorporates the spatial lag of the explanatory variables is the well-known *spatial lag of X* model (SLX). For instance, Álvarez and Barbero (2016) assumes that the level of technological knowledge depends on physical and human capital of both the own region and neighboring regions. Their KPF can be thus written as:

$$lnA_{it} = \alpha + \beta lnz_{it} + \theta \sum_{j\neq i}^{N} w_{ij}\, lnz_{jt} + v_{it} \quad (2)$$

where z_{it} stands now for physical and human capital variable. There is not a consensus about the most preferred specification (SLX vs. SAR) and whether the spillovers are *local* or *global*.[3] Moreover, empirical results indicate that both type of spillovers might play an

[2] The 'spatial lag' terminology used in spatial econometrics was originally introduced by Anselin (1988).
[3] The spillovers induced by the SAR model in (1) are *global* in the sense that shocks disturbing a firm might affect *all* other firms. In contrast, the SLX model in (2) yields more *local* spillover effects because they do not not involve endogenous feedback effects from neighbours to the neighbours and so on.

important role in the production of knowledge (Gumbau-Albert and Maudos, 2009; Charlot et al., 2015). If so, the model that should be estimated is the well-known *spatial Durbin* model (SDM), which can be written is as follows:

$$lnA_{it} = \alpha + \lambda \sum_{j\neq i}^{N} w_{ij}\, lnA_{jt} + \beta lnz_{it} + \theta \sum_{j\neq i}^{N} w_{ij}\, lnz_{jt} + v_{it} \tag{3}$$

Notice that, as customary in spatial econometrics, this model can be rewritten in a simpler fashion using matrix notation as follows:

$$lnA_t = \alpha + \lambda W lnA_t + \beta lnz_t + \theta W lnz_t + v_t \tag{4}$$

where lnA_t, lnz_t and v_t are $Nx1$ vectors, and the set of spatial weight terms in (3) are now written using a spatial weight NxN matrix W, where diagonal elements are equal to zero, and the off-diagonal elements are non-zero if the firm i is assumed to be correlated with firm j. Quite often, the off-diagonal elements are equal to one if both observations are located in adjacent locations. In many applications the weight matrix is also *row-standardized* with the number of adjacent units (i.e. $\sum_{j\neq i}^{N} w_{ij} = 1$).[4] In this case, $W lnA_t$ in (4) can be interpreted as the average values of the technological knowledge of adjacent firms.

Given the relevance of geography in the diffusion of knowledge and R&D, Fingleton and López-Bazo (2006), Ertur and Koch (2007) and Fischer (2011) have augmented the Solow neoclassical model by including both global and local spatial autocorrelation on growth and convergence. The technology of the whole economy is characterized by a Cobb–Douglas production function with constant returns to scale in per worker terms:

$$lny_{it} = lnA_{it} + \alpha lnk_{it} + v_{it} \tag{5}$$

where $y_{it} = Y_{it}/L_{it}$ is output per worker, $k_{it} = K_{it}/L_{it}$ is capital services per worker, and A_{it} captures the level of technological knowledge. As in (2), the above-mentioned authors define the technological knowledge term using a SLX specification, i.e.:

$$A_{it} = \Omega k_{it}^{\varphi} \prod_{j\neq i}^{N} k_{jt}^{\varphi\rho w_{ij}} \tag{6}$$

where the technological parameter $0 < \varphi < 1$ reflects the size of the home externalities and ρ allows formalizing spatial interdependence by means of the spatial weight terms w_{ij}. If we plug (6) into the neoclassical production function (5), we get a (per worker) production function with spatial interactions:

$$lny_{it} = ln\Omega + \beta lnk_{it} + \theta \sum_{j\neq i}^{N} w_{ij}\, lnk_{jt} + v_{it} \tag{7}$$

where $\beta = \alpha + \varphi$ and $\theta = \varphi\rho$. Therefore, the existence of knowledge spillovers explains why output per worker in region i depends on its own capital investment but also on neighbors' capital investment.

If we now introduce the production function (7) into a neoclassical growth model, we can obtain the output per worker at the steady state and the speed of convergence to the steady state. Interesting enough, the obtained *convergence* equation includes spatial lags in *both* the dependent and independent variables:

$$\dot{y}_{it} = \alpha + \lambda \sum_{j\neq i}^{N} w_{ij}\, \dot{y}_{jt} + \beta z_{it} + \theta \sum_{j\neq i}^{N} w_{ij}\, z_{jt} + v_{it} \tag{8}$$

[4] The choice of a proper spatial weight matrix is contentious. For instance, Tiefelsdorf et al. (1999) point out that this standardization procedure may emphasize the prevalence of the spatial dependence on those units with fewer connections.

where $\dot{y}_{it}$ is the annual rate of growth of output per worker, z_{it} is the logarithm of the sum of the labor rate of growth, the rate of depreciation and the rate of technical change, and the speed of convergence can be obtained from the estimated λ parameter.[5] The spatial convergence equation in (8) thus follows a SDM model and it predicts convergence if output (per worker) growth is a negative function of initial output (not shown), after controlling for the determinants of the steady state (i.e. labor rate of growth, the rate of depreciation and the rate of technical change) and the possible existence of spatial interdependence among nearest economies. More recent papers also include other determinants of economic growth and convergence in regions and countries, such as human capital and public sector (e.g. Alvarez and Barbero, 2016).

To finish this section, it is worth mentioning that the spatial specifications of the above models come from economic theory. In general, one of the main criticisms regarding the spatial econometric models is the absence of theoretical basis (Corrado and Fingleton, 2012). Therefore, a remarkable exception is the *spatial* neoclassical growth model in which the spatial specification relies on the existence of knowledge spillovers and learning processes.

3. Network inputs

This section presents several papers that argue that some inputs have network characteristics and generate external effects on neighboring production units (regions). For instance, Munnell (1992) points out that the transport infrastructure localized in a region could benefit other regions. Stiroh (2002,a,b) and Griliches (1991) also stated that ICTs and R&D activities can be treated as network inputs because they can generate externalities to other firms as well. In most cases, the 'network' nature of these inputs is because they indeed are public goods, i.e. they are inputs that one firm can use without reducing their availability to others and from which no one is excluded.

3.1 Transport Infrastructures

Transport network or transport infrastructure has been considered one of the public policy decisions that has the greatest impact on economic development, both for its effect on the structure of the population, and its capacity to reduce costs and increase production. This explains why many studies have tried to quantify the effect of transport infrastructure on private production.[6] More specifically, after the seminal paper by Aschauer (1989), there is a wide literature that has extended the traditional (aggregate) production function where the provision of infrastructures (KP_{it}) is complementary to labor (L_{it}) and private capital (K_{it}). Using a Cobb-Douglas specification and assuming constant returns to scale in private inputs, this production function can be written after taking as follows:

$$lny_{it} = lnA_{it} + \alpha lnk_{it} + \beta lnKP_{it} + v_{it} \tag{9}$$

where y_{it} and k_{it} are again output and capital services per worker, v_{it} is the noise term, and A_{it} can be interpreted as a total factor productivity index.

Note that the provision of infrastructures enters the production function as a standard factor of production. Straub (2011) states that the inclusion of the infrastructure

---

[5] For notational ease, we have omitted in this equation the initial output (real income) per worker, and the fraction of output that is saved.

[6] For a summary of this literature, see Cohen and Morrison (2004) and Pereira and Andraz (2013).

variables as simple inputs is questionable because, despite the increasing market mediation of infrastructure, this type of capital is not completely remunerated according to its marginal productivity in the real world. This has prompted several authors (see e.g. Duggal et al., 1999; and Hulten et al., 2005) to instead consider infrastructure as part of the total factor productivity term (A_{it}), i.e. as an efficiency-enhancing externality specifically linked to the accumulation of infrastructure capital.[7]

In addition, transport infrastructures generate (spillover) effects outside the geographical place where they are located, given their network characteristic. In other words, firms located in a region not only use the infrastructure of its own region but also the infrastructures located in neighboring regions. Therefore, firms use two public infrastructures, not only one as it is implicitly assumed in (9). For this reason, the majority of the literature examining spillovers effects attributed to public infrastructure adopts a similar strategy, i.e. the addition of spatial lags of KP_{it} as a standard input. Therefore, the production function that is estimated is the well-known SLX model:

$$lny_{it} = lnA_{it} + \alpha lnk_{it} + \beta lnKP_{it} + \theta \sum_{j\neq i}^{N} w_{ij}\, lnKP_{jt} + v_{it} \qquad (10)$$

Depending on the strategy followed to define the spatial weights (w_{ij}), some papers have confirmed the existence of *positive* spillover effects derived from investment in transport infrastructures (e.g. Cohen and Morrison, 2004, and Pereira and Andraz, 2004), while other studies find *negative* spillover effects (e.g. Boarnet, 1998; Álvarez and Delgado, 2012; Álvarez et al., 2016a). The latter studies conclude that negative spillover effects from transport infrastructures are found due to factor migration or when the set of neighboring regions are defined in economic terms (e.g. regions that are competitors or have similar characteristics), while positive spillovers are generally found when the neighboring firms are defined using geographical criteria.[8]

Other authors analyze the impact of infrastructures provision on economic performance using more comprehensive spatial models. Yu et al. (2013) summarize this specific literature and attribute their SDM production model to variations in the rate of capital (capacity) utilization, an unobservable production driver in many applications. To address this issue, Gajanan and Malhotra (2007) suggest modeling the rate of capital utilization as a function of the economic performance of the neighboring provinces. This empirical strategy is supported on the basis that each region accommodates its rate of capital utilization to meet the output increases in other regions (Burnside and Eichenbaum, 1996). In this sense, Arbues et al. (2015) and Álvarez et al. (2016b) assume that the flow of capital services per worker in (10) is $k_{it} = CU_{it} \cdot k_{it}^{*}$, where k_{it}^{*} is the stock of capital per worker. They next define their capacity utilization rate as $CU_{it} =$

[7] The Cobb-Douglas production function in (9) does not allow researchers to distinguish the direct effect of infrastructure (i.e. through the production of specific services) from the indirect effect (i.e. the efficiency-enhancing infrastructure externalities). Orea et al. (2019) points out that this problem can be addressed if we first use a *frontier* specification of the production model and then we treat the set of infrastructure variables as efficiency determinants.

