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Modelling Spillover Effects in Spatial Stochastic Frontier Analysis

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Abstract

In the last two decades, authors have begun to expand classical stochastic frontier (SF) models in order to include also some spatial components. Indeed, firms tend to concentrate in clusters, taking advantage of positive agglomeration externalities due to cooperation, shared ideas and emulation, resulting in increased productivity levels. Until now scholars have introduced spatial dependence into SF models following two different paths: evaluating global and local spatial spillover effects related to the frontier or considering spatial cross-sectional correlation in the inefficiency and/or in the error term. In this thesis, we extend the current literature on spatial SF models introducing two novel specifications for panel data. First, besides considering productivity and input spillovers, we introduce the possibility to evaluate the specific spatial effects arising from each inefficiency determinant through their spatial lags aiming to capture also knowledge spillovers. Second, we develop a very comprehensive spatial SF model that includes both frontier and error-based spillovers in order to consider four different sources of spatial dependence (i.e. productivity and input spillovers related to the frontier function and behavioural and environmental correlation associated with the two error terms). Finally, we test the finite sample properties of the two proposed spatial SF models through simulations, and we provide two empirical applications to the Italian accommodation and agricultural sectors. From a practical perspective, policymakers, based on results from these models, can rely on precise, detailed and distinct insights on the spillover effects affecting the productive performance of neighbouring spatial units obtaining interesting and relevant suggestions for policy decisions.

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Introduction

Overview

In the last two decades, authors have begun to expand classical stochastic frontier models (SF) in order to include also some spatial components. Indeed, firms tend to concentrate in clusters, taking advantage of positive agglomeration externalities due to cooperation, shared ideas and emulation, resulting in increased productivity levels. Thus, producers cannot be regarded as isolated entities and the hypothesis of cross-sectional independence underlying the basic SF model must no longer be considered valid. Until now authors have introduced spatial dependence into SF models following two different paths: evaluating global and local spatial spillover effects related to the frontier function (Adetutu et al., 2015; Glass, Kenjegalieva, and Sickles, 2016; Gude, Alvarez, and Orea, 2018; Ramajo and Hewings, 2018; Tsukamoto, 2019) or considering spatial cross-sectional correlation in the inefficiency (Areal, Balcombe, and Tiffin, 2012; Fusco and Vidoli, 2013; Schmidt et al., 2009) and/or in the error term (Orea and Alvarez, 2019).

Considering the first strand of literature, among the advantages of introducing the spatial lag of Y (SAR term) and of X (SLX term) in SF models, the most interesting one relates to the possibility of directly measuring direct and indirect effects originating from the variables that determine firms' productivity level and that also affect neighbouring producers. Specifically, the SAR term enables to capture productivity spillovers while the SLX term represents input spillovers, where the former refers to the attempt of less efficient producers to emulate the best practices of the industry leader in order to increase their productive capacity (Syverson, 2011), while the latter concerns the possibility that an extensive local market for workers and specialized inputs can allow clustered firms to better combine the productive factors reaching higher productivity levels (Porter, 1998). Among the consequences deriving from not taking global productivity spillovers into account, Glass, Kenjegalieva, and Sickles (2016) underlined that not introducing the spatial lag of the dependent variable in SF models can result in biased estimates due to an omitted variable bias.

On the other hand, considering spatial dependence in the error term is useful to take unobserved but spatially correlated variables such as environmental and climatic conditions or location-specific attributes into account. Moreover, introducing a spatial structure in the inefficiency error term allows capturing spatial correlation deriving from the specific attributes that commonly characterize all the producers belonging to the same area and that affect firms' efficiency. Between the cons of not considering these two sources of spatial correlation, ignoring spatial dependence in the inefficiency term can result in biased estimates of the inefficiency distribution and in different rankings of inefficiencies across agents (Areal, Balcombe, and Tiffin, 2012; Schmidt et al., 2009) while estimating a SF model without including cross-sectional dependence in the disturbance term can decrease the statistical efficiency of the model (Orea and Alvarez, 2019).

The aim of this thesis is to extend the current literature on spatial stochastic frontier models by introducing new spatial terms and further developing existing models. Specifically, in this work, we propose two different models for panel data: the Spatial Durbin Stochastic Frontier Model introducing spatial dependence in the determinants of firms' efficiency (SDF-STE) and the Spatial Durbin Stochastic Frontier Model considering cross-sectional spatial dependence both in the inefficiency and in the error term (SDF-CSD). Specifically, the thesis is organized as follows: Chapter 1 introduces the economic setting, discussing the concepts of industrial clusters, spatial agglomeration and spillover effects; Chapter 2 provides an overview of stochastic frontier (SF) models, starting from the baseline non-spatial specification up to recent developments introducing different spatial structures; Chapter 3 focuses on the two proposed models, the SDF-STE and the SDF-CSD model, describing the model specification, the estimation techniques, and the computation of the marginal effects and of the technical efficiency scores; Chapter 4 shows the results of the Monte Carlo simulations testing the finite sample properties of the two novel spatial estimators; Chapter 5 contains an empirical application of the SDF-STE model to the Italian accommodation sector; Chapter 6 presents an empirical application of the SDF-CSD model to the Italian agricultural sector. Moreover, Appendix A focuses on the link between the CES, the Cobb-Douglas and the Trans-Log production function and Appendix B shows different methods that can be used to compare non-nested models and provides an example using the two proposed specifications. All the codes used to perform the simulation studies can be retrieved at https://github.com/FedericaGalli17?tab=repositories.

Main Contributions

The SDF-STE Model

Positing in the first stream of research, in this thesis we propose a novel spatial SF model for panel data which includes three spatial terms capturing global productivity spillovers, local input spillovers and determinants of inefficiency spillover effects. Indeed, besides productivity and input spillovers, in economic geography literature, knowledge spillovers, meaning "*working on similar things and hence benefiting much from each other's research*" (Griliches, 1992, p.29), are usually acknowledged as the third kind of spatial effects. Knowledge and informational spillovers can increase firms' performance more than for isolated producers because the geographical concentration of firms stimulates their innovative activity, spreading new knowledge through a tacit diffusion process (Hoover, 1948). Despite the general consensus of economists about the relevant and positive role of knowledge spillovers in affecting clustered firms' industrial activity (Adams and Jaffe, 1996; Griffith, Harrison, and van Reenen, 2006; Levin and Reiss, 1988; Spence, 1984), to our knowledge, they have not yet been introduced in spatial stochastic frontier models. Specifically, firms' innovative activity can be considered as one of the main determinants of firms' efficiency level and therefore, knowledge spillovers can be identified as spatial effects arising from the factors that determine neighbouring firms' efficiency. Therefore, we introduce the possibility to evaluate whether the determinants of inefficiency of neighbouring firms affect the efficiency level of neighbours.

Hence, the first model developed in this thesis enables to evaluate different sources of spatial dependence using a spatial Durbin specification and introducing spillover effects in the determinants of inefficiency (hereinafter denoted as Z variables). Specifically, we propose a novel SF model for panel data (SDF-STE) which includes three spatial terms capturing global productivity spillovers through the SAR term, local input spillovers through the SLX term and determinants of inefficiency spillovers adding a new spatial term, that is the spatial lag of the Z variables. In particular, we differentiate between spillover effects influencing firms' productivity and efficiency levels. Indeed, while both global and local spatial spillovers are considered for the frontier function following Glass, Kenjegalieva, and Sickles (2016), we concentrate on local spillover effects associated with the determinants of firms' inefficiency because spatial dependence influencing neighbouring firms' efficiency level mainly arises from local factors such as emulation, face-to-face interactions, local cooperation, and individuals contact (Griliches, 1992). The SDF-STE model can be estimated using a ML estimation approach. Moreover, direct, indirect and total effects affecting firms' productivity and efficiency levels respectively originating from the productive inputs and from the determinants of firms' inefficiency can be computed following the method proposed by LeSage and Pace (2009).

The first new feature of the SDF-STE model consists in introducing the possibility of directly evaluating how each variable that determines the inefficiency level of neighbouring firms also affects nearby producers. This is achieved by adding the spatial lag of each inefficiency determinant in the inefficiency model. The second relevant feature of the model concerns his general and comprehensive specification enabling to capture different kinds of spatial spillovers across firms (i.e. productivity and input spillovers affecting the frontier function and local spillovers in the Z variables). Moreover, this model nests several existing spatial and non-spatial specifications, allowing to select the model that best fits the data testing different restrictions through likelihood ratio tests. From an applied perspective, the proposed spatial specification taking advantage of new lagged variables can provide policymakers with interesting and relevant policy implications that could have not been obtained using previous spatial SF models. Indeed, unlike the previous spatial SF models that allow evaluating the overall level of spatial dependence affecting firms' inefficiency level providing only generic information, the SDF-STE model allows evaluating the specific spatial effects arising from each inefficiency determinant giving rise to precise, detailed and distinct insights concerning spatial spillovers related to each variable of interest. This approach can be very useful for a variety of economic problems dealing with agglomeration economies, knowledge and *R&D* spillovers, technology diffusion, imitation, spatial networks and interactions, which are all relevant and current research topics in firm-level microdata applications, in productivity and efficiency analysis, in business-strategy literature, and in the context of regional sciences. The main methodological results concerning the SDF-STE model are summarized in the following paper:

Galli, F. (2023). "A spatial stochastic frontier model introducing inefficiency spillovers".
Journal of the Royal Statistical Society: Series C.
DOI: https://doi.org/10.1093/jrsssc/qlad012

The SDF-CSD Model

The second contribution developed in this thesis concerns a spatial Durbin stochastic frontier model for panel data introducing cross-sectional dependence both in the inefficiency and in the error term (SDF-CSD). This specification merges together all the different spatial structures mentioned before, obtaining a very comprehensive tool that takes four different sources of spatial dependence into account. Specifically, the SDF-CSD model introduces the spatial lag of Y and of X to capture global and local spatial spillovers related to the frontier function as proposed by Glass, Kenjegalieva, and Sickles (2016) and it also considers two spatial structures related to the inefficiency and to the error term in order to capture behavioural and environmental spatial correlation, following Orea and Alvarez (2019).

The most appealing feature of this novel spatial model is that it allows capturing spatial spillover effects while controlling for spatial correlation related to firms' efficiency and to unobserved but spatially correlated variables, bringing together the advantages related to the two different modelling approaches described before. Thus, while previous literature only considers frontier-based or error-based spillover effects, this is the first work that merges together the two different approaches, obtaining a very comprehensive specification never introduced before. Despite his complex spatial structure, one of the most remarkable features of the SDF-CSD model is that thanks to the modelling approach suggested by Orea and Alvarez (2019) for the two error terms, it can be estimated using standard maximum likelihood algorithms and it allows to straightforwardly interpret the effect of the inefficiency determinants. From an applied perspective, starting from the SDF-CSD model and making some LR tests for nested models, it is possible to test whether it is better to simplify the model specification considering only specific spatial lags or if a comprehensive spatial SF model is required. Thus, it is possible to precisely assess which kind of spatial effect is more appropriate for studying the phenomenon under investigation without making a priori assumptions on the spatial structure of the data. The main methodological results concerning the SDF-CSD model are summarized in the following paper:

Galli, F. (2022). “A spatial stochastic frontier model including both frontier and error based spatial cross-sectional dependence”. *Spatial Economic Analysis*.
DOI: http://dx.doi.org/10.1080/17421772.2022.2097729

Empirical Applications

In this thesis, an empirical application of the SDF-STE model is provided using data on the Italian accommodation sector while the SDF-CSD model is applied to the Italian agricultural sector. Estimating the SDF-STE model based on a sample of Italian hotels makes it possible to evaluate productivity, inputs and knowledge spillovers occurring in the Italian accommodation sector. In particular, by defining as determinants of hotels’ efficiency some variables referring to hotels’ innovative activity such as intangible capital, human capital, patents and trademarks, we are able to measure direct and indirect effects resulting from hotels’ internal innovation and influencing neighbouring accommodation facilities. The main results of this empirical application are summarized in the following paper:

Bernini, C., & Galli, F. (2023). “Innovation, productivity and spillover effects in the Italian accommodation industry”. *Economic Modelling* 119, 106145.
DOI: https://doi.org/10.1016/j.econmod.2022.106145

On the other hand, we take advantage of the SDF-CSD model to analyse the level of productivity of the Italian agricultural sector considering different kinds of spatial effects. In particular, this second model results to be particularly suitable for analysing the Italian agricultural sector due to the strong importance of unobserved location-specific attributes in this industry. Indeed, through the spatial structure attached to the random disturbance term, it is possible to consider spatial cross-sectional dependence arising from unobserved features common to nearby areas affecting agricultural production such as climatic, topographic, environmental, and soil conditions. Moreover, the spatial structure related to the determinants of firms’ efficiency allows us to capture behavioural spatial dependence arising from emulation behaviours of agricultural producers located in nearby areas and from policies and institutions operating at the local level. Starting from this empirical application, we extend the analysis paying particular attention to the role of subsidies in the following paper:

Bernini, C. & Galli, F. (2022). "Subsidies, productive performance and spatial effects: evidence from the Italian agricultural sector". Working paper

Chapter 1

Productivity, Geographical Clusters and Agglomeration Externalities

1.1 What Enhances Firms Productivity?

1.1.1 Evaluating Firms Productivity

"*Productivity is quite literally a matter of survival for businesses*" (Syverson, 2011, p. 327). Indeed, more productive firms are more likely to survive, compared to their less productive competitors. Therefore, evaluating the level of productivity of firms and understanding the possible determinants of productivity has become a matter of primary interest to researchers in many fields over the past couple of decades. Classically, productivity has been defined as an output-input ratio, with the purpose of measuring how much output is obtained from a given set of inputs. In analyzing productivity, the two main inputs usually considered are labour and capital. In particular, labour can be measured as the number of employees or employee hours while capital is traditionally measured as the establishment's book value or as its capital stock. However, in addition to these two observable inputs, there are a lot of different factors that contribute to determining firms' productivity level, both internal and external to the firm, as described in Subsections 1.1.2 and 1.1.3, respectively.

Productivity can be measured both by using single-factor productivity measures such as the marginal productivity of labour and capital or by multi-factor measures such as total factor productivity (TFP). All these quantities can be easily estimated by specifying a production function. A generic production function is

$$Y_i = af(L_i, K_i), \tag{1.1}$$

where Y_i is the output of firm i with $i = 1, ..., N$, f is a generic function of two inputs, labour (L) and capital (K), and a, representing total factor productivity, captures variations in the level of output that are not explained by shifts in the observable inputs that act through $f(.)$. The most common specifications for the production function, thanks to their good properties and fit, are the Cobb-Douglas function and the Transcendental Logarithmic (Trans-Log) function.

The Cobb-Douglas Function

Considering labour (L) and capital (K) as inputs, the Cobb-Douglas production function can be defined as in Eq.(1.2), where α and β represent the marginal productivity of capital and labour, respectively, while $\alpha + \beta$ is a measure of returns to scale. In particular, the returns to scale are increasing if $\alpha + \beta > 1$ (a 1% increase in the inputs determines a more than 1% increase in the level of output), constant if $\alpha + \beta = 1$ (a 1% increase in the inputs determines a 1% increase in the level of output), and decreasing if $\alpha + \beta < 1$ (a 1% increase in the inputs determines an increase in the level of output of less than 1%).

$$Y = aK^{\alpha}L^{\beta} \tag{1.2}$$

Specifying the production function using a Cobb-Douglas specification, total factor productivity can be estimated as

$$a = \frac{Y}{K^{\alpha}L^{\beta}}. \tag{1.3}$$

Considering the log-form and introducing all the generic inputs x_i for $i = 1, ..., N$, the Cobb-Douglas function can be written as in Eq.(1.4), where the α_is are the output elasticities to inputs. Applying logarithms allows estimating the function in Eq. (1.4) using standard least squares methods.

$$\log Y = a + \sum_{i=1}^{N} \alpha_i \log x_i \tag{1.4}$$

An important limitation of the Cobb-Douglas function is that it assumes constant elasticity of substitution between capital and labour. Indeed, the Cobb-Douglas production function with constant return to scales is a special case of the CES production function when the substitution parameter ρ approaches zero in the limit and thus, the elasticity of substitution σ equals 1. The derivation of the Cobb-Douglas production function starting from the CES function is presented in detail in Appendix A.

The Trans-Log Function

A more flexible production function, which allows for variable elasticity of substitution, is represented by the Trans-Log function, shown in Eq.(1.5). This production function is an approximation of the CES function using a second-order Taylor polynomial at $\rho = 0$, where ρ represents the substitution parameter. As for the Cobb-Douglas case, also the Trans-Log production function can be estimated using OLS because it is linear in parameters applying the double log form. More details on the derivation of the Trans-Log function and on the elasticity of substitution are shown in Appendix A.

$$\log Y = a + \sum_{i=1}^{N} \alpha_i \log x_i + \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} \gamma_{ij} \log x_i \log x_j \tag{1.5}$$

The Trans-Log function reduces to a Cobb-Douglas if $\gamma_{ij} = 0 \ \forall \ i = 1, ..., N; \ j = 1, ..., N$. Moreover, as in the previous case, a represents TFP, the α_is are the output elasticities to inputs, while the γ_{ij}s are measures of complementariness between the inputs x_i and x_j.

The main limit of the Cobb-Douglas and of the Trans-Log production function is that they do not take technical progress into account. However, it can be introduced including an additional term capturing the temporal dynamic. Moreover, traditionally only labour and capital are included as observable inputs, risking not to consider other relevant factors influencing firms' productivity levels. A detailed review of other internal and external factors that contribute to affecting firms' productivity is presented in the next subsections.

1.1.2 Internal Factors

Among the factors that directly impact the productivity level of firms, those operating within the plant play a fundamental role. Investigating the relationship between managerial talent, best practices and productivity, Bloom and van Reenen (2007) demonstrated that the correlation between firms' management practices and TFP is statistically significant and strong. Indeed, higher scores in management practices are related to higher levels of TFP, labour productivity, return to capital, sales growth, and probability of survival. Therefore, managers' ability and talent can determine wide differences in firms' productivity levels because of their leading role in handling labour, capital and intermediate inputs. In a similar way, several factors linked to human capital and labour quality, such as the education of workers, training, courses, employees' overall experience and tenure at the firm, may impact productivity. In particular, Ilmakunnas, Maliranta, and Vaini-Omäki (2004), using Finnish data, showed that workers' education and age positively affect the productivity level of firms.

As well as labour quality, also the quality of capital and intangible capital (among others, firms' reputation, know-how and loyal customer base) are important features that can influence productivity. In this framework, many researchers focused on analyzing the impact of a particular type of capital, information technology (IT), on the productivity level of firms. Specifically, Jorgenson, Ho, and Stiroh (2008) and Oliner, Sichel, and Stiroh (2007) demonstrated that aggregate U.S. productivity growth over the last decades was influenced by a remarkable IT-related productivity gain. Conversely, smaller IT investments contributed to slowing down the productivity growth over the same period in the European Union (van Ark, O'Mahony, and Timmer, 2008). Among all possible innovative efforts of firms, R&D is the component that can more easily be observed; thus, many studies on firm-level data investigated the connection between firms' R&D and productivity. In particular, Adams and Jaffe (1996) demonstrated that the positive impact of R&D activities on firms' productivity decreases as the distance between the research labs and the plant increases and that productivity depends more on the intensity of R&D than on its total amount. Between the unobservable sources of firms' intangible capital, learning by doing and informal research also play an important role. Indeed, also the simple act of operating can boost productivity, in fact, experience can be fundamental for managers to identify opportunities and design process improvements. For example, Kellogg (2009), considering oil and gas drilling in Texas, found that when producers and drillers work in pairs, the accumulated experience helps in increasing the productivity level more than for producers and drillers working alone.

Product innovation is another important factor that can help in enhancing productivity because, consequently to innovation in the quality of products, firms can increase the product price and therefore returns. Product innovation can be easily detected by productivity measures reflecting price variations but also patents are often used as a useful indicator. In this framework, Balasubramanian and Sivadasan (2011) demonstrated that patent grants are connected to TFP growth, firm size enlargement and the largest number of commodities produced. Similarly, also Bernard, Redding, and Schott (2010) found a positive association between TFP and the variety of products offered by firms.

In addition to these factors, also plant characteristics and firm structure decisions can impact productivity. For example, Atalay, Hortaçsu, and Syverson (2014), using data for private non-agricultural establishments in the U.S., demonstrated that vertical integration helps in boosting productivity while Schoar (2002) noted that conglomerated firms tend to have longer-lasting productivity levels. Investigating firms' specialization, Maksimovic and Phillips (2002) found that specialized firms have a strong productive advantage in particular segments while conglomerate firms tend to perform well in several industries but without showing exceptional results in any of these businesses.

1.1.3 External Factors

In addition to internal and controllable factors, also producers' operating environment can contribute to affecting firms' productivity levels. These external factors may not directly impact productivity but certainly, they have a fundamental role in shaping the context in which firms operate, and thus, they indirectly influence firms' performance.

Competition and pressures from competitors are between the main external factors affecting firms' productivity (Porter, 1990). Indeed, the existence of a highly competitive market raises the productivity bar so that any potential new firm has to achieve a certain minimum productivity level to enter the market. Moreover, competition could motivate managers and entrepreneurs to take innovative and more productive actions.

In this framework, Syverson (2004a) demonstrated that, in denser markets, firms show higher average productivity levels, higher lower-bound productivity levels and less productivity dispersion. Likewise, Schmitz (2005), analyzing the U.S. iron mining industry in 1980, found that competition led iron mining companies to improve their productivity level. Indeed, in that period, Brazilian low-cost mines began to deliver Brazilian ore to the American region of the Great Lakes, forcing major American ore producers to drastically change their production processes in order to face foreign competitors. Therefore, besides generating a selective effect, competition also concerns the presence of foreign import companies that threaten the local equilibrium forcing local producers to improve their production processes. For example, Pavcnik (2002) showed that trade liberalization in Chile in the 1970s caused stronger productivity growth in the manufacturing industry compared to other non-tradable sectors. Similarly, when Chinese firms began to export their products, European industries decided to exit the market or start innovating. In particular, between 1996 and 2007, in twelve European countries, TFP, the number of patents, R&D investments and IT adoptions, raised importantly to compete with Chinese producers (Bloom, Draca, and van Reenen, 2011). Moreover, comparing exporting firms with non-exporting ones, exporters tend to be more productive than non-exporters as de Loecker (2007a) found for Slovenian firms. Indeed, the author detected a strong productivity growth in Slovenian exporting companies after entering foreign markets.

Several studies (Andersson and Lööf, 2011; Bronzini and Piselli, 2009; Glaeser, Laibson, and Sacerdote, 2002; Romer, 1990) investigated how regions' intrinsic differences can affect the productivity gap of firms. In particular, higher levels of research and development, skilled human capital, good infrastructures, high quality of public institutions and propensity to innovate, are between the main regional characteristics that positively affect firms' performance. These kinds of externalities, originating within a geographical area, have been categorized by Jacobs (1969) as urbanization or localization economies. Concentrating on Italy, Aiello, Pupo, and Ricotta (2014) found that location matters in determining the level of TFP of firms using a multilevel modelling approach. Indeed, using data at the firm and regional level for Italian manufacturing firms between 2004 and 2006, they found that both territorial factors and the local environment in which firms are located influence firms' performance. Specifically, operating in a highly R&D-oriented region or in an area with an appropriate endowment of infrastructures and with efficient public services positively influences TFP. These findings are also helpful in explaining why firms located in the South of Italy are technologically lagging behind firms located in the rest of the country.

Moreover, proper market regulation and smarter forms of regulation can induce productivity growth. Indeed, as Knittel (2002) and Fabrizio, Rose, and Wolfram (2007) showed, shifts in the regulatory environment can boost productivity while decades of poor regulations can discourage firms to increase their productivity level (Bridgman, Qi, and Schmitz, 2009).

Finally, other important external factors influencing firms' productivity are spillover effects, meaning that firms' practices can influence the productivity level of neighbouring producers thanks to a tacit diffusion process. Alfred Marshall (1890), in his notable essay "*Principles of Economics*", was the first economist who recognized and described spillover effects related to the "industrial atmosphere" in which firms are embedded. Comparing Marshallian (spillovers), Portieran (local competition) and Jacobian (geographical and regional) externalities, Fazio and Maltese (2015), using micro-data from small and medium-sized Italian firms, demonstrated that, in the long run, only spillover effects among firms (Marshallian economies) matter in influencing firms' total factor productivity level while considering TFP growth, Jacobian and Porterian economies seems to be more effective. Despite authors recognized possible different sources of spatial externalities, in the last decades, spillover effects acquired a leading role in assessing firms' productivity level and researchers began to include and evaluate them in classical productivity models. After the introduction of the concept of geographical clusters in Section 1.2, spatial spillover effects are widely discussed in Section 1.3.

1.2 Geographical Clusters

Despite the growing globalization affecting goods, services, capital, technologies, cultural practices and human beings all over the planet, firms' innovative activity is still more linked to a regional scale. Indeed, a high concentration of institutions, rivals, highly specialized skills and knowledge helps in generating a long-lasting competitive advantage for local clusters being part of the global economy. In the world, highly innovative activities are mainly characterized by a regional connotation: Silicon Valley, the Research Triangle, and Route 122 around Boston are just some striking examples.

1.2.1 What is a Cluster?

Firms tend to gravitate toward similar locations and to concentrate in clusters (Henderson, Kuncoro, and Turner, 1955; Henderson, Shalizi, and Venables, 2001; Isard, 1956; Krugman, 1991). "*Clusters are geographic concentrations of interconnected companies and institutions in a particular field*" (Porter, 1998, p.78). Besides companies and institutions of a particular field, clusters can also include firms producing complimentary products, companies with related technologies and skills, manufacturers of specialized inputs, universities, training providers and technical support agencies. The borders of a cluster are defined by the linkages between the main companies belonging to the same cluster and, in most cases, they are enclosed within political boundaries, but they can also exceed more than one state. Examples of firms clustering are the textile-related companies in North and South Carolina, the high-performance auto companies in Southern Germany, and the fashion shoe companies in Northern Italy. Figure 1.1 shows firms' clustering in the United States, as a further example. Going beyond Porter's explanation of business clusters, Engel (2015) defined clusters of innovation (COI) as: "*Global economic hot spots where new technologies germinate at an astounding rate and where pools of capital, expertise,*

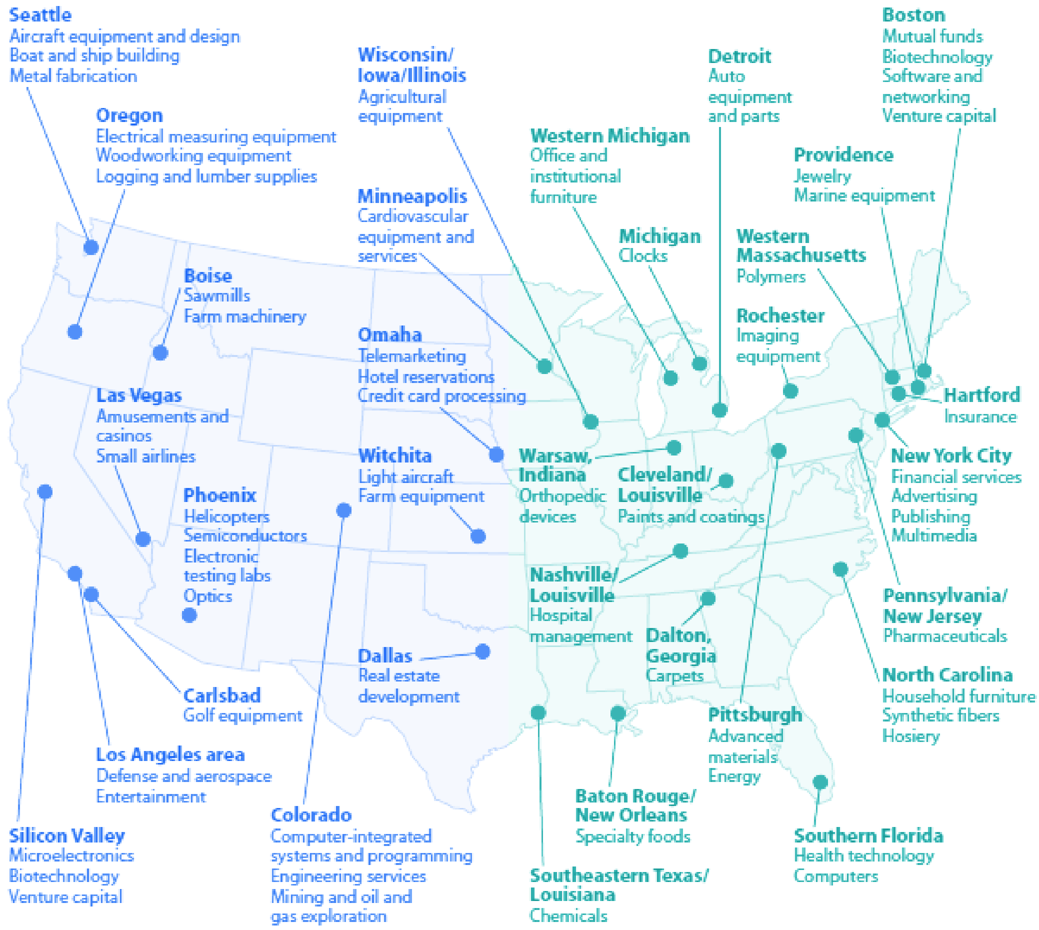

FIGURE 1.1: U.S. Clusters Map
Source: http://clustermapping.us/content/clusters-101

and talent foster the development of new industries and new ways of doing business". In particular, innovative clusters are characterized by high cooperation with educational and research institutions like universities, great support from public institutions and wide access to financing. Other fundamental features of COIs are their global dimension, the great mobility of people inside them, and the presence of multinational companies and interpersonal networks.

A further concept that addresses the role of location in fostering firms' competitiveness and performance is the one of industrial districts. The notion of industrial districts was first introduced by Giacomo Becattini in 1990 in his book "Industrial Districts and Inter-Firm Collaboration in Italy" as "*socio-territorial entities characterized by the active presence of both a community of people and a population of firms in one naturally and historically bounded area with a dominant industrial activity*". As the concept of cluster, also industrial districts relate to the impact of agglomeration of economic activities and interactions between co-located firms on economic performance. The notions of industrial district and cluster have often been used almost interchangeably. However, important differences characterize the two concepts. First, the main feature of industrial districts concerns the co-location of small and medium sized enterprises that mainly operate in light manufacturing sectors (Porter and Ketels, 2009). Differently from clusters, industrial districts do not include large companies in the regions but are characterized by a dense network of small companies. Second, industrial districts are defined by companies operating in a specific sector of activities that mainly belongs to the light manufacturing industry such as the shoes and textiles sectors in the North of Italy. Besides the economic connotation of industrial districts, also social and cultural factors characterize the concept of industrial district. Indeed, industrial districts generate in specific areas where a particular case of possible and likely social evolutions took place due to exogenous elements. The actors of industrial districts are therefore characterized by common values and a sense of belonging to the local community and to the place where production actually occurs. On the other hand, clusters usually emerge naturally from government or company actions, chance events, and the combination of beneficial endowments in a certain area such as the presence of infrastructures and proximity to communication routes. Moreover, also the presence of a leading firm in an area can stimulate the formation of other related firms nearby through a "true contagion" effect (Arbia, Espa, and Giuliani, 2021). To sum up, industrial clusters can take a multitude of configurations, being composed both by large and small companies belonging to different sectors and linked to different production stages as well as by institutions and universities. The main characteristic of industrial clusters relates to the diversity of economic actors belonging to the cluster that reinforces the performance of each one thanks to knowledge spillovers, human contact and exchange of ideas. Thus, industrial districts are just one type of a cluster while clusters are a broader concept that includes different possible configurations of companies and institutions (Porter and Ketels, 2009).

Spatial econometric models, like the ones proposed in this thesis, may be used to investigate spillover effects occurring both in clusters and in industrial districts. However, depending on the specific case under study, it is important to select the most appropriate spatial specification (i. e. choose a reasonable spatial weight matrix and include meaningful spatial lags). Indeed, different spatial lags reflect different kinds of spatial structures of the data such as local or global correlation schemes. For example, local approaches may be more suitable for analyzing spillover effects in industrial districts due to their regional connotation while a global perspective may better fit clusters due to their "contagion effect" characteristic.

1.2.2 Why Do Firms Cluster?

Alfred Marshall, studying the knitwear district of Northampton and the cutlery and knitwear district of Sheffield, clearly identified which are the three main advantages for clustered firms compared to firms operating alone:

- labour matching: firms' concentration allows the formation of a shared market for workers with industry-specific skills and thus, it guarantees a lower probability of labour shortage and unemployment. Moreover, it is more likely for firms to find workers with a sufficient level of skills, increasing the matching between labour demand and supply.

- input sharing: clusters can foster the production of non-tradable specialized inputs, and suppliers or manufacturers of related inputs can enter the cluster, reducing costs and guaranteeing firms wide accessibility and availability of specific products;
- knowledge spillovers: knowledge and informational spillovers can increase firms' productivity more than for isolated producers. Indeed, the geographical concentration of firms stimulates innovative activity, spreading new knowledge through a tacit diffusion process.

Other reasons for firms' agglomeration concern a concentrated customer base that helps in lowering business-related risks, greater availability of skills, inputs, assets and staff, local lenders and investors already aware of the cluster's features and the existence of a significant local market. Another advantage for firms concerns cost reduction thanks to lower transportation costs and to better access to a more diverse range of inputs and complementary products. All these benefits related to agglomeration economies and strong cluster environments foster entrepreneurship (Delgado, Porter, and Stern, 2010; Feldman, Francis, and Bercovitz, 2005; Glaeser and Kerr, 2009). Indeed, specialized workers belonging to the cluster can more easily recognize new opportunities related to products or services with whom they are familiar, and they can decide to start a new business. The birth of new firms within the cluster benefits all the other members and amplifies all the advantages outlined before, generating a positive feedback loop. Therefore, by clustering, firms can obtain efficiency gains and higher profit margins (Delgado, Porter, and Stern, 2010) and entrepreneurs entering the cluster can decrease risk, transaction costs and perceive lower entry barriers (Howells and Bessant, 2012). Hence, paradoxically, long-lasting advantages in an era of global competition are still local. An enduring competitive advantage arises from geographic, cultural and institutional proximity thanks to closer connections, greater motivation and better flows of information despite the growing advances in telecommunications, fast means of transportation, accessible markets and global competition.

1.2.3 How Do Clusters Originate and Develop?

Clusters' roots can derive both from historical circumstances or from unusual or stringent local needs (Porter, 1990). For example, the origin of the biotechnology, engineering and information technology cluster in Massachusetts can be traced back to the presence of MIT or Harvard University while Finland's environmental cluster resulted consequently to a local huge pollution problem. The existence of prior clusters concerning related industries or suppliers can also stimulate the birth of new clusters. Moreover, they can even result from random events, as exemplified by the telemarketing cluster in Omaha (Nebraska), which emerged thanks to the decision of the U.S. Air Force to place the Strategic Air Command in that area.

After the formation of a cluster, a self-reinforcing flow boosts its growth and development. Indeed, a growing and promising cluster attracts new businesses, talented entrepreneurs and individuals with new ideas or relevant skills. As a consequence, local institutions specialize, specific suppliers emerge, and also qualified training courses and infrastructures grow. In the development phase, firms specialized in different fields sharing matching technologies often intersect, giving birth to a vibrant, dynamic and competitive centre of innovation.

The most successful clusters can manage to keep their competitive advantage for centuries despite the external and internal factors that threaten their evolution continuously. Among the internal factors that can contribute to neutralizing clusters' competitive advantage, technological discontinuities are the most significant ones. Indeed, when the scientific and technical expertise of a cluster becomes obsolete or research institutions stagnate, clusters lose their competitive advantage. Besides technological discontinuities, also cartels, restrictions to competition, collective inertia, rigidities and over-consolidation can seriously affect clusters' competitiveness. Considering the external factors, demand shifts or changes in customers' needs can represent other significant threats.

1.3 Spillover Effects

Firms located in the same cluster and working on similar things tend to influence each other and affect the productivity level of nearby producers. Indeed, firms tend to share abilities and new knowledge with neighbours, and to benefit from an extensive local market for workers and specialized inputs, allowing them to combine the production factors more efficiently. These flows of information, knowledge, work and ideas are well-known as agglomeration externalities or spillover effects.

In the last decades, several authors have theoretically and empirically shown that the geographic concentration of firms leads to higher productivity levels, increased propensity to innovate and major internationalisation choices. Among the others, Baptista (2000, p. 516) underlined that "*geographical proximity stimulates networking between firms, thereby facilitating imitation and improvement*". Moreover, Bartelsman, Haskel, and Martin (2008) demonstrated that the productivity level of firms located in different countries converges faster to the productivity level of their domestic industry leader than to the one of the global leader.

Spatial spillovers across nearby firms can first of all depend on emulation processes. Indeed, less efficient producers can attempt to emulate the best procedures and practices of the productivity leader in closely related industries gaining a productive advantage (Syverson, 2011). Indeed, companies tend to keep an eye on the choices of other companies because they work in high uncertainty conditions, having only partial and asymmetric information (Leary and Roberts, 2014). Therefore, it is fundamental for them to compare with other firms and to try to obtain information. Obliviously some frictions exist, and less efficient producers can't fully replicate industry leaders' best practices, and emulation processes are far from perfect. The intensity of productivity spillovers can depend on the size of the cluster, in fact, it has been demonstrated that there is a positive association between the size of an industry in a region and the magnitude of the externalities among firms belonging to that industry (Tveteras and Battese, 2006). Crespi et al. (2008) and Keller and Yeaple (2009), showed that locating a firm nearby to a multinational company helps in intercepting more easily free information flows while Leary and Roberts (2014) demonstrated that peer effects are more evident between small and medium enterprises (SME) because for SMEs it is easier to obtain information from close firms. Moreover, Maté-Sanchez-Val, Lopez-Hernandez, and Mur-Lacambra (2017), analyzing the financial behaviour of SMEs, found that also financial decisions of peers strongly affect firms' financial sphere. Between all the different kinds of agglomeration externalities, knowledge spillovers are definitely those that have been more thoroughly investigated by researchers.

Knowledge spillovers have been defined by Griliches (1992, p. 29) as "*working on similar things and hence benefiting much from each other's research*". Geographic proximity is fundamental for the transmission of new knowledge because ideas and innovations are best transmitted via face-to-face interactions and individuals' contact (von Hipple, 1994). Indeed, it is easy to share information in an era where the world is continuously in touch thanks to a highly developed telecommunication network but flows of knowledge work in a different way. Indeed, knowledge is difficult to explain and codify through digital channels and, as Glaeser et al. (1992, p. 1126) stated, "*intellectual breakthroughs must cross hallways and streets more easily than oceans and continents*". Therefore, knowledge spreads better within geographical boundaries because of its tacit and uncodified nature (Baptista, 2000).

New knowledge can result from different internal sources such as learning by doing and informal or formal research. Other key factors that can contribute to generating internal new knowledge are a high degree of human capital, a highly skilled labour force or a high presence of researchers, scientists and engineers inside the firm. Usually, only formal research is taken into consideration in the analysis of firms' performance due to the complexity of quantifying the other sources. Typically, R&D expenditure is used as a proxy for formal research because it is considered the most important activity generating new knowledge. Alternatively to R&D, some authors also use the number of patents to evaluate firms' innovative activity. Besides the internal sources of new knowledge, several studies showed that knowledge spillovers have a relevant role in affecting firms' industrial activity (Levin and Reiss, 1988; Spence, 1984). Researchers commonly agree on the idea that R&D investments can spread over a large number of productive units. Adams and Jaffe (1996) demonstrated that both firms' internal R&D level and the level of R&D of other firms contribute to increasing firms' TFP. Griffith, Harrison, and van Reenen (2006), using patent data on UK firms, showed that the location in which firms innovate matters. Indeed, UK firms making R&D investments in the U.S. experienced faster productivity growth compared to firms with research labs located inside their UK plants. In particular, the productivity growth of UK firms was correlated with the growth of R&D stocks of American firms belonging to the same industry. These results suggest that for firms embedded in highly innovative clusters, it was easier to tap into new knowledge from U.S. technological leaders. Moreover, Jaffe (1986) found that the magnitude of spillovers between firms is a function of the "technological distance" between them, while Adams and Jaffe (1996) hypothesized that positive returns related to knowledge spillovers tend to decrease if the units are divided by institutional, cultural or geographical boundaries.

Glaeser et al. (1992) recognized two different forms of agglomeration forces spreading knowledge spillovers: productive specialization and diversification. Indeed, knowledge spillovers can originate both between firms operating in the same industry and among firms belonging to different sectors. Concentrating on industrial variety, it should be underlined that the transfer of information and new knowledge among producers belonging to different industries can be effective only if the different industries located in the same area share a similar technological and knowledge base. Otherwise, if the cognitive distance between firms is too large, it is very difficult for positive externalities to materialize (Nooteboom, 2000). Investigating the effect of firms' specialization and diversification on urban growth and local employment growth, most of the authors found that is product diversification that boosts local growth rather than productive specialization. Indeed, the variety of industries in a geographical cluster fosters knowledge spillovers, innovative activity and economic growth (Jacobs, 1969). Moreover, according to Krugman (1991), cities are the most relevant geographic unit of observation for knowledge spillovers because in cities there is a wide diversity of economic agents generating a large number of spillovers. On the other hand, analyzing the role of industrial specialization and diversification on firm-level productivity, Henderson (2003) and Martin, Mayer, and Mayneris (2011) demonstrated that industrial specialization has a leading role in determining firms' productivity while industrial diversification does not have any significant effect.

Concentrating on the channels through which knowledge spillovers flow across firms, Cohen and Levinthal (1989) stated that firms can make use of external knowledge thanks to their capacity to get in touch with ideas developed in other firms and to convert and adapt them to their industrial processes. In particular, Audretsch (1995), trying to identify the way in which knowledge spillovers occur, focused on individuals gravitating across firms, such as engineers, scientists, agents and workers. Indeed, individuals move easily across establishments located in the same area, having the opportunity to build up face-to-face relationships. Social activities are in fact one of the main mechanisms suggested in literature through which knowledge spillover occurs. Specifically, managers working in the same field can exchange ideas and learn from each other when they meet at trade shows, conferences, seminars, talks and social and professional clubs, building a strong network based on public relations and business contacts. In this way, individuals can share new ideas and knowledge, promoting the diffusion of intangible technological skills and capabilities (Saxenian, 1990). One of the most striking examples of this process is described by Saxenian (1994) that, concentrating on Silicon Valley, explained how the young workers of the semiconductor industry were used to meet after work having an aperitif and chatting about memories, circuits, RAM, tests, etc... Moreover, sociologists argued that also cultural differences among regions can contribute to influencing the innovative performance of firms. Indeed, communication and major exchanges between individuals help in transmitting knowledge, as demonstrated by the superior growth of the Silicon Valley region compared to Boston's Route 128, where individuals usually have a more introverted and solitary character (Saxenian, 1990). Therefore, also cultural differences have a relevant role in knowledge diffusion, influencing productivity growth and technological change.

Finally, differently from the classical hypothesis of firms' homogeneity adopted in the traditional economic literature, in the last decades, several authors argued that different knowledge outflows can occur according to different firms' individual characteristics (Munari, Sobrero, and Malipiero, 2012; Wang and Lin, 2013). Indeed, firms' heterogeneity, given by different organizational structures, sizes, technological levels and propensity to innovate, can influence the nature and the intensity of knowledge spillovers (Cainelli and Ganau, 2018, 2019). For example, firms with good technological capabilities mostly contribute to increasing the flow of external knowledge within the cluster while poorly innovative firms tend more to absorb new knowledge rather than spread it. Therefore, it is fundamental to consider firms' heterogeneity because, in analyzing knowledge spillovers occurring within industrial districts, different asymmetric patterns can emerge depending on the configuration of the cluster and the characteristics of the firms located inside it.

Trying to explain the heterogeneous behaviour of knowledge spillovers among firms with different characteristics, Acs and Audretsch (1994) found that firms of different sizes take advantage of knowledge spillovers differently. In particular, large firms are more willing to exploit new knowledge originating from their own laboratories and from private and large corporations while smaller companies tend to emulate larger companies belonging to the same cluster or share knowledge between them. Furthermore, larger firms are more able to absorb "advanced" external knowledge coming from universities and research centres due to their greater stock of accumulated knowledge. Besides having an advantage related to knowledge acquisition, larger firms also have a leading role in knowledge diffusion. Indeed, larger firms as multinational companies also act as knowledge producers and disseminators. Therefore, small firms located in highly innovative clusters are often able to easily start a new competitive business in highly technological markets such as biotechnology and computer software, undertaking a negligible amount of R&D investments thanks to knowledge spillovers originating from bigger companies belonging to the cluster (Audretsch, 1995). Moreover, Baptista (2000) found that knowledge spillovers within a geographical region are particularly relevant in the early stages of the industry life cycle while, according to Audretsch (1998), they tend to disperse as the industry becomes more concentrated. On the contrary, Glaeser et al. (1992) suggested that knowledge spillovers are further boosted by a high industrial concentration within a region, facilitating more and more firms' innovative activity and knowledge diffusion.

Chapter 2

An Econometric Approach for Productivity and Efficiency Analysis: Stochastic Frontier Models

2.1 Foundations of Stochastic Frontier Models

2.1.1 Cross-Sectional Models

Stochastic frontier (SF) models are the parametric tool that is most commonly used by researchers to analyse firms' productivity and efficiency. SF models allow evaluating firms' output as a function of certain defined inputs (Aigner and Chu, 1968) and they can be specified as in Eq.(2.1), where Y_i represents the maximum output obtainable by firm i with $i = 1, ..., N$, given the set of k inputs $\boldsymbol{x_i} = (x_{i1}, x_{i2}, ..., x_{ik})$ with associated unknown parameter vector $\boldsymbol{\beta}$ $(k \times 1)$. Moreover, in order to consider firms' random differences in the level of output given the same vector of inputs, a disturbance term ε_i is added to the model specification.

$$Y_i = f(\boldsymbol{x_i}, \boldsymbol{\beta}) + \varepsilon_i \tag{2.1}$$

Aigner, Lovell, and Schmidt (1977) and Meeusen and van Den Broeck (1977) firstly introduced the classical specification for the error term as being made up of two independent components, as shown in Eq.(2.2) considering a production function. In particular, v_i $(i = 1, ..., N)$ represents the random disturbance and it is assumed to be independently and identically distributed as $\mathcal{N}(0, \sigma_v^2)$, while u_i is assumed to be independently and identically distributed as $\mathcal{N}^+(0, \sigma_u^2)$ or alternatively, it can follow an exponential distribution. Thus, traditionally, u_i must satisfy the condition $u_i \geqslant 0$.

$$\varepsilon_i = v_i - u_i \tag{2.2}$$

Concerning the interpretation of these two components, the positive disturbance u_i reflects the fact that each firm's output must lie on or below the frontier $f(\boldsymbol{x_i}, \beta) +$

vi. Therefore, u_i represents the deviation in the firm's productivity level resulting from factors under the firm's control, such as technical and economic inefficiency. Conversely, v_i represents the random disturbance resulting from favourable or unfavourable external events such as luck, climate, topography, and machine performance (Aigner, Lovell, and Schmidt, 1977).

Further than considering a production function, also a cost function can be taken into consideration. In this case, Y_i collects the cost faced by the firm while $\boldsymbol{x_i}$ is a vector containing some cost determinants (for example prices of labour and capital). The main difference with a production function approach concerns the way in which ε_i is specified. Indeed, for a cost function $\varepsilon_i = v_i + u_i$ with $u_i \geqslant 0$ because u_i represents the cost increase due to inefficiency and thus, the inefficiency term has to be summed and not subtracted to the cost function (Schmidt and Lovell, 1977; Stevenson, 1980).

Usually, SF models are log-transformed in order to obtain a linear specification for $f(\boldsymbol{x_i}, \beta)$ and are estimated using classic maximum likelihood techniques. In particular, being the two error terms independent, the joint probability density function of v_i and u_i can be obtained as the product of the two marginal distributions (i.e. normal and truncated normal distribution, respectively). Subsequently, substituting in the joint probability density function of u_i and v_i the expression $v_i = \varepsilon_i - u_i$ derived from Eq.(2.2), the joint probability density function of u_i and ε_i can be obtained. Then, the joint probability density function of $\boldsymbol{\varepsilon} = (\varepsilon_1, ..., \varepsilon_N)$ can be found integrating out u_i and multiplying all the marginal distributions $f_{\varepsilon_i}(\varepsilon_i)$ for $i = 1, ..., N$. Finally, the likelihood function can be easily found substituting in the joint probability density function of $\boldsymbol{\varepsilon}$, the expression $\varepsilon_i = Y_i - \boldsymbol{x_i\beta}$, derived from the linear form of Eq.(2.1). In particular, following the reparametrization proposed by Battese and Corra (1977)

$$\sigma^2 = \sigma_u^2 + \sigma_v^2 \tag{2.3}$$

$$\lambda = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}, \tag{2.4}$$

the loglikelihood function associated with the linear model in Eq.(2.1)-(2.2) can be expressed as in Eq.(2.5), where Φ represents the cumulative distribution function of the standard normal random variable, and Θ is the vector of all parameters.

$$\begin{aligned}\mathcal{L}(\Theta; y) = &-\frac{N}{2}(\log 2\pi + \log \sigma^2) - \frac{1}{2\sigma^2}\sum_{i=1}^{N}(Y_i - \boldsymbol{x_i\beta})^2 \\ &+ \sum_{i=1}^{N}\log\left(1 - \Phi\left(\frac{(Y_i - \boldsymbol{x_i\beta})\sqrt{\lambda}}{\sigma\sqrt{1-\lambda}}\right)\right)\end{aligned} \tag{2.5}$$

Furthermore, technical efficiency scores (TE) can be derived as shown in Eq.(2.6), starting from the parameter estimates obtained maximising the loglikelihood function in Eq.(2.5). Technical efficiency scores, following Battese and Coelli (1988), are defined as the ratio between the mean production of firm i given its level of inefficiency and inputs, and the same quantity considering $u_i = 0$ (i.e. technical inefficiency equals zero and then, the firm is perfectly efficient).

$$TE_i = \frac{\exp(\boldsymbol{x_i}\boldsymbol{\beta} + v_i - u_i)}{\exp(\boldsymbol{x_i}\boldsymbol{\beta} + v_i)} = \exp(-u_i) \tag{2.6}$$

2.1.2 Panel-Data Models

Starting from this first baseline specification, Schmidt and Sickles (1984) extended the classic SF model introduced by Aigner, Lovell, and Schmidt (1977) in order to consider also different time periods. Therefore, they first introduced a SF model for panel data, as shown in Eq.(2.7) for $i = 1, ..., N$ and $t = 1, .., T$, where i indexes firms and t indexes time periods.

$$Y_{it} = \boldsymbol{x_{it}}\boldsymbol{\beta} + v_{it} - u_i \tag{2.7}$$

For $T = 1$ the model is exactly the stochastic frontier model proposed by Aigner, Lovell, and Schmidt (1977) for cross-sectional data while for $T > 1$ it is a straightforward generalization to panel data. The model can be estimated following different techniques such as ordinary least squares treating $(v_{it} - u_i)$ as the disturbance (although it is not recommended), using a within estimator assuming the u_i as fixed, using a generalized least squares estimation treating the u_i as random effects but without making any distributional assumption on them, and by maximum likelihood assuming independence between the two errors and making specific distributional assumptions on the inefficiency component.

A further step, proposed by Battese and Coelli (1995), consists in modelling the mean of the technical inefficiency error term as function of some inefficiency determinants $\boldsymbol{z_{it}}$ $(1 \times m)$ with associated parameter vector $\boldsymbol{\phi}$ $(m \times 1)$. Therefore, the model for panel data in Eq.(2.7) including some exogenous determinants of technical inefficiency can be expressed as

$$Y_{it} = \boldsymbol{x_{it}}\boldsymbol{\beta} + v_{it} - u_{it} \tag{2.8}$$

$$u_{it} \sim i.i.d.\ \mathcal{N}^+(\boldsymbol{z_{it}}\boldsymbol{\phi}, \sigma_u^2). \tag{2.9}$$

In particular, this model can be rewritten as in Eq.(2.10), where w_{it} is defined as an i.i.d. truncated normal random variable with zero mean and variance σ_u^2, and with point of truncation equal to $-\boldsymbol{z_{it}}\boldsymbol{\phi}$, so that $w_{it} \geqslant \boldsymbol{z_{it}}\boldsymbol{\phi}$.

$$Y_{it} = \boldsymbol{x_{it}}\boldsymbol{\beta} + v_{it} - (\boldsymbol{z_{it}}\boldsymbol{\phi} + w_{it}) \tag{2.10}$$

Reparametrizing the two variance parameters as in Eq.(2.3)-(2.4), the loglikelihood function associated with Eq.(2.10) can be expressed as in Eq.(2.11) and the parameter estimates can be obtained by implementing standard ML estimation techniques.

$$\begin{aligned}\mathcal{L}(\Theta; y) = & -\frac{1}{2}\sum_{i=1}^{N} T_i \left(\log 2\pi + \log \sigma^2\right) - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T_i}\left(Y_{it} - \boldsymbol{x}_{it}\boldsymbol{\beta} + \boldsymbol{z}_{it}\boldsymbol{\phi}\right)^2 \\ & - \sum_{i=1}^{N}\sum_{t=1}^{T_i}\left(\log \Phi\left(\frac{\boldsymbol{z}_{it}\boldsymbol{\phi}}{\sigma\sqrt{\lambda}}\right) - \log \Phi\left(\frac{(1-\lambda)\boldsymbol{z}_{it}\boldsymbol{\phi} - \lambda(Y_{it} - \boldsymbol{x}_{it}\boldsymbol{\beta})}{\sigma\sqrt{\lambda(1-\lambda)}}\right)\right)\end{aligned} \tag{2.11}$$

Starting from these non-spatial SF models assuming cross-sectional independence among firms, in the last two decades, many authors began to claim that the assumption of spatial independence is not appropriate, in fact, firms tend to cluster and share information. Therefore, firms can't be considered isolated entities and, in evaluating the level of productivity of firms, firms' location and interactions among nearby producers should be taken into account. In particular, as highlighted by Schmidt et al. (2009) and Glass, Kenjegalieva, and Sickles (2016), the omission of the spatial lag of the dependent variable capturing global productivity spillovers can result in biased estimates due to an omitted variable bias. Moreover, Fusco and Vidoli (2013) underlined that the violation of the classical independence assumption does not allow the assessment of classical statistical inference because the covariances of the SF errors can no longer be assumed to be zero.

At this point, it is worth discussing the difference between local and global spatial spillovers, since we will mention them until the end of the thesis. In general, a (spatial) spillover occurs when a causal relationship between the r-th characteristic of the i-th entity located at position i in space exerts a significant influence on the outcome y_j of an agent located at position j. As explained by Sage (2014), we can distinguish between local and global spatial effects depending on the underlying spatial process. We have local spatial dependence when spatial spillovers do not exhibit endogenous feedback effects and thus, spillovers only affect the neighbouring observations as defined by the spatial weight matrix. On the other way, we have global spatial dependence when there are endogenous feedback effects, and thus the r-th characteristic of the i-th entity impacts the outcomes of all areas (neighbours of the neighbours of i, neighbours of the neighbours of the neighbours of i, and so on) and not only peers defined by the spatial weight matrix. Following this mechanism, a change in X_r for the i-th spatial unit leads to a system wide change and results in a new long-run equilibrium. In general, we model local spillovers by including the spatial lags of the explanatory variables in the model while we consider global spatial effects when we introduce the spatial lag of the dependent variable. In spatial models considering only local spillovers, the coefficients related to the spatial lag of the explanatory variables can be straightforwardly interpreted as indirect effects since they reflect the average spillover effects to neighbouring units. On the other hand, in spatial models including the spatial lag of the dependent variable, direct and indirect effects have to be computed separately after the estimation since the model parameters do not coincide with the first partial derivatives due to the presence of endogenous interactions.

Thus, marginal effects can be computed as proposed by LeSage and Pace (2009) by summarizing the information contained in the matrix of partial derivatives associated with a change in each of the explanatory variables.

2.2 Taking Spatial Effects into Consideration

2.2.1 Early Models

The study by Druska and Horrace (2004) represents the first contribution taking spatial effects into consideration in evaluating firms' productivity using SF models for panel data. In particular, developing a spatial error stochastic frontier model with time-invariant fixed effects, they allowed the productive output of firm i to be a function of the spatial lag of productivity shocks experienced by nearby firms setting $u_{it} = (I_N - \rho M)^{-1}\varepsilon_{it}$. Their SF model can be written as in Eq.(2.12)-(2.13), where M is a $(N \times N)$ spatial weight matrix of known constants and ε_{it} is a zero-mean disturbance. Moreover, since they do not make any distributional assumption for the inefficiency component, the cross-sectional specific effects α_i can be interpreted as firm-level technical (in)efficiencies. Using the Schmidt and Sickles (1984) estimator, they applied their SF model to Indonesian rice farms allowing for spillovers across farms based on geographic proximity and weather conditions. Moreover, they suggested to compute technical inefficiency scores as $TE_i = \exp(\alpha_i - \max_j \alpha_j)$, following the approach proposed by Schmidt and Sickles (1984).

$$Y_{it} = \alpha_i + \boldsymbol{x_{it}\beta} + u_{it} \tag{2.12}$$

$$u_{it} = \rho M u_{it} + \varepsilon_{it} \tag{2.13}$$

Following a similar approach, Glass, Kenjegalieva, and Sickles (2013) considered a fixed effect SAR stochastic frontier model for panel data with time-variant technical efficiency, as shown in Eq.(2.14). Specifically, by adding the spatial lag of the dependent variable, the authors succeeded in computing the direct, indirect and total marginal effects of the explanatory variables taking spatial autocorrelation into account but, as in the previous case, they did not make any distributional assumption for the inefficiency error term. Moreover, defined $\delta_{it} = \alpha_i + \nu_i t + \rho_i t^2$, technical inefficiency scores can be computed as $TE_{it} = \hat{\delta}_{it} - \max_i(\hat{\delta}_{it})$, after having obtained consistent parameter estimates using standard ML techniques.

$$Y_{it} = \alpha_i + \nu_i t + \rho_i t^2 + \boldsymbol{x_{it}\beta} + \lambda \sum_{j=1}^{N} w_{ij} Y_{jt} + \varepsilon_{it} \tag{2.14}$$

Likewise, Han, Ryu, and Sickles (2016) proposed a SAR stochastic frontier model for panel data as shown in Eq.(2.15), assuming a time-invariant inefficiency term u_i and without making any distributional assumption for it. Moreover, they allowed the spatial weights $w_{ij,t}$ to vary over time and implemented a quasi-maximum likelihood (QML) estimation approach. Finally, defining $\alpha_i = \beta_0 - u_i$, they computed relative inefficiency (or efficiency) measures as $u_i^* = \max(\alpha_i) - (\alpha_i)$.

$$Y_{it} = \rho \sum_{j=1}^{N} w_{ij,t} Y_{jt} + \beta_0 + \boldsymbol{x_{it}} \beta - u_i + \varepsilon_{it} \tag{2.15}$$

Going beyond these first contributions taking into consideration spillover effects in SF models without making any distributional assumption on the inefficiency term u_i, in the next two subsections we discuss two different strands of spatial SF models based on distributional assumptions for both the two error terms. In particular, in subsection 2.2.2 we discuss spatial SF models considering global and local spatial dependence related to the frontier function that allow capturing for spillover effects while in subsection 2.2.3 we introduce spatial SF models capturing spatial dependence in the inefficiency and/or in the error term.

2.2.2 Considering Spatial Dependence in the Frontier Function

The study by Adetutu et al. (2015) represents the first work in this field. Specifically, they introduced the spatial lag of the exogenous variables to take local spatial dependence into consideration. The panel data model can be written as in Eq.(2.16) and it can be estimated using standard procedures for non-spatial SF models.

$$Y_{it} = \boldsymbol{\alpha} + TL(\boldsymbol{x_{it}}, t) + \boldsymbol{z_{it}} \boldsymbol{\beta} + \sum_{j=1}^{N} w_{ij} \boldsymbol{x_{jt}} \boldsymbol{\theta} + \sum_{j=1}^{N} w_{ij} \boldsymbol{q_{jt}} \boldsymbol{\nu} + v_{it} - u_{it} \tag{2.16}$$

In particular, α is the intercept, $TL(\boldsymbol{x_{it}}, t)$ represents the technology using a translog approximation, $\boldsymbol{z_{it}}$ is a vector of exogenous characteristics of firm i at time t, and $\boldsymbol{x_{jt}}$ and $\boldsymbol{q_{jt}}$ are vectors of inputs and exogenous characteristics of neighbouring firms j affecting the productivity level of firm i. Finally, w_{ij} is the generic element of the spatial weight matrix W, and $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\theta}$ and $\boldsymbol{\nu}$ are the unknown parameter vectors to be estimated. As in standard SF models, v_{it} is assumed to be normally distributed with zero mean and variance σ_v^2, while u_{it} follows a non-negative normal distribution with zero mean and variance σ_u^2. Moreover, v_{it} and u_{it} are both independently and identically distributed. Despite this model takes local spatial dependence into consideration, it fails to account for global spatial dependence, ignoring the endogenous autoregressive SAR term.

Glass, Kenjegalieva, and Sickles (2016) proposed a SAR stochastic frontier model and a spatial Durbin stochastic frontier model for panel data accounting for both global and local spatial dependence, as shown in Eq.(2.17) and in Eq.(2.18), respectively.

$$Y_{it} = \boldsymbol{x_{it}} \boldsymbol{\beta} + \rho \sum_{j=1}^{N} w_{ij} Y_{jt} + v_{it} - u_{it} \tag{2.17}$$

$$Y_{it} = \boldsymbol{x_{it}}\boldsymbol{\beta} + \rho \sum_{j=1}^{N} w_{ij} Y_{jt} + \sum_{j=1}^{N} w_{ij} \boldsymbol{x_{jt}}\boldsymbol{\theta} + v_{it} - u_{it} \tag{2.18}$$

In particular, $\boldsymbol{x_{it}}$ is a vector of firms' exogenous variables, $\sum_{j=1}^{N} w_{ij} Y_{jt}$ is the endogenous spatial lag of the dependent variable (SAR term), $\sum_{j=1}^{N} w_{ij} \boldsymbol{x_{jt}}$ is the exogenous spatial lag of the independent variables, while ρ and $\boldsymbol{\theta}$ are the scalar and the parameter vector respectively associated with the SAR and the SLX terms. Therefore, in the SAR model only the spatial lag of the dependent variable is taken into consideration while, using a spatial Durbin specification, both the spatial lag of the independent variables and of the dependent variable are taken into account. Moreover, the authors assumed the classical error structure, so that $v_{it} \sim i.i.d.\ \mathcal{N}(0, \sigma_v^2)$ and $u_{it} \sim i.i.d.\ \mathcal{N}^+(0, \sigma_u^2)$. The unknown parameters have been estimated by implementing a two-step pseudo maximum likelihood estimator.

The spatial Durbin SF model for panel data by Glass, Kenjegalieva, and Sickles (2016) has been further developed by Ramajo and Hewings (2018) adding the inefficiency error term structure proposed by Battese and Coelli (1992). In particular, the inefficiency term u_{it} has been modelled using a time-varying decay specification, as shown in Eq.(2.19), obtaining a very flexible spatial SF model for panel data.

$$u_{it} = \exp(-\eta(t - T))u_i, \quad u_i \sim \mathcal{N}^+(\mu, \sigma_u^2) \tag{2.19}$$

Therefore, firms' technical inefficiency level was assumed to increase or decrease exponentially depending on the sign of the decay parameter η. In particular, if $\eta > 0$ inefficiency decreases over time at a rate of $(100 \times \eta)\%$ per year, while if $\eta < 0$, technical inefficiency increases exponentially across time.

A second development of the spatial Durbin SF model by Glass, Kenjegalieva, and Sickles (2016) has been proposed by Gude, Alvarez, and Orea (2018). Specifically, the authors introduced a generalized version of the spatial Durbin SF model for panel data incorporating time-varying exogenous influences on both the degree of global and local spatial spillovers for each time period t, as shown in Eq.(2.20).

$$Y_{it} = \lambda(\boldsymbol{z_{it}})(WY)_{it} + \sum_{k=1}^{K} \beta_k x_{kit} + \sum_{k=1}^{K} \theta_k(\boldsymbol{z_{it}})(Wx)_{kit} + v_{it} - u_{it} \tag{2.20}$$

In particular, $(WY)_{it}$ stands for the endogenous spatial lag of the dependent variable, and the autoregressive parameter λ depends on the vector $\boldsymbol{z_{it}}$ of potential factors determining global spatial spillovers. Moreover, also the parameter θ_k related to the exogenous SLX term is modelled depending on a vector of potential factors $\boldsymbol{z_{it}}$ determining local spatial spillovers. Similarly, also the standard deviation σ_{uit} of the inefficiency error term, defined as $\sigma_{uit} = f_{it}(\boldsymbol{b_{it}})\sigma_u$, is function of firms' exogenous variables $\boldsymbol{b_{it}}$. This model, accounting for heteroscedasticity in the inefficiency term, can be numerically estimated through standard maximum likelihood estimation techniques.

Finally, Tsukamoto (2019) extended the spatial autoregressive stochastic frontier model for panel data by incorporating a model for the mean of the inefficiency error term, as proposed by Battese and Coelli (1995). Therefore, going beyond the standard spatial autoregressive SF model shown in Eq.(2.17), the author included a vector of exogenous variables $\boldsymbol{z_{it}}$ explaining technical inefficiency in modelling the mean of the inefficiency error term u_{it}, as shown in Eq.(2.21).

$$u_{it} \sim i.i.d.\ \mathcal{N}^{+}(\boldsymbol{z_{it}}\delta, \sigma_u^2) \tag{2.21}$$

Also in this case, the parameter estimates can be obtained numerically maximising the log-likelihood function satisfying the first-order conditions.

2.2.3 Considering Spatial Correlation in the Error Terms

The second branch of literature introducing spatial effects in SF models does not consider global and local spatial dependence related to the frontier function but assumes the inefficiency term and/or the error term to be spatially correlated. Schmidt et al. (2009) is the first contribution in this field, making technical inefficiency depend on a parameter that follows a prior distribution that captures unobserved spatial features. Specifically, for each unit j located in municipality i, they modelled the firm output Y_{ij} as a function of a vector $\boldsymbol{x_{ij}}$ of traditional inputs with associated parameter vector $\boldsymbol{\beta}$ and added a random error term v_{ij} that follows a standard normal distribution and an inefficiency component u_{ij} following an asymmetric normal distribution, independent from v_{ij}. Moreover, they considered each u_{ij} as depending on unobserved local effects α_i as shown in Eq.(2.22), and allowed the inefficiency term to vary across different municipalities. Assuming conditional autoregressive CAR priors for α_i, the authors estimated the unknown parameters using a Bayesian approach since the model does not have an analytical closed-form.

$$Y_{ij} = f(\boldsymbol{x_{ij}}, \boldsymbol{\beta}) - u_{ij}(\alpha_i) + v_{ij} \tag{2.22}$$

Differently from the cross-sectional model proposed by Schmidt et al. (2009), Areal, Balcombe, and Tiffin (2012) incorporated spatial dependence using an autoregressive specification for the inefficiency error term as shown in the panel data SF model in Eq.(2.23)-(2.24). In particular, ρ is the spatial parameter and u_{it} and $\widetilde{u}_{it}$ are latent variables whose distributional form is unknown. To estimate the unknown parameters, the authors assumed prior distributions for the latent errors and used a Gibbs sampler and two Metropolis-Hastings steps.

$$Y_{it} = \boldsymbol{x_{it}}\beta + v_{it} - u_{it} \tag{2.23}$$

$$u_{it} = \rho \sum_{j=1}^{N} w_{ij} u_{jt} + \widetilde{u}_{it} \tag{2.24}$$

Similarly, Tsionas and Michaelides (2016) considered a SF model decomposing the inefficiency error term into a spillover and an idiosyncratic component and developed a Bayesian estimator to estimate it. In particular, the spillover component ρWu aimed at capturing regional spillovers while the idiosyncratic term $\widetilde{u}$ was defined by a one-sided random variable.

Rewriting the specification of Eq.(2.23)-(2.24) for cross-sectional data as shown in Eq.(2.25), Fusco and Vidoli (2013) managed to solve the autoregressive error model of Areal, Balcombe, and Tiffin (2012) with a maximum likelihood estimation technique instead of using a Bayesian approach. Specifically, $\widetilde{u}_i$ was assumed to be distributed as $\mathcal{N}(0, \sigma^2_{\widetilde{u}})$ and spatial dependence was incorporated in the inefficiency term through an autoregressive specification.

$$Y_i = f(\boldsymbol{x_i}, \beta_i) + v_i - (1 - \rho \sum_{j=1}^{N} w_{ij})^{-1} \widetilde{u}_i \tag{2.25}$$

Moving from simple spatial models accounting for spatial dependence only in the inefficiency error term, the study by Herwartz and Strumann (2014) included the SAR term besides considering an autoregressive specification for the error term, obtaining a SARAR model for panel data. In particular, they implemented a two-step procedure to estimate it, obtaining technical inefficiency scores using a DEA approach in the first step and then regressing these scores to account for two distinct channels of spatial dependence using a SARAR specification, as shown in Eq.(2.26)-(2.27). The model in the second stage is estimated by means of a ML approach. More in detail, Y_{it} represents technical efficiency and it is based on DEA inefficiency scores; $\boldsymbol{x_{it}}$ is a vector containing observations on k explanatory exogenous variables; w_i contains individual effects; δ_t takes time effects into consideration, w_{ijt} and m_{ijt} are the generic elements of the two $(N \times N)$ spatial weight matrices W_t and M_t and ε_{it} follows a standard normal distribution with zero mean and variance σ^2. Moreover, λ_t measures the effect of neighbouring technical inefficiency scores on Y_{it}, while ρ_t quantifies spatial autocorrelation due to similar unobservable factors affecting firms' efficiency. Thus, in this specification, the authors only made distributional assumptions on the error term ε_{it} while inefficiency is measured using a non-parametric approach.

$$Y_{it} = \lambda_t \sum_{j=1}^{N} w_{ijt} Y_{jt} + \boldsymbol{x_{it}\beta} + w_i + \delta_t + v_{it} \tag{2.26}$$

$$v_{it} = \rho_t \sum_{j=1}^{N} m_{ijt} v_{jt} + \varepsilon_{it} \tag{2.27}$$

The authors also proposed a one-step estimation procedure making distributional assumptions on both the inefficiency term u_{it} and the error term v_{it}. However, in this second model, only spatial dependence related to the inefficiency error term was considered. In particular, the authors started from the non-spatial model proposed by Wang and Ho (2010) shown in Eq.(2.28)-(2.29) in which the inefficiency term u_{it} is modelled as the product of a positive function $h_{it} = f(\boldsymbol{z_{it}}\delta)$ of firms exogenous variables $\boldsymbol{z_{it}}$ and of a positive random variable u_i^*, varying across units but constant in time.

$$Y_{it} = \alpha_i + \boldsymbol{x_{it}\beta} + v_{it} - u_{it} \tag{2.28}$$

$$u_{it} = h_{it}u_i^*, \quad u_i^* \sim \mathcal{N}^+(\mu, \sigma_u^2) \tag{2.29}$$

Herwartz and Strumann (2014) added spatial effects in the specification of the inefficiency error term u_{it} modelling the scaling function h_{it} as function of region-specific random effects with time-varying variance. Due to the non-linearity of the likelihood function, the authors estimated the unknown parameters using a simulated ML approach.

Finally, Orea and Alvarez (2019) succeeded in obtaining a SF model for panel data with closed-form for the likelihood function considering cross-sectional effects in both the inefficiency and the error term, as shown in Eq.(2.30)-(2.34). Specifically, the error vector $\widetilde{v}_t$ was defined as a multivariate normal random variable with variance-covariance matrix Π accounting for unobserved but spatially correlated variables through M_γ. On the other hand, inefficiency depends on an industry-specific error term $\widetilde{u}_t$ common to all firms but varying in time and on cross-sectionally correlated firms' exogenous variables $\boldsymbol{z_{it}}$.

$$Y_{it} = X_{it}\beta + \widetilde{v}_{it} - \widetilde{h}_{it}\widetilde{u}_t \tag{2.30}$$

$$\widetilde{v}_t = (\widetilde{v}_{1t}, ..., \widetilde{v}_{Nt})^T \sim MVN\,(0, \Pi) \tag{2.31}$$

$$\Pi = \sigma_v^2 M_\gamma M_\gamma^T, \quad M_\gamma = (I_N - \gamma W)^{-1} \tag{2.32}$$

$$\widetilde{u}_t \sim \mathcal{N}^+\left(0, \sigma_u^2\right) \tag{2.33}$$

$$\widetilde{h}_{it} = (I_N - \tau W)^{-1} h_{it}, \quad h_{it} = f\left(\boldsymbol{z_{it}\delta}\right) \tag{2.34}$$

Defining the inefficiency error term as the product of two components following the scaling property (Wang and Schmidt, 2002) allows to obtain a closed form for the likelihood function and to estimate the model using standard ML techniques.

2.2.4 Our proposal

In this thesis two novel spatial SF models for panel data are developed: the spatial Durbin stochastic frontier model introducing spillover effects in the determinants of technical inefficiency (SDF-STE) and the spatial Durbin stochastic frontier model accounting for cross-sectional dependence in both the two error terms (SDF-CSD). The detailed specification and the estimation procedure of both models are presented in Chapter 3.

The SDF-STE model takes global and local spatial spillovers into consideration as proposed by Glass, Kenjegalieva, and Sickles (2016) and furthermore, it includes the spatial lag of the determinants of technical inefficiency, allowing to capture how the factors that determine firms' inefficiency level also affect neighbouring producers. Thus, the main new feature of this model concerns the possibility of capturing the specific spillover effects related to each inefficiency determinant distinguishing between spillovers affecting firms' production process and inefficiency level. While for the frontier function we consider both global and local spatial dependence using a spatial Durbin specification as proposed by Glass, Kenjegalieva, and Sickles (2016), for the inefficiency model we only consider local spatial effects because spatial dependence influencing neighbouring firms' efficiency level mainly arises from local factors such as emulation, face-to-face interactions, local cooperation, and individuals contact (Griliches, 1992). Thus, despite the introduction of the new spatial lag in the inefficiency model, the computational effort of estimating the SDF-STE model is fairly the same as estimating a spatial Durbin stochastic frontier model since only local spatial feedbacks are considered in the inefficiency model by introducing the exogenous spatial lag of the Z variables in the same fashion as the SLX model. In sum, the inclusion of the spatial lag of the inefficiency determinants is noteworthy from a conceptual and interpretative point of view in the face of a negligible higher complexity in the modelling approach.

On the other hand, the SDF-CSD model extends the spatial SF model developed by Orea and Alvarez (2019) including the SAR and SLX terms. Therefore, the SDF-CSD model allows considering global productivity spillovers, local input spillovers and spatial dependence related to both error terms, obtaining a very general specification that merges together the two main approaches followed by scholars in this field of research. The most appealing feature of this novel spatial model is that it allows capturing spatial spillover effects related to the frontier function while controlling for spatial correlation related to firms' efficiency (i.e. behavioural correlation) and to unobserved but spatially correlated variables (i.e. environmental correlation), distinguishing between four different sources of spatial dependence. Thus, being the SDF-CSD the most general model in this field in terms of number of spillover effects considered, in empirical applications, instead of choosing a priori the kind of spatial structure to be included based on subjective evaluations, it would be recommended to follow a general to specific approach starting from this general and comprehensive model. Thus, estimating the SDF-CSD model and making some LR tests can provide precise insights into which kind of spatial structure is more adequate to study the phenomenon under investigation. As usual, following a general to specific approach is more computationally expensive than starting by estimating simpler models. However, in this case, the computational burden is not so heavy since the SDF-CSD model can be estimated by adopting simple likelihood-based techniques. The only downside concerns the computational time that, with four different spatial lags, quickly increases as the number of spatial units and time periods raises.

Chapter 3

The Proposed Modelling Approaches

3.1 A Spatial Durbin Stochastic Frontier Model Introducing Spillover Effects in the Determinants of Firms' Efficiency

3.1.1 Model Specification

The specification of the spatial Durbin stochastic frontier model for panel data (N individuals and T time periods) with spatially lagged determinants of technical inefficiency (SDF-STE model) is defined in Eq.(3.1)-(3.4) for $i = 1, \dots, N$ and $t = 1, \dots, T$.

$$Y_{it} = X_{it}\beta + \rho \sum_{j=1}^{N} w_{ij} Y_{jt} + \sum_{j=1}^{N} w_{ij} X_{jt}\theta + v_{it} - u_{it} \tag{3.1}$$

$$v_{it} \sim i.i.d.\, \mathcal{N}\left(0, \sigma_v^2\right) \tag{3.2}$$

$$u_{it} \sim i.i.d.\, \mathcal{N}^+\left(\mu_{it}, \sigma_u^2\right) \tag{3.3}$$

$$\mu_{it} = Z_{it}\phi + \sum_{j=1}^{N} w_{ij} Z_{jt}\delta \tag{3.4}$$

Specifically, Y_{it} is the production output of firm i at time t; X_{it} is a $(1 \times k)$ vector containing the k production inputs used by firm i at time t with associated parameter vector β $(k \times 1)$; ρ is the parameter associated with the SAR term, capturing global spatial spillovers; w_{ij} is the element in the i-th row and j-th column of the row-normalized and time-invariant block diagonal spatial weight matrix W containing non-negative spatial weights to identify neighbours (indexed by $j = 1, \dots, N$) and elements equal to zero on the main diagonal; θ is the parameter vector $(k \times 1)$ associated with the SLX term capturing exogenous local spatial spillovers; v_{it} is the normally distributed error term with zero mean and variance σ_v^2 and u_{it}, representing technical inefficiency, is distributed as a truncated normal random variable with known mean μ_{it} and variance σ_u^2. We model the mean μ_{it} of the technical inefficiency error term u_{it} as function of m exogenous determinants represented by the Z_{it} variables, with corresponding parameter vector ϕ $(m \times 1)$.

Moreover, we add in Eq.(3.4) the spatial lag of the determinants of technical inefficiency with associated parameter vector δ $(m \times 1)$ to capture spatial dependence arising from the determinants of technical inefficiency of nearby firms. Through this term, it is possible to capture knowledge spillovers originating from nearby companies and affecting firms' efficiency levels. If we take a cost function into consideration instead of a production function, only the sign before the technical inefficiency error term changes in the specification of the SDF-STE model. Indeed, for a cost frontier, the inefficiency term has to be summed and not subtracted because it represents the cost increase due to inefficiency.

Assumptions on Eq.(3.1)-(3.4), following Elhorst (2010), include (i) $(I_{NT} - \rho W)$ is non-singular, where I_{NT} is the $(NT \times NT)$ identity matrix; (ii) row and columns sums of W and $(I_{NT} - \rho W)^{-1}$, before W is row-normalized, are uniformly bounded in absolute value as N goes to infinity (Kelejian and Prucha, 1998, 1999). For a symmetric W the first assumption is always satisfied as long as the range of ρ is defined by $\left(\frac{1}{\omega_{min}}, 1\right)$, where ω_{min} is the smallest real characteristic root of the spatial weight matrix W while the upper bound equals 1 for row-normalized W. Assumption (ii) limits the cross-sectional correlation, assuming that, when the distance separating two spatial units increases to infinity, it converges to zero. In particular, if W is a distance inverse spatial weight matrix, assumption (ii) can be guaranteed imposing a cut-off point d^* in W so that $w_{ij} = 0$ if $d_{ij} > d^*$, while assumption (ii) is always satisfied if W is a binary contiguity matrix.

The SDF-STE model nests several existing spatial and non-spatial SF models, as represented in Figure 3.1. Imposing $\delta = 0$ and $\theta = 0$ our model reduces to the spatial autoregressive stochastic frontier model for panel data incorporating a model for technical inefficiency (SARF-TE) proposed by Tsukamoto (2019). If $\delta = 0$ and $\phi = 0$ our model becomes the spatial Durbin stochastic frontier model (SDF) introduced by Glass, Kenjegalieva, and Sickles (2016). Moreover, if $\delta = 0$, $\phi = 0$ and $\theta = 0$ it coincides with the spatial autoregressive stochastic frontier model (SARF) by Glass, Kenjegalieva, and Sickles (2016). Imposing $\delta = 0$, $\rho = 0$ and $\phi = 0$ our model becomes the spatial stochastic frontier model introduced by Adetutu et al. (2015) that only includes the spatial lag of the exogenous variables (SLXF). Considering non-spatial SF model, if $\delta = 0$, $\theta = 0$ and $\rho = 0$ our model reduces to the stochastic frontier production function with a model for technical inefficiency effects (SF-TE) proposed by Battese and Coelli (1995). Finally, considering $\delta = 0$, $\theta = 0$, $\rho = 0$ and $\phi = 0$ our model becomes the classical SF model by Aigner, Lovell, and Schmidt (1977).