[8] The spillover effects also vary with the set of countries or regions examined and with the specification of the model in levels or in rates of growth. Indeed, in his revision of the literature, Straub (2011) finds that specifications using a standard production function in levels are generally more supportive of a positive effect of infrastructure than those using output (productivity) growth rates. He interprets this result as an indication that transitory effects are more often observed than long term effects. This authors also points out that in most cases, growth-accounting studies find lower levels of infrastructure externalities for more developed countries or regions than for developing ones.

$e^{\lambda_Y \sum_{j\neq i}^{N} w_{ij} lny_{jt} + \tau_{it}}$. Substituting this spatial specification of CU_{it} into (10), they obtain the following SDM model:

$$lny_{it} = lnA_{it} + \lambda \sum_{j\neq i}^{N} w_{ij}\, lny_{jt} + \alpha lnk_{it}^{*} + \beta lnKP_{it} + \theta \sum_{j\neq i}^{N} w_{ij}\, lnKP_{jt} + \varepsilon_{it} \tag{11}$$

where $\varepsilon_{it} = v_{it} + \alpha\tau_{it}$, $\lambda = \alpha\lambda_Y$. Notice that the production function (11) depends on the capital stock k_{it}^{*} *and* the spatial lag of the dependent variable, while the production function (10) only depends on capital services that were (implicitly) assumed to be proportional to the capital stock.

3.2. ICT and R&D activities

ICT can be considered as a network input because it may enable a process innovation itself (see, e.g. Black and Lynch, 2000 and Bresnahan et al., 2002). The main debate in this literature has to do with the empirical techniques used to link ICT and productivity growth. For instance, while Jorgenson and Stiroh (2000), Gordon (2000), Van Ark et al. (2003) and Van der Wiel (2001) use growth-accounting techniques with observed factor shares, other papers (e.g. Stiroh, 2002b) have questioned the use of growth-accounting techniques because the estimated factor shares (from an estimated production function) do not often coincide with their observed counterparts. Strobel (2016) suggests that the divergence in observed and estimated factor shares can be interpreted as evidence of the existence of ICT spillovers.

As ICT can generate externalities to other firms, van Leeuwen and van der Wiel (2003a,b) among other authors introduce spatial lags of the ICT variable into their production functions or growth accounting models. Using Dutch firm-level data, they find that the ICT spillovers are an important source of TFP growth. They also corroborate that the production function approach yields more significant and plausible results than the growth accounting approach. Most recent papers include more sophisticated specifications of the ICT spillovers. For instance, Strobel (2016) include the ICT spillovers as an intermediate input. While Bloom, et al. (2013) use the degree of product market proximity to compute the weight matrix W, Lychagin et al. (2010) use the geographical distance. Interestingly, the latter weight matrix seems to be more relevant for R&D spillovers than for ICT spillovers due to the network effects associated to ICT are not confined to a limited geographical space.

Since the seminal contribution by Griliches (1979), many empirical studies have provided solid evidence about the impact of R&D activities in firms' production using either firm or regional level data.[9] It should be noted that R&D is an input that create new ideas and innovation (Mairesse et al. 2005) that other firms can copy, and thus an important aspect is the possibility of externalities and knowledge spillovers (Audrestch and Feldman, 1996).[10] To this end, Bloom et al. (2013, 2018) and other authors extend the production function with variables measuring R&D spillovers based on spatial and technological proximity, and find remarkably spillovers associated to R&D activities.

[9] For firm level applications, see Hall and Mairesse (1995), Klette and Kortum (2004), and Rogers (2010). Regarding the second set of papers, Prenzel et al. (2018) highlight the relevance of regional and geographical characteristics in the impact of R&D investment on productivity.

[10] In this case, as pointed out by Grasjö (2006), the knowledge spillovers can be viewed as a pure externality, i.e. as an unintended side effect of firms' ordinary activities. Alternatively, knowledge can be transmitted by explicit agreements of transaction of knowledge.

Eberhardt et al. (2013) find as well that the estimated returns of private R&D are seriously biased if the R&D spillovers are ignored.

3.3. Local versus global

As shown before, the spatial production models allow us to examine the existence of spatial spillovers associated to public infrastructures. The issue here is the selection of an appropriate spatial specification in order to produce valid estimates, and to infer accurate predictions of the scope of the existing spillovers. In most of the above-mentioned papers, the authors use a specification of the production function that corresponds with the SLX model.

In this sense, LeSage (2014) states that most spatial spillovers are *local* in applied regional science modeling, but remarks that a network input, as for example a highway, represents a resource shared by numerous locations and it thus could also cause *global* spillovers. If so, the SDM model should be chosen instead of the SLX model. However, as pointed out by this author, the distinction between local and global spillovers based on estimated SLX vs SDM models could be somehow *artificial*, since it relies on the implicit assumption that the local spillovers in a SLX model only involve adjacent neighbors, but not higher-order neighbors. However, this is not true if the W matrix is defined in (very) broad terms, e.g. using the inverse of the distance between the totality of regions or adopting economic concepts of distance. In this case, most spatial observations will be involved, as it happens in the SDM model, but now using a SLX model.

Despite the above-mentioned discussion, LeSage and Pace (2010) state that most papers in this literate still maintain this artificial distinction because it facilitates to test for local versus global specifications. However, this test is only informative if the W matrix is defined in very narrow terms (using e.g. first-order neighbors) because the difference between the SLX and SDM models is larger. The same applies for SLX vs SAR models. In this sense, Gibbons and Overman (2012) show that the reduced forms of these two models are very similar if the W matrix is broadly defined.

In summary, the above discussion shows that it is necessary to pay much attention to the spatial specification of the model when we aim to capture spillover effects. However, this does not take place in practice. Indeed, as pointed out by Gibbons and Overman (2012) and Vega and Elhorst (2015), many empirical applications lack a proper justification for the selected spatial specification .[11]

4. Agglomeration economies

A vast literature confirming the relation between productivity and economies of density has appeared since the seminal paper by Ciccone and Hall (1996) on agglomeration economies. The theory of agglomeration economies proposes that firms benefit from the concentration of economic activity, via localization effects or urbanization economies (Fujita et al., 1999). Krugman (1998) and Fujita et al. (1999) show that the presence of agglomeration or concentration economies in geographical space might explain the existence of increasing returns to scale in many empirical applications.

[11] More thoughts about this can be found in the last section of this chapter.

The empirical literature measuring the effect of agglomeration economies on firms' productivity often are based on estimated production functions, which contain some representation of agglomeration economies.[12] This literature is focused on the relative importance of two different agglomeration economies. While *localization* economies are caused by industrial concentration (Combes and Gobillon, 2015), *urbanization* economies are associated to city size (Duranton and Puga, 2000). A survey of this literature can be found in Rosenthal and Strange (2008).

In general, there is no consensus in this literature about the production effect of the different agglomeration measures (Melo et al., 2009), although these studies usually find a positive productivity gains from urban agglomeration (Eberts and McMillen, 1999; Rosenthal and Strange, 2004; Combes and Gobillon, 2015). This lack of consensus has generated a heat debate on the level of disaggregation, the specification of the model, the econometric methods, or the measurements of agglomeration. Regarding the econometric issues, Combes and Gobillon (2015) propose several strategies to deal with potential endogeneity problems. Other source of differences is the existence of missing production drivers positively correlated with agglomeration, as for example land, local public infrastructures (Eberts and McMillen, 1999) or natural advantages of some locations (Ellison and Glaeser, 1999). Selection biases in location choice are also expected because productivity of firms can be conditioned to the density of their locations.[13] Other differences are likely caused by the use of different spatial concentration indexes that try to measure inequalities in the spatial distribution of economic activity. In this sense, Combes and Overman (2004) and Combes et al. (2008) identify six properties that an ideal index of spatial concentration should fulfil. As most concentration indexes based on clusters of firms do not satisfy all properties, Duranton and Overman (2005) and Arbia et al. (2010) suggest using distance-based spatial concentration indexes.