Therefore, following an approach similar to Manski (1993) for the general nesting spatial (GNS) model, our comprehensive model allows for various parametric restrictions, enabling a large set of modifications. Indeed, by implementing likelihood ratio tests and starting from our general specification, it is possible to select the model that best fits the data. Moreover, while the GNS model usually suffers from overparameterization issues since the significance levels of the variables included in the model tend to go down becoming insignificant, we didn't experience similar problems estimating our spatial SF specification. Indeed, the GNS model includes the spatial lag of the dependent variable,

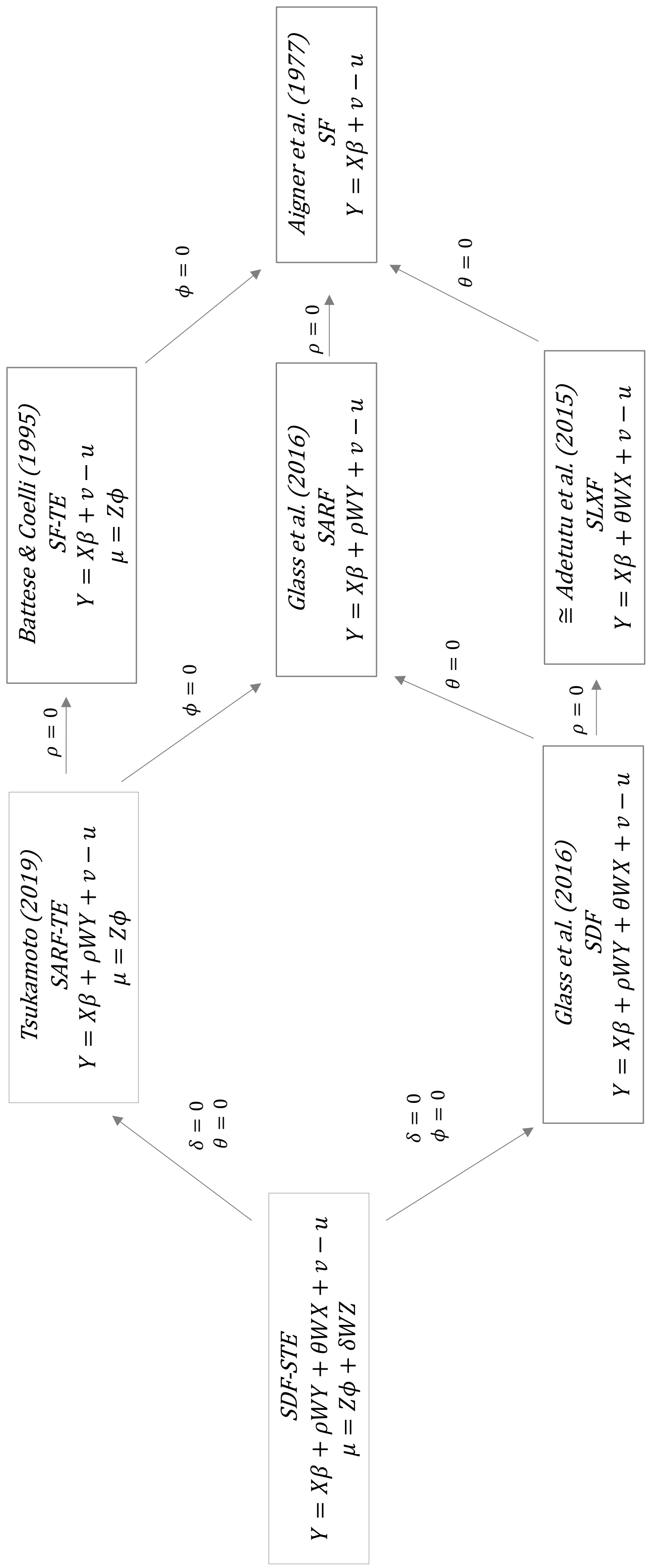

FIGURE 3.1: Nested Models

of the explanatory variables and of the error term to capture the average strength of spatial correlation among the errors. Differently, instead of considering the spatial lag of the error term, our model introduces the spatial lag of the inefficiency determinants related to the mean of the inefficiency error term. This spatial term does not add computational complexity since we are simply enlarging the set of exogenous determinants of the inefficiency model with new exogenous variables referring to neighbours. In sum, while the GNS specification usually does not outperform simpler spatial specifications due to weak identifiability, the SDF-STE model is not affected by overparameterization since two out of three spatial lags relate to exogenous local spatial effects in the same fashion as the SLX model. As an example, the empirical application in Chapter 5 shows that the SDF-STE model outperforms all simpler nested specifications.

3.1.2 The Likelihood Function

The likelihood function associated with the SDF-STE model can be calculated starting from the probability density functions of v_{it} and u_{it}. In particular, v_{it} has a normal distribution with zero mean and variance σ_v^2 as shown in Eq.(3.5) while u_{it} is distributed as a truncated normal random variable with mean μ_{it} and variance σ_u^2 as shown in Eq.(3.6), where Φ represents the cumulative distribution function of the standard normal random variable.

$$f_v(v_{it}) = \frac{1}{\sqrt{2\pi\sigma_v^2}} \exp\left(-\frac{v_{it}^2}{2\sigma_v^2}\right) \tag{3.5}$$

$$f_u(u_{it}) = \frac{1}{\sqrt{2\pi\sigma_u^2}\Phi\left(\frac{\mu_{it}}{\sigma_u}\right)} \exp\left(-\frac{(u_{it}-\mu_{it})^2}{2\sigma_u^2}\right), u_{it} \geqslant 0 \tag{3.6}$$

Therefore, the joint probability density function of v_{it} and u_{it}, assuming that v_{it} and u_{it} are independent, can be calculated as the product of $f_v(v_{it})$ and $f_u(u_{it})$, as shown in Eq.(3.7).

$$f_{uv}(u_{it}, v_{it}) = \frac{1}{2\pi\sigma_u\sigma_v\Phi\left(\frac{\mu_{it}}{\sigma_u}\right)} \exp\left(-\frac{v_{it}^2}{2\sigma_v^2} - \frac{(u_{it}-\mu_{it})^2}{2\sigma_u^2}\right) \tag{3.7}$$

Substituting $v_{it} = \varepsilon_{it} + u_{it}$ in Eq.(3.7), starting from the relationship $\varepsilon_{it} = v_{it} - u_{it}$, the joint probability density function of ε_{it} and u_{it} can be defined as

$$\begin{aligned} f_{\varepsilon u}(\varepsilon_{it}, u_{it}) &= \frac{1}{2\pi\sigma_u\sigma_v\Phi\left(\frac{\mu_{it}}{\sigma_u}\right)} \exp\left(-\frac{(\varepsilon_{it}+u_{it})^2}{2\sigma_v^2} - \frac{(u_{it}-\mu_{it})^2}{2\sigma_u^2}\right) \\ &= \frac{1}{2\pi\sigma_u\sigma_v\Phi\left(\frac{\mu_{it}}{\sigma_u}\right)} \exp\left(-\frac{(u_{it}-\mu_*)^2}{2\sigma_*^2} - \frac{\varepsilon_{it}^2}{2\sigma_v^2} - \frac{\mu_{it}^2}{2\sigma_u^2} + \frac{\mu_*^2}{2\sigma_*^2}\right), \end{aligned} \tag{3.8}$$

where

$$\mu_* = \frac{\sigma_v^2 \mu_{it} - \sigma_u^2 \varepsilon_{it}}{\sigma_v^2 + \sigma_u^2} \tag{3.9}$$

and

$$\sigma_*^2 = \frac{\sigma_v^2 \sigma_u^2}{\sigma_v^2 + \sigma_u^2}. \tag{3.10}$$

Afterwards, the probability density function of ε_{it} is obtained integrating out u_{it} from Eq.(3.8), as shown in Eq.(3.11a)-(3.11c).

$$f_\varepsilon(\varepsilon_{it}) = \frac{\exp\left(-\frac{\varepsilon_{it}^2}{2\sigma_v^2} - \frac{\mu_{it}^2}{2\sigma_u^2} + \frac{\mu_*^2}{2\sigma_*^2}\right)}{\sqrt{2\pi}\frac{\sigma_u \sigma_v}{\sigma_*}\Phi\left(\frac{\mu_{it}}{\sigma_u}\right)} \int_0^\infty \frac{\exp(-\frac{(u_{it}-\mu_*)^2}{2\sigma_*^2})}{\sqrt{2\pi\sigma_*^2}} du_{it} \tag{3.11a}$$

$$= \frac{\exp\left(-\frac{\varepsilon_{it}^2}{2\sigma_v^2} - \frac{\mu_{it}^2}{2\sigma_u^2} + \frac{\mu_*^2}{2\sigma_*^2}\right)}{\sqrt{2\pi(\sigma_u^2 + \sigma_v^2)}\Phi\left(\frac{\mu_{it}}{\sigma_u}\right)} \Phi\left(\frac{\mu_*}{\sigma_*}\right) \tag{3.11b}$$

$$= \frac{\exp\left(-\frac{(\varepsilon_{it}+\mu_{it})^2}{2(\sigma_v^2+\sigma_u^2)}\right)}{\sqrt{2\pi(\sigma_u^2 + \sigma_v^2)}\Phi\left(\frac{\mu_{it}}{\sigma_u}\right)} \Phi\left(\frac{\mu_*}{\sigma_*}\right) \tag{3.11c}$$

After having reparameterized Eq.(3.11c) following Eq.(3.12)-(3.13), the joint probability density function of $\boldsymbol{\varepsilon}$ can be obtained multiplying all the marginal distributions of ε_{it} and as shown in Eq.(3.14).

$$\sigma^2 = \sigma_u^2 + \sigma_v^2 \tag{3.12}$$

$$\lambda = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2} \tag{3.13}$$

$$f_\varepsilon(\boldsymbol{\varepsilon}) = \prod_{i=1}^{N}\prod_{t=1}^{T} \frac{\exp(-\frac{(\varepsilon_{it}+\mu_{it})^2}{2\sigma^2})}{\sqrt{2\pi\sigma^2}\Phi\left(\frac{\mu_{it}}{\sigma\sqrt{\lambda}}\right)} \Phi\left(\frac{(1-\lambda)\mu_{it} - \lambda\varepsilon_{it}}{\sigma\sqrt{\lambda(1-\lambda)}}\right) \tag{3.14}$$

Starting from $f_\varepsilon(\boldsymbol{\varepsilon})$, the probability density function of Y_{it} can be defined as the product of $f_\varepsilon(\boldsymbol{\varepsilon})$ and of the determinant of the Jacobian of the transformation from ε_{it} to Y_{it}. Indeed, since $\frac{\partial\varepsilon}{\partial Y} = (I_{NT} - \rho W)$, the endogeneity deriving from the inclusion of the spatial lag of the dependent variable has to be taken into account. Thus, substituting in Eq.(3.15) the expressions in Eq.(3.16)-(3.17) leads to the likelihood function of the SDF-STE model.

$$f_Y(Y) = |I_{NT} - \rho W| \prod_{i=1}^{N}\prod_{t=1}^{T} \frac{\exp(-\frac{(\varepsilon_{it}+\mu_{it})^2}{2\sigma^2})}{\sqrt{2\pi\sigma^2}\Phi\left(\frac{\mu_{it}}{\sigma\sqrt{\lambda}}\right)} \Phi\left(\frac{(1-\lambda)\mu_{it} - \lambda\varepsilon_{it}}{\sigma\sqrt{\lambda(1-\lambda)}}\right) \tag{3.15}$$

$$\mu_{it} = Z_{it}\phi + \sum_{j=1}^{N} w_{ij} Z_{jt}\delta \tag{3.16}$$

$$\varepsilon_{it} = Y_{it} - X_{it}\beta - \rho \sum_{j=1}^{N} w_{ij} Y_{jt} - \sum_{j=1}^{N} w_{ij} X_{jt}\theta \tag{3.17}$$

The final loglikelihood function, with $\Theta = (\beta, \rho, \theta, \phi, \delta, \lambda, \sigma^2)$ assuming that the panel is balanced, is shown in Eq.(3.18).

$$\begin{aligned} \mathcal{L}(\Theta; y) = \log|I_{NT} - \rho W| - \frac{NT}{2}\left(\log\sigma^2 + \log 2\pi\right) - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}(\mu_{it} + \varepsilon_{it})^2 \\ - \sum_{i=1}^{N}\sum_{t=1}^{T}\left[\log\Phi\left(\frac{\mu_{it}}{\sigma\sqrt{\lambda}}\right) - \log\Phi\left(\frac{\mu_{it}(1-\lambda) - \varepsilon_{it}\lambda}{\sigma\sqrt{\lambda(1-\lambda)}}\right)\right] \end{aligned} \tag{3.18}$$

If we take a cost function into consideration the loglikelihood function changes slightly in a few signs, as represented in Eq.(3.19).

$$\begin{aligned} \mathcal{L}(\Theta; y) = \log|I_{NT} - \rho W| - \frac{NT}{2}\left(\log\sigma^2 + \log 2\pi\right) - \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}(-\mu_{it} + \varepsilon_{it})^2 \\ - \sum_{i=1}^{N}\sum_{t=1}^{T}\left[\log\Phi\left(\frac{\mu_{it}}{\sigma\sqrt{\lambda}}\right) + \log\Phi\left(\frac{\mu_{it}(1-\lambda) - \varepsilon_{it}\lambda}{\sigma\sqrt{\lambda(1-\lambda)}}\right)\right] \end{aligned} \tag{3.19}$$

3.1.3 Estimation and First Derivatives

The parameter estimates can be obtained using a numerical maximization algorithm implemented in standard software. Since the parameter space for an autoregressive process is $\left(\frac{1}{\omega_{min}}, 1\right)$, where ω_{min} is the smallest eigenvalue of W, the autoregressive parameter ρ should be bounded to the previous interval. Moreover, σ^2 should be positive and $0 \leq \lambda \leq 1$. Specifically, if λ equals zero the OLS model should be preferred to the SF function because the variance of the inefficiency term is zero and therefore, the determinants of firms' efficiency can be included in the frontier function. Conversely, λ increases until 1 if the inefficiency effects are likely to be highly significant. Finally, to make the algorithm work better, the first derivatives of the loglikelihood function with respect to the unknown parameters can be supplied to the program.

Defined m_{it} and s_{it} as

$$m_{it} = \mu_{it}(1-\lambda) - \varepsilon_{it}\lambda \tag{3.20}$$

$$s_{it} = \sigma\sqrt{\lambda(1-\lambda)}, \tag{3.21}$$

the first derivatives of the loglikelihood function can be calculated as shown in the following equations.

$$\frac{\partial \mathcal{L}}{\partial \beta} = \sum_{t=1}^{T}\sum_{i=1}^{N}\left(\frac{(\mu_{it}+\varepsilon_{it})}{\sigma^2} + \frac{\lambda\phi\left(\frac{m_{it}}{s_{it}}\right)}{s_{it}\Phi\left(\frac{m_{it}}{s_{it}}\right)}\right) X_{it} \tag{3.22}$$

$$\frac{\partial \mathcal{L}}{\partial \rho} = -Ttr\left(\left(I_N-\rho W\right)^{-1} W\right) + \sum_{t=1}^{T}\sum_{i=1}^{N}\left(\frac{(\mu_{it}+\varepsilon_{it})}{\sigma^2} + \frac{\lambda\phi\left(\frac{m_{it}}{s_{it}}\right)}{s_{it}\Phi\left(\frac{m_{it}}{s_{it}}\right)}\right) \sum_{j=1}^{N} w_{ij}Y_{ij} \tag{3.23}$$

$$\frac{\partial \mathcal{L}}{\partial \theta} = \sum_{t=1}^{T}\sum_{i=1}^{N}\left(\frac{(\mu_{it}+\varepsilon_{it})}{\sigma^2} + \frac{\lambda\phi\left(\frac{m_{it}}{s_{it}}\right)}{s_{it}\Phi\left(\frac{m_{it}}{s_{it}}\right)}\right) \sum_{j=1}^{N} w_{ij}X_{ij} \tag{3.24}$$

$$\frac{\partial \mathcal{L}}{\partial \phi} = \sum_{t=1}^{T}\sum_{i=1}^{N}\left(-\frac{(\mu_{it}+\varepsilon_{it})}{\sigma^2} - \frac{\phi\left(\frac{\mu_{it}}{\sigma\sqrt{\lambda}}\right)}{\Phi\left(\frac{\mu_{it}}{\sigma\sqrt{\lambda}}\right)\sigma\sqrt{\lambda}} + \frac{\phi\left(\frac{m_{it}}{s_{it}}\right)(1-\lambda)}{\Phi\left(\frac{m_{it}}{s_{it}}\right)s_{it}}\right) Z_{it} \tag{3.25}$$

$$\frac{\partial \mathcal{L}}{\partial \delta} = \sum_{t=1}^{T}\sum_{i=1}^{N}\left(-\frac{(\mu_{it}+\varepsilon_{it})}{\sigma^2} - \frac{\phi\left(\frac{\mu_{it}}{\sigma\sqrt{\lambda}}\right)}{\Phi\left(\frac{\mu_{it}}{\sigma\sqrt{\lambda}}\right)\sigma\sqrt{\lambda}} + \frac{\phi\left(\frac{m_{it}}{s_{it}}\right)(1-\lambda)}{\Phi\left(\frac{m_{it}}{s_{it}}\right)s_{it}}\right) \sum_{j=1}^{N} w_{ij}Z_{ij} \tag{3.26}$$

$$\frac{\partial \mathcal{L}}{\partial \sigma^2} = -\frac{NT}{2\sigma^2} + \frac{1}{2\sigma^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\frac{(\mu_{it}+\varepsilon_{it})^2}{\sigma^2} + \frac{\phi\left(\frac{\mu_{it}}{\sigma\sqrt{\lambda}}\right)}{\Phi\left(\frac{\mu_{it}}{\sigma\sqrt{\lambda}}\right)}\frac{\mu_{it}}{\sigma\sqrt{\lambda}} - \frac{\phi\left(\frac{m_{it}}{s_{it}}\right)}{\Phi\left(\frac{m_{it}}{s_{it}}\right)}\frac{m_{it}}{s_{it}}\right) \tag{3.27}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = \sum_{t=1}^{T}\sum_{i=1}^{N}\left(\frac{\phi\left(\frac{\mu_{it}}{\sigma\sqrt{\lambda}}\right)}{\Phi\left(\frac{\mu_{it}}{\sigma\sqrt{\lambda}}\right)}\frac{\mu_{it}}{2\sigma\lambda\sqrt{\lambda}} - \frac{\phi\left(\frac{m_{it}}{s_{it}}\right)}{\Phi\left(\frac{m_{it}}{s_{it}}\right)}\left(\frac{(\mu_{it}+\varepsilon_{it})}{s_{it}} + \frac{(1-2\lambda)\frac{m_{it}}{s_{it}}}{2(1-\lambda)\lambda}\right)\right) \tag{3.28}$$

3.1.4 Technical Efficiency Scores

The technical efficiency scores are defined as the ratio between the mean production Y_{it} of firm i at time t and the mean production Y_{it} of firm i at time t in the case in which inefficiency equals zero, as shown in Eq.(3.29). Therefore, technical efficiency scores equal zero for fully inefficient firms and one for fully efficient firms.

$$TE_{it} = \frac{E(Y_{it}|u_i, X_{it}, t=1,2,...)}{E(Y_{it}|u_i=0, X_{it}, t=1,2,...)} \tag{3.29}$$

Following Battese and Coelli (1988), the technical efficiency score of firm i in period t is defined as $TE_{it} = E(\exp(-u_{it})|\varepsilon_{it})$. Concentrating on the SDF-STE model, technical efficiency scores can be calculated by substituting the parameter estimates in Eq.(3.30) for a production function, or in Eq.(3.31) for a cost function.

$$TE_{it} = \exp\left[-\mu_{it}(1-\lambda) + \varepsilon_{it}\lambda + \frac{1}{2}\left(\sigma\sqrt{(1-\lambda)\lambda}\right)^2\right] \cdot \left\{\frac{\Phi\left(\frac{\mu_{it}(1-\lambda)-\varepsilon_{it}\lambda}{\sigma\sqrt{(1-\lambda)\lambda}} - \sigma\sqrt{(1-\lambda)\lambda}\right)}{\Phi\left(\frac{\mu_{it}(1-\lambda)-\varepsilon_{it}\lambda}{\sigma\sqrt{(1-\lambda)\lambda}}\right)}\right\} \tag{3.30}$$

$$TE_{it} = \exp\left[-\mu_{it}(1-\lambda) - \varepsilon_{it}\lambda + \frac{1}{2}\left(\sigma\sqrt{(1-\lambda)\lambda}\right)^2\right] \cdot \left\{\frac{\Phi\left(\frac{\mu_{it}(1-\lambda)+\varepsilon_{it}\lambda}{\sigma\sqrt{(1-\lambda)\lambda}} - \sigma\sqrt{(1-\lambda)\lambda}\right)}{\Phi\left(\frac{\mu_{it}(1-\lambda)+\varepsilon_{it}\lambda}{\sigma\sqrt{(1-\lambda)\lambda}}\right)}\right\} \tag{3.31}$$

3.1.5 Marginal Effects

As evidenced by Elhorst (2014), in spatial models, the β estimates do not correspond to the partial derivatives of Y with respect to X when the spatial lag of Y is included in the model because changes in the generic regressor X of firm i influence the production output of firm j. Thus, for spatial models including the spatial autoregressive term, the estimated coefficients cannot be interpreted as elasticities. To show it, we rewrite the SDF-STE model in matrix notation using the reduced form, as shown in Eq.(3.32).

$$Y = (I_{NT} - \rho W)^{-1}(X\beta + WX\theta - Z\phi - WZ\delta - e + v) \tag{3.32}$$

In particular, Y is a $(NT \times 1)$ vector, X is a $(NT \times k)$ matrix of inputs, Z is a $(NT \times m)$ matrix of exogenous determinants of technical inefficiency, W is the $(NT \times NT)$ spatial weight matrix, I is a $(NT \times NT)$ identity matrix, v is a $(NT \times 1)$ random vector distributed as a multivariate normal random variable with zero mean and variance $I\sigma_v^2$, and e is a $(NT \times 1)$ random vector distributed as a multivariate truncated normal random variable with zero mean and variance $I\sigma_u^2$ with points of truncation equal to $-Z_{it}\phi - \sum_{j=1}^{N} w_{ij} Z_{jt}\delta$, so that, $e_{it} \geq -Z_{it}\phi - \sum_{j=1}^{N} w_{ij} Z_{jt}\delta$. The definition $u = Z\phi + WZ\delta + e$ is consistent with specifying the inefficiency term u as a non-negative truncation of a normal distribution with mean $\mu = Z\phi + WZ\delta$ and variance σ_u^2 (Battese and Coelli, 1995). Moreover, β and ϕ are $(k \times 1)$ and $(m \times 1)$ vectors of unknown parameters related respectively to the input variables and to the determinants of technical inefficiency, ρ is the parameter capturing global spatial spillovers, θ is a $(k \times 1)$ vector of parameters capturing local spatial spillovers, and δ is a $(m \times 1)$ vector of unknown parameters measuring spillover effects associated with the determinants of technical inefficiency.

The marginal effects of the generic regressor X_r $(r = 1, \ldots, k)$ on Y are defined as the partial derivatives of Y with respect to X_r, as shown in Eq.(3.33).

$$\frac{\partial Y}{\partial X_r} = (I_{NT} - \rho W)^{-1}(I_{NT}\beta_r + W\theta_r) \tag{3.33}$$

LeSage and Pace (2009) proposed to compute the marginal effects of X_r on Y starting from the matrix resulting from the right-hand side of Eq.(3.33). This matrix, referring for simplicity of presentation to the generic time period t, is denoted as $S_r(W)_t$ and it can be explicitly shown as in Eq.(3.34), where W is a $N \times N$ spatial weight matrix.

$$S_r(W)_t = (I_N - \rho W)^{-1} \begin{bmatrix} \beta_r & \cdots & w_{1N}\theta_r \\ \vdots & \ddots & \vdots \\ w_{N1}\theta_r & \cdots & \beta_r \end{bmatrix} \tag{3.34}$$

Therefore, (i) the direct effect of X_r on Y can be computed as the average of the diagonal elements of the matrix resulting from the product on the right-hand side of Eq.(3.33), (ii) the indirect effect can be found as the average of the sum of the non-diagonal elements of $S_r(W)$, (iii) the total effect is equal to the sum of the direct and the indirect effects. Specifically, direct, total and indirect effects can be computed as shown in Eq.(3.35)-(3.36)-(3.37), respectively, where i is a $(NT \times 1)$ vector of ones.

$$DE = \frac{1}{NT} tr(S_r(W)) \tag{3.35}$$

$$TE = \frac{1}{NT} i^T S_r(W) i \tag{3.36}$$

$$IE = TE - DE \tag{3.37}$$

In this way, when the model is specified using logarithms, it is possible to interpret these marginal effects as elasticities, evaluating the total impact of a covariate, the direct effect and the indirect one, taking spatial spillovers into consideration.

Similarly to the β estimates, also the ϕ estimates of the inefficiency model cannot be interpreted as elasticities due to the presence of the spatial lag of Y. In particular, given the unconditional definition of u that considers the frontier feedback effects, $u^\star = (I_{NT} - \rho W)^{-1}(Z\phi + WZ\delta + e)$, the first derivative of $u^\star$ with respect to a generic determinant Z_r equals

$$\frac{\partial u}{\partial Z_r} = (I_{NT} - \rho W)^{-1}(I_{NT}\phi_r + W\delta_r). \tag{3.38}$$

The product on the right-hand side of Eq.3.38, considering a generic time period t for simplicity of presentation, is defined as $M_r(W)_t$ and takes the following form

$$M_r(W)_t = (I_N - \rho W)^{-1} \begin{bmatrix} \phi_r & \cdots & w_{1N}\delta_r \\ \vdots & \ddots & \vdots \\ w_{N1}\delta_r & \cdots & \phi_r \end{bmatrix} \tag{3.39}$$

Therefore, ϕ_r and δ_r do not clearly coincide with the direct and indirect effect of the generic determinant Z_r on firms' inefficiency level and hence, following LeSage and Pace (2009), (i) the direct effect of Z_r on $u^\star$ can be computed as the average of the diagonal elements of the matrix on the right-hand side of Eq.(3.38), (ii) the indirect effect can be computed as the average of the sum of the non-diagonal elements of $M_r(W)$ and (iii) the total effect is equal to the sum of the direct and indirect effects.

The following issue concerns the estimation of the corresponding standard errors or t-values, which are needed to establish if the direct, indirect and total effects are statistically significant. In literature, there are two possible ways to compute the standard errors of the marginal effects. The first procedure, proposed by LeSage and Pace (2009), consists in simulating the distribution of the direct, indirect and total effects starting from the variance-covariance matrix obtained from the maximum likelihood estimates of the parameters. The variance-covariance matrix can be obtained through the analytical Hessian matrix or it can be approximated by the Hessian matrix resulting from ML numerical optimization algorithms. The simulation method requires to generate D combinations of the parameters for $d = 1, ..., D$ as defined in Eq.(3.40), in which the right-hand vector contains the maximum likelihood estimates of the unknown parameters, P denotes the upper-triangular Cholesky decomposition of the variance-covariance matrix associated with the ML estimates, and η denotes a $(J \times 1)$ vector containing random draws from a standard normal distribution, where J equals the number of parameters involved in the procedure.

$$\begin{bmatrix} \beta_d \\ \rho_d \\ \theta_d \\ \phi_d \\ \delta_d \\ \sigma^2_d \\ \lambda_d \end{bmatrix} = P^T \eta + \begin{bmatrix} \hat{\beta} \\ \hat{\rho} \\ \hat{\theta} \\ \hat{\phi} \\ \hat{\delta} \\ \hat{\sigma^2} \\ \hat{\lambda} \end{bmatrix} \tag{3.40}$$

Afterwards, the direct, indirect and total effects can be computed for every drawn d with $d = 1, ..., D$ as previously described, and the overall direct, indirect and total effect can be approximated by calculating the mean values over the D draws. Finally, the associated standard errors correspond to the standard deviations of the D draws, and the t-statistics can be found by dividing the mean values of the direct, indirect and total effects by the corresponding standard deviations.

The second method that can be used to compute the standard errors associated with the marginal effects consists in using the delta method following Eq.(3.41), as proposed by Glass, Kenjegalieva, and Sickles (2016). In particular, h represents the vector of the J unknown parameters involved in the transformation, $\hat{h}$ is a $(J \times 1)$ vector containing the ML estimates of the parameters of interest, g is a generic function of the parameters (in this case it corresponds to the transformation used to compute the marginal effects), $\partial g(\hat{h})$ represents the $(J \times 1)$ vector of first partial derivatives and Σ_h is the $(J \times J)$ variance-covariance matrix associated with the ML estimates of h.

$$\sqrt{N}(g(h) - g(\hat{h})) \xrightarrow{D} \mathcal{N}(0, \partial g(\hat{h})' \Sigma_h \partial g(\hat{h})) \tag{3.41}$$

Starting from (3.41), the standard errors associated with the g transformation can be found as

$$SD_{g(h)} = \sqrt{\partial g(\hat{h})' \Sigma_h \partial g(\hat{h})} \tag{3.42}$$

3.2 A Spatial Durbin Stochastic Frontier Model Introducing Spatial Cross-Sectional Dependence in Both Error Terms

3.2.1 Model Specification

The spatial Durbin stochastic frontier model allowing for spatial cross-sectional dependence both in the inefficiency and in the error term (SDF-CSD model) is specified as in Eq.(3.43)-(3.47)

$$Y_{it} = \rho \sum_{j=1}^{N} w_{ij} Y_{jt} + X_{it}\beta + \sum_{j=1}^{N} w_{ij} X_{jt}\theta + \widetilde{v}_{it} - \widetilde{h}_{it}\widetilde{u}_t \tag{3.43}$$

$$\widetilde{v}_t \sim MVN\,(0, \Pi) \tag{3.44}$$

$$\Pi = \sigma_v^2 M_\gamma M_\gamma^T, \quad M_\gamma = (I_N - \gamma W)^{-1} \tag{3.45}$$

$$\widetilde{h}_{it} = (I_N - \tau W)^{-1} h_{it}, \quad h_{it} = f\,(Z_{it}, \phi) \tag{3.46}$$

$$\widetilde{u}_t \sim \mathcal{N}^+\left(0, \sigma_u^2\right) \tag{3.47}$$

where Y_{it} represents the production output (usually expressed in log-form) of firm i at time t ($i = 1, \ldots, N$ and $t = 1, \ldots, T$) and X_{it} is a $1 \times k$ vector of production inputs used by firm i at time t with associated parameter vector β $(k \times 1)$. In order to take spatial dependence into consideration we include in the frontier function the spatial lag of the dependent variable and the spatial lag of the production inputs, detecting global and local spatial spillovers through ρ (1×1) and θ $(k \times 1)$, respectively. In particular, w_{ij} represents the generic element of the spatial weight matrix W, built as row-normalized $(N \times N)$ matrix. Moreover, the vector $\widetilde{v}_t = (\widetilde{v}_{1t}, ..., \widetilde{v}_{Nt})$ represents the error term distributed as a multivariate normal random variable with variance-covariance matrix equal to Π accounting for unobserved but spatially correlated variables thought the inclusion of M_γ, as defined in Eq.(3.45). Finally, assuming that the scaling property (Wang and Schmidt, 2002) holds, the inefficiency error term u_{it} is decomposed as the product of two components: a scaling function $\widetilde{h}_{it}$ and a basic distribution $\widetilde{u}_t$. Specifically, $\widetilde{h}_{it}$ depends on a positive function f of firm exogenous variables Z_{it} with associated parameter vector ϕ as specified in Eq.(3.46), and on the spatial lag $(I_N - \tau W)^{-1}$ capturing spatial dependence in the variables that determine technical efficiency. Therefore, this model allows both the technical inefficiency error term $u_{it} = \widetilde{h}_{it}\widetilde{u}_t$ and the random noise $\widetilde{v}_{it}$ to be cross-sectionally (spatially) correlated. Finally, as represented in Eq.(3.47), $\widetilde{u}_t$ is an industry-specific inefficiency term following a truncated normal distribution with mean 0 and variance σ_u^2. Therefore, inefficiency depends on an industry-specific error term common to all firms but varying in time, and on firm-specific exogenous variables affecting also neighbouring producers. The use of the scaling property in defining the inefficiency error term is fundamental to obtaining a closed form for the likelihood function. Indeed, considering cross-sectional dependence in the inefficiency error term generally precludes using standard maximum likelihood techniques for the estimation of the unknown parameters. However, defining u_{it} using the scaling property helps in overcoming this issue and allows to estimate the model using ML algorithms implemented in standard software.

As shown in Eq.(3.43)-(3.47), the main characteristic of the SDF-CSD model concerns the inclusion of four different spatial lags, allowing to capture four different sources of spatial dependence. This feature is highly relevant in empirical applications since each spatial lag relates to a different spatial process. First, the ρ parameter associated with the endogenous spatial lag of the dependent variable measures global productivity spillovers. Productivity spillovers may originate from collective behaviours resulting from face-to-face relationships, adoption of new similar technologies, exchange of ideas, learning from others, and the transmission of knowledge and best practices between peers (Billé, Salvioni, and Benedetti, 2018; Cardamone, 2020; Skevas and Lansink, 2020). Second, input spillovers captured through the θ parameters refer to the possibility that a greater availability of specific products, input suppliers, assets and workers with industry-specific skills in a certain area may influence firms' production processes (Marshall, 1890). Third, the spatial parameter τ associated with the spatial lag of the inefficiency component allows measuring behavioural spatial correlation related to firms' efficiency. Indeed, emulation behaviours of firms located in neighbouring areas as well as policies and institutions operating at the local level may affect peers' efficiency level (Areal, Balcombe, and Tiffin, 2012). Finally, the γ parameter in the random error structure captures environmental spatial dependence associated with spatial correlated but unobserved variables such as soil conditions or climatic, topographic and environmental characteristics (Schmidt et al., 2009). In sum, differently from previous simpler specifications, in empirical applications, the SDF-CSD model allows obtaining specific insights on the different kinds of spatial effects occurring between neighbours.

For the SDF-CSD model specified in Eq.(3.43)-(3.47), the following conditions must hold: (i) for a symmetric W, the spatial autoregressive parameters ρ, τ and γ must be within the range $\left(\frac{1}{\omega_{min}}, 1\right)$, where ω_{min} is the smallest eigenvalue of the spatial weight matrix W while the upper bound equals 1 if W is row-normalized; (ii) cross-sectional correlation must converge to zero when the distance separating two spatial units goes to infinity (Kelejian and Prucha, 1998, 1999). The first condition ensures that $(I_N - \rho W)$, $(I_N - \tau W)$ and $(I_N - \gamma W)$ are non-singular matrices and the second one guarantees that the row and the column sums of W, $(I_N - \rho W)^{-1}$, $(I_N - \tau W)^{-1}$ and $(I_N - \gamma W)^{-1}$, before W is row-normalized, are uniformly bounded in absolute value as N goes to infinity. In particular, assumption (ii) is always satisfied when W is a binary contiguity spatial weight matrix while for inverse distance matrices a cut-off point in the distance measure should be introduced (Elhorst, 2010).

3.2.2 The Likelihood Function

The likelihood function corresponding to the SDF-CSD model can be obtained starting from the probability density functions of $\widetilde{v}_t$ and u_t, where $\widetilde{v}_t = (\widetilde{v}_{1t}, ..., \widetilde{v}_{Nt})$ and $u_t = (u_{1t}, ..., u_{Nt})$. In particular, $\widetilde{v}_t$ follows a multivariate normal distribution with zero mean and variance-covariance matrix equal to Π, as shown in Eq.(3.48) while the inefficiency error term $u_t = \widetilde{h}_t \widetilde{u}_t$ is distributed as a truncated normal distribution with zero mean and variance σ_u^2 as shown in Eq.(3.49), with $\widetilde{h}_t = (\widetilde{h}_{1t}, ..., \widetilde{h}_{Nt})$.

$$f_{\widetilde{v}}(\widetilde{v}_t) = 2\pi^{-\frac{N}{2}} |\Pi|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}\widetilde{v}_t^T \Pi^{-1} \widetilde{v}_t\right) \tag{3.48}$$

$$f_u(u_t) = \frac{\widetilde{h}_t}{0.5\sqrt{2\pi}\sigma_u} \exp\left(-\frac{\widetilde{u}_t^2}{2\sigma_u^2}\right), \widetilde{u}_t \geqslant 0 \tag{3.49}$$

Assuming that $\widetilde{v}_t$ and u_t are independent, the joint probability density function of $\widetilde{v}_t$ and u_t can be easily found as the product of the two preceding marginal distributions, as shown in Eq.(3.50).

$$f_{\widetilde{v}u}(\widetilde{v}_t u_t) = \frac{\widetilde{h}_t (2\pi)^{-\frac{N}{2}} |\Pi|^{-\frac{1}{2}}}{0.5\sqrt{2\pi}\sigma_u} \exp\left(-\frac{1}{2}\widetilde{v}_t^T \Pi^{-1} \widetilde{v}_t - \frac{\widetilde{u}_t^2}{2\sigma_u^2}\right) \tag{3.50}$$

Therefore, the joint probability density function of ε_t and u_t in Eq.(3.51) can be obtained substituting $\widetilde{v}_t = \varepsilon_t + u_t = \varepsilon_t + \widetilde{h}_t \widetilde{u}_t$ in Eq.(3.50).

$$f_{\varepsilon u}(\varepsilon_t u_t) = \frac{\widetilde{h}_t (2\pi)^{-\frac{N}{2}} |\Pi|^{-\frac{1}{2}}}{0.5\sqrt{2\pi}\sigma_u} \exp\left(-\frac{1}{2}(\varepsilon_t + \widetilde{h}_t \widetilde{u}_t)^T \Pi^{-1} (\varepsilon_t + \widetilde{h}_t \widetilde{u}_t) - \frac{\widetilde{u}_t^2}{2\sigma_u^2}\right) \tag{3.51}$$

The probability density function of ε_t can be found integrating out $\widetilde{u}_t$ from Eq.(3.51), as shown in Eq.(3.52), where Φ represents the cumulative distribution function of the standard normal random variable and μ_* and σ_*^2 are defined as in Eq.3.53-3.54.

$$
\begin{aligned}
f_\varepsilon(\varepsilon_t) &= \frac{\widetilde{h}_t(2\pi)^{-\frac{N}{2}}|\Pi|^{-\frac{1}{2}}}{0.5\sqrt{2\pi}\sigma_u}\exp\left(-\frac{1}{2}\varepsilon_t^T\Pi^{-1}\varepsilon_t\right) \\
&\cdot\int_0^\infty \exp\left(-\frac{1}{2}\varepsilon_t^T\Pi^{-1}\widetilde{h}_t\widetilde{u}_t - \frac{1}{2}\widetilde{h}_t^T\widetilde{u}_t^T\Pi^{-1}\varepsilon_t - \frac{1}{2}\widetilde{h}_t^T\widetilde{u}_t^T\Pi^{-1}\widetilde{h}_t\widetilde{u}_t - \frac{\widetilde{u}_t^2}{2\sigma_u^2}\right)d\widetilde{u}_t \\
&= \frac{(2\pi)^{-\frac{N}{2}}|\Pi|^{-\frac{1}{2}}}{0.5\sigma_u}\exp\left(-\frac{1}{2}\varepsilon_t^T\Pi^{-1}\varepsilon_t\right)\exp\left(\frac{\mu_*^2}{2\sigma_*^2}\right)\sigma_*\Phi\left(\frac{\mu_*}{\sigma_*}\right)
\end{aligned}
\tag{3.52}
$$

$$
\mu_* = \frac{-\varepsilon_t^T\Pi^{-1}\widetilde{h}_t}{\widetilde{h}_t^T\Pi^{-1}\widetilde{h}_t + \frac{1}{\sigma_u^2}}
\tag{3.53}
$$

$$
\sigma_*^2 = \frac{1}{\widetilde{h}_t^T\Pi^{-1}\widetilde{h}_t + \frac{1}{\sigma_u^2}}.
\tag{3.54}
$$

The partial likelihood function, evaluated for each time period t at a time is shown in Eq.(3.55)-(3.57) and it is equal to the product of the probability density function $f_\varepsilon(\varepsilon_t)$ and of the determinant of the Jacobian deriving from the transformation from ε_t to Y.

$$
f_Y(Y) = |I_N - \rho W|\frac{(2\pi)^{-\frac{N}{2}}|\Pi|^{-\frac{1}{2}}}{0.5\sigma_u}\exp\left(\frac{-\varepsilon_t^T\Pi^{-1}\varepsilon_t}{2}\right)\exp\left(\frac{\mu_*^2}{2\sigma_*^2}\right)\sigma_*\Phi\left(\frac{\mu_*}{\sigma_*}\right)
\tag{3.55}
$$

$$
\varepsilon_t = (\varepsilon_{1t}, ..., \varepsilon_{Nt})
\tag{3.56}
$$

$$
\varepsilon_{it} = Y_{it} - X_{it}\beta - \rho\sum_{j=1}^N w_{ij}Y_{jt} - \sum_{j=1}^N w_{ij}X_{jt}\theta
\tag{3.57}
$$

The resulting partial loglikelihood function is shown in Eq.(3.58) referring to the generic time period t. The final loglikelihood function is equal to $\mathcal{L}(\Theta; y) = \sum_{t=1}^T \ell_t$.

$$
\begin{aligned}
\ell_t =& \log|I_N - \rho W| - \frac{N}{2}\log(2\pi) - \frac{1}{2}\log|\Pi| - \log(0.5\sigma_u) - \frac{1}{2}\varepsilon_t^T\Pi^{-1}\varepsilon_t \\
&+ \frac{1}{2}\left(\frac{\mu_*^2}{\sigma_*^2}\right) + \log\left[\sigma_*\Phi\left(\frac{\mu_*}{\sigma_*}\right)\right]
\end{aligned}
\tag{3.58}
$$

Consistent parameter estimates can be derived by maximising the final loglikelihood function. Since the parameter space for an autoregressive process is $(\frac{1}{\omega_{min}}, 1)$ where ω_{min} is the smallest eigenvalue of W, all the autoregressive parameters (ρ, τ, γ) should be bounded to the previous interval to ensure that $(I_N - \rho W)$, $(I_N - \tau W)$ and $(I_N - \gamma W)$ are non-singular matrices. Moreover, the two variance parameters σ_u^2 and σ_v^2 should only take positive values. The estimation of spatial autoregressive models involves the computation of the log-determinant resulting from the inclusion of the spatial lag of the dependent variable leading to computationally expensive and time-consuming routines. Indeed, $\log|I_N - \rho W|$ is the determinant of a large matrix and it needs to be recalculated at each iteration of the optimization procedure. One potential solution to speed up the computation of the log-determinant, as suggested by Pace and Barry (1997) is to use a vector of values for the log-determinant corresponding to different values of ρ calculated before optimization belonging the interval $(1/\omega_{min}, 1)$, where ω_{min} is the smallest eigenvalue of the spatial weight matrix W and the upper bound equals 1 for row-normalized spatial weight matrices. This involves calculating the vector of log-determinants only once during the estimation procedure and the final interpolated value for the log-determinant can be computed considering a sufficiently fine grid for ρ (for a review on these numerical approaches see LeSage and Pace (2009)). After having adequately handled the computation of the log-determinant, the unknown parameters of the SDF-CSD model can be simultaneously estimated numerically maximising the loglikelihood function using standard software.