It is worth mentioning that the above-mentioned papers have to do with the spatial location of the economic activity, but they do not use the SLX, SAR or SDM models introduced in previous sections because this literature ignores the existence of spillovers between "neighbors". A remarkable exception is Han et al. (2018) who follow Ertur and Kock (2007) and propose estimating an augmented version of the production function (5), where the TFP term (A_{it}) is modeled as a function of two indicators of urban agglomeration and their spatial lags, and the TFP term of neighboring cities:

$$A_{it} = Z_{it}^{\beta} \prod_{j \neq i}^{N} \left(Z_{jt}^{\theta} A_{jt}^{\lambda} \right)^{w_{ij}} \tag{12}$$

where Z_{it} is a vector of two agglomeration measures. In particular, Han et al. (2018) assume that technological interdependence among cities operates through spatial externalities, and the external effect of technology generated by specialization and diversification agglomeration of manufacturing in one city extends across its borders. They next plug (12) into (5) and estimate the following production function:[14]

$$lny_{it} = \beta lnZ_{it} + \alpha lnk_{it} + \lambda \sum_{j \neq i}^{N} w_{ij} lny_{jt} + \theta \sum_{j \neq i}^{N} w_{ij} lnZ_{jt} - \alpha\lambda \sum_{j \neq i}^{N} w_{ij} lnk_{jt} + v_{it} \tag{13}$$

[12] If real wages are proportional to labour productivity, this issue can be also examined using wage functions.

[13] In this sense, Combes et al. (2012) developed a formal test that allows examining whether firms' selection does not explain spatial productivity differences.

[14] For notational ease, we do not include any dynamic term in (13) as well as other production drivers measuring urbanization, human capital, government intervention, foreign direct investment and energy consumption.

The specification of knowledge spillovers in the TFP term yields an SDM model. Han et al. (2018) estimate this model using spatial econometric techniques and find evidence of the existence of spatial spillovers that are influenced by the use of economic and spatial definitions of proximity of the weighted matrix.

5. Spatial returns to scale

Glass et al. (2016a) introduce the idea of *spatial* returns to scale (RTS) by adapting well-known concepts introduced by LeSage and Pace (2009) in applied spatial econometrics to the measurement of classic technology characteristics, such as elasticities and returns to scale. They suggest computing three different returns to scale measures (i.e. internal, external, and total) once a spatial SAR and SDM production function is estimated.[15] To catch the differences among these three measures, assume that we have already estimated the following single input SDM production function:

$$lnY_{it} = \alpha + \beta lnX_{it} + \lambda \sum_{j\neq i}^{N} w_{ij} lnY_{jt} + \theta \sum_{j\neq i}^{N} w_{ij} lnX_{jt} + v_{it} \quad (14)$$

where Y_{it} and X_{it} are the output and input levels, λ is the spatial autoregressive parameter, and w_{ij} is an element of the spatial W matrix, which describes the strength of the spatial interaction between the units. Note that the spatial autoregressive parameter in (14) is common to all units. Therefore, the above equation is a homogeneous coefficient spatial model. Notice that (14) can be rewritten using matrix notation as follows:

$$lnY_t = (I - \lambda W)^{-1} \left[\alpha + \beta lnX_t + \theta W lnX_t + v_t\right] \quad (15)$$

where lnY_t, lnX_t and v_t are $Nx1$ vectors, and W is a NxN matrix of spatial weight terms. If the off-diagonal elements are equal to one if both observations are in adjacent locations and the weight matrix is row-standardized, $WlnX_t$ can be interpreted as the average input level of adjacent firms or regions.

5.1. Individual elasticities

Differentiating (15) with respect to own factor inputs (i.e. lnX_t) and the inputs of all the other units in the sample (i.e. $WlnX_t$) yields the following matrix of *direct* and *indirect* elasticities for each unit:

$$\begin{bmatrix} e_1 & e_{12} & \cdots & e_{1N} \\ e_{21} & e_2 & \cdots & e_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ e_{N1} & e_{N2} & \cdots & e_N \end{bmatrix} = (I - \lambda W)^{-1} \begin{bmatrix} \beta & \omega_{12}\theta & \cdots & \omega_{1N}\theta \\ \omega_{21}\theta & \beta & \cdots & \omega_{2N}\theta \\ \vdots & \vdots & \ddots & \vdots \\ \omega_{N1}\theta & \omega_{N2}\theta & \cdots & \beta \end{bmatrix} \quad (16)$$

where $e_i = \frac{\partial lnY_{it}}{\partial lnX_{it}} = m_{ii}\beta + \theta \sum_{n\neq i}^{N} m_{in} w_{ni}$ and $e_{in} = \frac{\partial lnY_{it}}{\partial lnX_{nt}} = m_{in}\beta + \theta \sum_{j\neq n}^{N} m_{ij} w_{jn}$ are direct and indirect elasticities respectively, and m_{in} is the element of the global multiplier $m = (I - \lambda W)^{-1}$ located on row i and column n.

The *direct* elasticity e_i in a spatial production function is interpreted in the same way as *own* elasticity in a non-spatial model, i.e. the rate of increase in a unit's output following a (proportional) increase in its own input variable(s). The above definition of e_i indicates that direct elasticity is own elasticity plus a feedback effect, which pass through other units via the spatial multiplier matrix and back to the unit which initiated

[15] As the authors pointed out, these three RTS measures can also be calculated using other primal and dual technology representations, such as cost, profit, revenue, and input and output distance functions.

the change. The *indirect* elasticity e_{in} is the rate of increase in a unit's output following an increase in the factor inputs of another unit in the sample.

It is worth noting that both e_i and e_{in} vary across units even though we have estimated common β and θ parameters for all observations. Notice also that if the estimated spatial production function uses a SAR specification and there are not local spatial spillovers associated to the input variables (i.e. $\theta = 0$), we get that both direct and indirect effects are simple adjustments of the original β parameter. However, even if a SAR specification is used, both elasticities still exhibit a non-linear relationship with the underlying model parameters.

5.2. Mean elasticities

LeSage and Pace (2009) suggest reporting mean values of direct and indirect concepts to facilitate interpretation. While the mean direct elasticity is computed as a simple arithmetic average of the diagonal elements of (16), i.e. $e^{Dir} = \frac{1}{N}\sum_{i=1}^{N} e_i$, the mean indirect elasticity is computed as the cumulative sum of the off-diagonal elements of (16) from each row, averaged over all rows, i.e. $e^{Ind} = \frac{1}{N}\sum_{i=1}^{N}(\sum_{n\neq i}^{N} e_{in})$. The mean total elasticity is next computed as the sum of the mean direct and mean indirect elasticities, i.e. $e^{Tot} = e^{Dir} + e^{Ind}$. To compute the t-statistics for the *mean* direct, mean indirect and mean total elasticities, LeSage and Pace (2009) and Elhorst (2014) propose conducting Monte Carlo experiments that simulate the distribution of the mean elasticities using the variance-covariance matrix associated with the ML estimates. Interesting enough, while Glass et al (2013) and Glass and Kenjegalieva (2019) use Bayesian simulation techniques to compute the t-statistics for the mean effects, they are calculated using the delta method in Glass et al (2014, 2016b).

5.3. Internal, external and total returns to scale

The main contribution of Glass et al. (2016a) is noticing that the above elasticities can be interpreted as measures of the technology's returns to scale in a spatial setting. As the spatial effects in (14) are related to inputs, this allows extending a classical characteristic of production to the spatial case.

They proposed three returns to scale measures: internal, external, and total.[16] The *internal* returns to scale is defined as the rate of increase in a unit's output following a proportional increase in its own input variable(s). The unit-specific internal RTS can be simply computed as e_i due to only a single input has been considered. The *external* returns to scale are defined as the rate of increase in a unit's output following an increase in the inputs of all the other units in the sample. Glass et al. (2016a) propose computing the unit-specific external RTS using the simple sum of indirect elasticities, that is, $\sum_{n\neq i}^{N} e_{in}$. Finally, *total* returns to scale is defined as the rate of increase in a unit's output following a simultaneous increase in its own inputs and the inputs of all the other units in the sample. Therefore, the calculation of total returns to scale is based on all N units in the sample simultaneously changing their inputs.[17] The unit-specific total RTS can be computed as $e_i + \sum_{n\neq i}^{N} e_{in}$.

[16] Using the standard terminology in spatial econometrics, they can be alternatively labelled as direct, indirect and total returns to scale.

[17] Glass et al. (2016a) also examine the concavity of the spatial production function and find that all definitions of concavity (i.e. internal, external and total) in a spatial setting depend on the specification of the spatial weight matrix.

Glass et al. (2016a) also used simple arithmetic averages to summarize their RTS results. While *mean* internal returns to scale is computed as $\frac{1}{N}\sum_{i=1}^{N} e_i$, mean external returns to scale is computed as $\frac{1}{N}\sum_{i=1}^{N}(\sum_{n\neq i}^{N} e_{in})$. Finally, *mean* total returns to scale is the sum of the mean internal returns to scale and the mean external returns to scale. Using these three mean values, the spatial production function exhibits decreasing returns if $RTS < 1$. Constant returns appear if $RTS = 1$. Finally, the spatial production function exhibits increasing returns if $RTS > 1$.