3.2.3 Technical Efficiency Scores

Following Orea and Alvarez (2019), technical efficiency scores can be found starting from the Jondrow et al. (1982) estimator as $TE_{it} = \exp(-E\left(u_{it}|\hat{\varepsilon}_{it}\right))$, where the conditional expectation of u_{it} given $\hat{\varepsilon}_{it}$ is shown in Eq.(3.59). Specifically, $\boldsymbol{\phi}$ represents the probability density function of a standard normal random variable, $\widetilde{h}_{it} = (I_N - \hat{\tau}W)^{-1}f(Z, \hat{\phi})$, μ_* and σ_*^2 are computed substituting the parameter estimates in Eq.(3.53)-(3.54), and ε_{it} in Eq.(3.53) is computed as shown in Eq.(3.60).

$$E\left(u_{it}|\hat{\varepsilon}_{it}\right) = \widetilde{h}_{it} E\left(\widetilde{u}_t|\hat{\varepsilon}_{it}\right) = \widetilde{h}_{it}\left[\mu_* + \frac{\sigma_* \boldsymbol{\phi}\left(\frac{\mu_*}{\sigma_*}\right)}{\boldsymbol{\phi}\left(\frac{\mu_*}{\sigma_*}\right)}\right] \tag{3.59}$$

$$\hat{\varepsilon}_{it} = Y_{it} - X_{it}\hat{\beta} - \hat{\rho}\sum_{j=1}^{N} w_{ij}Y_{jt} - \sum_{j=1}^{N} w_{ij}X_{jt}\hat{\theta} \tag{3.60}$$

3.2.4 Marginal Effects

As for the SDF-STE model, also for the SDF-CSD model, the β estimates cannot be interpreted as marginal effects because when spatial lag of Y is included in the model, changes in the generic regressor X_r of firm i also influence the production output of firm j. To show this, the SDF-CSD model is written in the reduced form in Eq.(3.61), where Y is a $(NT \times 1)$ vector representing firms' output, X is a $(NT \times k)$ matrix containing the k production inputs with associated parameter vector β $(k \times 1)$, W is the $NT \times NT$ spatial weight matrix, I is an $NT \times NT$ identity matrix, $\widetilde{v}$ is the error term distributed as shown in Eq.(3.44)-(3.45) and u is the inefficiency error term specified following the scaling property as described in the previous section. Moreover, ρ is the autoregressive parameter capturing global spatial spillovers, θ is the parameter vector $(k \times 1)$ associated with input spillovers, τ, belonging to the spatial structure included in the scaling function, is the parameter capturing behavioural correlation depending on spillovers effects related to the determinants of firms' inefficiency and γ, embedded in the structure of $\widetilde{v}$, is the spatial parameter capturing environmental spatial dependence associated with unobserved but spatially correlated variables.

$$Y = (I_{NT} - \rho W)^{-1}(X\beta + WX\theta + \widetilde{v} - u) \tag{3.61}$$

Computing the first derivative of Y with respect to the generic regressor X_r leads to the same expression shown in Eq.(3.33), and therefore, the computation of the direct, indirect, and total effects of the X variables on Y can be computed as shown in Eq.(3.35)-(3.36)-(3.37), following the method proposed by LeSage and Pace (2009). The related standard errors or t-statistics can be computed either through the simulation method proposed by LeSage and Pace (2009) or using the delta method, as previously described in paragraph 3.1.5.

In order to compute the marginal effect of a generic Z variable on firms' inefficiency level, we consider the unconditional definition of firms' inefficiency. Indeed, within our SDF-CSD framework, the expression $u_{it} = (I_N - \tau W)^{-1} f(Z_{it}, \phi)\widetilde{u}_t$ provides a measure of u_{it} that is conditional on the frontier feedback effects. Starting from the reduced form in Eq.(3.61), the unconditional definition of the inefficiency error term is given by $u^{\star}_{it} = (I_N - \rho W)^{-1} u_{it}$. Thus, the first derivative of $u^{\star}_{it}$ with respect to Z, representing the marginal effect of Z on $u^{\star}_{it}$, includes the spatial filter $(I_N - \rho W)^{-1}$ related to the endogenous spatial lag of Y, as shown in Eq.(3.62a)-(3.62c). However, it should be noted that both the conditional and the unconditional definition of the inefficiency error term lead to the same interpretation of ϕ.

$$\frac{\partial \log(u^*)}{\partial Z_{it}} = \frac{\partial \log((I_N - \rho W)^{-1}(I_N - \tau W)^{-1} \exp(Z_{it}\phi)\widetilde{u}_t)}{\partial Z_{it}} \tag{3.62a}$$

$$= \frac{\partial \log((I_N - \rho W)^{-1})}{\partial Z_{it}} + \frac{\partial \log((I_N - \tau W)^{-1})}{\partial Z_{it}} + \frac{\partial (Z_{it}\phi)}{\partial Z_{it}} + \frac{\partial \log(\widetilde{u}_t)}{\partial Z_{it}} \tag{3.62b}$$

$$= \phi \tag{3.62c}$$

In particular, we specify $f(Z_{it}, \phi) = \exp(Z_{it}\phi)$ and we apply the logarithm to u^*, as suggested by Wang and Schmidt (2002), to generate a very simple expression for the effect of the generic determinant Z_r on firm's inefficiency level. Indeed, the interpretation of ϕ is straightforward, as it represents the marginal effect of Z_r on the logarithm of the level of technical inefficiency of firms.

Chapter 4

Monte Carlo Simulations

4.1 SDF-STE Model

To verify the final sample properties of the first new spatial estimator, we run some Monte Carlo experiments after having simulated NT data. In particular, we defined the input variable X and the determinant of technical inefficiency Z as $(NT \times 1)$ standard normal random vectors; W as a $(NT \times NT)$ block diagonal and row normalized spatial weight matrix; the error term v as a $(NT \times 1)$ normal random vector with zero mean and variance σ_v^2 and the error term e as a $(NT \times 1)$ truncated normal random vector with zero mean and variance σ_u^2 with point of truncation equal to $-Z_{it}\phi - \sum_{j=1}^{N} w_{ij} Z_{jt}\delta$, so that, $e_{it} \geq -Z_{it}\phi - \sum_{j=1}^{N} w_{ij} Z_{jt}\delta$ for $i = 1, \ldots, N$ and $t = 1, \ldots, T$. Therefore, using a production function approach, the dependent variable vector Y $(NT \times 1)$ is defined as

$$Y = (I_{NT} - \rho W)^{-1}(X\beta + WX\theta + v - Z\phi - WZ\delta - e). \tag{4.1}$$

To evaluate the impact of different choices on the estimation bias, the standard deviation (SD) and the mean squared error (MSE), three blocks of simulations were performed. In particular, in the first block of simulations, we evaluated how considering different values for N and T ($N = 100, 200, 300$ and $T = 5, 10, 15$) differently impact the final sample properties of the estimated parameters. In this first block of simulations, the true values of the parameters are fixed at $\{\beta = 0.50,\ \rho = 0.30,\ \theta = 0.30,\ \phi = 0.50,\ \delta = 0.50,\ \sigma_v^2 = 0.10,\ \sigma_u^2 = 0.10\}$. Therefore, following the reparameterization shown in Eq.(3.12)-(3.13) in Chapter 3, $\sigma^2 = 0.20$ and $\lambda = 0.50$. Conversely, in the second block of simulations, the true values of the parameters vary one by one along the different trials considering three different true values (0.15,0.65, and 0.90), while N and T are fixed at $N = 100$ and $T = 10$. All the simulations are performed using 1000 repetitions. In these first two blocks of simulations, the spatial weight matrix W is defined as a binary contiguity spatial weight matrix. Finally, in the third block of simulations, we considered different kinds of spatial weight matrices keeping N and T constants at $N = 300$ and $T = 5$ as well as the true values of the parameters. In particular, we took different kinds of inverse distance spatial weight matrices into consideration, as inverse distance truncated W and inverse distance W considering only the n nearest neighbours (further details are described below). The results of the three blocks of simulations, considering a production frontier, are shown in Table 4.1 for different values of N and T, in Table 4.2for different true values of the parameters, and in Table 4.3 for different choices of the spatial weight matrix W.

The results of the first block of simulations in Table 4.1 show that the bias of all the parameters is negligible, even considering small values for N and T such as $T = 5$ and $N = 100$. Nevertheless, the bias reduces more and more as N and T increase, quickly approaching zero. Likewise, also the SD and the MSE tend to decrease increasing the numerosity of N and T and in particular, considering more time periods helps in obtaining a faster reduction of the bias and of the MSE. All these features can also be observed in Figure 4.1 which shows the results of the first block of simulations for different values of N, with T fixed at $T = 5$ using some boxplots. In particular, the median estimate (red continuous line) always approaches the true value of the parameters (green dotted line) for θ, ϕ, δ and λ, while increasing N helps in obtaining a more accurate estimate of β, ρ and σ^2. Moreover, it is fundamental to consider a sufficiency high numerosity because the box length (i.e. the interquartile range) reduces considerably as N increases and also the occurrence of outliers decreases. Therefore, even if the parameter estimates are anyhow very near or equal to the true values, considering a sufficiently large sample is very important to increase the efficiency of the estimates.

Table 4.2, collecting the results for the second block of simulations, shows that the estimates are robust to different changes in the true value of one parameter at a time, keeping all the others constant, even for a small numerosity ($T = 5$ and $N = 100$). Indeed, the bias is always very near zero while the SD and the MSE remain fairly constant in all the simulations belonging to this second block.

Finally, Table 4.3 shows the results of the simulations considering different kinds of spatial weight matrices. If in the previous simulations a binary contiguity spatial weight matrix was taken into consideration, here W indicates an inverse distance spatial weight matrix, W50 and W30 indicate two inverse distance spatial weight matrices truncated at 50 and 30km, respectively, and W250n, W100n and W50n stand for three inverse distance spatial weight matrices considering only the 250, 100, and 50 nearest neighbours, respectively. All these spatial weight matrices are row standardized and they have been created starting from a random sub-sample of 300 observations belonging to the North-West macro-area from the AIDA sample used in the application discussed in Chapter 5. Moreover, for all these simulations T is fixed at 5 and the number of replications is equal to 1000 as in the previous cases.

The results show that the parameters that do not depend on the spatial weight matrix W (β, ϕ, and the two variances σ^2 and λ) are not affected by changes in the spatial weight matrix. On the contrary, in most cases, the bias, the SD and the MSE of ρ, θ and δ (i.e. the parameters that depend on the spatial weight matrix) tend to decrease as the number of neighbours diminishes, considering the same typology of W. Moreover, for

$N = 300$, the binary contiguity spatial weight matrix used in the results of the previous simulation is the one that minimizes the bias of ρ, θ and δ, compared to the other specifications of W. However, the estimated parameters are still unbiased even considering different kinds of spatial weight matrices. Therefore, the choice of W has very little impact on the final sample properties of the estimated parameters of the SDF-STE model.

TABLE 4.1: SDF-STE Model: Monte Carlo Simulation Results
For different values of N and T

T=5	**N=100**			**N=200**			**N=300**		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	0.0011	0.0180	3.06e-04	0.0001	0.0123	1.55e-04	0.0004	0.0104	0.0001
ρ	-0.0013	0.0425	0.0017	-0.0002	0.0296	9.36e-04	-0.0010	0.0257	0.0007
θ	0.0008	0.0371	0.0013	0.0006	0.0251	7.36e-04	0.0007	0.0231	0.0006
ϕ	0.0004	0.0349	0.0012	-0.0002	0.0246	5.70e-04	-0.0005	0.0190	0.0004
δ	0.0007	0.0576	0.0032	0.0020	0.0445	0.0021	0.0011	0.0373	0.0014
σ^2	-0.0023	0.0162	2.83e-04	-0.0001	0.0129	1.57e-04	-0.0002	0.0097	0.0001
λ	-0.0007	0.0656	0.0045	0.0022	0.0489	0.0025	-0.0001	0.0393	0.0017

T=10	**N=100**			**N=200**			**N=300**		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	0.0005	0.0126	0.0002	0.0010	0.0090	0.0001	-9.15e-05	0.0072	5.37e-05
ρ	-0.0008	0.0289	0.0009	-0.0015	0.0213	0.0005	-4.62e-04	0.0182	3.20e-04
θ	-4.10e-05	0.0251	0.0006	0.0011	0.0184	0.0004	1.62e-04	0.0159	2.42e-04
ϕ	0.0014	0.0246	0.0006	0.0010	0.0167	0.0003	4.71e-04	0.0134	1.79e-04
δ	-0.0009	0.045	0.0022	0.0011	0.0332	0.0011	6.11e-04	0.0257	6.48e-04
σ^2	-0.0003	0.0120	0.0001	-0.0003	0.0090	0.0001	-1.52e-04	0.0068	5.06e-05
λ	0.0015	0.0443	0.0020	0.0009	0.0345	0.0012	3.06e-04	0.0276	7.92e-04

T=15	**N=100**			**N=200**			**N=300**		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	0.0004	0.0101	0.0001	-0.0010	0.0071	5.18e-05	2.30e-04	0.0070	3.39e-05
ρ	-0.0010	0.0233	0.0007	-0.0011	0.0183	3.28e-04	1.33e-04	0.0185	2.45e-04
θ	0.0007	0.0204	0.0006	0.0012	0.0165	2.76e-04	-3.37e-04	0.0160	1.78e-04
ϕ	-0.0005	0.0199	0.0004	0.0008	0.0134	1.88e-04	-2.42e-04	0.0137	1.28e-04
δ	0.0011	0.0367	0.0014	0.0020	0.0263	7.13e-04	-9.41e-04	0.0281	5.19e-04
σ^2	-0.0002	0.0098	0.0001	4.81e-05	0.0072	5.30e-05	-5.67e-04	0.0067	3.29e-05
λ	-0.0001	0.0354	0.0017	0.0016	0.0309	6.25e-04	-7.17e-04	0.0309	5.13e-04

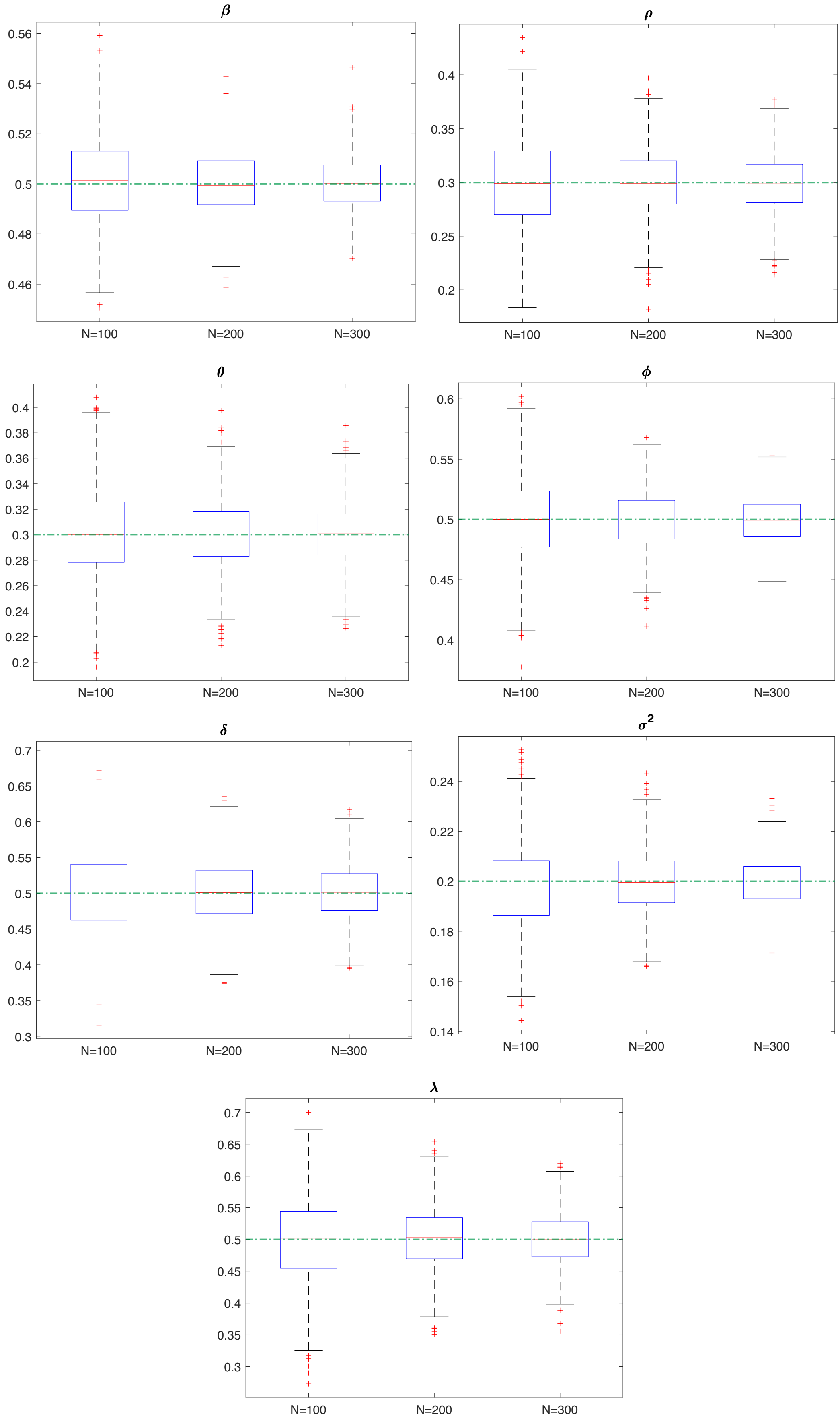

FIGURE 4.1: SDF-STE Model: Boxplots (T=5)

TABLE 4.2: SDF-STE Model: Monte Carlo Simulation Results
For different values of the parameters (T=10, N=100)

β	0.15			0.65			0.90		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-0.0001	0.0120	0.0002	0.0005	0.0127	0.0002	0.0004	0.0125	0.0001
ρ	0.0007	0.0302	0.0010	-0.0008	0.0286	0.0009	-0.0024	0.0314	0.0010
θ	0.0005	0.0211	0.0005	0.0001	0.0282	0.0008	0.0016	0.0375	0.0014
ϕ	0.0002	0.0253	0.0006	0.0014	0.0246	0.0006	0.0006	0.0265	0.0006
δ	-0.0020	0.0451	0.0020	-0.0009	0.0449	0.0022	0.0033	0.0531	0.0026
σ^2	-0.0012	0.0120	0.0001	-0.0003	0.0119	0.0001	-1.83e-05	0.0132	0.0001
λ	-0.0025	0.0466	0.0024	0.0015	0.0440	0.0020	0.0018	0.0425	0.0025

ρ	0.15			0.65			0.90		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-0.0004	0.0119	0.0001	0.0001	0.0125	0.0001	-1.76e-04	0.0120	0.0001
ρ	-0.0014	0.0338	0.0011	-0.0011	0.0185	0.0004	-1.95e-04	0.0066	3.85e-05
θ	0.0016	0.0273	0.0007	0.0009	0.0247	0.0006	2.34e-04	0.0240	0.0006
ϕ	0.0009	0.0233	0.0005	-0.0009	0.0245	0.0006	1.93e-04	0.0246	0.0006
δ	-0.0021	0.0453	0.0020	0.0033	0.0473	0.0020	2.59e-05	0.0453	0.0018
σ^2	-0.0009	0.0118	0.0001	-0.0001	0.0149	0.0002	-2.52e-04	0.0166	0.0002
λ	-0.0009	0.0461	0.0022	0.0022	0.0515	0.0029	-9.13e-04	0.0614	0.0039

θ	0.15			0.65			0.90		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-0.0003	0.0123	0.0002	0.0001	0.0126	0.0001	0.0004	0.0135	0.0002
ρ	-0.0009	0.0338	0.0011	-3.09e-05	0.0297	0.0009	-0.0016	0.0259	0.0006
θ	0.0001	0.0296	0.0009	-0.0001	0.0278	0.0009	0.0010	0.0275	0.0007
ϕ	-0.0012	0.0232	0.0006	-0.0002	0.0233	0.0006	0.0005	0.0231	0.0006
δ	0.0014	0.0507	0.0029	0.0011	0.0469	0.0025	0.0014	0.0433	0.0020
σ^2	-0.0002	0.0112	0.0001	-0.0012	0.0113	0.0001	-0.0008	0.0116	0.0001
λ	0.0007	0.0541	0.0026	-0.0009	0.0474	0.0022	0.0015	0.0485	0.0022

ϕ	0.15			0.65			0.90		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	0.0006	0.0121	0.0001	-0.0003	0.0127	0.0002	0.0005	0.0136	0.0002
ρ	0.0008	0.0364	0.0011	-0.0001	0.0295	0.0009	-0.0001	0.0234	0.0006
θ	0.0007	0.0299	0.0008	0.0002	0.0271	0.0007	-0.0004	0.0246	0.0006
ϕ	0.0001	0.0273	0.0006	-0.0009	0.0243	0.0006	0.0016	0.0293	0.0009
δ	0.0005	0.0439	0.002	0.0008	0.0502	0.0028	-0.0016	0.0526	0.0031
σ^2	-0.0015	0.0139	0.0001	-0.0011	0.0123	0.0002	-0.0006	0.0189	0.0004
λ	-0.0042	0.0509	0.0024	-0.0008	0.0503	0.0024	0.0004	0.0352	0.0014

Table 4.2– continued from previous page

δ	**0.15**			**0.65**			**0.90**		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-2.93e-05	0.0124	0.0001	-3.21e-05	0.0138	0.0002	0.0004	0.0134	0.0002
ρ	9.77e-05	0.0311	0.0009	0.0009	0.0269	0.0007	-0.0001	0.0265	0.0008
θ	5.69e-04	0.0277	0.0007	-0.0017	0.0293	0.0008	-0.0006	0.0251	0.0007
ϕ	-5.83e-05	0.0245	0.0005	-0.0015	0.0292	0.0008	0.0015	0.0305	0.0010
δ	4.98e-04	0.0457	0.0019	0.0004	0.0542	0.0027	-0.0012	0.0524	0.0028
σ^2	-7.56e-04	0.0136	0.0002	-0.0011	0.0191	0.0004	-0.0005	0.0181	0.0003
λ	9.08e-05	0.0457	0.0025	-0.0012	0.0378	0.0015	0.0005	0.0339	0.0013

σ_v^2, σ_u^2	**0.80, 0.10**			**0.10, 0.80**			**0.11, 0.09**		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	0.0006	0.0302	0.0009	-0.0001	0.0173	0.0003	-0.0003	0.0124	0.0001
ρ	-0.0016	0.0360	0.0014	0.0003	0.0233	0.0006	-0.0016	0.0317	0.0009
θ	-0.0002	0.0511	0.0026	0.0015	0.0325	0.0010	0.0017	0.0279	0.0007
ϕ	0.0014	0.0501	0.0027	0.0015	0.0506	0.0024	0.0010	0.0237	0.0005
δ	-0.0020	0.0930	0.0095	-0.0061	0.0925	0.0080	-0.0018	0.0456	0.0020
σ^2	-0.0032	0.0428	0.0019	-0.0048	0.0552	0.0030	-0.0008	0.0122	0.0002
λ	0.0022	0.0343	0.0011	-0.0005	0.0161	0.0003	-0.0007	0.0495	0.0025

TABLE 4.3: SDF-STE Model: Monte Carlo Simulation Results
Sensitivity to the choice of W

N=300, T=5	**W**			**W50**			**W30**		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	0.0007	0.0096	0.0001	0.0008	0.0098	0.0001	0.0008	0.0098	0.0001
ρ	-0.0091	0.0492	0.0026	-0.0056	0.0306	0.0010	-0.0037	0.0256	0.0007
θ	0.0052	0.0534	0.0030	0.0043	0.0354	0.0013	0.0029	0.0299	0.0009
ϕ	0.0002	0.0210	0.0004	0.0002	0.0204	0.0004	0.0002	0.0205	0.0004
δ	0.0055	0.0878	0.0071	0.0045	0.0522	0.0027	0.0047	0.0439	0.0018
σ^2	0.0011	0.0138	0.0002	0.0002	0.0102	0.0001	-0.0003	0.0095	0.0001
λ	0.0069	0.0564	0.0034	0.0040	0.0429	0.0018	0.0017	0.0381	0.0015

N=300, T=5	**W250n**			**W100n**			**W50n**		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	0.0002	0.0095	0.0001	0.0002	0.0096	0.0001	0.0002	0.0096	0.0001
ρ	-0.0031	0.0478	0.0026	-0.0020	0.0427	0.0020	-0.0016	0.0380	0.0015
θ	-0.0005	0.0512	0.0027	-0.0010	0.0457	0.0021	-0.0010	0.0411	0.0017
ϕ	-0.0012	0.0216	0.0004	-0.0012	0.0215	0.0004	-0.0012	0.0213	0.0004
δ	-0.0032	0.0928	0.0083	-0.0028	0.0775	0.0059	-0.0021	0.0661	0.0044
σ^2	0.0004	0.0129	0.0002	0.0001	0.0120	0.0001	-0.0001	0.0114	0.0001
λ	0.0021	0.0516	0.0033	0.0013	0.0480	0.0027	0.0011	0.0448	0.0023

4.2 SDF-CSD Model

In order to test the finite sample properties of the SDF-CSD model we implemented some simulation studies generating NT data. In particular, we defined for each time period t with $t = 1, \dots, T$: the input variable X as a $(N \times 1)$ standard normal random vector; the exogenous variable Z that explains technical inefficiency as a $(N \times 1)$ standard normal random vector; h as an exponential function of the exogenous variable Z with associated coefficient ϕ, and W as a $(N \times N)$ row-normalized spatial weight matrix. Moreover, we specified v as a multivariate normal random vector $(N \times 1)$ with zero mean and variance-covariance matrix equal to Π, as shown in Eq.(4.2)-(4.3).

$$v \sim MVN(0, \Pi) \tag{4.2}$$

$$\Pi = \sigma_v^2 (I_N - \gamma W)^{-1} ((I_N - \gamma W)^{-1})^T \tag{4.3}$$

The inefficiency error term $\widetilde{u}$, common to all firms but varying in time, is generated as a random value drawn from a truncated normal distribution with zero mean and variance σ_u^2. Therefore, following the scaling property, the complete inefficiency error term u $(N \times 1)$ accounting for cross-sectional dependence, is equal to the product of $\widetilde{u}$, of the positive function of firms' exogenous variable h, and of the spatial filter $(I_N - \tau W)^{-1}$, as shown in Eq.(4.4).

$$u = (I_N - \tau W)^{-1} h\widetilde{u} = (I_N - \tau W)^{-1} \exp(Z\phi)\widetilde{u} \tag{4.4}$$

The dependent variable Y, for each time period t ($t = 1, ..., T$), is generated as an $(N \times 1)$ vector, as

$$Y = (I_N - \rho W)^{-1} (X\beta + WX\theta + v - u). \tag{4.5}$$

As for the SDF-STE model, if we consider a cost function instead of a production approach, Y should be generated by summing u in the frontier function instead of subtracting it. As before, also in this case we implemented three blocks of simulations following a production function approach. In particular, in the first block of simulations, we let N and T vary across different values ($N = 100, 200, 300$ and $T = 5, 10, 15$), keeping the true values of the parameters constant, while in the second one we consider different true values for the parameters (0.15,0.65, and 0.90) with N and T fixed at $N = 100$ and $T = 10$. Finally, in the third block of simulations, we evaluate whether considering different spatial weight matrices affects the final sample properties of the estimated parameters. In particular, in the first two blocks of simulations, W has been defined as a binary contiguity spatial weight matrix, while in the third block of simulations, also inverse distance spatial weight matrices with different truncation criteria have been taken into consideration, keeping the true values of the parameters and N and T constant. In the first and third blocks of simulations, the true values of the parameters are fixed at $\{\beta = 0.50,\ \rho = 0.30,\ \theta = 0.30,\ \phi = 0.50,\ \tau = 0.30,\ \gamma = 0.30,\ \sigma_u^2 = 0.10,\ \sigma_v^2 = 0.20\}$. All the simulations are performed using 1000 repetitions. Table 4.4 shows the results of the Monte Carlo experiment for different values of N and T, Table 4.5 shows how the final sample properties of estimated parameters are affected by changes in one true value of the parameters at the time, keeping N and T constant, while Table 4.7 takes different kinds of spatial weight matrices into consideration with T and N fixed at 5 and 300, respectively.

The results in Table 4.4 show that $\beta, \theta, \gamma, \sigma_u^2$ and σ_v^2 are estimated correctly even with a very small numerosity of N and T while the estimation of the other parameters (ρ, ϕ, τ) improves increasing N or considering more time periods. In particular, ρ, ϕ and τ tend to be slightly underestimated with a very small N and $T = 5$ but overall, the bias of all parameters approaches zero considering sufficiently high values for N and T. Likewise, the SD and the MSE quickly tend to decrease as the numerosity of the sample increases. These features can also be observed in Figure 4.2 fixing $T = 5$. Indeed, the median estimate always approaches the true value of the parameter (green dotted line) for β and τ. For ρ, θ, ϕ and γ the bias decreases as N increases while for the two variance parameters, σ_u^2 and σ_v^2, the median estimates slightly underestimate the true values of the parameters. Moreover, increasing N also helps in reducing the interquartile range (i.e. the variability) and thus, in increasing the estimation's efficiency. Finally, also the number of outliers decreases for sufficiently high values of N, in particular considering ϕ, τ and σ_v^2.

Table 4.5 shows how the results of the simulations change considering different true values for the parameters, fixing $N = 100$ and $T = 10$. The results indicate that the estimates are robust to different choices of the true values of β, ρ, θ and τ, even considering $N = 100$. Indeed, the bias is always very near zero and the SD and the MSE are quite stable across the different trials. On the contrary, if $\phi = 0.15$, τ is underestimated (the bias is -0.0245); if $\gamma = 0.65$, τ and γ are underestimated (the bias are -0.0581 and -0.0218, respectively), and if $\gamma = 0.90$, ρ is overestimated (the bias is 0.0228) while τ is underestimated (the bias is -0.0413). Moreover, some problems can be detected by changing the true values of the two variance parameters. In particular, σ_u^2 tend to be underestimated (the bias are -0.0359 and -0.0316) in the first and in the third trial ($\sigma_u^2 = 0.80$ and $\sigma_v^2 = 0.10$; $\sigma_u^2 = 0.50$ and $\sigma_v^2 = 0.50$), while in the second simulation ($\sigma_u^2 = 0.10$ and $\sigma_v^2 = 0.80$) ϕ is overestimated and γ is underestimated (the bias are 0.0282 and -0.0382). Moreover, also the SD and the MSE associated with the biased parameter show quite high values, indicating that we also have problems with the estimation's efficiency. Therefore, we repeated this second block of simulations considering a higher sample numerosity ($N = 300$).

Table 4.6 shows that increasing the sample numerosity and thus considering $N = 300$, helps in obtaining less biased and more efficient estimates of the parameters. Indeed, in all trials, the bias decreases and the SD is about half of the SD detected with $N = 100$. In particular, for $\phi = 0.15$ the bias of τ decreases from -0.0245 to -0.0131, for $\gamma = 0.65$ the bias of τ and γ decreases from -0.0581 and -0.0218 to -0.0130 and -0.0090, respectively, while for $\gamma = 0.90$ the bias of ρ and τ reduces from 0.0228 and -0.0413 to 0.0082 and -0.0114, respectively. Finally, considering the two variances, for $\sigma_u^2 = 0.80$ and $\sigma_v^2 = 0.10$, the bias of σ_u^2 decreases from -0.0359 to -0.0153, for $\sigma_u^2 = 0.10$ and $\sigma_v^2 = 0.80$, the bias of ϕ and τ reduces from 0.0282 and -0.0382 to 0.0113 and -0.0072, respectively, while for $\sigma_u^2 = 0.50$ and $\sigma_v^2 = 0.50$, the bias of σ_u^2 from -0.0316 reaches the value of -0.0168 with $N = 300$. Therefore, considering a sufficiently high sample numerosity is fundamental to obtaining unbiased and more efficient estimates.

Finally, Table 4.7 shows the results of the simulations considering different kinds of spatial weight matrices. Differently from the previous simulations taking a binary contiguity spatial weight matrix into consideration, here, in the first sub-table of Table 4.7, the spatial weight matrix is defined as a dense inverse distance or as a truncated inverse distance matrix while in the second sub-table, the spatial weight matrix is an inverse distance matrix taking only the n nearest neighbours into consideration. In particular, W indicates a dense inverse distance spatial weight matrix, W50 and W30 indicate two inverse distance spatial weight matrices truncated at 50 and 30 kilometres, respectively, and W250n, W100n and W50n stand for three inverse distance spatial weight matrices considering only the 250, 100, and 50 nearest neighbours, respectively. As in the previous case, all these spatial weight matrices have been created starting from a random sub-sample of 300 observations belonging to the macro-area North-West of the AIDA sample used in the application discussed in Chapter 5. Moreover, all these spatial weight matrices are symmetric and row standardized, while T is fixed at 5 and the number of replications is equal to 1000.

The results shown in Table 4.7 indicate that the bias of β, ρ, θ, ϕ and of the two variance parameters σ_u^2 and σ_v^2 is not affected by the choice of a dense inverse distance spatial weight matrix or of an inverse distance truncated W. Conversely, τ and γ tend to be underestimated if a large number of neighbours is taken into consideration. Indeed, the bias of τ and γ is equal to -0.0661 and -0.0206 choosing a dense W, while it decreases to -0.0172 and -0.0079 truncating W at 30 kilometres. Moreover, also the standard deviations associated with these two parameters tend to be quite high considering a dense W but they tend to decrease for W50 and W30. Similarly, τ and γ tend to be underestimated when W is defined as an inverse distance spatial weight matrix considering the n nearest neighbours and the number of neighbours is high, but the bias decreases for decreasing n. Indeed, using W250n the bias associated with τ and γ is equal to -0.0545 and -0.0131 respectively, but it reduces to -0.0283 and -0.0034 for W50n. Thus, to obtain unbiased and more efficient estimates for the unknown parameters using the SDF-CSD model it is better to consider a binary contiguity spatial weight matrix or an inverse distance truncated W. This issue has already been addressed by Mizruchi and Neuman (2008) that suggested to prefer sparse spatial weight matrices when using spatial models. Indeed, in accordance with our simulation results, they demonstrated that dense inverse distance matrices are likely to produce negatively biased parameter estimates and that this bias becomes more severe at higher levels of network density. Moreover, as demonstrated by the Monte Carlo simulations carried out by Elhorst (2010) to test the consistency of the estimated parameters for the Manski model, estimating a model with spatial effects among the dependent variable, the independent variables and the disturbance terms can lead to inconsistent parameter estimates since the endogenous and the exogenous interactions are hardly distinguishable from each other. Generally, the solution adopted in empirical applications consists in simplifying the model by removing one of the three spatial effects. Alternatively, it can be assumed that the spatial weight matrix W is not identical among the different spatial terms. Therefore, we also try to consider separate neighbourhood matrices to evaluate if the bias detected tends to diminish.

In the SDF-CSD model four different kinds of spatial effects are taken into consideration: global spatial spillovers, local spatial spillovers, spatial dependence in the inefficiency term and spatial dependence in the error term, respectively captured by the parameters ρ, θ, τ, and γ. Therefore, to test whether the bias of τ and γ reduces considering two different kinds of spatial weight matrices simultaneously, we consider all the possible combinations of W and $W0$ associated with the four kinds of spatial effects described above. As in the previous simulations, W represents a dense inverse distance spatial weight matrix and $W0$ is a binary continuity spatial weight matrix. The results in Table 4.8 indicate that considering two different kinds of spatial weight matrices is sufficient to cut off the bias of γ, regardless of the combination of W and $W0$ chosen across the four spatial effects. Conversely, to obtain an unbiased estimate of τ it is necessary to consider a limited number of neighbours. Indeed, when a binary contiguity spatial weight matrix is used to capture spatial dependence in the inefficiency term, the bias of τ approaches zero, while if a dense W is taken into consideration, the bias of τ can reach a value up to -0.0313. Nevertheless, it should be noticed that -0.0313 is half of the bias detected in the simulation using a dense inverse distance spatial weight matrix for all four spatial effects (-0.0661). Therefore, using different spatial weight matrices to differentiate among the different kinds of spatial effects considered in the model is anyhow beneficial. However, to obtain perfectly unbiased results it is necessary to associate to τ a sparse spatial weight matrix, as a binary contiguity or an inverse distance truncated spatial weight matrix. Moreover, considering two different kinds of spatial weight matrices for the different spatial effects also helps in reducing the standard deviation of the estimated parameters and the MSE. In conclusion, the only limitation in estimating the SDF-CSD model without bias is to necessarily assume that the spillover effects associated with the inefficiency error term result from closest neighbours. Indeed, considering a sparse spatial weight matrix for this spatial effect ensures unbiased estimates for all the four spatial parameters included in the SDF-CSD model. This limitation should not be considered too restrictive because spatial dependence influencing neighbouring firms' efficiency level mainly arises from local factors such as local cooperation, face-to-face interactions, and individual contact (Griliches, 1992). Indeed, geographic proximity is fundamental for interaction, cooperation and for the transmission of new knowledge.

TABLE 4.4: SDF-CSD Model: Monte Carlo Simulation Results
For different values of N and T

T=5	N=100			N=200			N=300		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	0.0009	0.025	0.0007	0.0005	0.0197	0.0004	0.0005	0.0143	0.0003
ρ	-0.0130	0.1390	0.0216	-0.0023	0.1145	0.0149	-0.0085	0.0769	0.0114
θ	0.0065	0.0747	0.0067	-0.0009	0.0604	0.0045	0.0035	0.0455	0.0034
ϕ	0.0119	0.1077	0.0127	0.0070	0.0691	0.0072	0.0127	0.0724	0.0054
τ	-0.0173	0.2059	0.0494	-0.0158	0.1443	0.0287	0.0002	0.1468	0.0199
γ	0.0047	0.1534	0.0245	-0.0037	0.1108	0.0161	0.0052	0.0813	0.0127
σ_u^2	0.0022	0.0370	0.0054	0.0044	0.0568	0.0052	-0.0001	0.0540	0.0048
σ_v^2	-0.0048	0.0128	0.0002	-0.0028	0.0094	0.0001	-0.0017	0.0075	0.0001

T=10	N=100			N=200			N=300		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-0.0005	0.0174	0.0004	-0.0005	0.0133	0.0002	0.0003	0.0115	0.0001
ρ	-0.0044	0.0956	0.0157	-0.0008	0.0766	0.0073	-0.0043	0.0678	0.0054
θ	0.0005	0.0527	0.0045	-0.0011	0.0425	0.0022	0.0019	0.0373	0.0017
ϕ	0.0097	0.0573	0.0048	0.0027	0.0339	0.0019	0.0026	0.0373	0.0015
τ	-0.0092	0.0915	0.0254	-0.0094	0.0877	0.0123	-0.0015	0.0882	0.0092
γ	-0.0017	0.0966	0.0170	-0.0030	0.0780	0.0081	0.0021	0.0702	0.0061
σ_u^2	0.0014	0.0442	0.0029	0.0021	0.0755	0.0024	-0.0002	0.0502	0.0023
σ_v^2	-0.0027	0.0093	0.0001	-0.0013	0.0066	4.25e-05	-0.0009	0.0053	2.88e-05

T=15	N=100			N=200			N=300		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-0.0004	0.0161	0.0003	-0.0002	0.0119	0.0001	2.66e-05	0.0094	0.0001
ρ	-0.0043	0.0846	0.0085	0.0060	0.0724	0.0053	-0.0004	0.0577	0.0033
θ	0.0016	0.0515	0.0027	-0.0035	0.0386	0.0016	-0.0004	0.0332	0.0010
ϕ	0.0083	0.0758	0.0026	0.0055	0.0307	0.0013	-0.0030	0.038	0.0008
τ	-0.0001	0.1422	0.0141	-0.0051	0.0883	0.0082	-0.0103	0.0874	0.0053
γ	0.0004	0.0998	0.0095	-0.0087	0.0742	0.0058	-0.0023	0.0631	0.0037
σ_u^2	-0.0020	0.0159	0.0019	-0.0011	0.0374	0.0016	-0.0004	0.0298	0.0015
σ_v^2	-0.0019	0.0078	0.0001	-0.0008	0.0055	3.06e-05	-0.0004	0.0044	1.69e-05

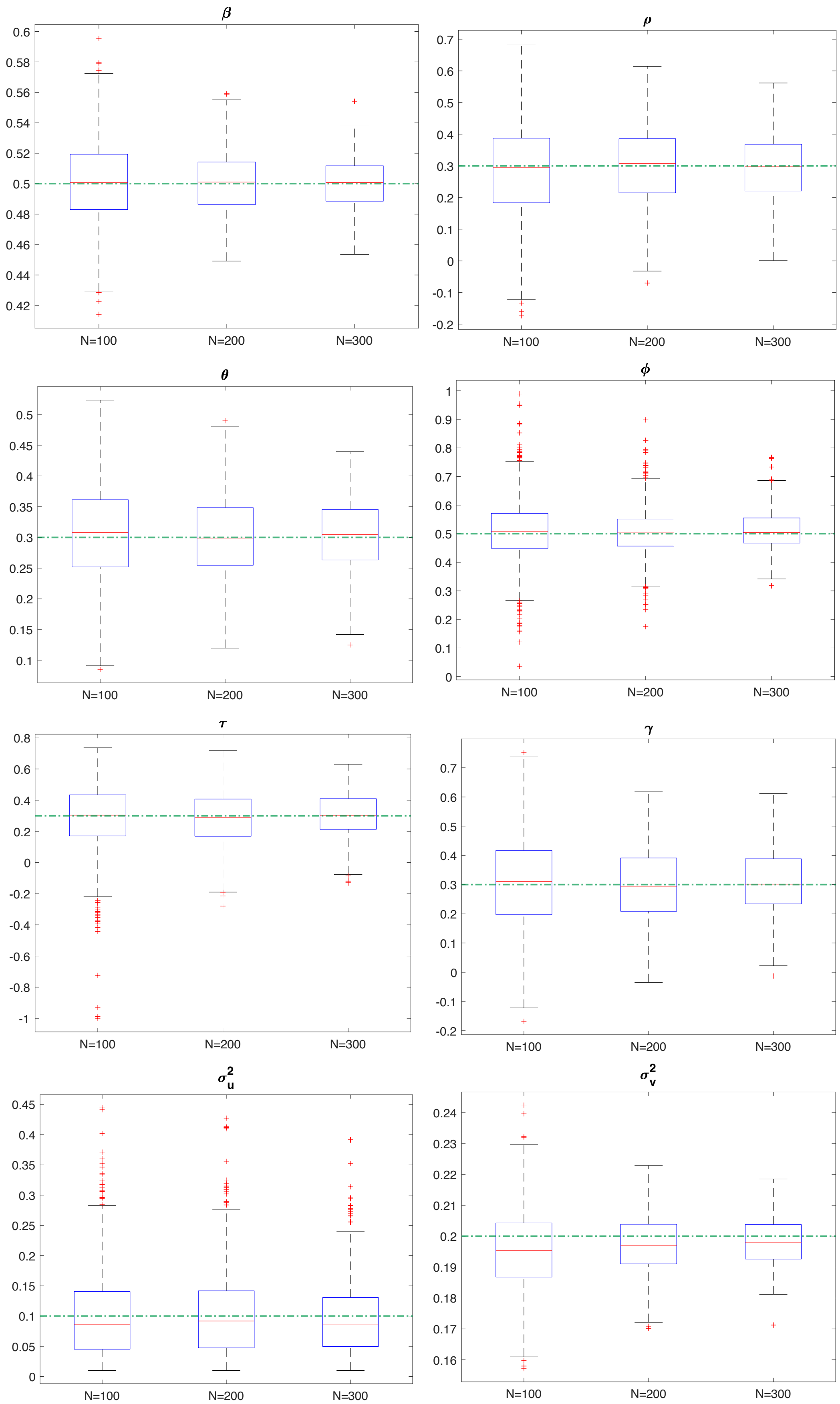

FIGURE 4.2: SDF-CSD Model: Boxplots (T=5)

TABLE 4.5: SDF-CSD Model: Monte Carlo Simulations Results
For different values of the parameters (T=10, N=100)

β	0.15			0.65			0.90		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-0.0002	0.0196	0.0004	-0.0003	0.0187	0.0004	-0.0001	0.0208	0.0005
ρ	-0.0065	0.1161	0.0174	0.0014	0.0883	0.0112	-0.0037	0.0821	0.0076
θ	-0.0010	0.0313	0.0011	-0.0031	0.0683	0.0057	0.0018	0.0804	0.0070
ϕ	0.0127	0.0570	0.0061	0.0094	0.0688	0.0050	0.0100	0.0572	0.0060
τ	-0.0076	0.1758	0.0300	-0.0126	0.1445	0.0213	-0.0029	0.1372	0.0208
γ	0.0003	0.1295	0.0175	-0.0068	0.1043	0.0129	0.0011	0.0937	0.0084
σ_u^2	-0.0045	0.0578	0.0027	-0.0014	0.0481	0.0028	-0.0028	0.0589	0.0028
σ_v^2	-0.0033	0.0093	0.0001	-0.0024	0.0093	0.0001	-0.0022	0.0090	0.0001

ρ	0.15			0.65			0.90		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-0.0015	0.0209	0.0004	0.0012	0.0187	0.0004	0.0011	0.0165	0.0003
ρ	0.0071	0.1292	0.0163	-0.0089	0.0466	0.0033	-0.0045	0.0150	0.0004
θ	-0.0054	0.0692	0.0045	0.0044	0.0397	0.0020	0.0033	0.0286	0.0010
ϕ	0.0106	0.0562	0.0060	0.0098	0.0598	0.0060	0.0064	0.0668	0.0063
τ	-0.0172	0.1782	0.0282	0.0058	0.1254	0.0203	0.0087	0.1134	0.0191
γ	-0.0109	0.1361	0.0160	0.0081	0.0724	0.0059	0.0067	0.0486	0.0026
σ_u^2	-0.0035	0.0597	0.0028	-0.0022	0.0567	0.0029	0.0005	0.0567	0.0032
σ_v^2	-0.0029	0.0090	0.0001	-0.0014	0.0093	0.0001	-0.0009	0.0091	0.0001

θ	0.15			0.65			0.90		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-0.0001	0.0191	0.0003	-0.0001	0.0210	0.0005	-0.0001	0.0197	0.0005
ρ	-0.0085	0.1453	0.0218	-0.0023	0.0609	0.0040	-0.0015	0.0489	0.0023
θ	0.0038	0.0788	0.0061	-0.0002	0.0409	0.0017	-0.0004	0.0371	0.0013
ϕ	0.0050	0.1019	0.0046	0.0089	0.0576	0.0059	0.0084	0.1011	0.0059
τ	-0.0154	0.1948	0.0330	-0.0016	0.1179	0.0172	-0.0010	0.1553	0.0155
γ	-0.0016	0.1453	0.0227	0.0009	0.0734	0.0050	0.0008	0.0629	0.0035
σ_u^2	-0.0005	0.0412	0.0027	-0.0012	0.0594	0.0028	-0.0018	0.0314	0.0028
σ_v^2	-0.0031	0.0090	0.0001	-0.0018	0.0089	0.0001	-0.0016	0.0091	0.0001

ϕ	0.15			0.65			0.90		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	0.0001	0.0184	0.0004	0.0001	0.0201	0.0004	0.0001	0.0173	0.0004
ρ	-0.0079	0.095	0.0143	-0.0074	0.1126	0.0129	-0.0037	0.0794	0.0134
θ	0.0033	0.0532	0.0042	0.0034	0.0637	0.0039	1.46e-05	0.0436	0.0041
ϕ	0.0086	0.0502	0.0059	0.0028	0.0704	0.0027	0.0051	0.0420	0.0015
τ	-0.0245	0.2699	0.0763	-0.0049	0.1356	0.0169	-0.0072	0.0675	0.0145
γ	0.0010	0.0962	0.0156	8.78e-06	0.1153	0.0142	-0.0015	0.0732	0.0150
σ_u^2	0.0084	0.0864	0.0055	-0.0005	0.0342	0.0023	-0.0012	0.0352	0.0022
σ_v^2	-0.0024	0.0090	0.0001	-0.0022	0.0090	0.0001	-0.0026	0.0091	0.0001

Table 4.5– continued from previous page

τ	**0.15**			**0.65**			**0.90**		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-2.54e-05	0.0162	0.0004	-0.0004	0.0176	0.0004	-3.64e-05	0.0167	0.0003
ρ	-0.0049	0.0786	0.0122	1.09e-05	0.0845	0.0153	0.0015	0.0772	0.0078
θ	0.0011	0.0501	0.0039	-0.0022	0.0459	0.0046	-0.0010	0.0459	0.0025
ϕ	0.0064	0.0546	0.0042	0.0065	0.0763	0.0051	0.0021	0.0420	0.0031
τ	-0.0085	0.1684	0.0282	-0.0162	0.0504	0.0105	-0.0030	0.0172	0.0005
γ	-0.0028	0.1007	0.0139	-0.0053	0.0793	0.0170	-0.0052	0.0864	0.0093
σ_u^2	-0.0001	0.0419	0.0026	0.0048	0.0351	0.0034	-0.0039	0.0820	0.0035
σ_v^2	-0.0026	0.0097	0.0001	-0.0028	0.0090	0.0001	-0.0018	0.0093	0.0001

γ	**0.15**			**0.65**			**0.90**		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	0.0006	0.0212	0.0004	-0.0021	0.0195	0.0004	-0.0013	0.0174	0.0005
ρ	-0.0108	0.1321	0.0140	0.0149	0.1001	0.0138	0.0228	0.0687	0.0082
θ	0.0043	0.0756	0.0043	-0.0070	0.0554	0.0035	-0.0092	0.0414	0.0025
ϕ	0.0083	0.0643	0.0043	0.0110	0.0625	0.0076	0.0081	0.0529	0.0112
τ	-0.0024	0.1738	0.0231	-0.0581	0.3475	0.0939	-0.0413	0.1478	0.0452
γ	0.0088	0.1439	0.0158	-0.0218	0.0972	0.0113	-0.0168	0.0344	0.0430
σ_u^2	-0.0019	0.0427	0.0028	0.0085	0.0888	0.0057	0.0014	0.1332	0.0035
σ_v^2	-0.0024	0.0095	0.0001	-0.0015	0.0094	0.0001	-0.0004	0.0096	0.0001

σ_u^2, σ_v^2	**0.80, 0.10**			**0.10, 0.80**			**0.50, 0.50**		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-0.0001	0.0152	0.0002	-0.0017	0.0359	0.0015	-1.25e-05	0.0295	0.0010
ρ	-0.0032	0.0771	0.0061	0.0022	0.1390	0.0249	-0.0103	0.1216	0.0208
θ	0.0005	0.0443	0.0019	-0.0044	0.0871	0.0093	0.0023	0.0752	0.0068
ϕ	0.0027	0.0147	0.0004	0.0282	0.1124	0.0242	0.0105	0.0413	0.0031
τ	-0.0008	0.0920	0.0069	-0.0382	0.2746	0.0795	-0.0048	0.1694	0.0266
γ	0.0012	0.0896	0.0070	-0.0114	0.1526	0.0253	0.0031	0.1372	0.0205
σ_u^2	-0.0359	0.3798	0.1170	0.0026	0.0836	0.0061	-0.0316	0.2596	0.0558
σ_v^2	-0.0010	0.0045	0.0000	-0.0165	0.0377	0.0018	-0.0090	0.0239	0.0006

TABLE 4.6: SDF-CSD Model: Monte Carlo Simulations Results
For different values of the parameters (T=10, N=300)

β	0.15			0.65			0.90		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-0.0001	0.0115	0.0001	0.0002	0.0109	0.0001	4.10e-05	0.0114	0.0001
ρ	-0.0019	0.1003	0.0081	-0.0022	0.0596	0.0039	-0.0006	0.0585	0.0033
θ	-0.0009	0.0234	0.0004	0.0009	0.0413	0.0019	0.0005	0.0554	0.0030
ϕ	0.0037	0.0287	0.0014	0.0040	0.0338	0.0018	0.0034	0.0366	0.0021
τ	-0.0062	0.1453	0.0115	1.81e-06	0.0747	0.0084	-0.0018	0.0862	0.0080
γ	-4.48e-05	0.1142	0.0086	-4.37e-05	0.0650	0.0042	-0.0019	0.0639	0.0037
σ_u^2	-0.0019	0.0739	0.0020	0.0009	0.0554	0.0024	0.0002	0.0530	0.0025
σ_v^2	-0.0015	0.0062	3.09e-05	-0.0010	0.0054	2.76e-05	-0.0010	0.0052	2.76e-05

ρ	0.15			0.65			0.90		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-0.0006	0.0097	0.0001	0.0004	0.0106	0.0001	0.0003	0.0093	0.0001
ρ	0.0069	0.0620	0.0066	-0.0029	0.0324	0.0015	-0.0012	0.0120	0.0002
θ	-0.0044	0.0345	0.0017	0.0021	0.0269	0.0008	0.0015	0.0188	0.0004
ϕ	0.0024	0.0205	0.0016	0.0033	0.0481	0.0014	0.0034	0.0579	0.0019
τ	-0.0093	0.0626	0.0092	0.0015	0.0865	0.0067	0.0010	0.0851	0.0063
γ	-0.0085	0.0629	0.0067	0.0021	0.0474	0.0026	0.0012	0.0311	0.0011
σ_u^2	-0.0012	0.1085	0.0023	-0.0016	0.0178	0.0024	-0.0005	0.0158	0.0026
σ_v^2	-0.0009	0.0052	2.84e-05	-0.0004	0.0056	3.07e-05	-0.0003	0.0055	2.99e-05

θ	0.15			0.65			0.90		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	0.0002	0.0104	0.0001	0.0001	0.0115	0.0001	-0.0005	0.0117	0.0001
ρ	0.0017	0.1002	0.0106	0.0010	0.044	0.0018	0.0005	0.0318	0.0009
θ	-0.0007	0.0531	0.0029	-0.0001	0.0273	0.0007	-0.0007	0.0220	0.0004
ϕ	0.0040	0.0362	0.0013	0.0020	0.0364	0.0013	-0.0013	0.0462	0.0016
τ	-0.0099	0.1368	0.0136	-0.0015	0.0766	0.0046	-0.0059	0.0682	0.0044
γ	-0.0061	0.1071	0.0113	-0.0025	0.0508	0.0025	-0.0013	0.0403	0.0014
σ_u^2	0.0017	0.0385	0.0024	0.0033	0.0389	0.0025	0.0021	0.0331	0.0024
σ_v^2	-0.0015	0.0056	2.93e-05	-0.0007	0.0053	2.59e-05	-0.0005	0.0054	2.65e-05

ϕ	0.15			0.65			0.90		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-0.0001	0.0113	0.0001	-0.0003	0.0103	0.0001	-0.0001	0.0109	0.0001
ρ	-0.0005	0.0739	0.0050	0.0026	0.0581	0.0049	-0.0004	0.0680	0.0048
θ	0.0003	0.0397	0.0016	-0.0008	0.0326	0.0014	0.0003	0.0366	0.0015
ϕ	0.0032	0.0322	0.0015	0.0016	0.0243	0.0009	0.0015	0.0122	0.0004
τ	-0.0131	0.1127	0.0231	-0.0090	0.0637	0.0066	-0.0049	0.0618	0.0055
γ	-0.0017	0.0753	0.0057	-0.0046	0.0610	0.0054	-0.0020	0.0692	0.0053
σ_u^2	0.0034	0.0833	0.0031	0.0008	0.0731	0.0021	-0.0004	0.0772	0.0021
σ_v^2	-0.0010	0.0052	2.71e-05	-0.0008	0.0053	2.83e-05	-0.0009	0.0053	2.70e-05

Table 4.6– continued from previous page

τ	**0.15**			**0.65**			**0.90**		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	0.0006	0.0115	0.0001	0.0004	0.0113	0.0001	0.0005	0.0098	0.0001
ρ	-0.0038	0.0688	0.0054	-0.0017	0.0675	0.0046	-0.0007	0.0492	0.0028
θ	0.0008	0.0400	0.0017	-0.0002	0.0391	0.0014	0.0005	0.0292	0.0010
ϕ	0.0041	0.0327	0.0017	0.0036	0.0359	0.0017	0.0004	0.0287	0.0012
τ	0.0020	0.0934	0.0106	-0.0029	0.0534	0.0031	-0.0010	0.0117	0.0001
γ	0.0014	0.0735	0.0059	-0.0005	0.0715	0.0051	0.0002	0.0539	0.0034
σ_u^2	-0.0004	0.0721	0.0022	0.0009	0.0671	0.0024	0.0018	0.0629	0.0023
σ_v^2	-0.0012	0.0052	2.75e-05	-0.0011	0.0052	2.72e-05	-0.0010	0.0053	2.70e-05

γ	**0.15**			**0.65**			**0.90**		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	0.0005	0.0119	0.0001	-0.0006	0.0109	0.0001	-0.0006	0.0107	0.0001
ρ	-0.0068	0.0765	0.0051	0.0068	0.0746	0.0050	0.0082	0.0465	0.0019
θ	0.0033	0.0467	0.0017	-0.0028	0.0355	0.0013	-0.0031	0.0258	0.0006
ϕ	0.0024	0.0317	0.0013	0.0029	0.0412	0.0020	0.0027	0.0433	0.0028
τ	0.0014	0.1065	0.0087	-0.0130	0.0886	0.0097	-0.0114	0.0922	0.0099
γ	0.0057	0.0857	0.0060	-0.0090	0.0579	0.0038	-0.0065	0.0262	0.0006
σ_u^2	-0.0001	0.0550	0.0023	3.97e-05	0.0565	0.0024	0.0016	0.0688	0.0027
σ_v^2	-0.0008	0.0057	2.94e-05	-0.0005	0.0061	3.30e-05	0.0001	0.0058	3.11e-05

σ_u^2, σ_v^2	**0.80, 0.10**			**0.10, 0.80**			**0.50,0.50**		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	0.0002	0.0071	0.0001	0.0005	0.0182	0.0004	0.0005	0.0145	0.0003
ρ	-0.0034	0.0350	0.0024	-0.0094	0.0665	0.0144	-0.0093	0.0550	0.0102
θ	0.0014	0.0220	0.0007	0.0033	0.0477	0.0045	0.0036	0.0390	0.0031
ϕ	0.0011	0.0079	0.0001	0.0113	0.0593	0.0068	0.0045	0.0219	0.0008
τ	0.0019	0.0444	0.0027	-0.0072	0.1420	0.0322	0.0016	0.0823	0.0125
γ	0.0024	0.0443	0.0028	0.0043	0.0773	0.0143	0.0056	0.0652	0.0102
σ_u^2	-0.0153	0.4547	0.1213	-0.0014	0.0656	0.0031	-0.0168	0.2773	0.0502
σ_v^2	-0.0004	0.0027	7.29e-06	-0.0077	0.0240	0.0005	-0.0038	0.0144	0.0002

TABLE 4.7: SDF-CSD Model: Monte Carlo Simulation Results
Sensitivity to the choice of W (N=300, T=5)

	W			W50			W30		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-0.0001	0.0119	0.0002	-0.0002	0.0127	0.0002	-0.0003	0.0136	0.0002
ρ	-0.0020	0.1094	0.0326	0.0007	0.1148	0.0077	0.0011	0.0650	0.0050
θ	0.0004	0.0920	0.0135	-0.0029	0.0666	0.0041	-0.0024	0.0484	0.0025
ϕ	0.0041	0.0675	0.0089	-0.0015	0.1097	0.0054	-0.0012	0.0399	0.0045
τ	-0.0661	0.2800	0.0723	-0.0255	0.1288	0.0263	-0.0172	0.0881	0.0196
γ	-0.0206	0.1686	0.0364	-0.0106	0.0951	0.0098	-0.0079	0.0675	0.0063
σ_u^2	0.0069	0.0891	0.0060	0.0027	0.0268	0.0050	0.0003	0.0831	0.0045
σ_v^2	-0.0017	0.0076	0.0001	-0.0015	0.0076	0.0001	-0.0015	0.0074	0.0001

	W250n			W100n			W50n		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-0.0005	0.0121	0.0002	0.0004	0.0122	0.0002	-0.0001	0.0125	0.0002
ρ	-0.0096	0.1615	0.0304	-0.0128	0.1059	0.0240	-0.0135	0.1336	0.0175
θ	0.0016	0.1212	0.0129	0.0036	0.0839	0.0104	0.0055	0.0818	0.0076
ϕ	0.0054	0.0934	0.0087	0.0060	0.0571	0.0079	0.0019	0.1116	0.0080
τ	-0.0545	0.3273	0.0730	-0.0372	0.2092	0.0531	-0.0283	0.1419	0.0429
γ	-0.0131	0.2033	0.0333	-0.0062	0.1452	0.0258	-0.0034	0.1201	0.0187
σ_u^2	0.0073	0.0526	0.0064	0.0081	0.1369	0.0056	0.0068	0.0270	0.0062
σ_v^2	-0.0015	0.0075	0.0001	-0.0015	0.0073	0.0001	-0.0016	0.0074	0.0001

TABLE 4.8: SDF-CSD Model: Monte Carlo Simulations Results
Sensitivity to the choice of W, using two different W matrices (N=300, T=5)

	W W W0 W0			**W0 W0 W W**			**W0 W W0 W**		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-0.0002	0.0115	0.0001	-0.0001	0.0126	0.0002	-0.0001	0.0125	0.0002
ρ	-0.0040	0.0575	0.0038	-0.0003	0.0286	0.0009	-0.0004	0.0265	0.0007
θ	0.0027	0.0636	0.0042	-0.0002	0.0275	0.0008	0.0004	0.0586	0.0030
ϕ	0.0066	0.0471	0.0059	-0.0009	0.0781	0.0089	0.0020	0.0403	0.0036
τ	-0.0003	0.0658	0.0126	-0.0310	0.0930	0.0348	-0.0037	0.0742	0.0095
γ	0.0007	0.0332	0.0011	-0.0066	0.0753	0.0055	-0.0065	0.0756	0.0056
σ_u^2	0.0074	0.1130	0.0058	0.0101	0.0854	0.0070	0.0010	0.1419	0.0046
σ_v^2	-0.0007	0.0074	0.0001	-0.0007	0.0077	0.0001	-0.0007	0.0077	0.0001

	W W0 W W0			**W0 W W W0**			**W W0 W0 W**		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-0.0003	0.0125	0.0002	-0.0004	0.0122	0.0001	-0.0003	0.0122	0.0001
ρ	-0.0046	0.0560	0.0032	-0.0012	0.0384	0.0016	-0.0038	0.0718	0.0065
θ	-0.0003	0.0231	0.0005	0.0002	0.0546	0.0026	-0.0005	0.0225	0.0005
ϕ	-0.0010	0.0749	0.0083	-0.0017	0.0756	0.0082	0.0026	0.0616	0.0049
τ	-0.0296	0.1112	0.0374	-0.0302	0.0918	0.0334	-0.0045	0.0733	0.0090
γ	-0.0004	0.0337	0.0012	0.0003	0.0490	0.0028	-0.0073	0.1163	0.0124
σ_u^2	0.0095	0.0879	0.0063	0.0099	0.0925	0.0064	0.0029	0.1049	0.0052
σ_v^2	-0.0007	0.0077	0.0001	-0.0008	0.0077	0.0001	-0.0008	0.0076	0.0001

	W W W W0			**W0 W0 W0 W**			**W0 W0 W W0**		
	Bias	SD	MSE	Bias	SD	MSE	Bias	SD	MSE
β	0.0001	0.0140	0.0002	-0.0004	0.0126	0.0001	-0.0001	0.0116	0.0001
ρ	-0.0030	0.0580	0.0044	0.0013	0.0286	0.0009	-0.0056	0.0685	0.0045
θ	0.0008	0.0359	0.0016	-0.0012	0.0275	0.0007	0.0056	0.0739	0.0049
ϕ	-0.0016	0.0765	0.0085	0.0022	0.0781	0.0030	-0.0050	0.1017	0.0059
τ	-0.0313	0.0923	0.0345	-0.0067	0.0930	0.0097	-0.0309	0.2600	0.0337
γ	0.0009	0.0633	0.0055	-0.0033	0.0753	0.0050	-0.0007	0.0332	0.0011
σ_u^2	0.0102	0.0934	0.0065	0.0014	0.0854	0.0050	0.0080	0.0686	0.0062
σ_v^2	-0.0011	0.0077	0.0001	-0.0011	0.0077	0.0001	-0.0011	0.0076	0.0001

Table 4.8– continued from previous page

	W W W0 W			**W W0 W W**			**W0 W W0 W0**		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	0.0001	0.0124	0.0002	0.0003	0.0117	0.0001	0.0000	0.0114	0.0001
ρ	-0.0126	0.0805	0.0134	-0.0004	0.0831	0.0076	0.0012	0.0423	0.0018
θ	0.0051	0.0769	0.0070	-0.0002	0.0213	0.0004	-0.0016	0.0466	0.0022
ϕ	0.0012	0.0672	0.0062	0.0033	0.0971	0.0064	0.0006	0.0296	0.0044
τ	-0.0050	0.0745	0.0093	-0.0282	0.2432	0.0388	-0.0102	0.0613	0.0137
γ	-0.0020	0.1233	0.0188	-0.0151	0.1284	0.0135	-0.0041	0.0529	0.0029
σ_u^2	0.0058	0.1004	0.0057	0.0060	0.0427	0.0056	0.0028	0.1769	0.0051
σ_v^2	-0.0009	0.0076	0.0001	-0.0012	0.0074	0.0001	-0.0010	0.0073	0.0001

	W W0 W0 W0			**W0 W W W**		
	Bias	*SD*	*MSE*	*Bias*	*SD*	*MSE*
β	-0.0004	0.0116	0.0001	-0.0004	0.0114	0.0001
ρ	-0.0034	0.0468	0.0023	0.0008	0.0219	0.0005
θ	-0.0006	0.0199	0.0004	-0.0006	0.0505	0.0029
ϕ	0.0013	0.0515	0.0042	0.0021	0.0375	0.0075
τ	-0.0061	0.0881	0.0092	-0.0237	0.0660	0.0285
γ	0.0015	0.0328	0.0011	-0.0053	0.0747	0.0051
σ_u^2	0.0030	0.0672	0.0054	0.0081	0.2263	0.0067
σ_v^2	-0.0011	0.0072	0.0001	-0.0010	0.0073	0.0001

NB. In the title of each simulation we report the different spatial weight matrices respectively associated with the four different spatial lags of the SDF-CSD model in the following order: spatial lag of Y, spatial lag of X, spatial lag of u, spatial lag of v. In particular, W refers to a dense inverse distance matrix while $W0$ refers to a binary contiguity matrix.

Chapter 5

Innovation, Productivity and Spillover Effects in the Italian Accommodation Industry

5.1 Innovation, Productivity and Agglomeration in Tourism Clusters

5.1.1 Tourism as a Clustered Industry

The tourism sector is one of the fastest growing and most profitable industrial sectors of Italy, contributing to 13% of the Italian GDP (including indirect effects) and giving employment to 14.7% of the Italian workforce in 2017 (OECD, 2020). Moreover, Italy is the fourth most visited country by international tourists, and it contains 55 World Heritage Sites, which is more than any other country in the world. Small and medium enterprises (SMEs) constitute the majority of Italian accommodation facilities and moreover, they represent the "*life blood of the travel and tourism industry worldwide*" (Erkkila, 2004, p.23). Tourism destinations can be seen as forms of industrial clusters, made up of groups of SMEs that cooperate to build up a successful tourism product (Novelli, Schmitz, and Spencer, 2006). Therefore, SMEs clusters, through networking, alliances, active collaboration and innovation can succeed in successfully competing in the global tourism market through local cooperation (Smeral, 1998). Indeed, SMEs located in tourism clusters can accumulate new knowledge and innovate more easily than isolated hotels (Marco-Lajara et al., 2019).

In recent tourism literature, tourism clusters have begun to be considered as a form of industrial clusters (Jackson and Murphy, 2002; Shaw and Williams, 2009). Indeed, a tourism destination is composed of a conglomeration of competing and collaborating activities trying to cooperate to reach a greater exposure and to build up a successful tourism product (Jackson and Murphy, 2006). Specifically, tourism clusters are defined as a set of linked activities such as accommodations, attractions, services, tour operators, travel agents and complementary products that contribute to the tourism experience (Wang and Fesenmaier, 2007). Moreover, many destinations also collaborate with governments, residents, training centres and research institutions to further develop the cluster's competitive advantage. Hence, tourism clusters, similarly to manufacturing clusters, benefit from the existence of positive spillover effects resulting from spatial proximity, trust, and shared values that encourage cooperation, social contact, and imitation (Shaw and Williams, 2009). As a consequence, clustered hotels experiment higher productivity levels thanks to enhanced knowledge and innovation sharing (Adam and Mensah, 2013). Differently from manufacturing clusters, the birth of tourism clusters depends on spontaneous concentration processes generating from positive customers feedbacks in terms of demand (Yang, 2012). Other peculiarities of the tourism clusters concern the intangible nature of the product sold, the inseparability between consumption and production, and a high demand fluctuability and uncertainty (Zhang, Song, and Huang, 2009). Therefore, hoteliers should carefully evaluate where to locate. Indeed, locating too close to competitors is risky due to the possibility of losing loyal customers to established hotels, while locating too far from rivals does not allow to benefit from positive agglomeration spillovers. Specifically, Baum and Haveman (1997)'s results show that new hotels tend to place near established hotels that are similar in terms of price and that are different in terms of size as if the benefits of agglomeration economies are greater than costs considering hotels of similar price while costs are greater than agglomeration benefits if hotels locate too near to similarly-sized hotels.

Investigating the structure of tourism clusters, Michael (2003) identified tourism clusters as diagonal clusters. Differently from horizontal and vertical clusters that refer to the co-location of firms selling the same products and to the co-location of an industry's supply chain respectively, diagonal clusters are characterized by the concentration of complementary or symbiotic firms. Therefore, even if the products offered can be quite different, each firm adds value to the activity of the other firms, creating a network in which separate products and services are linked together to form a unique item. In this framework, a tourism destination can be seen as a diagonal cluster in the sense that different industries belonging to the same destination (as transport, accommodation, restaurants, entertainment and attraction, etc.) work together to build up a valuable tourism experience.

5.1.2 Innovation in the Tourism Sector

Authors have always recognized the importance of innovation in the tourism sector, both for multinational companies and for SMEs (Poon, 1993, 1994). Indeed, innovation, as well as investments in human capital and research and development, allows hotels to remain competitive and to achieve higher profitability levels (Marco-Lajara et al., 2016). Hence, innovation is fundamental to tourism development and competitiveness (Jackson and Murphy, 2002, 2006), and it can be fostered by investments in physical capital, skills and human capital, technology and new knowledge, and by a fertile competitive environment. In particular, as demonstrated by Blake, Sinclair, and Soria (2006), insufficient investments in physical capital do not constrain increases in productivity, while skilled workers are fundamental to competitiveness. Moreover, the lack of new knowledge is the prevailing barrier to product and process innovation.

As underlined by Hjalager (2002), process innovation is more influential in the tourism sector compared to product innovation. Specifically, process innovation refers to quality improvements in existing operational processes used to produce goods and services or to the introduction of new procedures. One of the most important sources of process innovation in the hospitality sector is human resources. Good human resources management practices are positively associated with employee and customer satisfaction and with service quality, competitive advantage, better organizational performance and lower turnover rates (Cho et al., 2006). Indeed, according to Wikhamn (2019), customer satisfaction is positively affected by innovation and sustainable human resource practices.

Anyhow, the tourism sector is characterized by low levels of research and development, lack of resources, rapid changes in ownership, high labour mobility, low salaries, low educational levels and reluctance to take risks (Weidenfeld, Williams, and Bultler, 2010). According to Orfila-Sintes, Crespì-Cladera, and Martinez-Ros (2005), three to five stars hotels tend to be more innovative compared to smaller hotels while hotels belonging to a chain, hotels in leased properties, and hotels under management contracts tend to overcome the average innovation rate. Similarly, also Sundbo, Orfila-Sintes, and Sørensen (2007) demonstrated that the innovative performance of tourism firms is related to size. Moreover, they also showed that the level of professionalism (i.e. the ability to apply business and training plans, quality control systems, academic employees, and IT) is a significant determinant of innovation in the tourism sector. Nevertheless, the tourism sector is mainly composed of SMEs that hardly invest in R&D and therefore, due to the complexity of innovating inside the firm, the external environment in which hotels are embedded is a fundamental source of new knowledge and innovation.

In this framework, Sundbo, Orfila-Sintes, and Sørensen (2007) showed that the existence of a favourable network contributes to determining the innovativeness of tourism firms. Similarly, analyzing survey data from 900 hospitality firms in Sweden, Backman, Klaesson, and Öner (2017) showed that the most consistent firm-level variable that contributes to increasing innovation in the hotel sector is the engagement in cooperation with the other actors of the sector, such as suppliers, customers, competitors, and research organizations. Moreover, Hameed, Nisar, and Wu (2021), investigating the link between external knowledge, internal innovation and performance of 285 hotels situated in Pakistan, demonstrated that external knowledge and internal innovation positively affect firms' open innovation performance, leading to service innovation and increased business performance. In this framework, also Stojčić, Vojvodić, and Butigan (2019), analyzing the performance of the Croatian hospitality industry during the period 2012-2014, found that knowledge and skills transfer through organizations foster service innovation, confirming that the external sources of knowledge are fundamental drivers of innovation.

5.1.3 Knowledge Sharing and Transmission

According to Argote and Ingram (2000), knowledge is embedded in three basic elements of an organisation: members, tools, and tasks. Specifically, as underlined by Enz, Canina, and Walsh (2006), the three main components of knowledge are (i) human capital, skills and experiences, (ii) operational knowledge coded into processes, policies and procedures and (iii) customer capital represented by the brand value. New knowledge can be obtained by improving the quality of existing procedures or through R&D investments, creating new working processes and registered trademarks (Marco-Lajara et al., 2016). However, SMEs usually undertake few R&D investments due to their lack of financial and human resources.

Theoretically, knowledge can be divided into explicit and tacit knowledge. Explicit knowledge refers to the knowledge capital of an organisation and it is independent of its workers (Cooper, 2006). Its main characteristics are that it is transferable and codable in forms, documents, and electronic databases (Weidenfeld, Williams, and Bultler, 2010). On the other side, tacit knowledge is hard to formalize and codify and it is highly intuitive, unarticulated, personal, and based on people's learning and collaborative experiences (Cooper, 2006). According to Nonaka (1991), tacit knowledge tends to be context-specific, and it is very often converted into habits and routines. As identified by Weidenfeld, Williams, and Bultler (2010), tacit and explicit knowledge can be transferred one into another across neighbours in four ways: (i) tacit to tacit through socialisation, networks, shared ideas, learning by observation, and individual contact; (ii) tacit to explicit through meetings and brainstorming that allow the formalization of informal good practises; (iii) explicit to explicit through the use of documents, papers, and databases; (iv) explicit to tacit through new ideas generating from formal documents or learning by doing. While it is quite easy to transfer explicit knowledge, tacit knowledge is less easy to interpret and transfer among individuals and thus, it is a key source of competitive advantage (Shaw and Williams, 2009). Nevertheless, tacit knowledge flows more easily in tourism clusters thanks to shared ideas between individuals, learning by observation, human relationships, imitation, and a stronger social and economic network (Yang, 2012).

Concentrating on the vehicles by which knowledge can be transferred across neighbours, Kacker (1988) identified foreign direct investments and learning regions as the two main channels. Indeed, transnational firms can benefit from knowledge coming from the home country, reusing and transferring it. On the other hand, learning regions refer to places where the concentration of hotels and the existence of a strong network of individuals trusting in common values generates a positive environment that facilitates learning and knowledge transfer. In particular, Hall and Williams (2008) recognized learning by observation, imitation and demonstration, inter-firm exchanges, labour mobility, and knowledge brokers as the four main channels of knowledge transfer that operate at the firm and individual level. Therefore, in the accommodation sector, neighbours' emulation, inter-firm exchanges and collaboration with competitors and suppliers are fundamental sources of knowledge. Indeed, in the tourism sector, imitation and emulation are quite easy to adopt (Decelle, 2006; Hjalager, 2002) because the operational processes are quite evident and also the technological level is basic (Weidenfeld, Williams, and Bultler, 2010). Moreover, the tourism sector is characterized by a strong seasonal fluctuation of labour, and labour mobility contributes to boosting tacit knowledge transfers across firms through the physical movements of workers with a high level of skills and capabilities, also defined as "knowledgeable tourism workers" (Shaw and Williams, 2009). Finally, also knowledge brokers, identified as those individuals who operate within and across distinctive knowledge communities as consultants, representatives, and suppliers have a key role in transmitting new knowledge (Tushman and Scanlan, 1981).

Despite the key role of recruiting skilled employees and belonging to a beneficial network, as evidenced by Yang (2010), the exploitation and development of knowledge inside the firm depend primarily on the individual attitudes to sharing and learning. Indeed, some employees can feel insecure or scared to express their ideas and opinions, others may be not interested in sharing, and these bad feelings can impede knowledge transfer and acquisition. Therefore, it is fundamental for hotels managers to develop a working climate that promotes cooperation and learning activities so that employees can perceive the workplace as a familiar environment in which they can feel free and open in discussing job-related matters (Yang, 2010) and where fairness, support, rewards, and healthy job conditions are supported (Rhoades and Eisenberger, 2002). In this framework, the role of the leader is fundamental (Yang, 2007b); indeed, the leader should promote good human relationships among employees and should stimulate his workers to transfer their talents, ideas, and experiences, enabling knowledge creation through social activities and training sessions (Roth, 2003). Therefore, human resource management has a key role both in the recruiting phase, to acquire knowledgeable workers, and in the management phase, to guarantee opportunities and new perspectives for employees improving their level of satisfaction. By this way, it is possible to minimize staff's potential losses and to create a positive working environment that stimulates knowledge creation and transfer (Yang, 2007a). Moreover, the intensity at which new knowledge is assimilated depends on the absorptive capacity of hotels. According to Yang (2010), absorptive capacity is the most important prerequisite for success in the accommodation sector because identifying new sources of knowledge, assimilating them, and applying them to commercial ends guarantees a successful knowledge transfer. The degree of absorptive capacity of hotels depends on factors such as the organizational structure, the open-mindedness of the head, and management practices (Cooper, 2006). In this regard, SMEs tend to have limited absorptive capacity but good flexibility and adaptability (Cohen and Levinthal, 1990). Specifically, absorptive capacity is positively associated with hotels' size (Marco-Lajara et al., 2019) and negatively associated with an extensive work-related experience that prevents from adapting to new processes and ideas (Yang, 2010).

5.1.4 Agglomeration Externalities and Productivity

Agglomeration economies are particularly relevant in the tourism sector because the service offered is inseparable in time and space and because tourism demand and supply are localized in specific concentrated places (Majewska, 2017). The tourism sector is characterized by two different types of spatial agglomeration externalities: production enhancements and heightened demand (Chung and Kalnins, 2001, 2004; Marshall, 1890). The former refers to an enhancement of the quality and efficiency of the services offered in the accommodation sector due to knowledge spillovers, easier access to qualified complementary services, a major availability of skilled employees and better coordination of policies and related actions, while the latter concerns the fact that hotel districts tend to attract larger pools of tourists. Therefore, production enhancement depends primarily on information spillovers, enhanced cooperation, and joint problem solving, which favour the adoption of efficient means of service delivery (Chung and Kalnins, 2001). However, this first mechanism is characterized by distance decay. Thus, hotels that are located beyond a certain radius may not benefit from these positive externalities (Adam and Mensah, 2013).