Glass et al. (2016a) find positive labor and positive capital spillovers in their empirical application to a set of European countries over the period 1990–2011. While they cannot reject constant internal and external returns to scale, they reject constant total returns to scale in favor of increasing total returns. Their findings thus provide some empirical support for the endogenous growth theories which are based on the assumption of increasing total returns to scale, although their increasing total returns to scale are not caused by knowledge spillovers as in Romer (1986, 1987).

5.4. Economy wide returns to scale

The above mean RTS measures mimic the approach suggested by LeSage and Pace (2009) to summarize their marginal effects. Similar, but not the same, expressions can be found if we aim to compute aggregate or economy-wide returns to scale from the whole set of basic production units or regions. First notice that the aggregate or economy-wide technology can be defined as:

$$Y_t = G(X_{1t}, \dots, X_{Nt}) = \sum_{i=1}^{N} Y_{it} = \sum_{i=1}^{N} f_i(X_{it}, X_{-it}) \tag{17}$$

where X_{-it} is the vector of inputs of all the other units (regions) in the sample, and f_i is the production function of unit i, which depends on its own inputs and the inputs of other units under the presence of spatial spillovers. Notice that $G(x_{1t}, \dots, x_{Nt})$ is not separable in individual inputs because all regional outputs depend on own and neighboring inputs.[18] Differentiating the above economy-wide technology with respect to all inputs and assuming that all individual inputs increase in the same proportion, we get after some straightforward algebra that economy-wide returns to scale (hereafter, E) can be measured as:

$$E = \sum_{i=1}^{N} s_i e_i + \sum_{i=1}^{N} s_i (\sum_{n\neq i}^{N} e_{in}) \tag{18}$$

It is now worth mentioning that, if the estimated model is a SAR model, the economy-wide measure of returns to scale is a simple weighted average of all direct elasticities, i.e. $E = \sum_{i=1}^{N} s_i e_i$. In summary, we should use a weighted not a simple arithmetic average of individual elasticities if we are willing to compute economy wide RTS. In other words, LeSage and Pace (2009) and Glass et al (2016a) mean measures of total, direct and indirect effects cannot be used to measure aggregate (economy wide) RTS except all units (regions) are of similar size.

5.5. Returns to scale in heterogeneous coefficient models

The increasing availability of large (panel) data sets explains why important contributions have been made in recent years to estimate spatial models with autoregressive coefficients that vary across units. For instance, Malikov and Sun (2017)

[18] In contrast the aggregate technology in a non-spatial model is separable in individual inputs as it can be written as $Y = \sum_{i=1}^{N} f_i(X_i)$.

and Sun and Malikov (2018) compute the spatial autoregressive values from an unknown smooth function of a set of environmental factors. Gude et al (2018) do so using a parametric function and in a frontier setting. They use a heteroscedastic version of the spatial stochastic frontier models introduced by Glass et al. (2016b) as they allow for province-specific degrees of spatial dependence.[19]

To simplify the task of interpreting estimates of direct and indirect effects from the model, LeSage and Pace (2009) and Elhorst (2014) proposed using arithmetic averages of either diagonal or off-diagonal elements of (16). However, LeSage and Chih (2016 and 2017) stated later that scalar summary measures are not consistent with the notion of parameter heterogeneity. In this case, we should report observation-level effects estimates. For the case of the heterogeneous coefficient SAR panel model, the N diagonal elements of the matrix should be provided to produce direct effects estimates for each of the units (regions). As estimates of unit-specific indirect effects, it is recommended to follow the proposal of LeSage and Chih (2016) and use the cumulative sum of off-diagonal elements in each row of (16).

6. Spatial stochastic frontier models

Although there is extensive spatial econometric literature dealing with spatial interactions across spatial units, the literature on efficiency analysis has not generally taken spatial effects into account. Several studies have found that failure to account for spatial correlation effects in SF models results in biased estimates of efficiency scores (e.g. Schmidt et al., 2009). For this reason, it is important to use an econometric framework that allows controlling for the presence of cross-sectional dependence when measuring the efficiency performance of spatially distributed production units.[20]

This section offers a brief discussion of the small but evolving literature on spatial stochastic frontier modelling.[21] This literature tries to overcome this issue by including spatial autoregressive terms in their models. Generally speaking, this literature can be split into two groups, depending on whether distributional assumptions are made for the inefficiency term.

6.1. Distribution-free models

The first group of papers estimate *panel* spatial models based only on the distribution of the noise term and without making any distributional assumption for the inefficiency component of the error term. Examples of papers that belong to this group

[19] Allowing for unit-specific spatial coefficients not only will lead to less biased conclusions but also to richer conclusions (see e.g. Gude et al, 2018), especially when the spatial data represent firm-level rather than regional observations (see e.g. LeSage and Chih, 2016). However, Sun and Malikov (2018) state that such models are also useful in the estimation of growth models as it is expected in this literature that the intensity of knowledge spillovers greatly depend on institutional and cultural compatibility of neighbouring countries.

[20] It should be stressed that not only it is important to control for spatial spillovers in efficiency analyses, but also for the existence of heterogeneous spatial dependence parameters. Indeed, Gude et al. (2018) find that the standard efficiency estimates (i.e. the estimated "u" term) change a lot when they (incorrectly) use a common spatial dependence parameter for all observations. The efficiency results are expected to change even more if the total efficiency scores proposed by Glass et al. (2016b) are computed because these efficiency measures include direct and indirect spatial effects that not only depends on the abovementioned "u" term but also on the estimated spatial dependence parameters, which might vary significantly across observations.

[21] The content of this section is highly inspired in Orea and Álvarez (2019).

are Druska and Horrace (2004) and Glass et al. (2013, 2014). The model estimated in these papers can be summarized using the following single-input production function:

$$lnY_{it} = \alpha_{it} + \beta lnX_{it} + \lambda \sum_{j\neq i}^{N} w_{ij} lnY_{jt} + \theta \sum_{j\neq i}^{N} w_{ij} lnX_{jt} + \varepsilon_{it} \tag{19}$$

where Y_{it} and X_{it} are respectively the output and input levels of unit i, λ is the spatial autoregressive parameter, α_{it} is a unit-specific effect that can be defined as time-invariant (i.e. $\alpha_{it} = \alpha_i$) or as an individual-specific parameterized function of time (i.e. $\alpha_{it} = \alpha_{0i} + \alpha_{1i}t + \alpha_{2i}t^2$), and ε_{it} is a noise term that might also be spatially correlated as in Druska and Horrace (2004). The individual efficiency scores are simply computed from the cross-sectional specific effects using the approach in Schmidt and Sickles (1984) (hereafter SS) and Cornwell et al. (1990) (hereafter CSS). In this setting, the observation with the largest individual effect in each period is placed on production frontier and the efficiency estimates are the exponential of the difference between the best performing individual effect and the corresponding effect for each of the other observations in the sample.[22]

Druska and Horrace (2004) implicitly assumed in equation (19) that $\lambda = \theta = 0$. They ignored any spatial correlation in the frontier as because they interpreted the production function as a purely deterministic (engineering) process where the production units control all the inputs. This assumption allowed them to focus their application on spatial correlations associated with the noise term as they developed a *spatial error* (SEM) model with time-invariant fixed effects, which were used later to calculate unit-specific efficiency scores using the SS estimator.[23] The residual term in this model is assumed to follow a SAR process, that is: $\varepsilon_{it} = v_{it} + \rho \sum_{j\neq i}^{N} w_{ij}\, \varepsilon_{jt}$. The error term in this model consists of two components, an idiosyncratic noise term (v_{it}) and a spatial component that relates a unit's random shocks to the random shocks of neighbouring units. Glass et al. (2013) is a similar type of study as they use the fixed effects from a SAR stochastic frontier model to estimate time-varying efficiency using the CSS approach. They use maximum likelihood techniques as Glass et al. (2014), who extended the CSS methodology to the spatial autoregressive case and estimate direct, indirect and total efficiencies for each production unit.

6.2. Distribution-based models

The second group of spatial stochastic frontier models follows most of the non-spatial stochastic frontier literature by making assumptions about the distribution of both the noise and inefficiency terms. This group is not entirely homogenous as some papers allow the frontier to be spatially correlated across production units (e.g. Adetutu et al., 2015; and Glass et al., 2016b), while other papers allow the error terms to be spatially correlated (e.g. Schmidt et al. 2009; Areal et al., 2012; and Tsionas and Michaelides, 2016). Most of these models can be summarized using the following single-input production function:

$$lnY_{it} = \alpha + \beta lnX_{it} + \lambda \sum_{j\neq i}^{N} w_{ij} lnY_{jt} + \theta \sum_{j\neq i}^{N} w_{ij} lnX_{jt} + v_{it} - u_{it} \tag{20}$$

This equation includes two error terms, v_{it} and u_{it}. While the former term is a symmetric error term measuring pure random shocks, the latter term is a non-negative

[22] That is, efficiency is measured as $EF_{it} = \exp\left(\alpha_{it} - max_j(\alpha_{jt})\right)$.