On the other side, customers may prefer to choose places where they may find hotel rooms at lower prices due to competition among clustered hotels and where there is higher availability of services and attractions. Indeed, tourism agglomeration is also associated with diversity because denser tourism areas can provide a wider range of activities, services, and attractions (Yang, 2016). As a result, tourists tend to be more satisfied with their travel experience leading to customer loyalty, repeat visits, and repurchasing behaviours (Petrick and Backman, 2002), generating a self-reinforcing process that produces new business opportunities that strengthen the tourism cluster (Yang, 2012). Moreover, as the tourism cluster grows up, also public and private tourism-related institutions increase, providing more and more benefits and support to the local cluster (Tang and Tang, 2006).

Focusing on the supply side, one of the main factors that contribute to generating positive agglomeration externalities among hotels located in clusters is knowledge spillovers. Several recent studies analyzed the connection between tourism clusters, internal and external knowledge, and hotels' productivity, finding different and controversial results. Peiró-Signes et al. (2015), analyzing the impact of locating inside or outside U.S. tourism clusters on hotel economic performance using a concentration measure, suggested that belonging to a cluster improves hotels' productivity. Moreover, they demonstrated that the positive effect of agglomeration is more pronounced for luxury, upscale hotels and chain-managed hotels while it is less evident for resorts and airport locations. Differently, Baum and Mezias (1992), evaluating the impact of localized competition on hotels' failure rates for the Manhattan hotel industry in 1898-1990, found that hotels located in denser regions tend to experience higher failure rates. Taking internal and external knowledge into consideration, Marco-Lajara et al. (2016), using multiple linear regression, showed that internal knowledge such as human resources and the value of registered trademarks have a prevalent role in explaining hotels' profitability compared to R&D investments. Moreover, they found that external knowledge coming from similar activities, universities, and technological research institutions significantly contributes to hotel profitability, but they didn't find a connection between knowledge coming from capital alliances and vocational training centres and profitability. Moreover, Marco-Lajara et al. (2019) demonstrated that agglomeration is positively associated with hotel profitability but with a lower effect than the one expected. Considering external knowledge, the authors didn't find evidence of a significant positive effect of agglomeration on the acquisition of external knowledge, and consequently on profitability. Differently, using longitudinal data from lodging firms located in Southern China, Zhang et al. (2015) found that local entrepreneurs tend to imitate successful pioneering businesses. Hence, tacit knowledge spillovers among hotels located in the same region contribute to a successful local development of the tourism sector considering an extended time period.

From a macroeconomic point of view, the tourism sector considerably contributes to the economic regeneration and development of an entire nation (Thomas and Long, 2001). Therefore, several studies concentrated on the effect of tourism clusters and agglomeration on local or national productivity. Investigating the impact of tourism agglomeration economies on UK regional productivity, Kim et al. (2021) found a positive effect of spatial agglomeration on hotel productivity due to knowledge spillovers and skilled labour pooling using a spatial panel data model. Moreover, Yang (2012), using a dynamic panel data model, showed a positive association between tourism agglomeration and the development of Chinese provinces in the time period 2000-2009. The same authors, in 2016, examining the impact of tourism agglomeration on labour productivity in Chinese provinces from 2000 to 2011, found a positive association between agglomeration density and productivity level but they showed that the level of diversity of the tourism industry negatively affects labour productivity.

Despite the recent and strong interest of researchers in investigating the impact of external sources of innovation and agglomeration economies on the productive outcome of hotels, a clear assessment of the magnitude, typology and sources of these spatial effects is still lacking. Indeed, while scholars widely investigated the link between industrial agglomeration, innovation, and productivity from an empirical perspective considering the manufacturing, agricultural, and high-tech sectors, this topic is still relatively unexplored in the tourism sector (for a comprehensive review of previous studies on agglomeration and innovation see Carlino and Kerr (2015) and Binder (2019) for a focus on the tourism industry). However, for tourism-based countries such as Italy, begin aware of the dynamics characterising neighbouring accommodation facilities is fundamental both for hotels and destination managers and for policymakers. Hence, this study aims at providing new micro-economic insights on how the different sources of innovation, both internal and external to the firm, contribute to determining the economic performance of Italian hotels, extending the current literature on industrial agglomeration to the accommodation sector at the firm level. In particular, we concentrate on the following research questions: (Q1) what sources of internal innovation contribute to increasing the productive performance of the Italian accommodation sector?; (Q2) what external innovative factors affect the efficiency level of neighbouring hotels; (Q3) do competition or agglomeration forces prevail?

To investigate the nature and the extent of agglomeration externalities occurring in the accommodation industry and affecting hotels' productivity and efficiency levels, we take advantage of the SDF-STE model developed in this thesis. The SDF-STE model allows to precisely disentangling three different kinds of spatial spillover effects occurring across neighbouring firms, i.e. productivity, inputs, and determinants of inefficiency spillovers, thanks to the introduction of the spatial lag of the dependent variable, of the input variables and of the inefficiency determinants, respectively. Through this model, we are able to capture (i) the overall level of global spatial dependence in the sector; (ii) spillover effects related to labour and capital; (iii) specific spatial effects related to the different sources of firms' innovative activity (human capital and intangible capital investments, patents and trademarks filing). The main characteristic of the SDF-STE consists in introducing the possibility of directly evaluating how each variable that determines the inefficiency level of neighbouring firms also affects nearby producers, giving rise to precise, detailed and distinct insights concerning spatial spillovers related to each source of internal innovation.

5.2 Literature Review of Stochastic Frontier Models in the Tourism Industry

Hotels' productive efficiency has been mainly investigated using a non-parametric approach, the data envelopment analysis (DEA). Therefore, there are not many empirical applications estimating a stochastic frontier model in this sector. Moreover, in the majority of these contributions, the cost function approach has been preferred over the production one. However, as emphasized by Barros (2005), firms have inputs under control and they try to maximise the level of output conditional on the market demand, then, according to the author, using a production function is "the natural choice". Moreover, it is very difficult to define complex cost structures and to obtain reliable data on the prices of the productive factors (Bernini and Guizzardi, 2010). Thus, in this empirical application, we select a production function approach.

In tourism literature, Chen (2007) applied a stochastic frontier cost function to analyse hotels' efficiency in Taiwan, finding that the efficiency level of chain hotels is higher than the one of independent hotels. Moreover, the authors did not find evidence of a significant impact of hotels' location and scale on their efficiency level. Differently, Barros (2004), concentrating on Pousadas de Portugal, a Portuguese state-owned hotel chain, and estimating a stochastic cost frontier model, found that location and economies of scale are key factors in determining hotels' efficiency. Moreover, using a one-stage cost approach to estimate efficiency scores for international hotels located in Taiwan in the period 1997-2006, Hu et al. (2010) found that being located near international airports has a positive effect on hotels' efficiency, but not for hotels located outside metropolitan areas. Evaluating time-varying cost efficiency of the lodging industry of Gran Canaria (Spain) in the time period 1991-2002, Perez-Rodriguez and Acosta-Gonzalez (2007) estimated a translog cost function using the models proposed by Battese and Coelli (1992) and Battese and Coelli (1995) and showed that not all hotels of Gran Canaria work at the minimum level of cost. Furthermore, they found that hotels' efficiency increased during the period of expansion of the accommodation sector of Gran Canaria, favoured by higher labour productivity levels.

On the other hand, using a production function approach, Bernini and Guizzardi (2010) analyzed the productive performance of the Italian tourism sector using a frontier function with a model for technical inefficiency following the specification proposed by Battese and Coelli (1995). They showed that the average technical efficiency score of Italian tourism firms is in line with international standards even if it tends to decrease over time. This negative dynamic over time can depend on the general difficulty of tourism firms in innovating and implementing quality-effective improvements. Moreover, the authors demonstrated that the main drivers of efficiency are internal to the firm and are related to human resources management, which plays a key role in determining a good hotel performance. Furthermore, investigating how heterogeneity in the accommodation sector affects firms' efficiency for hotels located in Emilia-Romagna, Bernini and Guizzardi (2012), using a frontier production function estimated over different clusters, demonstrated that seasonality is the environmental factor that mostly contributes to influencing hotels' productive processes. In addition to this, also hotels' size and quality resulted to be important factors in explaining hotels' efficiency, but mainly for non-seasonal, medium/low star-rated, and small hotels.

Furthermore, in the last few years, authors have begun to apply also Bayesian estimation techniques to stochastic frontier modelling (a detailed description of the theory and implementation of Bayesian techniques to SF models can be found in Assaf, Oh, and Tsionas (2017)). In this framework, using a Bayesian stochastic frontier approach for estimating profit efficiency and its determinant for Spanish hotels in the time period 2010-2014, Arbelo, Arbelo-Pérez, and Pérez-Gómez (2018), demonstrated that greater hotel size, belonging to a chain, and locating in a resort area are all factors that have a positive effect on hotels' efficiency level. Moreover, also customer satisfaction positively contributes to hotels' profit efficiency.

Pavlyuk (2012) is the only contribution using a spatial stochastic frontier model to investigate the performance of tourism firms from a macroeconomic point of view. In particular, the author analyzed the regional-specific factors affecting the number of visitors within the Baltic States (Estonia, Latvia, Lithuania) using a stochastic frontier model containing the spatial lag of the dependent variable both in the frontier function and in the efficiency model to evaluate how the number of tourists in neighbouring regions affects both the model output and the efficiency level of a given region. The results show that, in the Baltic States, the competition effects are stronger than the cooperation ones both for the number of visitors to neighbouring regions and for regional efficiency levels.

Nevertheless, no studies have yet investigated the accommodation sector's productive performance using a spatial stochastic frontier production function from a microeconomic perspective. Indeed, the current studies have only focused on standard linear regression models, structural models, or concentration measures to investigate agglomeration externalities in tourism clusters leading to different and controversial results. Our spatial stochastic frontier approach allows to separate the random error from inefficiency and to simultaneously estimate the frontier function and the efficiency model, distinguishing between productivity and efficiency determinants. Moreover, differently from other approaches, through the introduction of three different spatial terms, it is possible to capture global productivity spillovers as well as indirect effects related to the input variables and to the determinants of firms' inefficiency. Therefore, in this study, we take advantage of the SDF-STE model to disentangle the different kinds of spatial spillover effects affecting the economic performance of Italian hotels. The results from this study would be very useful for policymakers to design ad hoc place-based policies that exploit the existence and the magnitude of the different spatial effects characterizing nearby hotels to stimulate the productivity of the entire sector.

5.3 The Empirical Model

The econometric model used in this application is the spatial Durbin stochastic frontier model introducing spillover effects in the determinants of firms' efficiency (SDF-STE) introduced in Chapter 3. The SDF-STE model results the be particularly suitable for this empirical application because the spatial lag of the inefficiency determinants considered in this model allows to precisely evaluate how the different sources of hotels' innovation influence neighbouring firms' efficiency levels. Indeed, in this application, we consider as inefficiency determinants different variables that measure hotels' innovative activity such as human capital and intangible investments and patents and trademark filing. Thus, here we prefer the SDF-STE model to the SDF-CSD because, through the new spatial lags of the Z variables in the inefficiency model introduced in the first one, we are able to measure if, and to what extent, the different external sources of innovation influence Italian hotels' performance.

The model specification for the frontier function is shown in Eq.(5.1) for $i, j = 1, ..., 5409$ $(i \neq j)$ and $t = 2011, ..., 2019$. In particular, a translog specification is used to model the frontier production function due to its higher flexibility compared to a Cobb-Douglas specification. Indeed, the translog function allows for variable elasticity of substitution and makes it possible to obtain firm-specific elasticities to inputs and return to scales.

$$
\begin{aligned}
Y_{it} = \beta_0 + \beta_L L_{it} + \beta_K K_{it} + \beta_{LL} L_{it}^2 + \beta_{KK} K_{it}^2 + \beta_{LK} L_{it} K_{it} + \beta_t t + \beta_{2t} t^2 + \beta_{tL} t L_{it} \\
+ \beta_{tK} t K_{it} + \rho \sum_{j=1}^{N} w_{ij} Y_{jt} + \theta_L \sum_{j=1}^{N} w_{ij} L_{jt} + \theta_K \sum_{j=1}^{N} w_{ij} K_{jt} - u_{it} + v_{it}
\end{aligned} \tag{5.1}
$$

Specifically, as standard in the tourism literature (Bernini and Guizzardi, 2010; Roget and Gonzales, 2006; Smeral, 2007) Y_{it} is defined as the logarithm of the value-added of hotel i at time t and L_{it} and K_{it}, representing the two production inputs, are the logarithms of the number of employees and of fixed assets, respectively. Following Glass, Kenjegalieva, and Sickles (2016), we assume Hicks-neutral technical change and therefore the time trend variable t and its square are added to the specification of the frontier function (t has a minimum value of 1 for the year 2011 and it increases by 1 for each year, reaching a maximum value of 9 for 2019). Furthermore, also the interactions between time and the two inputs are taken into consideration. Moreover, the spatial lag of the dependent variable and the spatial lag of the two production inputs are introduced in the model specification to take global and local spatial dependence into account. In particular, ρ captures global spatial dependence while θ_L and θ_K capture how the level of labour and capital of firm i is influenced by the level of inputs of neighbouring firms j, with $j = 1, ..., N$. To identify neighbouring hotels, we use a time-invariant row-standardized inverse distance spatial weight matrix, having all zeros on the main diagonal. Therefore, w_{ij} indicates the weight associated with each pair of spatial units i,j and before row-normalization, it is equal to $\frac{1}{d_{ij}}$ where d_{ij} is the distance between the two units expressed in kilometres. While contiguity matrices are usually chosen when dealing with areal data, defining W as an inverse distance matrix is a common specification when working with points data as it allows to consider the relations of neighbours with all territorial units considering the exact spatial position of each element in the sample. Moreover, using a dense inverse distance matrix has several advantages. First of all, it implies not choosing an arbitrary truncation point or a cut-off for the number of neighbours so that subjective choices related to defining the neighbouring hotels do not affect the estimation results. Second, compared to inverse squared or polynomial distance matrices, a simple inverse distance matrix assumes that the relations between neighbouring observations are linear, which means that the strength of the relationship varies proportionally to the distance. Finally, with respect to matrices based on economic distance, it ensures that the spatial weights are exogenous. However, in subsection 5.5.5 we test the robustness of our results with respect to alternative spatial weight matrices. In particular, we define various truncation points for W at a 200, 100, 50 and 30 kilometres radius around each spatial unit and we consider the 400, 250, 100, 50 and 30 nearest neighbours. At last, u_{it} is the inefficiency error term distributed as a truncated normal random variable with mean μ_{it} and variance σ_u^2 while v_{it} is the normally distributed error term with zero mean and variance σ_v^2, and u_{it} and v_{it} are assumed to be independent random variables. We model the mean μ_{it} of firms' technical inefficiency as shown in Eq.(5.2).

$$
\begin{aligned}
\mu_{it} = {} & \phi_0 + \phi_{hum} Hum_{it} + \phi_{Int} Int_{it} + \phi_{pat} Pat_{it} + \phi_{trad} Trad_{it} + \phi_{size} Size_{it} + \phi_{dsize} DSize_{it} \\
& + \delta_{hum} \sum_{j=1}^{N} w_{ij} Hum_{jt} + \delta_{Int} \sum_{j=1}^{N} w_{ij} Int_{j_{it}t} + \delta_{pat} \sum_{j=1}^{N} w_{ij} Pat_{jt} + \delta_{trad} \sum_{j=1}^{N} w_{ij} Trad_{jt} \\
& + \delta_{size} \sum_{j=1}^{N} w_{ij} Size_{jt} + \delta_{dsize} \sum_{j=1}^{N} w_{ij} DSize_{jt} + \phi_{city} City_{it} + \phi_{cult} Cult_{it} + \phi_{sea} Sea_{it} \\
& + \phi_{lake} Lake_{it} + \phi_{mou} Mou_{it} + \phi_{csea} CSea_{it} + \phi_{cmou} CMou_{it} + \phi_{more} More_{it} \\
& + \phi_{nocat} Nocat_{it} + \phi_{notur} Notur_{it}
\end{aligned}
\tag{5.2}
$$

We assume that the mean of the inefficiency error term depends on some determinants under the firm's control and on spillover effects coming from neighbours. Between the internal factors affecting hotels' efficiency, we consider the hotel's size and a firm's innovative activity, proxied by patents and trademark filing, human capital exploitation, and intangible investments. To measure a hotel's innovative activity we include in the model the following variables: Hum, Int, Pat and $Trad$. In particular, Hum proxies average firms' investments for workers, and it is defined as the logarithm of the ratio between the total annual labour costs and the number of employees. In the absence of data on the quality and education of workers for proxying human capital, firm income statement data can be considered as the best approximation for measuring human resources value (Lev and Schwartz, 1971; Wyatt and Frick, 2010). Labour costs (including wages and training costs) per worker can be used as a proxy per human capital investments based on the assumption that firms with higher average labour costs per employee tend to recruit highly skilled workers (Le and Pomfret, 2011; Sari, Khalifa, and Suyanto, 2016) since wages tend to vary more across firms for differences in human capital than because of worker rents (Benkovskis, 2018; Hsieh and Klenow, 2009). Besides salaries, incentives, study grants, awards and social security costs, labour cost measures generally include a substantial part of recruiting and training costs because they are usually performed within the company by the firm's staff (Garcia-Ayuso, Moreno-Campos, and Sierra-Molina, 2000). Moreover, Lajili and Zeghal (2006) demonstrated that, between other indices, indicators based on total labour expenditures are associated with higher abnormal returns, indicating that investors tend to perceive labour costs as a measure of human capital assets, rewarding it with greater market value. Thus, since the cost of investing in human capital is proportional to the cost of labour (Rhee and Pyo, 2010; Sydler, Haefliger, and Pruks, 2014), we can assume labour cost as a proxy variable for human capital.

Following Bernini and Guizzardi (2010), the amount of firms' investments in intangibles (Int) is measured as the logarithm of the ratio between total capital (immaterial plus material) and fixed capital. Therefore, this variable equals 0 for hotels that do not make any investment in intangible capital while it shows increasing values as investments in immaterial capital raise. Firms' innovative activity, competitiveness and success may be strongly related to investments in intangible assets (Montresor and Vezzani,

2016) because they allow new knowledge acquisition and process improvements. Intangible capital represents, among other things, the value of a company's information and communication technology (ICT), firm's organizational capital, and R&D investments. ICT application in accommodation facilities allows to speed up hotels' management procedures, upgrade the quality of economic operations, purchase tourist services online, communicate hotels' promotions and sales, recognize customers' profiles and offer personalized services, etc., and thus, it supports hotels' efficient functioning and competitiveness (Jaremen, 2016; Soteriades, Aivalis, and Varvaressos, 2004). On the other hand, R&D activity performed by hotels aims to raise the performance of existing operations by means of new or improved technologies, new job profiles, collaborative structures, and authority systems, to approach new markets and customer segments and to enable additional advantages to be offered to customers such as more comprehensive facilities and quality upgraded and speedier services (Hjalager, 2002). Examples of product and process innovation in the hotel industry concern environmentally sustainable practices, loyalty programs, computerised management and monitoring systems, robots for cleaning and maintenance, self-service devices, electronic marketing, use of ICT in operations, automatic check-in and check-out, the introduction of touch sensitive machines, virtual reality and smartphone apps, computerized reservation systems, technologies that ensure the mobility of people, luggage and goods such as x rays and iris-recognition, etc (Hjalager, 2010; Jacob, Florido, and Aguiló, 2010; Jacob and Groizard, 2007; Jiménez-Zarco, Martínez-Ruiz, and Izquierdo-Yusta, 2011). For a comprehensive review of hotels' innovative activity see Medina-Munoz, Medina-Munoz, and Zuniga-Collazos (2013).

Focusing on product innovation, patents are a very commonly used indicator because patenting allows the firm to protect the newly developed products as trade secrets, giving the innovative firm a competitive advantage (Hameed, Nisar, and Wu, 2021). As demonstrated by Succurro and Boffa (2018), intellectual property is a powerful and commonly used tool in the accommodation sector aiming at developing a tourism brand strategy and securing firms' competitive advantage. In this framework, more and more tourism firms rely on registered patents and/or trademarks to protect their innovative activity. In particular, trademarks are useful for granting the owner the exclusive use of the mark and for preventing its use by others, protecting valuable tools such as brands, logos, catchphrases or slogans. Specifically, trademarks help to protect highly valuable intangible assets, increasing hotels' visibility and reputation (Marco-Lajara et al., 2016) and thus, they can be used as an indicator for service innovation (Gotsch and Hipp, 2012). On the other hand, patents are related to product innovation. In particular, hotels register patents related to accommodation services such as door security systems, free-standing swimming pools, and elevators with self-load bearing systems, food and beverage preparation and distribution services, internal organization devices and to tourism management tools such as data protection systems and electrical devices. Therefore, to capture intellectual properties related to product innovation we introduce in the model a dummy variable (Pat) that equals 1 if, in the whole period considered (2011-2019), the hotel has registered at least one patent, and 0 otherwise. In line with Pat, we measure registered trademarks by introducing in the model a dummy variable (*Trad*) that equals 1 if in the time period considered, the hotel has registered at least one trademark.

Finally, hotel size is proxied by the logarithm of the number of managers of the hotel (*Size*) in line with Bernini and Guizzardi (2010, 2012). In addition, enterprises driven by trained managers tend to use more capital and external finance and have different types of customers, encouraging innovative practices and the introduction of new technologies (Porta and Shleifer, 2008). Thus, besides measuring hotel size, the number of managers can also be considered an additional indicator of innovation other than intangible investments, human capital, patents, and trademarks. Computing the logarithm implies obtaining missing values for those hotels with zero managers. Therefore, following the procedure suggested by Battese (1997), we substitute the missing values in *Size* with zero values and we take those hotels having zero managers into consideration including in the model a dummy variable (*DSize*) that equals 1 if the number of managers at the hotel is zero and 0 otherwise.

Besides hotels' size and innovative activity, we also take hotels' location into consideration. Specifically, hotels' location is taken into account including in the model some municipality dummy variables identifying the destination typology in which the hotel is located using the tourism municipality classification carried out by ISTAT in 2019. In particular, the dummy variable *City* refers to big cities with multidimensional tourism demand, *Cult* to cultural, artistic, historical, or landscaped destinations, *Sea* to maritime destinations, *Lake* to lake destinations, *Mou* to mountain destinations, *CSea* to destinations that are both maritime and cultural, *CMou* to destinations that are both mountain and cultural, *More* to destinations that have more than two characteristics, *Nocat* to tourism destinations that cannot be categorized in this scheme, *Notur* to non-tourism destinations and *Therm* refers to thermal destinations and it is identified as the reference group.

Focusing on external influences, we also consider if and how the factors that contribute to determining the level of efficiency of Italian hotels also affect neighbouring hotels' efficiency level, introducing in the model the spatial lag of *Size*, *DSize*, *Hum*, *Int*, *Pat* and *Trad*. Therefore, the unknown parameters δ_{Size}, δ_{DSize}, δ_{Hum}, δ_{Int}, δ_{Pat} and δ_{Trad} allow computing spillover effects affecting firms' efficiency level resulting from being located near to a big facility, near to a hotel making large investments in human capital and/or in intangibles or near to highly innovative hotels that have registered patents or trademarks in the period considered. Therefore, differently from previous models estimated in tourism literature, this modelling approach allows us to detect the specific spillover effects affecting hotels' efficiency level obtaining new clear insights on the existence of agglomeration and/or competition effects related to the different sources of hotels' innovation.

The unknown parameters (β, ρ, θ, ϕ, δ, σ_u^2, σ_v^2) can be simultaneously estimated maximizing the loglikelihood function shown in Eq.(3.18) in Chapter 3 using a numerical maximization algorithm implemented in Matlab. In particular, the two variance parameters have been reparameterized, following Battese and Coelli (1995), as $\sigma^2 = \sigma_u^2 + \sigma_v^2$ and $\lambda = \sigma_u^2/\sigma^2$. Testing various parameter restrictions through likelihood ratio tests, or using the AIC or BIC information criteria, it can be tested whether it is better the consider this general model introducing three different kinds of spatial spillover effects or simpler nested specifications. In particular, if $\delta, \theta = 0$ our model reduces to the SARF-TE model introduced by Tsukamoto (2019), if $\delta, \phi = 0$ this model becomes the SDF model estimated by Glass, Kenjegalieva, and Sickles (2016), if $\delta, \phi, \theta = 0$ it simplifies to the SARF model by Glass, Kenjegalieva, and Sickles (2016), if $\delta, \phi, \rho = 0$ it becomes the SLXF model estimated by Adetutu et al. (2015), if $\delta, \theta, \rho = 0$ this model reduces to the non-spatial SF-TE model introduced by Battese and Coelli (1995), while if $\delta, \phi, \theta, \rho = 0$ the SDF-STE model collapses to the traditional non-spatial stochastic frontier model by Aigner, Lovell, and Schmidt (1977).

Finally, it is well-known that the β estimates obtained from spatial models including the spatial lag of the dependent variable cannot be interpreted in a meaningful way because they do not represent marginal effects. Indeed, when the spatial lag of Y is included in the model, this endogenous interaction enters the computation of the first derivatives and the β estimates do not coincide anymore with the marginal effects. In particular, the first derivatives of the dependent variable with respect to labour (L) and capital (K), referring to a Translog specification, are shown in Eq.(5.3)-(5.4) respectively, using matrix notation.

$$\frac{\partial Y}{\partial L} = (I_{NT} - \rho W)^{-1}(I_{NT} \cdot (1_{NT}^T \otimes (\beta_L 1_{NT} + 2\beta_{LL} L + \beta_{LK} K + \beta_{tL} t)) + \theta_L W) \tag{5.3}$$

$$\frac{\partial Y}{\partial K} = (I_{NT} - \rho W)^{-1}(I_{NT} \cdot (1_{NT}^T \otimes (\beta_K 1_{NT} + 2\beta_{KK} K + \beta_{LK} L + \beta_{tK} t)) + \theta_K W) \tag{5.4}$$

Therefore, starting from the two matrices obtained from the right-hand side of Eq.(5.3)-(5.4), direct, indirect and total effects can be calculated as proposed by LeSage and Pace (2009). In particular, direct effects can be found as the average of the diagonal element of that matrix, indirect effects can be defined as the average of the sum of non-diagonal elements, while total effects are the sum of the previous two.

Similarly to the β estimates, we can also compute the direct, indirect, and total effects of the determinants of firms' inefficiency on firms' inefficiency level u following a procedure similar to the previous one. Indeed, the spatial filter $(I_{NT} - \rho W)^{-1}$ also enters in the first derivative of u with respect to Z and thus, the ϕ and the δ estimates do not coincide with the direct and indirect effects of a generic determinant Z on u. In particular, the first derivative of u with respect to a generic determinant of firms' inefficiency Z is shown in Eq.(5.5). Starting from the matrix obtained from the right-hand side of Eq.(5.5), the marginal effects of the Z variables on u can be computed straightforwardly, following a procedure analogous to the one described above.

$$\frac{\partial u}{\partial Z} = (I_{NT} - \rho W)^{-1}(\phi_Z I_{NT} + \delta_Z W) \qquad Z = Hum, Int, Pat, Trad, Size \tag{5.5}$$

5.4 Data and Variables

5.4.1 Data, Cleaning Procedure and Comparison with the Population

The data used for the analysis are collected from the AIDA-Bureau Van Dijk database, which provides information on the consolidated accounts of Italian companies. In particular, we concentrated on the ATECO 55 sector, which refers to the Italian accommodation industry, in the time period 2011-2019. The AIDA databank is largely used in empirical research because of the high coverage of both the firms observed within sectors and balance sheet information. In our analysis the sample coverage is on average 12.7% in terms of firms belonging to the Italian accommodation sector, reaching 12.65% for firms with less than 200 employees and 57.89% for firms with more than 200 employees. These rates are much higher than the coverage of alternative surveys such as the ISTAT survey on Income Accounts of Enterprises, whose sample coverage is on average about 2% for all Italian firms with less than 250 employees and 79% for all Italian firms over 250 employees. Moreover, only in the AIDA databank, the geographical localisation is provided, allowing us to implement our spatial analysis. All these advantages motivated us to use the AIDA databank for our analysis. Specifically, we downloaded all data referring to firms belonging to the ATECO55 sector, that is the Italian accommodation sector, in the time period 2011-2019.

Starting from a sample of more than 20,000 individual observations available yearly, we ended up with a balanced panel of 5409 firms for each year due to a necessary cleaning procedure. Firstly, we dropped all the observations having missing values for the value-added and for the number of employees in all the years of the analysis and we also dropped all the observations having negative values for the value-added in at least one year, ending up with a sample of 14,241 firms. Next, we interpolated the missing values in the variables value added, number of employees, fixed capital, immaterial capital and personnel costs and then we dropped all the observations still reporting at least one missing value in one year after the interpolation procedure. The percentage of interpolated values is 12.4% in 2019, 5.9% in 2018, 8.7% in 2017, 11.2% in 2016, 13.6% in 2015, 15.1% in 2014, 16.7% in 2013, 17.3% in 2012, 17.7% in 2011. The mean for the whole period is 13.2%. Afterwards, we dropped all the observations having value-added, fixed capital and personnel costs less than one thousand and number of employees less than one to avoid generating missing values computing logarithms. At the end of the procedure, we obtained a final cleaned sample consisting of 5,409 observations. Finally, starting from the addresses provided by the AIDA database, we geolocated each observation using the R package "ggmap" which exploits the Google Geocoding API service of the Google Cloud Platform Console to find the precise latitude and longitude of each firm.

Table 5.1 and Table 5.2 compare our sample with the corresponding population by

TABLE 5.1: Comparison between Sample and Population
Number of Firms, Year 2011

Macroarea		Class of Employees 1-5	6-9	10-15	16-19	20-49	50-99	100-199	200+	Tot.
North-West	*Pop.*	5396	916	579	157	236	35	17	14	7350
	Sample	362	189	226	74	129	29	12	9	1029
	Cov.	6.71	20.63	39.03	47.13	54.66	82.86	70.59	64.29	14.00
North-East	*Pop.*	11487	1520	1074	311	584	87	20	5	15088
	Sample	448	274	281	115	256	56	9	5	1442
	Cov.	3.90	18.03	26.16	36.98	43.84	64.37	45.00	100.00	9.56
Center	*Pop.*	8405	878	575	149	238	50	16	15	10326
	Sample	553	287	267	76	143	36	13	4	1378
	Cov.	6.58	32.69	46.43	51.01	60.08	72.00	81.25	26.67	13.34
South	*Pop.*	5464	546	334	114	207	36	8	2	6711
	Sample	402	185	162	87	151	34	8	2	1034
	Cov.	7.36	33.88	48.50	76.32	72.95	94.44	100.00	100.00	15.41
Islands	*Pop.*	2602	262	142	43	76	17	5	2	3149
	Sample	241	87	94	27	58	11	5	2	526
	Cov.	9.26	33.21	66.20	62.79	76.32	64.71	100.00	100.00	16.70
Tot.	*Pop.*	33354	4122	2704	774	1341	225	66	38	42624
	Sample	2006	1022	1030	379	737	166	47	22	5409
	Cov.	6.01	24.79	38.09	48.97	54.96	73.78	71.21	57.89	12.69

Pop.=Population; *Cov.*=Coverage

TABLE 5.2: Comparison between Sample and Population
Number of Employees, Year 2011

Macroarea		**Class of Employees** 1-5	6-9	10-15	16-19	20-49	50-99	100-199	200+	Tot.
North-West	*Pop.*	11596	6603	6969	2723	6802	14913	2301	6391	58298
	Sample	4240	1403	2723	1282	3830	2001	1557	2365	19401
	Cov.	36.56	21.25	39.07	47.08	56.31	13.42	67.67	37.01	33.28
North-East	*Pop.*	22536	11123	13015	5386	16603	5779	2819	2190	79451
	Sample	828	2070	3405	1996	7589	3839	1217	2190	22280
	Cov.	3.67	18.61	26.16	37.06	45.71	66.43	43.17	100.00	28.04
Center	*Pop.*	16090	6383	6909	2556	6930	3219	2273	4866	49226
	Sample	2006	2146	3267	1319	4104	2267	1922	752	17914
	Cov.	12.47	33.62	47.29	51.60	59.22	70.43	84.56	15.45	36.39
South	*Pop.*	10116	3974	4050	1989	6010	2461	1012	613	30225
	Sample	2189	1382	1955	1497	4447	2282	1012	613	15822
	Cov.	21.64	34.78	48.27	75.26	73.99	92.73	100.00	100.00	52.35
Islands	*Pop.*	4619	1894	1714	742	2273	1171	589	922	13924
	Sample	551	638	1176	467	1705	804	589	922	7130
	Cov.	11.93	33.69	68.61	62.94	75.01	68.66	100.00	100.00	51.21
Tot.	*Pop.*	64957	29977	32657	13396	38618	27543	8994	14982	231124
	Sample	9814	7639	12526	6561	21675	11193	6297	6842	82547
	Cov.	15.11	25.48	38.36	48.98	56.13	40.64	70.01	45.67	35.72

Pop.=Population; *Cov.*=Coverage

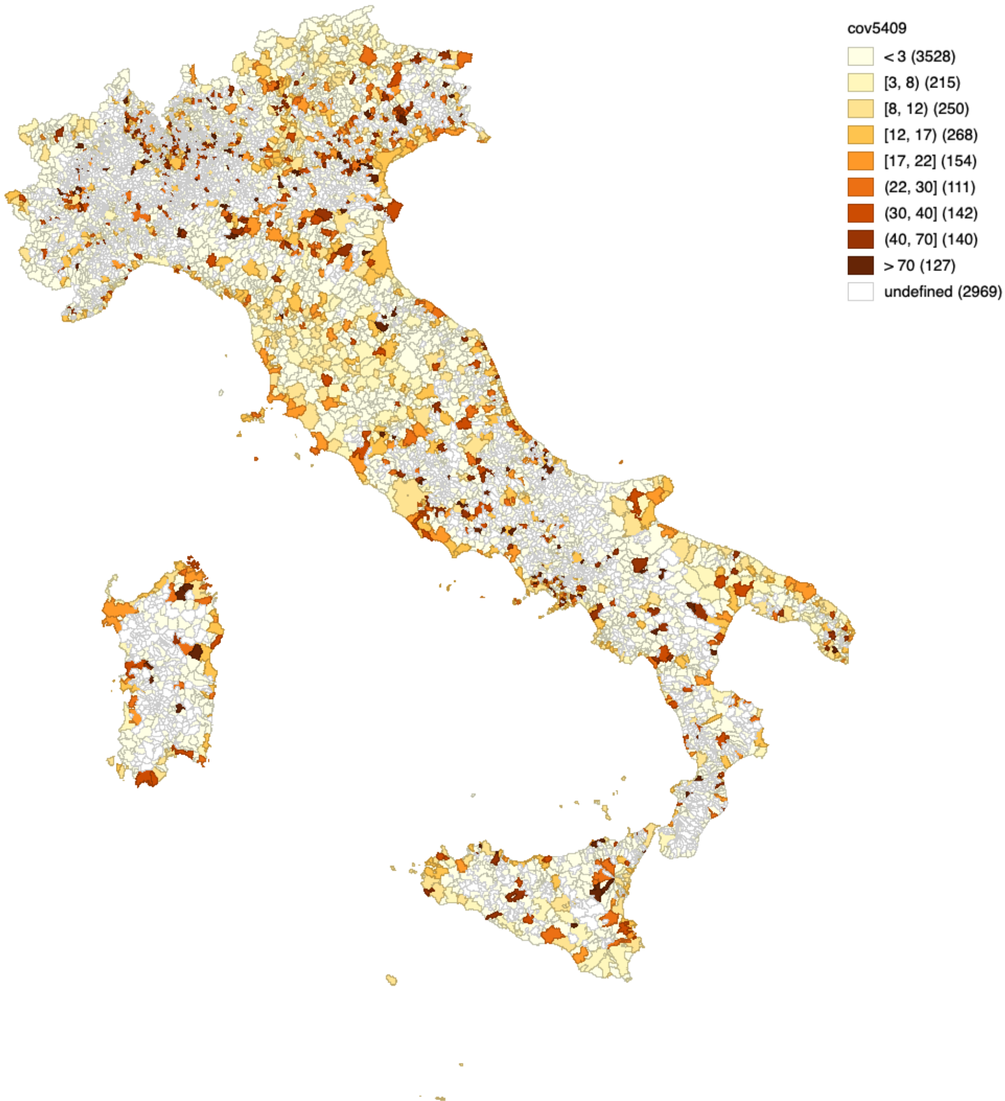

FIGURE 5.1: Sample Coverage Map by Municipalities

class of employees and macro area. In particular, the former shows the coverage of our sample referring to the number of firms while the latter concerns the total number of employees. Population data were retrieved from the Industry and Services Census carried out by Istat in 2011. Table 5.1 shows that firms' coverage rate is lower for smaller hotels (on average 6.01% for hotels from 1 to 5 employees) while it increases considering bigger hotels, reaching the maximum value of 73.78% for hotels with 50-99 employees. Overall, the representativeness of our sample is good, covering the 12.69% of the ATECO55 population. Considering the number of employees in 2011, the coverage rate of our sample is very good, reaching a value of 35.72% overall. As in the previous case, the coverage rate is lower for smaller hotels (15.11%) compared to bigger ones but, considering the total number of employees, the difference is less remarkable. Moreover, both for the number of firms and for the total number of employees, the coverage rate is higher for hotels located in the South of Italy and in the Islands while it is smaller for firms located in the North-East of Italy.

Examining hotels' coverage rate by Italian municipalities, Figure 5.1 shows that our sample is quite evenly distributed in the Italian territory. In particular, 2969 out of 7904 Italian municipalities in the year 2018 do not have any tourism facility in their territory (undefined category). Considering the coverage rate of our sample at the municipal level, in 3528 municipalities of the remaining 4935 the coverage rate is smaller than 3%, while in 1407 municipalities it is higher than 3%.

5.4.2 Descriptive Statistics

Table 5.3 describes all the variables used in the analysis (i.e. output, inputs and inefficiency determinants) and it shows some descriptive statistics. Only 2.1% of hotels from our sample are very small hotels (i.e. hotels with a number of managers equal to zero) and this is due to the data cleaning procedure that excluded the very small enterprises from our sample (i.e. hotels with value-added, fixed capital and personnel costs less than one thousand and the number of employees less than one). This feature can also be observed looking at the 10th percentile of the value-added (more than 68 thousand euros) which is quite near to the mean value (more than 323 thousand euros). Looking at the number of employees, the 10th percentile is equal to 2 employees, while the mean and the 90th percentile are equal to 8.67 and 33.12, respectively. Concentrating on the innovative activity undertaken by firms, it can be observed that Hum, which proxies human capital, has a very concentrated distribution between the 10th and the 90th percentiles, with a mean cost for employees equal to more than 22 thousand euros per year. This variable reflects hotels' managers' propensity to invest few resources in human capital, pay low wages, invest little money in training and courses, and hire employees with low educational levels. Moreover, many hotels from our sample invest very little money in intangible capital, indeed, Int, proxying investments in intangible capital, has zero value for 19.65% of units in our sample while the median annual expenditure on intangibles equals 18 thousand euros overall and 37 thousand euros for hotels investing in intangibles. Nevertheless, the distribution of Int is positively skewed and the 90th percentile equals 425 thousand euros per year, indicating that hotels' innovative activity is higher than usually believed. In addition, it can be noticed that the 16.8% and the 12.1% of hotels from our sample have registered, in the time period considered, at least one patent or trademark, respectively. Concentrating on the typology of destinations, according to the municipality classification carried out by ISTAT, 20.4% of tourism facilities from our sample are located in big cities, 20.1% are in maritime and cultural destinations, 15.6% are in maritime destinations, 11.8% are not in categorizable destinations, 9.5% are in cultural, landscaped, historical, or artistic destinations, 6.2% are located in destinations that have more than two vocations, 5.6% are in cultural and mountain destinations, 4.9% are in thermal destinations, 2.8% are in lake destinations, 2.6% are in mountain destinations and only 0.5% of hotels are located in non-tourism destinations.

Figure 5.2 shows how firms' innovative activity is distributed on the Italian territory at the municipal level. In particular, the "undefined" category refers to municipalities that do not contain any hotels while the "not in sample" category refers to municipalities that are not covered by our sample data. Considering the remaining municipalities, Figure 5.2 shows that hotels investing in human capital are predominantly located in the North of Italy (specifically in Trentino Alto Adige, on the coast of Veneto and in Emilia-Romagna) and in the Center of Italy, mainly in Tuscany, Umbria, and Lazio. Concentrating on the South of Italy, the Apulia region, the South of Sicily, and the Northern and Southern coast of Sardinia are the areas in which hotels make larger investments in human capital. The distribution of Int is similar to the one of Hum across Italy. The main difference concerns the area of Trentino Alto Adige and in general all the North-East of Italy in which hotels do not make as many investments in intangible capital as they do in human resources. Conversely, hotels located on the coast of Campania tend to invest more in Int than in human capital. Finally, in most municipalities, hotels do not register any patent (1046 municipalities) or trademark (1136 municipalities). As for Hum and Int, patenting is more common in some municipalities of the North-East of Italy, of the Apulia region, and of the West coast of Sicily while municipalities in which hotels register trademarks more frequently are mostly located in Trentino Alto Adige, in the Center of Italy, in Apulia, and in the Southern tip of Sicily and Sardinia.