[23] The SEM models have not been very popular in non-frontier settings because the spatial dependence that is accounted for in these models is not a representation of substantive economic spillovers (LeSage and Pace, 2009).

error term measuring unit-specific inefficiency. The above equation describes the so-called *spatial Durbin frontier* (SDF) model proposed by Glass et al. (2016b) that accounts for both local and global spatial interactions. If we assume in (20) that $\theta = 0$, we get the so-called *spatial autoregressive stochastic frontier* (SARF) model. If in addition we assume that $\lambda = 0$, we get the traditional non-spatial stochastic frontier model. If we however assume that one or both error terms in (20) are spatially correlated, we get a *spatial error stochastic frontier* (SEF) model. The latter model can be viewed as a vehicle to resuscitate the interest of the scientific community, policymakers and regulators in SEM models because, unlike the traditional SEM model, we have two random terms in a frontier analysis framework and controlling for spatial spillovers in both random terms does matter due to the (different) economic consequences of such correlations.[24]

Another restricted specification of (20) is provided by Adetutu et al. (2015) who propose a stochastic SLX frontier model because they only include spatial lags of the exogenous variables as frontier determinants (i.e. they assumed $\lambda = 0$, but allowed θ to take non-zero values). As they limit their analysis to *local* spatial dependence, their model can be estimated using the standard procedures for the non-spatial stochastic frontier. This model, however, overlooks any global spatial dependence as they omit the endogenous autoregressive variable. Glass et al. (2016b) estimate a SARF model that only accounts for global spillovers, and a SDF model that accounts for both global and local spatial dependence. To minimize issues relating to convergence, these authors adopt a pseudo maximum likelihood estimator and estimate their model in two steps, first estimating a non-frontier SDM model and then splitting the first-stage residuals into the idiosyncratic error and time-variant efficiency. Gude et al (2018) generalize the above SARF and SDF models in two aspects. First, they allow for heteroscedastic specifications of the inefficiency term. Second, both models allow the researchers to identify the determinants of the spatial dependence among the Spanish provinces. A parallel paper focusing on the EU regions is Ramajo and Hewings (2018) that explicitly consider (common) spatial spillover effects by including a spatial lag of the dependent variable at the frontier.

Another set of papers allows the inefficiency term to be spatially correlated. In these papers the one-sided error term consists of two components, an idiosyncratic one and a spatial component that relates a unit's inefficiency to the inefficiency of neighboring units. Standard maximum likelihood techniques are not used here because the addition of spatial lagged inefficiency terms does not yield a closed form for the likelihood function, and several computational algorithms are proposed to conduct simulation-based inference and efficiency measurement. For instance, Areal et al. (2012) avoid this issue by using a Gibbs sampler and two Metropolis-Hastings steps to estimate the spatial dependence of firms' efficiency. A similar model is proposed by Tsionas and Michaelides (2016), who develop a Bayesian estimator for a model that allows for spillover effects in inefficiency. Schmidt et al. (2009) also adopt a Bayesian approach to estimate a variety of spatial stochastic frontier models. In contrast to the previous papers, their inefficiency term does not follow a spatial autoregressive process but it depends on a latent (unobserved) local effect. In several specifications, they assume that the local effects follow a conditional autoregressive distribution which depends on its neighbors. Similarly, Herwartz and Strumann (2014) estimate a frontier model with region-specific random effects in the inefficiency term that allows for spatial dependence. As their likelihood function does not attain a closed-form solution, the model is estimated by simulated ML.

[24] This conclusion is motivated later in Section 8.

Previous spatial stochastic frontier models have focused solely on spatial spillovers in either the inefficiency term or the noise term. Thus, they have tended to neglect one or the other of these sources of spatial correlation. Orea and Álvarez (2019) have recently proposed a new stochastic frontier model that permits separate but simultaneous analyses of the spatial correlations of both noise and inefficiency terms, which are likely to be of a different nature. Their model can be written as:

$$lnY_{it} = \beta lnX_{it} + \tilde{v}_{it}(\rho) - \tilde{u}_{it}(\tau) \qquad (21)$$

where now the noise and inefficiency terms are spatially correlated using spatial moving average (SMA) or spatial autoregressive (SAR) stochastic processes, and the coefficients ρ and τ measure the degrees of spatial correlation between firms' noise and inefficiency terms, respectively. In order to get a closed form for the likelihood function, Orea and Álvarez (2019) assumed that the basic inefficiency term u_{it} possesses the scaling property in the sense that the idiosyncratic inefficiency term can be written as a function of exogenous variables times an industry-specific or economy wide inefficiency term. The above specification implies that the distribution of the inefficiency term is not affected by the spatial transformation. This is the crucial aspect of the model that enables them to get a tractable likelihood function that can be maximized using standard software.[25]

6.3. Estimating efficiency in spatial frontier models[26]

The presence of the endogenous autoregressive variable in the spatial frontier model requires correcting the individual efficiency estimates, i.e. $\xi_{it} = \exp\left(-u_{it}\right)$, that have been obtained using Jondrow et al. (1982) or Schmidt and Sickles (1984) . Glass et al. (2016b) and Kutlu (2018) have suggested two alternative methods to carry out this adjustment. While Glass et al. (2016b) estimate the corrected efficiencies as $\xi_{it}^{tot} = (I - \lambda W)^{-1}\xi_t$, Kutlu (2018) propose estimating the total efficiency as $\xi_{it}^{tot} = exp[-(I - \lambda W)^{-1}u_t]$. Note that Kutlu's efficiency calculation has the global multiplier $(I - \lambda W)^{-1}$ inside the exponential operator, whereas Glass et al.'s efficiency calculation has the global multiplier outside the exponential operator. This subtle difference has important practical consequences.

If we use the global multiplier after the exponential operator, ξ_{it}^{tot} might be larger than unity, which is a necessary condition for total efficiency being well-defined. In order to address this concern, Glass et al. (2016b) adapt the Schmidt and Sickles (1984) method and compute relative efficiencies by normalizing the above (absolute) efficiencies with the most efficient observation. As pointed out by Kutlu (2018), this approach is however sensitive to the best performance in each period being an outlier. His proposal is in line with the distribution-based methods as he does not carry out any posterior normalization because $(I - \lambda W)^{-1}u_t$ is always non-negative as long as $0 \leq \lambda < 1$.

7. Spatial TFP growth decomposition

Interest in the analysis of productivity at regional level has grown considerably in recent years as productivity growth is one of the most important drivers behind regional income. Thus, analyzing how regional productivity evolves over time is essential to provide insights for the promotion of productivity growth in the future. In the recent

[25] Some portions of the model can also be estimated using non-linear least squares (NLLS).
[26] This subsection is inspired in Kutlu (2018).

literature analyzing the determinants of productivity, there is a general consensus about the importance of spillover effects.

An estimated frontier production function can constitute the building block for the measurement of TFP growth and its decomposition into its basic sources. The traditional non-spatial TFP growth decomposition (see e.g. Orea, 2002) includes three components: changes in technical efficiency (EC), technical change (TC), and a scale effect (SE) that relies on scale elasticity values and on changes in input quantities, and therefore it vanishes under the assumption of constant returns to scale or constant input quantities.

Glass et al. (2013) extend the standard TFP growth decomposition to include direct (own) and indirect (spillover) components using a spatial autoregressive production frontier model.[27] Once the model is estimated, they compute time-varying efficiency scores from the cross-sectional specific effects using CSS. They next use the so-called quadratic identity lemma to obtain the following TFP growth decomposition:[28]

$$T\dot{F}P_{it} = T\dot{E}_{it} + \bar{\eta}_{it}^{Dir} + \sum_{k=1}^{K} \overline{SF}_{kit}^{Dir} \dot{X}_{kit} + \left(\bar{\eta}_{it}^{Ind} + \sum_{k=1}^{K} \overline{SF}_{kit}^{Ind} \dot{X}_{kit}\right) \tag{22}$$

where a dot over a variable stands for rate of growth, a line over a variable stands for arithmetic averages in t and $t-1$, η_{it} and e_{it} are output elasticities with respect to time and input levels, SF_{kit} is a scale factor that vanishes under constant returns to scale, and *Dir* and *Ind* denote elasticities and scale factors which are calculated using the relevant direct and indirect marginal effects. The first three terms in (22) are respectively direct (own) EC, TC and SE productivity components that can be found in non-spatial TFP growth decompositions. However, the above direct components differ from the standard non-spatial ones because they contain feedback effects i.e. effects which pass through other units via the spatial multiplier matrix and back to the unit which initiated the change. The last two components above are <u>indirect</u> components associated respectively to technical change and the size effect, which do not appear in a non-spatial setting.

Later on, Glass and Kenjegalieva (2019) extended their previous TFP growth decomposition by adding spatial spillovers associated to the change in technical efficiency.[29] Once individual efficiency scores are obtained, they estimate the direct, indirect and total efficiencies using the method outlined in Subsection 6.3.[30] They next extend use the growth of these three efficiencies as part of their new spatial decomposition of TFP growth. In addition, they include the growth in direct, indirect and total allocative efficiency growth components, which can be viewed as an extension of the allocative efficiency growth component introduced by Kumbhakar and Lovell (2000) in a non-spatial setting. They propose a four-component spatial TFP growth decomposition:

$$T\dot{F}P_{it} = \bar{\eta}_{it}^{Tot} + \sum_{k=1}^{K} \overline{SF}_{kit}^{Tot} \dot{X}_{kit} + T\dot{E}_{it}^{Tot} + \sum_{k=1}^{K} (\bar{s}_{kit}^{Tot} - \bar{e}_{kit}^{Tot}) \dot{p}_{kit} \tag{23}$$

[27] In particular, Glass et al. (2013) estimate a fixed-effect SAR spatial panel model using maximum likelihood techniques.

[28] Aggregating the direct and indirect components, this decomposition can be alternatively written as $T\dot{F}P_{it} = T\dot{E}_{it} + \bar{\eta}_{it}^{Tot} + \sum_{k=1}^{K} \overline{SF}_{kit}^{Tot} \dot{X}_{kit}$.

[29] Their extension, however, relies on a different spatial stochastic frontier model because they compute firms' efficiency using the spatial SAR and Durbin stochastic (cost) frontiers introduced by Glass et al. (2016a, 2016b) that are estimated using (pseudo) maximum likelihood techniques.

[30] Direct efficiency for a unit is interpreted in the same way as own efficiency from a non-spatial model but, in contrast, comprises own efficiency plus efficiency feedback. The indirect efficiency is the sum of the efficiency spillovers to a unit from all the other units in the sample. Total efficiency is the sum of its direct and indirect efficiencies.

where s_k^{Tot} is the total input expenditure share weight, and p_k stands for input prices. The first two components in (23) are the TC and SE productivity components that already appeared separated into direct and indirect effects in equation (22). The third component captures the impact of a rise or fall in total efficiency, which Glass and Kenjegalieva (2019) in turn decomposed into its direct and indirect parts. The last term captures the effect of a change in total allocative efficiency (AE), which again can be decomposed into direct and indirect changes in allocative efficiency.

8. Final remarks

Spatial spillovers can be defined as the impact of changes to input (explanatory) variables in a unit on the output (dependent) variable values in other units. Units could be firms, cities, regions, and so forth depending on the nature of the study. As Vega and Elhorst (2015) point out, a valuable aspect of spatial econometric models is that the magnitude and significance of spatial spillovers can be empirically assessed. To achieve this aim, several spatial specifications have been proposed in the literature that rely on imposing model structure in the form of a spatial weight matrix W, which reduces the number of parameters to be estimated.

However, this literature has been criticized due it often lacks theoretical background and it suffers from non-negligible identification problems because it is generally difficult to distinguish different spatial models from each other without assuming prior knowledge about the true data-generating process, which is often not possessed in practice (see e.g. Partridge, 2012; and Corrado and Fingleton, 2012). The same applies to the weight matrix as the true W is generally unknown. Several papers have tried to address this issue by combining several spatial weight matrices that are often used in the spatial econometric literature to capture spatial spillovers. To achieve this aim, Case et al. (1993) and Qu and Lee (2015) used a known function of geographic and economic distance between units. While Sun (2016) does so using non-parametric techniques, the generalized spatial stochastic frontier models introduced by Gude et al (2018) also use a parametric function to estimate a combination of spatial weight matrices.

Another identification problem highlighted by Gibbons and Overman (2012) and Vega and Elhorst (2015) occurs when the unknown parameters of a model cannot be uniquely recovered from their reduced-from specification even if the spatial econometric model and W are correctly specified. Gibbons and Overman (2012) propose the use of natural experiments and microeconomic data sets, a solution that often is not possible in standard applications in production economics where it is compulsory use real data. Vega and Elhorst (2015, p. 342) suggest taking the SLX model as point of departure,[31] unless the researcher has an underlying theory or coherent economic argument pointing toward a different model.

The authors of this chapter share this view: applied researchers in production economics are encouraged to find sound economic arguments to *first* justify the existence of spatial spillovers, and *second* to select the appropriate spatial specification of their production (cost, profit or distance) functions when spillovers are expected. However, as the economic arguments in production economics are of different nature than in other

[31] They show that the SLX specification not only is more flexible in modelling spatial spillover effects than other specifications, but also it is the simplest one. Moreover, in contrast to other spatial econometric models, standard instrumental variables (IV) approaches can be used to investigate whether (part of) the input variables and their spatially lagged values are endogenous.

research fields, the preferred specifications in each field may differ. In this sense, it is worth mentioning that the SAR, SLX or SDM specifications are the preferred specifications in standard (i.e. non-frontier) spatial econometric settings because the spatial dependence that is accounted for in the SEM model is often not a representation of substantive economic spillovers. Notice as well that the spatial spillovers in the SAR, SLX and SDM specifications are treated as determinants of the estimated production/cost function, i.e. as technological drivers. This treatment is, however, more difficult to justify in production analyses using firm-level data. For instance, Orea et al. (2018) did not use a frontier-based spatial specification in their application to electricity distribution firms because the Norwegian regulator did not see major systemic technical reasons for the cost of an electricity distribution firm to be affected by those of an adjacent firm to any significant degree. Similarly, Druska and Horrace (2004, p. 186) point out that we do not need a model with spatial correlations in the frontier if the technology is viewed as a purely deterministic (engineering) process where the firm controls all the inputs.

Moreover, in a stochastic frontier analysis of firms' efficiency, we have two random terms. Orea and Álvarez (2019) state that controlling for spatial spillovers in both noise and inefficiency terms does matter due to the significant *and* different economic consequences of such correlations. They argue that while the spatial specification of the noise terms is likely capturing an environmentally induced correlation, the spatial specification of the inefficiency term will likely capture a kind of behavioral correlation. Both spatial specifications of the error terms are important, although for different reasons. On one hand, a model specification with spatial correlation in the *noise* term is useful as it accounts for unobserved but spatially correlated variables that if ignored might result in biased estimates of efficiency scores (Orea et al., 2018). Thus, the effect of spatially correlated error terms in a stochastic frontier model is not as benign as in a standard spatial econometric model. On the other hand, a model with spatial correlation in the *inefficiency* term is useful when firms tend to "keep an eye" on the decisions of other peer firms trying to overcome the limitations caused by the lack of information (Mate-Sánchez-Val et al., 2017), firms are regulated using benchmarking techniques (Orea and Álvarez, 2018), or they simply emulate each other (Areal et al., 2012). As these issues provide interesting information on firms' performance, the recent spatial stochastic frontier literature is resuscitating the interest of the scientific community, policymakers, and managers in spatial error-based models, which have not been very popular so far.

The spatial production models are also useful when some firms benefit from (best practices implemented in) adjacent firms. As Vidoli et al. (2016) pointed out, this could especially be the case if local firms belong to communitarian networks (e.g. cooperatives) characterized by a collaborative environment, exchange of technical advice and continuous interaction, or common technicians (consultants) are advising all local firms. In this sense, the literature on spatial production economics summarized in this chapter is highly related to emerging literature on network production functions, where the network structure is endogenous. For instance, Horrace et al. (2016) develops a model where worker's productivity, is a function of the productivities of the co-workers on her team or, in our spatial framework, where firm's production is a function of another firms' production. Horrace and Jung (2018) propose a similar model but in a stochastic frontier framework, where worker-level inefficiency is correlated with a manager's selection of worker teams. As the endogeneity of the network structure (i.e. the W matrix in a spatial setting) is of primary concern in this literature, various estimation techniques have been recently developed in the econometrics of network literature to address this issue. As

Gibbons et al. (2015) point out, these methods are likely very helpful in spatial settings in other to deal with the endogeneity of some popular economic-based weigh matrices.

References

Adetutu, M., Glass, A. J., Kenjegalieva, K. and Sickles, R. C. (2015). The effects of efficiency and TFP growth on pollution in Europe: a multistage spatial analysis. *Journal of Productivity Analysis*, 43, 307-326.

Álvarez, I. and Barbero, J. (2016). The public sector and convergence with spatial interdependence: empirical evidence from Spain. *Applied Economics*, Vol. 48(24), 2238-2252.

Álvarez, I. and Delgado, M. J. (2012). High capacity road networks and spatial spillovers in Spanish regions. *Journal of Transport Economic and Policy*, 46, 281–292.

Álvarez, I. Condeço-Melhorado, A. M., Gutiérrez, J. Zofío, J. L. (2016a). Integrating Network Analysis with the Production Function Approach to Study the Spillover Effects of Transport Infrastructure. *Regional Studies*, 50(6), 996-1015.

Alvarez, I., Barbero, J. and Zofio, J. L. (2016b). A spatial autoregressive panel model to analyze road network spillovers on production. *Transportation Research Part A: Policy and Practice*, Vol. 93, 83-92.

Anselin, L. (1988). *Spatial Econometrics: Methods and Models*. Kluwer Academic Publishers: Dordrecht, Germany.

Arbia, G., Espa, G., Giuliani, D. and Mazzitelli, A. (2010). Detecting the existence of space-time clustering of firms, in *Advances in Spatial Econometrics*, edited by Arbia, G. and Kelejian, H., pages 311-323.

Arbues, P., Baños, J. F. and Mayor, M. (2015). The spatial productivity of transportation infrastructure. *Transportation Research Part A: Policy and Practice*, Vol. 75, 166-177.

Areal, F. J., Balcombe, K. and Richard, T. (2012). Integrating spatial dependence into Stochastic Frontier Analysis. *The Australian Journal of Agricultural and Resource Economics*, 56, 521-541.