Finally, Figure 5.3 shows the Local Moran statistic (LISA) significance cluster map at a significance level of 5%, allowing to identify local geographical clusters and determining the degree of spatial dependence. Considering all the observations having a value-added greater than zero in the year 2019 (7508), it can be noticed that only 1842 hotels are not affected at all by local spatial dependence at a significance level of 5%. On the other hand, local clusters located in the North-Center of Italy are high-high and low-high clusters, indicating that hotels in this area are mainly surrounded by hotels having a high level of value-added. Conversely, in the South-Center of Italy, there are low-low and high-low clusters, suggesting that hotels located in the South-Center of Italy are mostly

TABLE 5.3: Variables Description

Variable	Definition	Min	10th Perc.	Mean	90th Perc.	Max	SD
Y	$\log(ValueAdded)$	0.001	4.23	5.78	7.32	12.01	1.25
L	$\log(NumberEmployees)$	0	0.69	2.16	3.50	7.47	1.08
K	$\log(FixedCapital)$	0	3.47	6.37	8.86	13.40	2.18
t	*Time*	1	1	5	9	9	2.58
Hum	$\log\left(\frac{PersonnelCosts}{NumberEmployees}\right)$	0	2.25	3.10	3.76	7.56	0.73
Int	$\log\left(\frac{TotalCapital}{FixedCapital}\right)$	0	0	0.31	3.76	7.67	0.60
Pat	1 if $PatentRights > 0$	0	-	0.17	-	1	0.37
Trad	1 if $RegisteredTrademarks > 0$	0	-	0.12	-	1	0.33
Size	$\log(NumberManagers)$	0	0	0.54	1.39	3.76	0.67
DSize	1 if *NumberManagers=0*	0	-	0.02	-	1	0.14
City	1 if *BigCity*	0	-	0.20	-	1	0.40
Cult	1 if *Cultural*	0	-	0.10	-	1	0.29
Sea	1 if *Sea*	0	-	0.16	-	1	0.36
Lake	1 if *Lake*	0	-	0.03	-	1	0.17
Mou	1 if *Mountain*	0	-	0.03	-	1	0.16
CSea	1 if *Cultural&Sea*	0	-	0.20	-	1	0.40
CMou	1 if *Cultural&Mountain*	0	-	0.06	-	1	0.23
Therm	1 if *Thermal*	0	-	0.05	-	1	0.12
More	1 if *MoreThanTwoVocations*	0	-	0.06	-	1	0.24
Nocat	1 if *NotCategorizable*	0	-	0.12	-	1	0.32
Notur	1 if *NonTourismDestination*	0	-	0.01	-	1	0.07

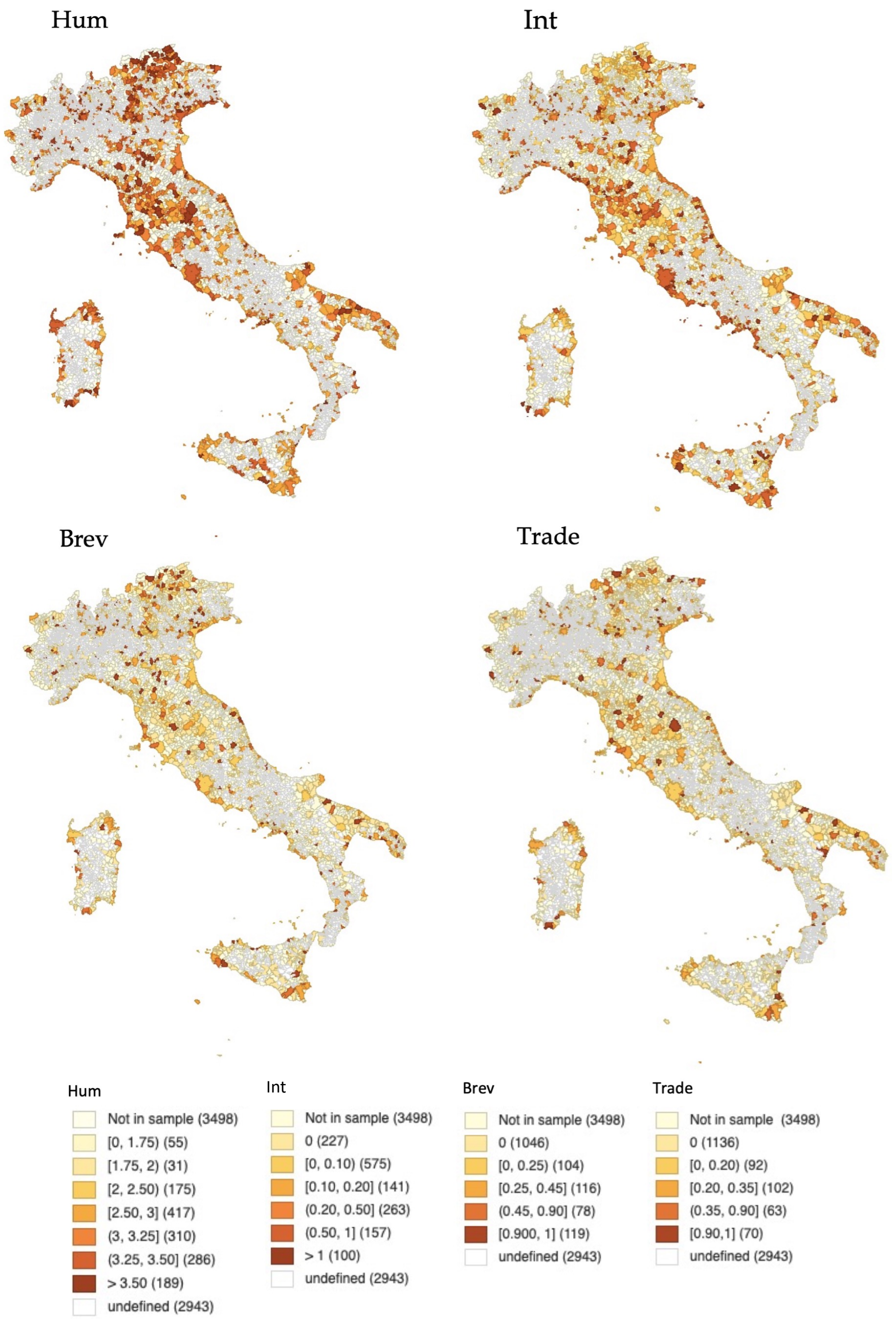

FIGURE 5.2: Innovation across Italian Municipalities

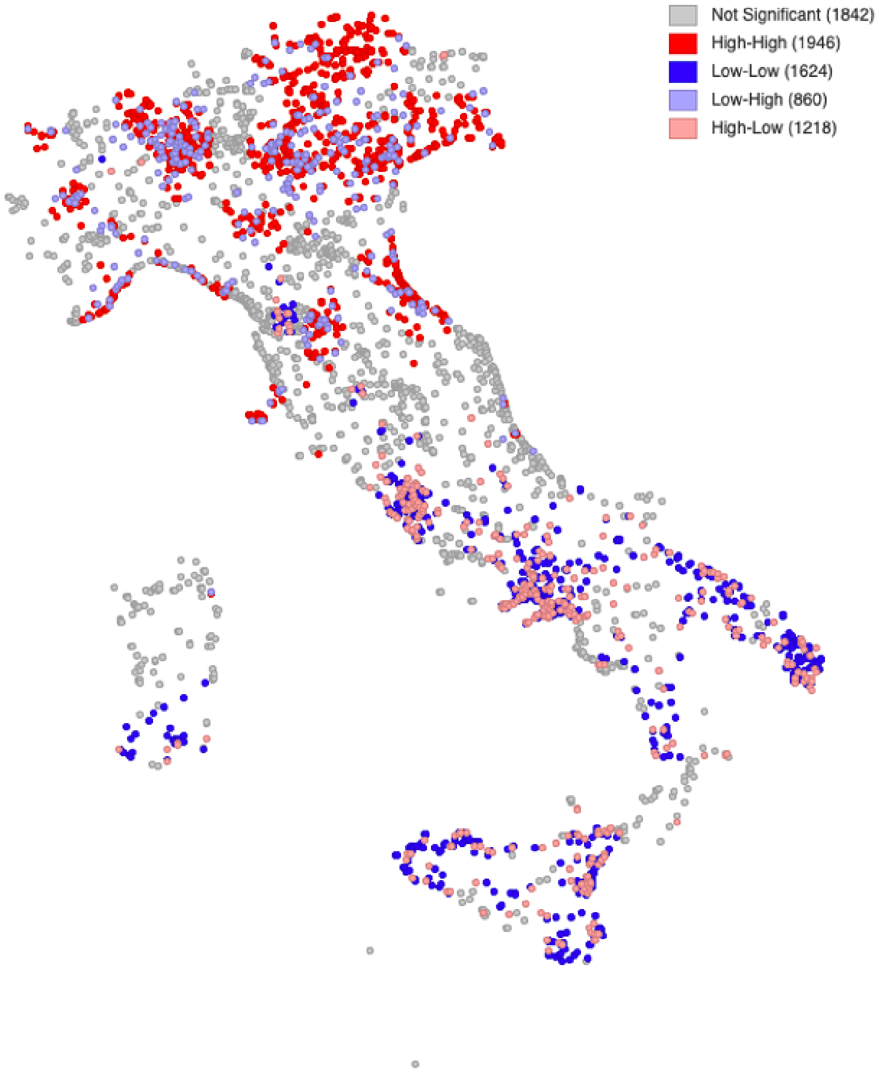

FIGURE 5.3: LISA Significance Cluster Map: Value Added 2019 (5% Significance Level)

nearby to hotels with low levels of value-added. The area around Florence, in which there are significant low-low and high-low clusters, is the only exception to this clear separation into two areas characterized by two distinct typologies of local clusters (i.e. high-high and low-high clusters in the North-Center and low-low and high-low clusters in the South-Center of Italy).

5.5 Results

5.5.1 Estimation Results and Model Selection

Table 5.4 shows the estimation results of the SDF-STE model and of all the nested models, starting from the two non-spatial specifications (SF and SF-TE), passing to spatial models that do not take the determinants of technical inefficiency into consideration (SLXF, SARF, and SDF) and ending with the SARF-TE that includes a model for the determinants of firms' inefficiency but that only considers the spatial lag of Y as a spatial effect. Comparing the estimation results of the nested models, it can be noticed that the estimated β and ϕ coefficients are quite robust to different model specifications. Nevertheless, the β and the ϕ estimates cannot be interpreted in a meaningful way when the spatial lag of Y is included in the model because they no longer represent simple partial derivatives. Thus, in the next subsection, the related marginal effects are discussed separately. Considering the functional form of the production frontier, the interaction parameter β_{LK} and the parameters related to squared labour and capital (β_{LL} and β_{KK}) are always significantly different from zero at a 1% significance level indicating that the translog specification does not reduce to a Cobb-Douglas one. This insight is confirmed by the result of the LR test that indicates rejecting the null hypothesis of reducing the model to a simpler Cobb-Douglas specification at a 1% significance level (the test statistic equals 2214.9).

Concentrating on the spatial autoregressive parameter, it can be noticed that the estimates of ρ are positive and significant at the 1% significance level across all the models introducing the SAR term, indicating that positive spillover effects occur at the global level in the Italian accommodation sector. Moreover, ρ appears to be almost doubled if the determinants of firms' efficiency are not included in the model specification, in fact, it equals 0.352 and 0.168 using respectively the SARF and the SARF-TE model while it equals 0.604 and 0.351 using the SDF and the SDF-STE specification, respectively. Indeed, as already observed by Tsukamoto (2019) for the SARF and the SARF-TE models, when the determinants of firms' efficiency are not considered in spatial stochastic frontier models, the spatial autoregressive parameter absorbs some of the heterogeneity related to technical inefficiency and it tends to be overestimated.

To compare the different nested models, different criteria can be used, such as the Akaike Information Criteria (AIC), the Schwarz/Bayesian Information Criteria (BIC) or alternatively, some Likelihood Ratio Tests for nested models can be implemented. Looking at the AIC and BIC values contained in Table 5.5 for all the estimated nested models, it can be noticed that the model specification that minimizes both information criteria is

TABLE 5.4: Nested Models Results

	SF		SF-TE		SLXF		SARF		SDF		SARF-TE		SDF-STE	
	Coef.	*t-stats*	*Coef.*	*t-stats*	*Coef.*	*t-stats*	*Coef.*	*t-stats*	*Coef.*	*t-stats*	*Coef.*	*t-stats*	*Coef.*	*t-stats*
β_0	3.635***	38.63	6.665***	7.68	2.929***	30.17	1.630***	6.46	1.404***	16.06	6.095***	15.41	5.467***	13.71
β_L	0.633***	38.63	0.665***	85.11	0.629***	30.17	0.626***	61.35	0.628***	60.42	0.660***	83.53	0.662***	84.87
β_K	0.070***	10.64	0.077***	17.04	0.071***	10.95	0.073***	12.03	0.074***	12.11	0.077***	17.13	0.077***	17.20
β_{LL}	0.090***	42.76	0.057***	40.43	0.089***	44.50	0.089***	49.33	0.090***	49.78	0.057***	40.50	0.057***	40.57
β_{KK}	0.019***	31.50	0.010***	25.00	0.019***	31.17	0.019***	37.00	0.019***	37.20	0.010***	25.00	0.010***	22.50
β_{LK}	-0.050***	-33.40	-0.029***	-26.46	-0.050***	-33.60	-0.051***	-36.43	-0.051***	-36.57	-0.030***	-26.82	-0.029***	-29.00
β_t	0.067***	10.08	0.005	0.96	0.082***	12.36	0.059***	9.22	0.024***	3.97	0.002	0.43	-0.005	-1.09
β_{2t}	-0.007***	-14.00	-0.001**	-2.75	-0.009***	-17.40	-0.007***	-11.83	-0.004***	-7.60	-0.001***	-3.00	-0.001*	-1.25
β_{tL}	0.006***	5.08	0.004***	4.88	0.006***	5.25	0.006***	6.40	0.006***	5.64	0.004***	5.13	0.004***	5.00
β_{tK}	0.001**	2.00	0.001***	3.50	0.001**	1.83	0.001**	2.00	0.001**	1.80	0.001**	3.25	0.001***	3.00
ρ	-	-	-	-	-	-	0.352***	10.14	0.604***	31.30	0.168***	8.48	0.351***	18.30
θ_L	-	-	-	-	0.175***	6.98	-	-	-0.340***	-15.10	-	-	-0.216***	-11.33
θ_K	-	-	-	-	0.049***	4.64	-	-	-0.069***	-7.20	-	-	0.006	0.78
ϕ_0	-	-	5.363***	6.22	-	-	-	-	-	-	5.784***	14.64	5.251***	13.23
ϕ_{hum}	-	-	-0.653***	-210.74	-	-	-	-	-	-	-0.646***	-208.42	-0.647***	-208.58
ϕ_{Int}	-	-	-0.116***	-29.05	-	-	-	-	-	-	-0.116***	-29.82	-0.115***	-29.54
ϕ_{pat}	-	-	-0.054***	-9.38	-	-	-	-	-	-	-0.054***	-9.31	-0.054***	-9.53
ϕ_{trad}	-	-	-0.039***	-5.91	-	-	-	-	-	-	-0.037***	-5.55	-0.038***	-5.78
ϕ_{size}	-	-	-0.039***	-11.54	-	-	-	-	-	-	-0.037***	-10.46	-0.037***	-10.57
ϕ_{dsize}	-	-	0.069***	4.73	-	-	-	-	-	-	0.077***	5.33	0.081***	5.66
δ_{hum}	-	-	-	-	-	-	-	-	-	-	-	-	0.160***	7.31
δ_{Int}	-	-	-	-		-	-	-	-	-	-	-	-0.072***	-2.71
δ_{pat}	-	-	-	-	-	-	-	-	-	-	-	-	0.099***	2.80
δ_{trad}	-	-	-	-	-	-	-	-	-	-	-	-	0.039	0.97
δ_{size}	-	-	-	-	-	-	-	-	-	-	-	-	-0.013	-0.70
δ_{dsize}	-	-	-	-	-	-	-	-	-	-	-	-	-0.358***	-3.85
ϕ_{city}	-	-	-0.070***	-6.50	-	-	-	-	-	-	-0.076***	-7.04	-0.064***	-5.94
ϕ_{cult}	-	-	0.041***	3.56	-	-	-	-	-	-	0.008	0.73	0.016*	1.43
ϕ_{sea}	-	-	-0.071***	-6.57	-	-	-	-	-	-	-0.109***	-10.07	-0.095***	-8.89
ϕ_{lake}	-	-	-0.149***	-9.64	-	-	-	-	-	-	-0.160***	-10.36	-0.139***	-9.06
ϕ_{mou}	-	-	0.015	0.96	-	-	-	-	-	-	-0.017***	-1.09	-0.007	-0.45
ϕ_{csea}	-	-	-0.057***	-5.39	-	-	-	-	-	-	-0.099***	-9.47	-0.085***	-8.12
ϕ_{cmou}	-	-	-0.058***	-4.50	-	-	-	-	-	-	-0.075***	-5.89	-0.065***	-5.04
ϕ_{more}	-	-	-0.040***	-3.17	-	-	-	-	-	-	-0.064***	-5.15	-0.047***	-3.77
ϕ_{nocat}	-	-	0.072***	6.52	-	-	-	-	-	-	0.041***	3.69	0.052***	4.71
ϕ_{notur}	-	-	0.051*	1.60	-	-	-	-	-	-	0.002	0.06	0.015	0.48
ϕ_{therm}	-	-	omit.	-	-	-	-	-	-	-	omit.	-	omit.	-
σ^2	0.705	-	0.203	-	0.694	-	0.678	-	0.660	-	0.200	-	0.199	-
λ	0.621	-	0.035	-	0.614	-	0.613	-	0.586	-	0.882	-	0.879	-
TE	0.64	-	0.67	-	0.64	-	0.64	-	0.64	-	0.61	-	0.62	-

$***: pvalue \leq 0.01$; $**: pvalue \leq 0.05$; $*: pvalue \leq 0.10$; omit=omitted

TABLE 5.5: AIC, BIC and Likelihood Ratio Tests

Model	LL	AIC	BIC	LL Test: H0	Num. Constraints	Test Statistic	Decision
SF	-48071.51	96167.02	96272.54	$\delta, \phi, \theta, \rho = 0$	26	36419.22	Reject
SF-TE	-30197.16	60452.32	60707.32	$\delta, \theta, \rho = 0$	8	670.52	Reject
SLXF	-47905.03	95838.06	95961.16	$\delta, \phi, \rho = 0$	24	36086.26	Reject
SARF	-47414.20	94854.40	94968.71	$\delta, \phi, \theta = 0$	25	35104.60	Reject
SDF	-47221.12	94472.24	94604.14	$\delta, \phi = 0$	23	34718.44	Reject
SARF-TE	-29944.60	59949.20	60212.99	$\delta, \theta = 0$	8	165.40	Reject
SDF-STE	-29861.90	59799.80	60133.95	-	-	-	-

the SDF-STE. Moreover, also using the Likelihood Ratio Test, we always reject the null hypothesis of reducing the number of parameters of the SDF-STE model in favour of a simpler specification. Therefore, our novel spatial estimator is the preferred one, being the one that best fits the data. For completeness, in Appendix B we also estimate the SDF-CSD model developed in this thesis using data on Italian hotels. However, while through the SDF-STE we are able to measure the specific spatial effects arising from each inefficiency determinant obtaining precise insights on spatial spillovers originating from each source of hotels' innovative activity, through the SDF-CSD we are only able to capture the overall level of spatial dependence related to hotels' efficiency, hiding important insights which instead have a central role in this empirical application given our research objectives. Moreover, also the Vuong test for non-nested models and the Takeuchi information criteria shown in Table B.1 confirms a better fit of the SDF-STE model compared to SDF-CSD using these data.

5.5.2 Marginal Effects

Focusing on the marginal effects related to the preferred SDF-STE model, both direct and indirect effects as well as total effects can be computed, as shown in Table 5.6. The direct effects of labour and capital on hotels' value-added are equal to 0.743 and 0.136, respectively, while the indirect effects equal 0.071 and 0.082, respectively. Therefore, while the direct effect of labour is much greater in magnitude than the one of capital (i.e. the accommodation sector is a labour-intensive industry), the indirect effect of capital is slightly higher than the one of labour, meaning that having bigger hotels as neighbours positively influences firms' productivity more than having as neighbours hotel that invest in labour. Finally, the total effects of labour and capital are equal to 0.814 and 0.218, respectively. Hence, the return to scale parameter equals 1.032 (significantly different from 1 at a 5% significance level), indicating the presence of increasing returns to scale. Considering

TABLE 5.6: Marginal Effects

Variable	**Direct Effect**		**Indirect Effect**		**Total Effect**	
	Coef.	*t-stats*	*Coef.*	*t-stats*	*Coef.*	*t-stats*
L	0.743***	297.04	0.071***	5.14	0.814***	81.39
K	0.136***	72.11	0.082***	13.84	0.218***	32.61
t	0.006***	6.96	0.004***	7.34	0.010***	7.54
Hum	-0.647***	-47.59	-0.103***	-5.30	-0.750***	-24.12
Int	-0.116***	-9.30	-0.171***	-8.91	-0.287***	-10.04
Pat	-0.054***	-4.22	0.122***	4.78	0.069**	1.99
Trad	-0.037***	-2.85	0.039*	1.31	0.002	0.05
Size	-0.037***	-3.10	-0.040***	-2.76	-0.077***	-3.26

$***$: *pvalue* $\leq$ 0.01; $**$: *pvalue* $\leq$ 0.05; $*$: *pvalue* $\leq$ 0.10

technical change over years, it can be observed that the coefficient related to time is positive and significant considering both direct, indirect, and total effects, indicating that the production frontier shifts upward during time thanks to technological change.

Moving to the determinants of hotels' efficiency, Hum, Int, Pat, $Trad$, and $Size$, all have a negative and significant direct effect on firm inefficiency level indicating that all the different sources of internal innovation considered in this study, as well as size, positively influence hotels' performance. Human capital (-0.647) is the factor that contributes most to negatively affecting the inefficiency level of Italian hotels followed by investments in intangible capital (-0.116). Indeed, human capital is a key source of innovation in the accommodation industry because of the intangible nature of this sector and of the simultaneity of production and consumption in service delivery (Ottenbacher, 2007). Specifically, in order to obtain a 10% increase in efficiency, Italian hotels need to invest about 215 thousand euros in intangibles or alternatively, to increase labour investments per worker by around 3.60 thousand euros yearly. Moreover, in line with the results of Orfila-Sintes, Crespì-Cladera, and Martinez-Ros (2005), we find that hotels' size is positively associated with efficiency as larger firms have the advantage of economies of scale in innovation activities (Camisón-Zornosa et al., 2004). Finally, also the direct effects related to registered patents and trademarks result to be positively associated with hotels' efficiency level, increasing firm visibility and protecting product and service innovations (Marco-Lajara et al., 2016).

Considering the indirect effects, our findings indicate that all the different sources of innovation considered in the study significantly impact neighbouring accommodation facilities but with different effects. Indeed, while we detect positive spillovers related to firms' intangible investments, size, and human capital investments, innovative activity associated with patents and trademarks generates negative spatial effects among neighbouring hotels. Among the sources of innovation that generate positive feedback, Int is the variable that contributes the most to positively affecting neighbours (-0.171). The magnitude of the coefficient related to the indirect marginal effect of Int is greater than the one associated with the direct effect, indicating that overall, positive spillovers generating from hotels' innovative activity overcome direct internal effects. According to our results, hotels benefit more from the innovative activity performed by neighbours than from internal investments highlighting the fundamental role played by the few innovators in the sector as knowledge and innovation disseminators. Thus, despite the difficulty of innovating inside the firm due to the peculiarities of this industry, in the accommodation sector, it is fairly easy to adopt new knowledge coming from neighbours because the operational processes are quite evident and also the technological level is basic (Decelle, 2006; Hjalager, 2002; Weidenfeld, Williams, and Bultler, 2010).

Besides having neighbours performing an intense innovative activity, also having nearby hotels that invest in human capital generates a positive and significant spillover effect (-0.103) but differently from Int, the direct effect associated with Hum greatly exceeds the indirect one. Therefore, positive feedback effects also generate from skilled human resources in neighbouring accommodation facilities thanks to social contact, shared ideas between individuals, learning by observation, human relationships, and imitation (Yang, 2012). However, internal investments in human capital retain a key role in this sector due to their direct connection with customer satisfaction, service quality, and better organizational performance that in turn lead to increased hotel performance (Cho et al., 2006). Finally, considering hotel size, the estimated coefficient for the indirect marginal effect of *Size* indicates that, in line with the positive indirect effect related to capital, having big hotels as neighbours positively influences a hotel's performance. Indeed, bigger hotels tend to be more innovative with respect to smaller and medium-sized hotels generating positive spillover effects that are beneficial to all neighbouring accommodation facilities.

On the other hand, the indirect effects of *Pat* and *Trad* on hotels' inefficiency are both significant and positive (0.122 and 0.039, respectively), indicating that hotels are disadvantaged when neighbouring firms registered trademarks or patents in the previous years. Therefore, the protective function performed by patents and trademarks is found to be effective, because, in addition to providing innovative firms with a productivity advantage, it also weakens neighbouring hotels through negative spillover effects. These results are in line with Haschka and Herwartz (2020) who demonstrated that patent blocking might be crucial for innovative firms to strategically secure their technological expertise, generating negative competitive spillovers. Specifically, they showed that there is a negative association between the successful performance of competitors and the efficiency of the innovative process of peers, proxied by patents. Indeed, patents give innovative firms the exclusive right to commercialize the newly patented products for a certain period of time. Similarly, registered trademarks are used to protect hotels' highly valuable intangible assets and to differentiate firm services from potentially competing services (Hameed, Nisar, and Wu, 2021).

To sum up, our results suggest that while the performance of Italian hotels is mainly boosted by skilled labour and qualified human resources considering internal factors, positive spatial effects are primarily linked to capital, and in particular, to intangible capital, as far as external factors are concerned. Thus, despite the Italian accommodation sector results to be a labour-intensive sector, also investments in fixed and intangible capital are fundamental to driving the regeneration of this industry thanks to positive spatial externalities arising from them.

5.5.3 TE Scores

Starting from the estimates of the SDF-STE model shown in Table 5.4, the technical efficiency scores can be computed for each firm belonging to the sample and for each time period as shown in Eq.(3.30) in Chapter 3 adapting the definition given by Battese and Coelli (1988) to the SDF-STE model. The distribution of the TE scores is shown in the upper panel of Figure 5.4. The mean value of the TE scores is 0.62 along all the time periods considered and their distribution is approximately normal with a heavier right tail with respect to the left one. Considering the time trend of the average yearly TE scores, it can be noticed from the lower panel of Figure 5.4 that the level of technical efficiency of Italian hotels increased from 2012 to 2013, then remained quite stable until 2017, and in the end, it decreased again in the last two years of the analysis.

Considering the geographical distribution of the TE scores across Italy, Figure 5.5 shows the average TE scores per municipality. It can be noticed that the most efficient areas of Italy in terms of the accommodation sector are the regions of Trentino-Alto-Adige, Lombardy, Emilia-Romagna, Tuscany, Umbria, and Apulia and the coastal areas of Veneto, Lazio, Sicily, and Sardinia. In general, hotels located both on the Tyrrhenian and on the Adriatic coast reach high efficiency scores, while the only internal areas achieving good efficiency levels belong to the regions of Trentino-Alto-Adige, Emilia-Romagna, Tuscany, and Umbria.

Finally, Figure 5.6 represents the Lisa significance cluster map for the TE scores in the year 2019 in order to investigate whether significant local spatial dependence occurs across nearby tourism facilities in terms of efficiency levels. The results from this exploratory spatial analysis reveal that the majority of Italian hotels are affected by significant spatial dependence at a 5% significance level. Similarly to Figure 5.3 for the value-added, also considering Italian hotels' efficiency levels it appears that the North of Italy is mostly characterized by high-high and low-high clusters, while low-low and high-low clusters are mostly located in the Centre and in the South of Italy. Despite this

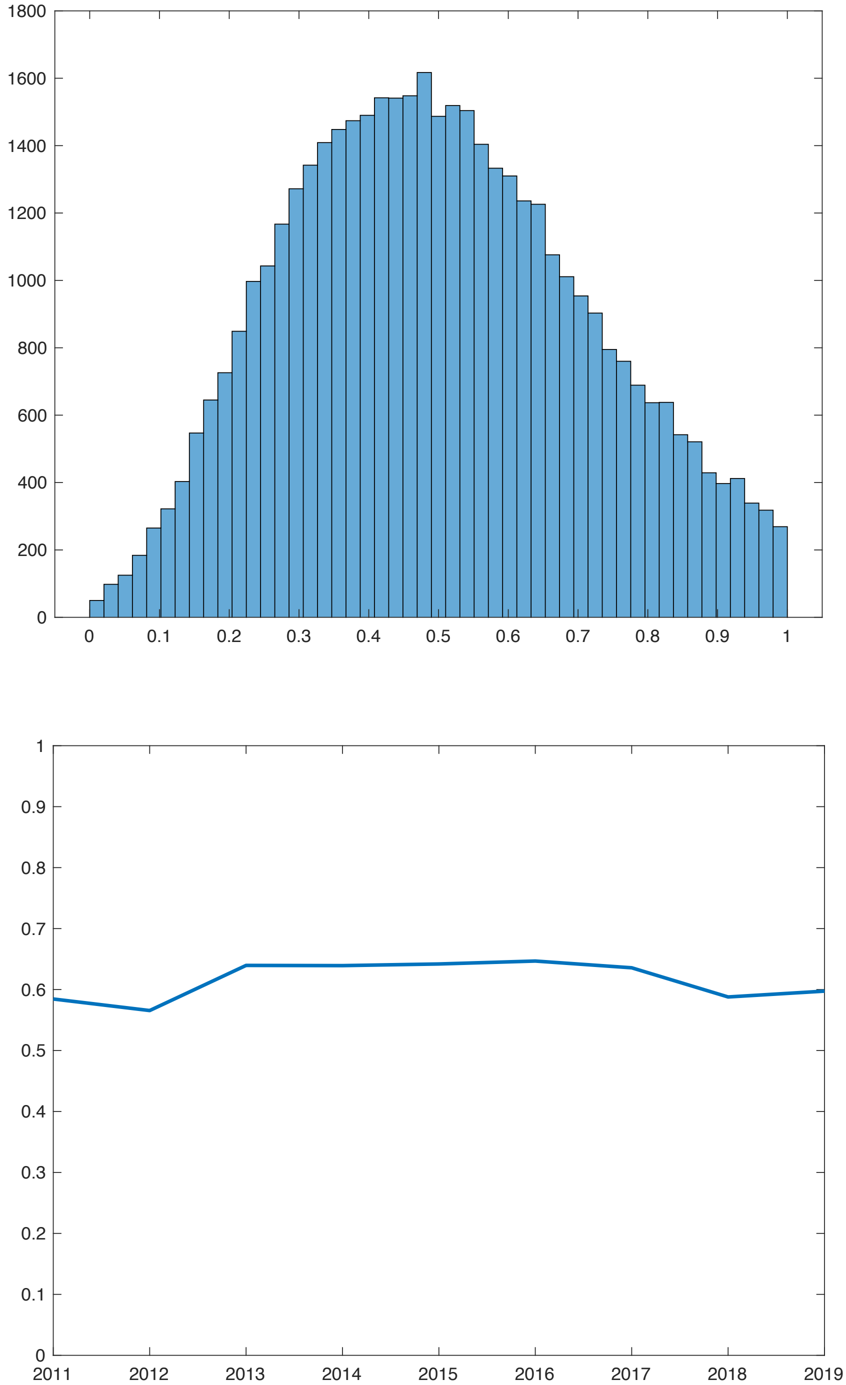

FIGURE 5.4: TE Scores: Distribution and Time Trend

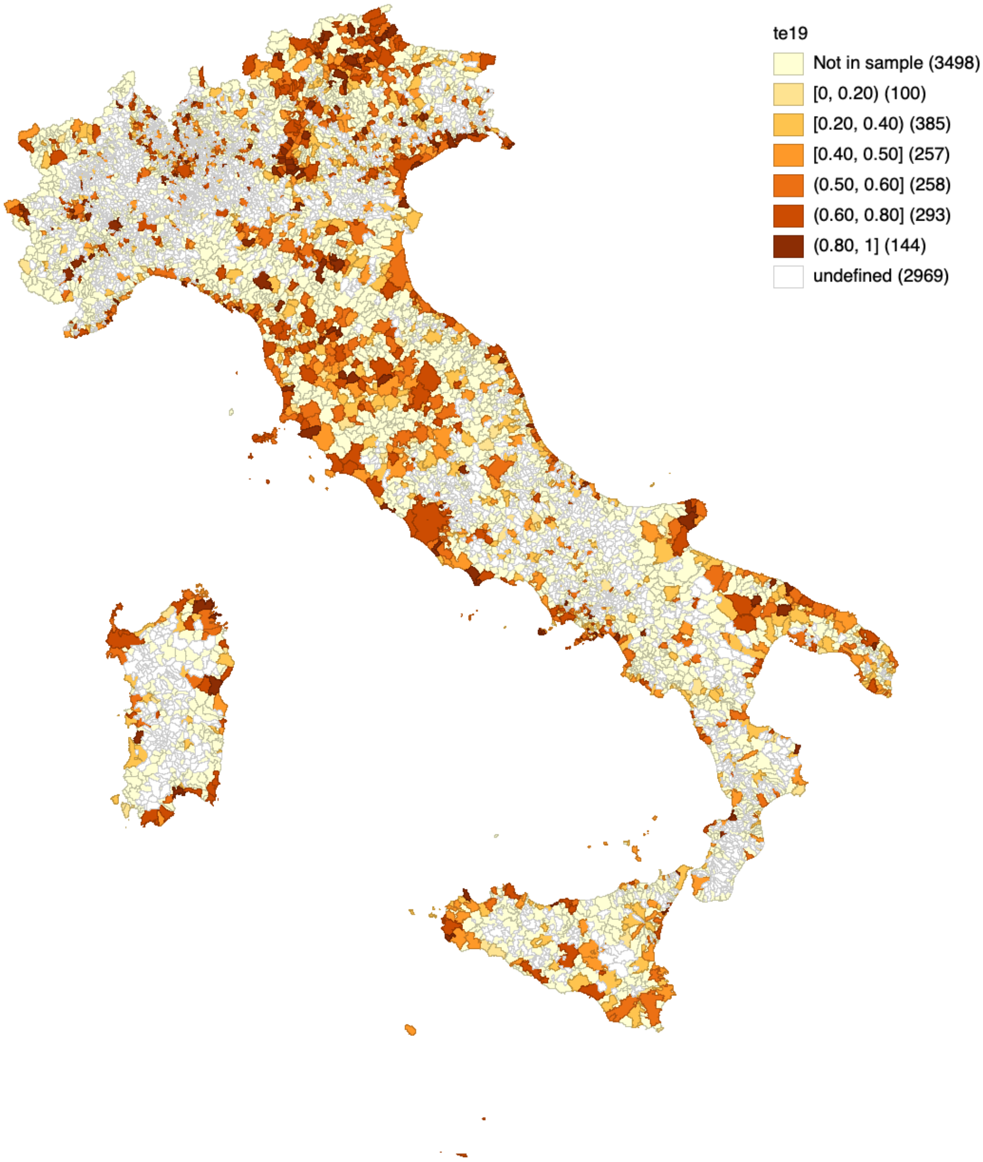

FIGURE 5.5: TE Municipality Map

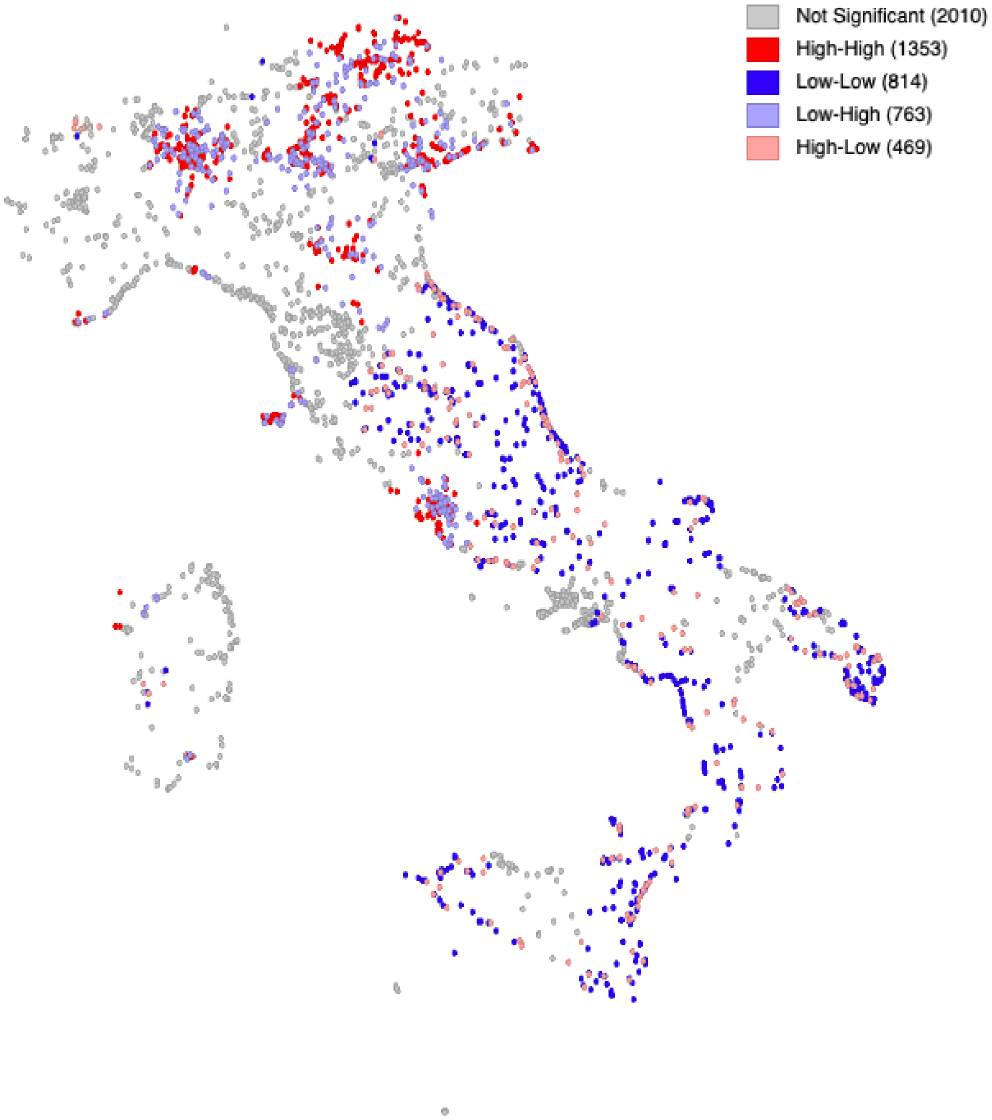

FIGURE 5.6: LISA significance cluster map: TE Scores 2019
(5% Significance Level)

clear division, there are some exceptions such as the area around Rome and the Tuscan archipelago which are mostly characterized by the presence of high-high and low-high clusters in spite of being located in the Center of Italy. Looking at the differences with respect to Figure 5.3, it can be noticed that, in the Romagna Riviera, despite the presence of significant high-high and low-high productivity clusters, hotels mainly belong to low-low and high-low clusters considering their efficiency level proxied by the TE scores. Conversely, the area of Rome results to be characterized by the presence of low-low and high-low productivity clusters and high-high and low-high efficiency clusters. Moreover, spatial dependence is not significant in the central internal areas of Italy in terms of productivity while significant low-low and high-low clusters occur considering the TE scores. On the other hand, the region of Liguria, the Southern coast of Sardinia, and the areas around Naples and Florence are characterized by significant productivity clusters while there is no significant local spatial dependence in the efficiency level of accommodation facilities located in these territories.