Ark, B. van, Inklaar, R. and McGuckin, R. H. (2003). ICT and productivity in Europe and the United States: where the differences come from, May.

Aschauer, D. A. (1989). Is public expenditure productive?. *Journal of Monetary Economics*, 23(2), 177-200.

Audretsch, D. B. and Feldman, M. P. (1996). R&D Spillovers and the Geography of Innovation and Production. *American Economic Review*, 86, 630-640.

Audretsch, D. B. and Feldman, M. P. (2004). Knowledge Spillovers and the Geography of Innovation. In *Handbook of Regional and Urban Economics*, edited by Henderson, J. V. and Thisse J. F., 2713-39. San Diego, CA: Elsevier.

Black, S. E. and Lynch, L. M. (2000). *What´s driving the new economy: the benefits of workplace innovation*. NBER Working Paper No. 7479, January.

Bloom, N., Lucking, B. and Reenen, J. van (2018). *Have R&D Spillovers Changed?*. CEP Discussion Paper No 1548 May 2018.

Bloom, N., Schankerman, M. and Reenen, J. van (2013). Identifying Technology Spillovers and Product Market Rivalry. *Econometrica*, 81, 1347-1393.

Boarnet, M. G. (1998). Spillovers and the locational effects of public infrastructure, *Journal of Regional Science*, 38, 381–400.

Bottazzi, L. and Peri, G. (2003). Innovation and spillovers in regions: evidence from European patent data. *European Economic Review*, 47 (4), 687–710.

Bresnahan, T. F., Brynjolfsson, E. and Hitt, L. M. (2002). Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence. *Quarterly Journal of Economics*, Vol. 117, 339-376.

Burnside, C. and Eichenbaum, M. (1996). Factor-hoarding and the propagation of business-cycle shocks. *American Economic Review*, 86, 1154–1174.

Case, A. C., Rosen, H. S., and Hines, J. R. (1993). Budget spillovers and fiscal-policy interdependence: Evidence from the States. *Journal of Public Economics*, 52, 285–307.

Charlot, S., Crescenzi, R. and Musolesi, A. (2015). Econometric modelling of the regional knowledge production function in Europe. *Journal of Economic Geography*, 15 (6), 1227–1259.

Ciccone, A. and Hall, R. E. (1996). Productivity and the density of economic activity. *American Economic Review*, 86(1):54–70.

Cohen, J. P., and Morrison, P. C. J. (2004). Public infrastructure investment, interstate spatial spillovers, and manufacturing costs. *Review of Economics and Statistics*, 86(2), 551-560.

Combes, P. and Overman, H. (2004). The Spatial Distribution of Economic Activities in the European Union, *in* Henderson V. and Thisse, J.-F. (eds.), *Handbook of Regional and Urban Economics: Cities and Geography*. Amsterdam: Elsevier.

Combes, P. P. and Gobillon, L. (2015). The Empirics of Agglomeration Economies. In G. Duranton, Henderson, J.V. and Strange, W.C. (Eds.), *Handbook of Urban and Regional Economics 5,* Elsevier.

Combes, P. P., Duranton, G., Gobillon, L., Puga, D., and Roux, S. (2012). The productivity advantages of large markets: Distinguishing agglomeration from firm selection. *Econometrica*, 80(6), 2543-2594.

Combes, P. P., Mayer, T. and Thisse, J. F. (2008). *Economic Geography: The integration of Regions and Nations*. Princeton University Press, New Jersey.

Cornwell, C., Schmidt, P. and Sickles, R. C. (1990). Production Frontiers with Cross-Sectional and Time-Series Variation in Efficiency Levels. *Journal of Econometrics*, 46, 185-200.

Corrado, L. and Fingleton, B. (2012). Where is the Economics in Spatial Econometrics?. *Journal of Regional Science*, Vol. 52 (2), 210-239.

Cunha, P. and Neves, T. (2018). Spillovers in the production of knowledge: A meta-regression analysis. *Research Policy*, 47, 750–767.

Druska V. and Horrace W. C. (2004). Generalized moments estimation for spatial panel data: Indonesian rice farming. *American Journal of Agricultural Economics,* 86, 185-198.

Duggal, V., Saltzman, C. and Klein, L. (1999). Infrastructure and productivity: a Nonlinear Approach. *Journal of Econometrics*, 92 (1), 47-74.

Duranton, G. and Overman, H. G. (2005). Testing for localization using micro-geographic data. *Review of Economic Studies*, 72(4):1077-1106.

Duranton, G. and Puga, D. (2000). Diversity and Specialization in Cities: Why, Where and When does it matter?. *Urban Studies*, Vol. 37 (3), 533–555.

Eberhardt, M., Helmers, C. and Strauss, H. (2013). Do spillovers matter when estimating private returns to R&D?. *Review of Economics and Statistics*, 95 (2), 436–448.

Eberts, R. W. and McMillen, D. P. (1999). Agglomeration Economies and Urban Public Infrastructure. In *Handbook of Regional and Urban Economics*, Vol. 3, Applied Urban Economics, edited by Paul Cheshire, and Edwin S. Mills. Amsterdam: Elsevier Science, pp. 1455-1495.

Elhorst, J. P. (2014). Spatial Panel Models, in Fischer, M.M. and NijKamp, P. (eds.). *Handbook of Regional Science,* Springer.

Ellison, G. and Glaeser, E. L. (1999). The geographic concentration of industry: Does natural advantage explain agglomeration?. *American Economic Review Papers and Proceedings,* 89(2):311-316.

Ertur, C. and Koch, W. (2007). Growth, Technological Interdependence and Spatial Externalities: Theory and Evidence. *Journal of Applied Econometrics*, 22, 1033–1062.

Fingleton, B. and Lopez-Bazo, E. (2006). Empirical Growth Models with Spatial Effects. *Papers in Regional Science*, 85, 177–198.

Fischer, M. (2011). A Spatial Mankiw-Romer-Weil Model: Theory and Evidence. *The Annals of Regional Science*, 47(2), 419–436. doi:10.1007/s00168-010-0384-6.

Fujita, M., Krugman, P. R. and Venables, A. J. (1999). *The Spatial Economy: Cities, Regions and International Trade*. Mit Press, Cambridge.

Gajanan, S. and Malhotra, D. (2007). Measures of capacity utilization and its determinants: a study of Indian manufacturing. *Applied Economics*, 39, 765–776.

Gibbons, S. and Overman, H. G. (2012). Mostly pointless spatial econometrics?. *Journal of Regional Science*, 52, 172-191.

Gibbons, S., Overman, H. G. and Patacchini, E. (2015). Spatial methods. In *Handbook of regional and urban economics* (Vol. 5, pp. 115-168). Elsevier.

Glass, A. J., Kenjegalieva, K., and Sickles, R. C. (2014). Estimating efficiency spillovers with state level evidence for manufacturing in the US. *Economics Letters,* 123(2), 154-159.

Glass, A. J., Kenjegalieva, K., and Sickles, R. C. (2016a). Returns to scale and curvature in the presence of spillovers: evidence from European countries. *Oxford Economic Paper*, 68(1), 40-63.

Glass, A. J., Kenjegalieva, K., and Sickles, R. C. (2016b). A spatial autoregressive stochastic frontier model for panel data with asymmetric efficiency spillovers. *Journal of Econometrics*, 190(2), 289-300.

Glass, A. J., Kenjegalieva, K., and Paez-Farrell, J. (2013). Productivity growth decomposition using a spatial autoregressive frontier model. *Economics Letters*, 119(3), 291-295.

Glass, A. J. and Kenjegalieva, K. (2019). A spatial productivity index in the presence of efficiency spillovers: evidence for US banks 1992-2015. *European Journal of Operational Research*, 273, 1165-1179.

Gordon, R. J. (2000). Does the 'New Economy' measure up to the great inventions of the past?, *Journal of Economic Perspectives*, Vol. 14(4), 49-77.

Gråsjö, U. (2006). Spatial spillovers of knowledge production: an accessibility approach (Doctoral dissertation, Internationella Handelshögskolan).

Griliches, B. (1979). Issues in Assessing the Contribution of Research and Development to Productivity Growth. *The Bell Journal of Economics*, 10(1), 92-116.

Griliches, Z. (1991). *The search for R&D spillovers*. Working Paper No. 3768, NBER Working Papers Series.

Gude, A., Alvarez, I. and Orea, L. (2018). Heterogeneous spillovers among Spanish provinces: a generalized spatial stochastic frontier model. *Journal of Productivity Analysis*, 50(3), 155-173.

Gumbau-Albert, M. and Maudos, J. (2009). Patents, technological inputs and spillovers among regions. *Applied Economics*, 41(12), 1473–1486.

Hall, B. H. and Mairesse, J. (1995). Exploring the relationship between R&D and productivity in French manufacturing firms. *Journal of Econometrics*, 65, 263-293.

Han, F., Xie, R. and Fang, J. (2018). Urban agglomeration economies and industrial energy efficiency. *Energy*, 162, 45-59.

Herwartz, H. and Strumann, C. (2014). Hospital efficiency under prospective reimbursement schemes: an empirical assessment for the case of Germany. *The European Journal of Health Economics*, 15(2), 175-186.

Horrace W. C., Liu X, and Patacchini, E. (2016). Endogenous network production functions with selectivity. *Journal of Econometrics*, 190(2), 222–232.

Horrace, W. C. and Jung, H. (2018). Stochastic frontier models with network selectivity. *Journal of Productivity Analysis*, *50*(3), 101-116.

Hulten, C. R., Bennathan, E. and Srinivasan, S. (2005). *Infrastructure, Externalities, and Economic Development: A Study of Indian Manufacturing Industry*. Mimeo, Washington DC: World Bank.

Jaffe, A. B. (1986). Technological opportunity and spillovers of R&D: evidence from firms' patents, profits and market value. *American Economic Review*, 76 (5), 984–1001.

Jondrow, J., Lovell, C. K., Materov, I. S., and Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics*, 19(2-3), 233-238.

Jorgenson, D. W. and Stiroh, K. J. (2000). Raising the Speed Limit: U.S. Economic Growth in the Information Age. *Brookings Papers on Economic Activity*, 125-211.

Klette, T. J. and Kortum, S. (2004). Innovating Firms and Aggregate Innovation. *Journal of Political Economy*, 112, 986-1018.

Krugman, P. (1998). What´s new about the New Economic Geography?. *Oxford Review of Economic Policy*, Oxford University Press, Vol. 14(2), 7-17.

Kumbhakar, S. C., and Lovell, C. A. K. (2000). *Stochastic Frontier Analysis*. Cambridge University Press.

Kutlu, L. (2018). Estimating efficiency in a spatial autoregressive stochastic frontier model. *Economics Letters*, 163, 155-157.

Leeuwen, G. van and Wiel H.P. van der (2003a). *Do ICT spillovers matter?* CPB Discussion Paper No. 26.

Leeuwen, G. van and Wiel H.P. van der (2003b). *Spillover Effects of ICT*. CPB Report No. 3.

LeSage, J. P., and Chih, Y. Y. (2016). Interpreting heterogeneous coefficient spatial autoregressive panel models. *Economics Letters*, 142, 1-5.

LeSage, J. P., and Chih, Y. Y. (2017). A Bayesian spatial panel model with heterogeneous coefficients. *Regional Science and Urban Economics*. In Press.

LeSage, J. P., and Pace, R. K. (2009). *Introduction to Spatial Econometrics*. CRC Press.

LeSage, J. P. (2014). What Regional Scientists Need to Know about Spatial Econometrics. *The Review of Regional Studies*, 44, 13-32.

Lesage, J. P. and Pace, R. K. (2010). Spatial Economic Model. *Handbook of Applied Spatial Analysis*, Springer Berlin, Heidelberg, 377-407.

Lychagin, S., Pinkse, J., Slade, M.E. and Reenen, J. van (2010). *Spillovers in Space: Does Geography Matter?.* NBER Working Paper No. 16188.

Mairesse J., Mohnen, P. and Kremp, E. (2005). The Importance of R&D and Innovation for Productivity: A Reexamination in the Light of the French Innovation Survey. *Annals of Economics and Statistics*, 79/80, 486-527.

Malikov, E. and Sun, Y. (2017). Semiparametric estimation and testing of smooth coefficient spatial autoregressive models. *Journal of Econometrics*, 199 (1), 13-34.

Maté-Sánchez-Val, M., López-Hernandez, F. and Mur-Lacambra, J. (2017). How do neighbouring peer companies influence SMEs' financial behaviour? *Economic Modelling*, 63, 104-114.

Melo, P.C., Graham, D.J. and Noland, R.B. (2009). A meta-analysis of estimates of urban agglomeration economies. *Regional Science and Urban Economics*, 39, 332-342.

Munnell, A.H. (1992). Policy Watch: Infrastructure Investment and Economic Growth. *Journal of Economic Perspectives*, American Economic Association, Vol. 6(4), 189-198.

Orea, L. (2002). Parametric decomposition of a Generalized Malmquist productivity index. *Journal of productivity Analysis*, 18(1), 5-22.

Orea, L., Álvarez, I. and Jamasb, T. (2018). A spatial stochastic frontier model with omitted variables: Electricity distribution in Norway. *Energy Journal*, 39 (3), 93-117.

Orea, L. and Alvarez, I. (2019). A new stochastic frontier model with cross-sectional effects in both noise and inefficiency terms. *Journal of Econometrics*, forthcoming.

Orea, L., Álvarez, I. and Servén, L. (2019). A two-level top-down decomposition of aggregate productivity growth: the role of infrastructure, in *Advances in Efficiency and Productivity II*, Lovell, K., Pastor, J.T., Zhu, Z. and Aparicio, J. (Editors), Springer International Series in Operations Research and Management Sciences.

Pakes, A. and Griliches, Z. (1984). *Patents and R&D at the Firm Level: A First Look. In: R&D, Patents and Productivity*. University of Chicago Press. pp. 55–72.

Partridge, M. D., Boarnet, M., Brakman, S. and Ottaviano, G. (2012). Introduction: whither spatial econometrics?. *Journal of Regional Science*, 52(2), 167-171.

Pereira, A. M., and Andraz, J. M. (2013). On the economic effects of public infrastructure investment: A survey of the international evidence. *Journal of Economic Development*, 38(4), 1-37.

Pereira, A. M. and Andraz, J. M. (2004). Public highway spending and State spillovers in the USA. *Applied Economics Letters*, 11, 785-8.

Prenzel, P., Ortega-Aviles, R., Cozza, C. and Piva, M. (2018). Interplay between regional and industrial aspects in the R&D productivity link: evidence from Europe. *Regional Studies*, Vol. 52(5), 659-672.

Qu, X. and Lee, L. (2015). Estimating a spatial autoregressive model with an endogenous spatial weight matrix. *Journal of Econometrics*, 184, 209–232.

Ramajo, J., and Hewings, G. J. (2018). Modeling Regional Productive Performance Using a Spatial Stochastic Frontier Approach: New Evidence for Europe (1995-2007). *Regional Studies*, 52(10), 1372-1387.

Rogers, M. (2010). R&D Productivity: using UK firm-level data to inform policy. *Empirica*, Vol. 37(3), 329-359.

Romer, P. M. (1987). Growth based on increasing returns due to specialization. *American Economic Review*, 72, 56-62.

Romer, P. M. (1986). Increasing returns and long-run growth. *Journal of Political Economy*, 94 (5), 1002-1037.

Rosenthal, S. S. and Strange, W. C. (2004). Evidence on the nature and sources of agglomeration economies. In Henderson, V. and Thisse, J.-F., editors, *Handbook of Regional and Urban Economics,* volume 4, pages 2119-2171. North-Holland, Amsterdam, 2004.

Rosenthal, S. S. and Strange, W. C. (2008). The attenuation of human capital spillovers. *Journal of Urban Economics*, 64, 373-389.

Schmidt, A. M., Moreira, A. R., Helfand, S. M., and Fonseca, T. C. (2009). Spatial stochastic frontier models: accounting for unobserved local determinants of inefficiency. *Journal of Productivity Analysis*, 31(2), 101-112.

Schmidt, P. and Sickles, R. C. (1984). Production frontiers and panel data. *Journal of Business and Economic Statistics*, 2, 367–374.

Stiroh, K. J. (2002a). Information Technology and the US productivity revival: What do the industry data say?. *American Economic Review*, 92(5), 1559-1576.

Stiroh, K. J. (2002b). Are ICT spillovers driving the new economy?. *Review of Income and Wealth*, 48(1), 33-57.

Straub, S. (2011). Infrastructure and Development: A Critical Appraisal of the Macro-level Literature, *Journal of Development Studies*, 47 (05), pp.683-708.

Strobel, T. (2016). ICT intermediates and productivity spillovers-Evidence from German and US manufacturing sectors. *Structural Change and Economic Dynamics*, 37, 147-163.

Sun, Y. (2016). Functional-coefficient spatial autoregressive models with nonparametric spatial weights. *Journal of Econometrics*, 195(1), 134-153.

Sun, Y. and Malikov, E. (2018). Estimation and Inference in Functional-Coefficient Spatial Autoregressive Panel Data Models with Fixed Effects. *Journal of Econometrics*, 203(2), 359-378.

Tiefelsdorf, M., Griffith, D. A. and Boots, B. (1999). A variance-stabilizing coding scheme for spatial link matrices. *Environment and Planning A*, 31, pp. 165–180

Tsionas, E. G. and Michaelides, P. G. (2016). A spatial stochastic frontier model with spillovers: evidence for Italian regions. *Scottish Journal of Political Econo*my 63(3), 243-257.

Vega, S. H. and Elhorst, J. P. (2015). The SLX model. *Journal of Regional Science*, Vol. 55 (3), pp. 339–363.

Vidoli, F., Cardillo, C., Fusco, E. and Canello, J. (2016). Spatial nonstationarity in the stochastic frontier model: An application to the Italian wine industry. *Regional Science and Urban Economics*, 61, 153-164.

Wiel, H. P. van der (2001). *Does ICT boost Dutch productivity growth?*, CPB Document No. 016.

Yu, N., de Jong, M., Storm, S. and Mi, J. (2013). Spatial spillover effects of transport infrastructure: evidence from Chinese regions. *Journal of Transport Geography*, 28, 56–66.