TABLE 5.7: Spatial Weight Matrices: Descriptive Statistics

	Mean w_{ij}	**Min neigh.**	**10th perc.**	**Mean neigh.**	**90th perc.**	**Max neigh.**	**Islands**
W	0.0093	5409	5409	5409	5409	5409	0
W200t	0.0074	14	247	986.03	1603	2030	0
W100t	0.0066	5	104	341.29	526	733	0
W50t	0.0062	0	34	158.61	332	442	1
W30t	0.0059	0	12	98.53	263	412	4
W400n	0.0079	400	400	400	400	400	0
W250n	0.0073	250	250	250	250	250	0
W100n	0.0059	100	100	100	100	100	0
W50n	0.0049	50	50	50	50	50	0
W30n	0.0042	30	30	30	30	30	0

Mean w_{ij} is calculated before row-normalization;
neigh=neighbours; perc.=percentile

5.5.4 Does distance matter in shaping agglomeration externalities?

The effect of agglomeration externalities can vary depending on the spatial distance considered (Arbia, 1989). Indeed, it is interesting to evaluate if the magnitude of the spatial effects detected before is robust to different specifications of the spatial weight matrix. This further analysis can allow us to precisely identify how the indirect effects are affected by the geographical distance considered. This information can be very relevant

TABLE 5.8: Sensitivity to the Choice of W: Inverse Distance Truncated W

	W		W200t		W100t		W50t		W30t	
	Coef.	*t-stats*	*Coef.*	*t-stats*	*Coef.*	*t-stats*	*Coef.*	*t-stats*	*Coef.*	*t-stats*
β_0	5.467***	13.71	5.876	14.86***	6.058***	15.07	6.244***	15.27	6.439***	15.35
β_L	0.662***	84.87	0.661***	84.76	0.662***	84.83	0.661***	84.76	0.661***	84.71
β_K	0.077***	17.20	0.078***	17.29	0.078***	17.27	0.078***	17.29	0.078***	17.29
β_{LL}	0.057***	40.57	0.057***	40.71	0.057***	40.64	0.057***	40.64	0.057***	40.57
β_{KK}	0.010***	22.50	0.010***	25.00	0.01***	25.00	0.01***	25.00	0.01***	25.00
β_{LK}	-0.029***	-29.00	-0.030***	-29.60	-0.030***	-29.70	-0.030***	-29.60	-0.029***	-29.50
β_t	-0.005	-1.09	-0.001	-0.24	-0.001	-0.20	-0.001	-0.09	0.001	0.23
β_{2t}	-0.001*	-1.25	-0.001**	-2.00	-0.001**	-2.00	-0.001**	-2.00	-0.001**	-2.00
β_{tL}	0.004***	5.00	0.004***	5.00	0.004***	5.00	0.004***	5.00	0.004***	5.00
β_{tK}	0.001***	1.25	0.001***	3.00	0.001***	3.00	0.001***	3.00	0.001***	3.00
ρ	0.351***	18.30	0.253***	18.06	0.212***	17.82	0.171***	9.23	0.132***	15.13
θ_L	-0.216***	-11.33	-0.146***	-10.57	-0.119***	-10.15	-0.091***	-9.23	-0.064***	-7.47
θ_K	0.006	0.78	0.008*	1.42	0.007*	1.49	0.005*	1.26	0.001	0.14
ϕ_0	5.251***	13.23	5.402***	13.71	5.493***	13.70	5.575***	13.67	5.625***	13.43
ϕ_{hum}	-0.647***	-208.58	-0.646***	-208.26	-0.0645***	-208.06	-0.644***	-207.74	-0.644***	-207.87
ϕ_{Int}	-0.115***	-29.54	-0.116***	-29.62	-0.115***	-29.59	-0.115***	-29.56	-0.115***	-29.56
ϕ_{pat}	-0.054***	-9.53	-0.054***	-9.51	-0.053***	-9.33	-0.053***	-9.30	-0.053***	-9.30
ϕ_{trad}	-0.038***	-5.78	-0.038***	-5.89	-0.039***	-5.92	-0.039***	-6.00	-0.038***	-5.91
ϕ_{size}	-0.037***	-10.57	-0.036***	-10.37	-0.037***	-10.66	-0.038***	-10.94	-0.039***	-11.09
ϕ_{dsize}	0.081***	5.66	0.080***	5.58	0.079***	5.51	0.080***	5.54	0.077***	5.35
δ_{hum}	0.160***	7.31	0.116***	7.55	0.085***	6.50	0.055***	4.95	0.036***	3.74
δ_{Int}	-0.072***	-2.71	-0.061***	-3.23	-0.060***	-3.71	-0.052***	-3.84	-0.032***	-2.69
δ_{pat}	0.099***	2.80	0.094***	3.51	0.070***	3.03	0.037**	1.90	0.022*	1.31
δ_{trad}	0.039	0.97	0.033	1.10	0.035*	1.34	0.020	0.89	0.009	0.44
δ_{size}	-0.013	-0.70	-0.026**	-2.02	-0.020**	-1.73	-0.012	-1.20	-0.015**	-1.77
δ_{dsize}	-0.358***	-3.85	-0.230***	-3.43	-0.182***	-3.14	-0.134***	-2.73	-0.108***	-2.59
ϕ_{city}	-0.064***	-5.94	-0.069***	-6.46	-0.066***	-6.22	-0.062***	-5.87	-0.059***	-5.63
ϕ_{cult}	0.016*	1.43	0.019**	1.62	0.017*	1.52	0.019**	1.63	0.024**	2.13
ϕ_{sea}	-0.095***	-8.89	-0.096***	-8.94	-0.095***	-8.83	-0.089***	-8.41	-0.083***	-7.81
ϕ_{lake}	-0.139***	-9.06	-0.133***	-8.67	-0.131***	-8.55	-0.134***	-8.76	-0.133***	-8.67
ϕ_{mou}	-0.007	-0.45	-0.004	-0.25	-0.011	-0.72	-0.019	-1.25	-0.012	-0.78
ϕ_{csea}	-0.085***	-8.12	-0.085***	-8.38	-0.086***	-8.30	-0.080***	-7.71	-0.072***	-6.96
ϕ_{cmou}	-0.065***	-5.04	-0.055***	-4.32	-0.060***	-4.66	-0.063***	-4.84	-0.061***	-4.77
ϕ_{more}	-0.047***	-3.77	-0.045***	-3.67	-0.045***	-3.68	-0.044***	-3.59	-0.040***	-3.24
ϕ_{nocat}	0.052***	4.71	0.053***	4.78	0.053***	4.84	0.053***	4.86	0.0542***	4.97
ϕ_{notur}	0.015	0.48	0.012	0.39	0.013	0.41	0.012	0.38	0.011	0.34
ϕ_{therm}	omit.		omit.		omit.		omit.		omit.	
σ^2	0.199	-	0.199	-	0.199	-	0.199	-	0.200	-
λ	0.879	-	0.888	-	0.886	-	0.885	-	0.882	-

$***: pvalue \leq 0.01$; $**: pvalue \leq 0.05$; $*: pvalue \leq 0.10$; omit=omitted

TABLE 5.9: Sensitivity to the Choice of W: Nearest Neighbours

	W400n		**W250n**		**W100n**		**W50n**		**W30n**	
	Coef.	*t-stats*	*Coef.*	*t-stats*	*Coef.*	*t-stats*	*Coef.*	*t-stats*	*Coef.*	*t-stats*
β_0	5.969**	15.63	6.046***	16.27	6.205***	16.31	6.359***	15.99	6.429***	16.38
β_L	0.662***	84.87	0.662***	84.87	0.662***	84.87	0.662***	84.87	0.663***	85.00
β_K	0.078***	17.33	0.078***	17.33	0.078***	17.33	0.078***	17.33	0.078***	17.33
β_{LL}	0.057***	40.71	0.057***	40.71	0.057***	40.71	0.057***	40.71	0.057***	40.71
β_{KK}	0.010***	25.00	0.010***	25.00	0.010***	25.00	0.010***	25.00	0.010***	25.00
β_{LK}	-0.030***	-30.00	-0.03***	-30.00	-0.03***	-30.00	-0.03***	-30.00	-0.03***	-30.00
β_t	-0.001**	-0.23	-0.001	-0.23	-0.001	-0.23	-0.001	-0.23	-0.001	-0.23
β_{2t}	-0.001***	-2.50	-0.001***	-2.50	-0.001***	-2.50	-0.001***	-2.50	-0.001***	-2.50
β_{tL}	0.004***	5.00	0.004***	5.00	0.004***	5.00	0.004***	5.00	0.004***	5.00
β_{tK}	0.001***	2.50	0.001***	2.50	0.001***	2.50	0.001***	2.50	0.001***	2.50
ρ	0.234***	18.14	0.217***	18.08	0.180***	17.31	0.153***	19.15	0.131***	15.23
θ_L	-0.132***	-10.39	-0.122***	-10.34	-0.101***	-9.90	-0.081***	-10.98	-0.067***	-7.98
θ_K	0.005***	0.94	0.004	0.82	0.004	0.93	0.003	1.03	0.006**	1.71
ϕ_0	5.442**	14.29	5.481***	14.80	5.546***	14.62	5.633***	14.33	5.661***	14.45
ϕ_{hum}	-0.645***	-208.06	-0.645***	-208.06	-0.644***	-207.74	-0.644***	-207.74	-0.644***	-207.74
ϕ_{Int}	-0.115***	-29.49	-0.115***	-29.49	-0.115***	-29.49	-0.116***	-29.49	-0.116***	-29.74
ϕ_{pat}	-0.053***	-9.30	-0.053***	-9.30	-0.053***	-9.30	-0.052***	-9.30	-0.052***	-9.12
ϕ_{trad}	-0.038***	-5.85	-0.038***	-5.85	-0.039***	-6.00	-0.039***	-6.00	-0.039***	-6.00
ϕ_{size}	-0.037***	-10.57	-0.038***	-10.86	-0.038***	-10.86	-0.038***	-10.86	-0.038***	-10.86
ϕ_{dsize}	0.080***	5.56	0.080***	5.56	0.079***	5.49	0.079***	5.49	0.078***	5.42
δ_{hum}	0.097***	6.78	0.084***	6.27	0.062***	5.30	0.044***	5.90	0.031***	3.23
δ_{Int}	-0.050***	-2.91	-0.052***	-3.25	-0.057***	-4.04	-0.044***	-4.56	-0.039***	-3.45
δ_{pat}	0.067***	2.73	0.046**	2.02	0.024	1.22	0.020*	1.37	0.012	0.75
δ_{trad}	0.045**	1.58	0.044**	1.65	0.028	1.20	0.033*	1.35	0.032**	1.70
δ_{size}	-0.017***	-1.39	-0.017*	-1.48	-0.017**	-1.65	-0.021**	-1.81	-0.017**	-1.98
δ_{dsize}	-0.196**	-3.06	-0.181***	-3.01	-0.151***	-2.87	-0.155***	-3.23	-0.144***	-3.42
ϕ_{city}	-0.067***	-6.32	-0.064***	-6.04	-0.058***	-5.52	-0.061***	-5.52	-0.063***	-6.06
ϕ_{cult}	0.015***	1.32	0.014	1.23	0.017*	1.49	0.017*	1.49	0.018*	1.58
ϕ_{sea}	-0.096***	-8.97	-0.095***	-8.88	-0.09***	-8.49	-0.089***	-8.49	-0.088***	-8.30
ϕ_{lake}	-0.129***	-8.43	-0.133***	-8.69	-0.135***	-8.82	-0.135***	-8.82	-0.137***	-8.95
ϕ_{mou}	-0.008**	-0.51	-0.015	-0.95	-0.017	-1.08	-0.018	-1.08	-0.016	-1.01
ϕ_{csea}	-0.088***	-8.46	-0.087***	-8.37	-0.081***	-7.79	-0.079***	-7.86	-0.077***	-7.48
ϕ_{cmou}	-0.060***	-4.65	-0.061***	-4.73	-0.063***	-4.88	-0.064***	-4.92	-0.063***	-4.92
ϕ_{more}	-0.045***	-3.63	-0.045***	-3.63	-0.044***	-3.58	-0.044***	-3.58	-0.044***	-3.58
ϕ_{nocat}	0.053***	4.82	0.053***	4.82	0.050***	4.55	0.046***	4.55	0.046***	4.18
ϕ_{notur}	0.012*	0.38	0.006	0.19	0.002	0.06	-0.002	-0.06	-0.002	-0.06
ϕ_{therm}	omit.		omit.		omit.		omit.		omit.	
σ^2	0.1994		0.199		0.199		0.199		0.199	
λ	0.8881		0.895		0.896		0.916		0.908	

$***: pvalue \leq 0.01$; $**: pvalue \leq 0.05$; $*: pvalue \leq 0.10$; omit=omitted

TABLE 5.10: Marginal Effects: Sensitivity to the Choice of W

		W	**W200t**	**W100t**	**W50t**	**W30t**	**W400n**	**W250n**	**W100n**	**W50n**	**W30n**
L	*Direct*	0.743***	0.738***	0.738***	0.738***	0.738***	0.738***	0.738***	0.738***	0.739***	0.738***
	Indirect	0.071***	0.056***	0.048***	0.043***	0.038***	0.054***	0.049***	0.039***	0.038***	0.034***
	Total	0.814***	0.794***	0.079***	0.782***	0.776***	0.792***	0.787***	0.777***	0.777***	0.772***
K	*Direct*	0.136***	0.136***	0.148***	0.148***	0.147***	0.148***	0.148***	0.147***	0.148***	0.147***
	Indirect	0.082***	0.056***	0.048***	0.036***	0.023***	0.050***	0.046***	0.037***	0.030***	0.028***
	Total	0.218***	0.192***	0.196***	0.184***	0.170***	0.198***	0.194***	0.184***	0.178***	0.175***
t	*Direct*	0.006***	0.007***	0.007***	0.008***	0.009***	0.008***	0.008***	0.008***	0.008***	0.008***
	Indirect	0.004***	0.003***	0.002***	0.002***	0.001***	0.002***	0.002***	0.002***	0.002***	0.001***
	Total	0.010***	0.010***	0.009***	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***	0.009***
Hum	*Direct*	-0.647***	-0.646***	-0.646***	-0.645***	-0.645***	-0.0646***	-0.645***	-0.645***	-0.645***	-0.645***
	Indirect	-0.103***	-0.063***	-0.065***	-0.066***	-0.056***	-0.069***	-0.070***	-0.066***	-0.063***	-0.061***
	Total	-0.750***	-0.709***	-0.711***	-0.710***	-0.700***	-0.715***	-0.715***	-0.711***	-0.708***	-0.706***
Int	*Direct*	-0.116***	-0.117***	-0.117***	-0.116***	-0.116***	-0.116***	-0.116***	-0.116***	-0.117***	-0.117***
	Indirect	-0.171***	-0.120***	-0.106***	-0.085***	-0.053***	-0.099***	-0.097***	-0.094***	-0.072***	-0.061***
	Total	-0.287***	-0.236***	-0.222***	-0.202***	-0.169***	-0.216***	-0.213***	-0.210***	-0.189***	-0.178***
Pat	*Direct*	-0.054***	-0.053***	-0.052***	-0.053***	-0.053***	-0.053***	-0.052***	-0.052***	-0.052***	-0.052***
	Indirect	0.122***	0.107***	0.073***	0.033	0.017	0.071***	0.044**	0.017	0.013	0.006
	Total	0.0688**	0.054*	0.021	-0.019	-0.036	0.018	-0.008	-0.035	-0.039	-0.046*
Trad	*Direct*	-0.037***	-0.038***	-0.038***	-0.039***	-0.038***	-0.038***	-0.038***	-0.039***	-0.039***	-0.038***
	Indirect	0.039*	0.031	0.034	0.016	0.004	0.047*	0.045*	0.025	0.031	0.03
	Total	0.002	-0.007	-0.04	-0.023	-0.034	0.009	0.007	-0.013	-0.007	-0.008
Size	*Direct*	-0.037***	-0.037***	-0.038***	-0.039***	-0.039***	-0.037***	-0.038***	-0.038***	-0.038***	-0.039***
	Indirect	-0.040***	-0.048***	-0.035**	-0.022*	-0.023**	-0.034***	-0.032***	-0.028**	-0.031***	-0.025**
	Total	-0.077***	-0.084***	-0.073***	-0.061***	-0.062***	-0.071***	-0.070***	-0.067***	-0.069***	-0.064***

$***: pvalue \leq 0.01$; $**: pvalue \leq 0.05$; $*: pvalue \leq 0.10$

to policymakers in order to understand if place-based policies exploiting the existence of spatial interactions tend to be more effective at the local or global level.

Therefore, we estimate the SDF-STE model in Eq. (5.1)-(5.2) considering different kinds of spatial weight matrices. Specifically, we substitute the dense inverse distance spatial weight matrix W used until now with different truncated inverse distance spatial weight matrices considering only a certain radius around the i^{th} observation or the n nearest observations as neighbours. In particular, we define W200t, W100t, W50t, and W30t as inverse distance spatial weight matrices truncated at 200, 100, 50, and 30 kilometres respectively, while W400n, W250n, W100n, W50n, and W30n indicate inverse distance spatial weight matrices considering only the 400, 250, 100, 50, and 30 nearest neighbours, respectively. Some descriptive statistics for these different spatial weight matrices are shown in Table 5.7. The most relevant difference between the two types of spatial weight matrices previously defined concerns the fact that the number of neighbours changes for each spatial unit using a truncated W while every unit has the same number of neighbours in the second case. Moreover, starting from a truncation point of 50 km some units are considered islands (i.e. observations with no neighbours). However, in both cases, the mean spatial weight w_{ij} tends to decrease as the radius or the number of nearest neighbours considered decreases.

Table 5.8 and Table 5.9 show how the estimation results are affected by different choices of the spatial weight matrix. In particular, it can be noticed that the β and the ϕ estimates are robust to different changes of W, as well as the estimates associated with the two variance parameters σ^2 and λ. Therefore, as expected, only the spatial parameters ρ, θ, and δ are affected by different choices of the spatial weight matrix. Specifically, the degree of global spatial dependence captured through ρ tends to decrease as the number of neighbours considered in the analysis decreases, passing from a maximum value of 0.351 using a dense inverse distance W, to 0.132 and 0.131 considering W30t and W30n, respectively. This is due to a reduction of the w_{ij} values used to weight the spatial units, as shown in the first column of Table 5.7. Consequently to a reduction in the value of ρ, also the estimated local spatial dependence associated with the two inputs (θ) and the determinants of technical inefficiency (δ) modifies.

To interpret the estimated coefficients in a meaningful way, direct, indirect and total marginal effects should be computed, as shown in Table 5.10. Results in Table 5.10 indicate that considering a dense inverse distance spatial weight matrix leads to a slight overestimation of the indirect effects with respect to the case in which a sparse spatial weight matrix is used. Indeed, while the direct effect of labour and capital are quite stable across the different trials, the indirect effects of L and K pass from a maximum value of 0.071 and 0.082 to 0.034 and 0.023, respectively but they remain always positive and significant. Similarly, also the direct effects associated with Hum, Int, Pat, $Trad$, and $Size$ result to be constant even if the spatial weight matrix changes while the indirect effects decrease as the number of neighbours reduces. Considering the indirect effects of the determinants of hotels' inefficiency on u, while the indirect effects associated with human capital, intangible investments, and firms' size are always negative and significant across all the different trials, the indirect effect of patents results to be significant only using W, W200t, W100t, W400n, and W250n and the indirect effect of trademarks only for W, W400n, and W250n. Hence, patents and trademarks seem to generate negative spillovers and to effectively protect new products and ideas only considering high distances, while the indirect effect resulting from having neighbours that have registered trademarks and/or patents is not significant for hotels that are very close to the innovative firm. Thus, negative spatial spillovers generated from registered patents or trademarks apply at a global level but are not significant at a local level. Indeed, at a local level, positive externalities due to interpersonal contact and shared ideas at meetings and events can occur, eliminating patents' and trademarks' blocking function.

To sum up, our results indicate that while the estimated direct effects are stable across the different specifications of W, the indirect effects tend to raise in magnitude as the geographical distance considered to identify neighbouring units increases. Thus, spatial spillover effects occurring in the Italian accommodation sector tend to cumulate across space, in line with the results of Cainelli and Ganau (2018) for the Italian manufacturing industry. Hence, it would be more effective for policymakers to develop plans aiming at fostering the innovativeness of the whole sector at the national level without focusing on single local areas to entirely exploit the existing spatial interactions.

5.5.5 Robustness Check

Besides spatial individual heterogeneity, unobserved individual-specific effects such as entrepreneurial or managerial skills are likely relevant to hotel performance and the productive outcome of hotels may be endogenously related to the input variables or to the inefficiency determinants. Moreover, it is quite plausible that hotels with good prospects can decide to locate in areas close to competitors to benefit from local advantages, generating endogeneity issues due to omitted variables. However, to date, in stochastic frontier models literature, there are no current available methods dealing together with spatial heterogeneity, individual heterogeneity and endogeneity.

However, given the relevant role of both individual effects and endogeneity issues, in this section, we compare our results to other SF approaches that allow considering individual-specific effects or controlling for possible endogeneity in order to test the robustness of our baseline estimates. Specifically, when dealing with individual heterogeneity we compare our non-spatial results corresponding to the Battese and Coelli (1995) specification with those of the non-spatial true fixed effect stochastic frontier model introduced by Greene (2005a) because, at the moment, there are no available spatial SF models controlling for individual heterogeneity. On the other hand, following Castiglione and Infante (2014) and de Vries and Koetter (2011), we partially attempt to control for the presence of endogeneity by introducing in our SDF-STE model lagged input variables and lagged determinants of inefficiency. Specifically, we model the productive outcome

TABLE 5.11: Robustness Check with Fixed Effects

	SF-TE		Fixed Effects	
	Coeff.	*t-stats*	*Coeff.*	*t-stats*
β_0	6.665***	7.68	6.826***	5.17
β_L	0.665***	85.11	0.652***	84.51
β_K	0.077***	17.04	0.081***	18.17
β_{LL}	0.057***	40.43	0.054***	39.34
β_{KK}	0.010***	25	0.010***	24.07
β_{LK}	-0.029***	-26.46	-0.028***	-26.42
β_t	0.005	0.96	0.006	1.48
β_{2t}	-0.001**	-2.75	-0.001***	-3.35
β_{tL}	0.004***	4.88	0.004***	5.28
β_{tK}	0.001***	3.5	0.001***	3.55
ϕ_0	5.363***	6.22	5.206***	6.13
ϕ_{hum}	-0.653***	-210.74	-0.633***	-205.52
ϕ_{Int}	-0.116***	-29.05	-0.110***	-27.61
ϕ_{pat}	-0.054***	-9.38	-0.045***	-7.47
ϕ_{trad}	-0.039***	-5.91	-0.044***	-6.6
ϕ_{size}	-0.040***	-11.54	-0.048***	-13.03
ϕ_{dsize}	0.069***	4.73	0.067***	4.6
Dest. dummies	yes	-	yes	-
σ^2	0.20	-	0.16	-
λ	0.86	-	0.85	-

$***: pvalue \leq 0.01$; $**: pvalue \leq 0.05$; $*: pvalue \leq 0.10$

TABLE 5.12: Robustness Check with Lagged variables

	SDF-STE			Lag-1			Lag-2	
	Coeff.	*t-stats*		*Coeff.*	*t-stats*		*Coeff.*	*t-stats*
β_0	5.467***	13.71	β_0	5.947***	15.62	β_0	5.372***	12.57
β_L	0.662***	84.87	$\beta_{L(t-1)}$	0.660***	70.26	$\beta_{L(t-2)}$	0.635***	53.80
β_K	0.077***	17.20	$\beta_{K(t-1)}$	0.058***	10.87	$\beta_{K(t-2)}$	0.053***	8.22
β_{LL}	0.057***	40.57	$\beta_{LL(t-1)}$	0.057***	35.38	$\beta_{LL(t-2)}$	0.059***	32.72
β_{KK}	0.010***	22.50	$\beta_{KK(t-1)}$	0.011***	27.50	$\beta_{KK(t-2)}$	0.011***	22.40
β_{LK}	-0.029***	-29.00	$\beta_{LK(t-1)}$	-0.031***	-25.92	$\beta_{LK(t-2)}$	-0.032***	-24.46
β_t	0.005	1.09	β_t	0.009	1.27	β_t	0.043***	4.00
β_{2t}	-0.001**	-1.25	β_{2t}	-0.003***	-5.00	β_{2t}	-0.006***	-7.13
β_{tL}	0.004***	5.00	$\beta_{tL(t-1)}$	0.005***	4.80	$\beta_{tL(t-2)}$	0.006***	4.69
β_{tK}	0.001***	3.00	$\beta_{tK(t-1)}$	0.004***	7.20	$\beta_{tK(t-2)}$	0.004***	6.50
ρ	0.351***	18.30	ρ	0.359***	18.03	ρ	0.367***	17.40
θ_L	-0.216***	-11.33	$\theta_{L(t-1)}$	-0.219***	-10.77	$\theta_{L(t-2)}$	-0.219***	-10.03
θ_K	0.006	0.78	$\theta_{K(t-1)}$	0.007	0.78	$\theta_{K(t-2)}$	0.006	0.62
ϕ_0	5.251***	13.23	ϕ_0	5.749***	15.44	ϕ_0	5.269***	12.52
ϕ_{hum}	-0.647***	-208.58	$\phi_{hum(t-1)}$	-0.602***	-176.94	$\phi_{hum(t-2)}$	-0.583***	-149.36
ϕ_{Int}	-0.115***	-29.54	$\phi_{Int(t-1)}$	-0.126***	-27.98	$\phi_{Int(t-2)}$	-0.129***	-25.31
ϕ_{pat}	-0.054***	-9.53	ϕ_{pat}	-0.081***	-12.42	ϕ_{pat}	-0.106***	-14.28
ϕ_{trad}	-0.038***	-5.78	ϕ_{trad}	-0.057***	-7.70	ϕ_{trad}	-0.077***	-9.12
ϕ_{size}	-0.037***	-10.57	ϕ_{size}	-0.045***	-11.54	ϕ_{size}	-0.054***	-11.98
ϕ_{dsize}	0.081***	5.66	ϕ_{dsize}	0.082***	5.02	ϕ_{dsize}	0.081***	4.39
δ_{Hum}	0.160***	7.31	$\delta_{Hum(t-1)}$	0.121***	5.14	$\delta_{Hum(t-2)}$	0.108***	4.15
δ_{Int}	-0.072***	-2.71	$\delta_{Int(t-1)}$	-0.051***	-1.72	$\delta_{Int(t-2)}$	-0.03	-0.89
δ_{Pat}	0.099***	2.80	δ_{Pat}	0.127***	3.20	δ_{Pat}	0.146***	3.21
δ_{Trad}	0.039	0.97	δ_{Trad}	0.050	1.10	δ_{Trad}	0.039	0.75
δ_{Size}	-0.013	-0.70	δ_{Size}	-0.023	-1.10	δ_{Size}	-0.032*	-1.34
δ_{dsize}	-0.358***	-3.85	δ_{dsize}	-0.327***	-3.11	δ_{dsize}	-0.307***	-2.55
Dest. dummies	yes	-	Dest. dummies	yes	-	Dest. dummies	yes	-
σ^2	0.199	-	σ^2	0.225	-	σ^2	0.258	-
λ	0.879	-	λ	0.371	-	λ	0.515	-

$***: pvalue \leq 0.01$; $**: pvalue \leq 0.05$; $*: pvalue \leq 0.10$

TABLE 5.13: Robustness Check with Lagged variables and Fixed Effects

	SF-TE			FE and Lag-1			FE and Lag-2	
	Coeff.	*t-stats*		*Coeff.*	*t-stats*		*Coeff.*	*t-stats*
β_0	6.665***	7.68	β_0	6.737***	16.21	β_0	6.181***	26.16
β_L	0.665***	85.11	$\beta_{L(t-1)}$	0.652***	74.5	$\beta_{L(t-2)}$	0.634***	63.08
β_K	0.077***	17.04	$\beta_{K(t-1)}$	0.062***	12.28	$\beta_{K(t-2)}$	0.059***	10.13
β_{LL}	0.057***	40.43	$\beta_{LL(t-1)}$	0.054***	35.15	$\beta_{LL(t-2)}$	0.058***	32.73
β_{KK}	0.010***	25.00	$\beta_{KK(t-1)}$	0.011***	24.6	$\beta_{KK(t-2)}$	0.012***	22.77
β_{LK}	-0.029***	-26.46	$\beta_{LK(t-1)}$	-0.030***	-25.15	$\beta_{LK(t-2)}$	-0.031***	-23.31
β_t	0.005	0.96	β_t	0.044***	7.70	β_t	0.101***	11.25
β_{2t}	-0.001**	-2.75	β_{2t}	-0.005***	-11.64	β_{2t}	-0.009***	-13.68
β_{tL}	0.004***	4.88	$\beta_{tL(t-1)}$	0.003***	3.76	$\beta_{tL(t-2)}$	0.003***	2.87
β_{tK}	0.001***	3.50	$\beta_{tK(t-1)}$	0.004***	8.21	$\beta_{tK(t-2)}$	0.004***	6.97
ϕ_0	5.363***	6.22	ϕ_0	4.974***	14.62	ϕ_0	5.633***	14.33
ϕ_{hum}	-0.653***	-210.74	$\phi_{hum(t-1)}$	-0.578***	-166.44	$\phi_{hum(t-2)}$	-0.555***	-141.30
ϕ_{Int}	-0.116***	-29.05	$\phi_{Int(t-1)}$	-0.123***	-27.28	$\phi_{Int(t-2)}$	-0.128***	-24.71
ϕ_{pat}	-0.054***	-9.38	ϕ_{pat}	-0.073***	-10.80	ϕ_{pat}	-0.099***	-12.96
ϕ_{trad}	-0.039***	-5.91	ϕ_{trad}	-0.067***	-8.83	ϕ_{trad}	-0.088***	-10.20
ϕ_{size}	-0.040***	-11.54	ϕ_{size}	-0.059***	-14.19	ϕ_{size}	-0.070****	-14.75
ϕ_{dsize}	0.069***	4.73	ϕ_{dsize}	0.068***	4.13	ϕ_{dsize}	0.066***	3.49
Dest. dummies	yes	-	Dest. dummies	yes	-	Dest. dummies	yes	-
σ^2	0.20	-	σ^2	0.18	-	σ^2	0.21	-
λ	0.86	-	λ	0.84	-	λ	0.85	-

$***: pvalue \leq 0.01$; $**: pvalue \leq 0.05$; $*: pvalue \leq 0.10$

of period t as a function of labour and capital at time $t-1$ and of the 1-year lag of intangible investments and human capital. Furthermore, we also make a second robustness check considering a two-year lag. Starting from individual effects, as shown in Table 5.11, our non-spatial estimates are robust to the different modelling approach and thus, unobserved individual heterogeneity has a negligible impact on the estimation results. Concerning endogeneity, the results shown in Table 5.12 confirm the robustness of our estimates to simultaneity issues related to the input variables and to the determinants of inefficiency. Finally, in Table 5.13 we show the results of the final robustness check controlling for both individual fixed effects and endogeneity using lagged variables starting from the non-spatial specification proposed by Battese and Coelli (1995). Overall, the results are in line with our baseline estimates, showing that distortions arising from individual unobserved effects and endogeneity are negligible.

5.6 Final Remarks

Scholars have widely acknowledged the relevance of spatial interactions in affecting the productivity level of hotels belonging to tourism clusters. However, to date, no studies have yet clearly identified the different typologies, the magnitude, and the sources of these spatial effects. Thus, using georeferenced data and taking advantage of the SDF-STE model, in this chapter we provide new insights on the spatial spillover effects related to the determinants of hotels' innovative activity.

Results from this analysis indicate that the Italian accommodation sector is a labour-intensive sector with a high exploitation of internal human resources rather than investments in intangible capital. Therefore, to achieve higher profitability levels, hotels, from an internal point of view, rely more on innovation related to human capital, knowledgeable and skilled workers, and improved service quality than on product innovation generated by intangible investments (Q1). Considering spillover effects, we find that the innovative activity performed by neighbours significantly spreads across space (Q2) generating both agglomeration and competition effects (Q3). In particular, our results show that having nearby hotels that invest in labour and capital positively affects the level of productivity of neighbouring hotels. Similarly, having neighbours who invest in human capital has a positive effect on hotels' efficiency level as well as having neighbours making intense innovative activity. In particular, we detect a greater positive indirect effect of intangible investments on firm efficiency compared to the direct one, meaning that spillover effects generated by highly innovative hotels have a stronger cumulative impact on neighbouring firms than on the innovator itself. Therefore, despite being a labour-intensive sector, investments in intangible capital by a few innovative hotels contribute to the development of the whole Italian accommodation sector. In addition, having bigger hotels as peers positively affect the efficiency level of nearby firms. Conversely, registered patents and/or trademarks generate negative spillovers across neighbours thanks to a strong protection and blocking function. Thus, different sources of innovation generate different spatial effects, both positive and negative.

Our findings have important implications both from a theoretical and a practical perspective. From a scientific point of view, we empirically confirm the key role played by innovation in the hotel sector as a promoter of competitive advantage in tourism destinations. Moreover, in line with the industrial agglomeration theory, this paper extends to the Italian accommodation industry previous findings on other industrial sectors regarding the relevance of firms' location choices and of spatial interactions in influencing the level of competitiveness of neighbouring units. New insights from this study on spatial patterns affecting hotels' performance concern (i) the evidence of significant spatial effects both at the global and local level; (ii) the existence of different spillovers in terms of magnitude and signs resulting from the different sources of internal innovation.

From a practical perspective, insights from this analysis can be useful both for accommodation managers to improve their production processes by innovating and creating hotel networks and alliances, and for policymakers to design place-based policies supporting hotels' innovative activity and spatial interactions across tourism firms. Public incentives for the tourism sector should be aimed at stimulating hotels' innovative activity due to its high association with hotel performance. Since innovation is still an underdeveloped activity in the accommodation industry, external push factors are fundamental to spurring product and process innovation in the hospitality industry. Efficient innovation policies in this sector should stimulate innovations that allow energy savings and the sustainable management of resources in order to pursue sustainability, help hospitality businesses to create synergies that help overcome the limitations deriving from the small size, and motivate hotels' managers to personalize their offer thanks to the possibility of profiling customers in an increasingly specific and detailed manner. In addition, other accessible innovations such as IT adoption, improvements in customer service and in administrative practices, architectural and infrastructural renovation, and collaboration with the other actors in the sector should be promoted. Policymakers should therefore encourage accommodation facilities to network and create a healthy competitive environment allowing the transmission of new knowledge and innovation. In particular, innovative activity performed by bigger hotels tends to spread out to all neighbouring small and medium-sized hotels that are more unwilling to innovate. Therefore, by reinforcing hotels' networking and cooperation, the few big innovators in the sector may act as role models and knowledge disseminators for all those small entrepreneurs who are the main providers of hospitality services. This diffusion mechanism can foster and sustain the growth of the tourism sector and consequently, of the whole Italian economy.

Chapter 6

Productive Performance and Spatial Effects: Evidence from the Italian Agricultural Sector

6.1 The Main Characteristics of the Italian Agricultural Sector

6.1.1 Introduction to the Italian Agricultural Sector

The second empirical application of this thesis concentrates on the Italian agricultural sector. Indeed, Italy is one of the largest agricultural producers among the EU 24 countries and the agricultural sector is the largest manufacturing sector in Italy. In particular, in 2018 the total agricultural production reached EUR 55.8 billion while the total production value reached 113.7 billion euros (fi-compass, 2020).

The Italian agricultural sector tends to be more concentrated in Northern regions than in the whole country (Brasili and Fanfani, 2015) and it is characterized by inadequate resources and unqualified personnel, unable to develop new technologies (Cardamone, 2020). Innovation tends to be generally assimilated by equipment and capital goods rather than expressed by indicators such as R&D or patents (Maietta, 2015). Anyway, innovation is essential to be competitive in foreign markets and to produce sustainable, healthy, and good-quality products that can meet consumers' needs. Therefore, to make up for the lack of new technologies and innovations that can lead to a more efficient food production (Ciliberti, Bröring, and Martino, 2016), farms tend to share information, knowledge and best practices (de Martino and Magnotti, 2018). As a consequence, internal R&D investments are replaced by external sources of knowledge (Acosta, Coronado, and Romero, 2015) and thus, in the Italian agricultural sector, networking and collaboration among firms have become essential practices that can help in spreading knowledge and fostering innovation. In addition to peers, firms tend to borrow advanced expertise also from other industries like the pharmaceutical, biotechnological or chemical sectors (Rama, 2008). Moreover, also universities and research institutes have a central role in sharing information and new knowledge with farms. Hence, Italian farms manage to be competitive despite their difficulties in innovating thanks to clustering, geographical proximity and to an intensive flow of productivity and knowledge spillovers (Cardamone, 2020). Therefore, in evaluating the level of productivity and efficiency of the Italian agricultural industry, it is necessary to consider farms' location and to take spatial dependence into consideration due to the strong concentration and territorial specialization of this sector.

6.1.2 The Main Determinants of Competitiveness

Concentrating on the agricultural sector, Latruffe (2010) widely discussed what are the main factors, both internal and external to the farm, that contribute to determining firms' competitiveness. Between the factors controllable by firms, a great debate concerns farms' size. Indeed, to take decisions concerning firms' structural changes, it is important to understand how the link between competitiveness and firm size works. Despite the relevance of this issue, it is still not clear whether small farms perform better than bigger ones, or vice versa. Indeed, Buckwell and Davidova (1993) theorized that farms run by family members have an advantage due to higher motivation given by family labour, while Hall and LeVeen (1978) claimed that economies of scale and wider access to the input market can favour bigger farms. Both theories were supported by several studies and, in addition, other authors proved that the relationship between farms' performance and size is U-shaped (Latruffe et al., 2005). Probably, all these different results may depend on the variety of indicators for size used by authors. Indeed, size can be measured in many different ways, such as utilised agricultural area, total output produced, farm value-added, herd size, labour, assets, etc... Scholars also found controversial results investigating the connection between farms' degree of specialization and competitiveness. Indeed, farm specialization can boost productivity because it makes the farmer specialize in a few particular activities, improving specific management skills (Brümmer, 2001), while diversification can be beneficial to productivity because it reduces the risks related to crop loss or disease (Bojnec and Latruffe, 2009). Moreover, many studies considered the socio-demographic characteristics of the farmer as a proxy for farmers' management skills. In most cases, the effect of a farmer's age on a farm's efficiency is found to be negative (Brümmer and Loy, 2000), probably due to the unwillingness of older farmers to innovate and adopt new technologies. As expected, a farmer's education is usually found to be positively associated with productivity (Latruffe et al., 2004) while, considering gender, there seem to be no differences in farms run by women or men (Quisumbing, 1996).

Considering the external factors (i.e. not controllable by firms), factor endowments and demand conditions play a fundamental role in affecting farms' performance. Indeed, resource availability is fundamental to generating competitive advantage, and changes in buyers' needs and preferences can influence firms' productive processes and practices (Porter, 1990). For example, people's belief that pasta was a low-calorie and low-fat food, made the Italian pasta processing sector become a highly competitive industry over the period 1988-1992 (Venturini and Boccaletti, 1998). Moreover, also government interventions and public policies may have a strong influence on producers and may affect competitiveness. Among others, public investments in R&D can help in spreading new technologies among firms and can boost farms' productivity. Besides public expenditures in R&D, also investments in infrastructures can be beneficial for firms' productivity growth, in particular considering investments in public transportation (Latruffe, 2010).

Among existing public interventions related to agricultural production, scholars principally concentrated on determining the effect of EU subsidies on farms' performance. Indeed, since 1962 the European Union started supporting agriculture and rural areas through the EU Common Agricultural Policy (CAP). This European policy, accounting for roughly 40% of the EU budget, is considered one of the major drivers of change in the agricultural sector, thanks to its direct effects on income and to the orientation of farming activities. In particular, in the first phase, supports were paid per hectare and only for specific crops while starting in 2003, the European Commission approved a major reform of the CAP based on the decoupling of direct payments, meaning that income payments were detached from the production of specific crops and from their yields. Scholars largely concentrated on assessing the effectiveness of the CAP in supporting farmers' performance and in improving the environmental impact of agricultural production which is one of the main goals of the CAP. Different theoretical studies (Ciaian and Swinnen, 2009; Hennessy, 1998) suggested that subsidies can both have a positive and a negative impact on farms. On one hand, subsidies can lower farmers' motivation to work efficiently, they can distort the production structure of farms leading to allocative inefficiency and they can generate soft budget constraints that lead to an inefficient use of resources. On the other hand, they can also act as a source of credit and allow farmers to innovate thanks to increased credit access, reduced risk aversion, and higher productive investments. Results from empirical studies on this topic are mixed and inconclusive. Brümmer and Loy (2000) found that the European farm credit program negatively affected the technical efficiency of German farms over the period 1987-1994. Differentiating among coupled (before 2003) and decoupled (after 2003) subsidies, Rizov, Pokrivcak, and Ciaian (2013) demonstrated that the CAP negatively affected the EU countries' agricultural sector until the implementation of the decoupling reform while, after the reform, the link between subsidies and farms performance became more nuanced and in several EU-15 countries it turned out to be positive. Examining specialised Dutch dairy farms over the period 2009–2016, Skevas and Lansink (2020) found that a one-unit (i.e. €10,000) increase in subsidies leads to a 2% decrease in farms' technical inefficiency. Finally, considering the impact of the CAP post-2013, including the new 'greening' requirements for direct payments, on agricultural land-use intensification and environment in Austria for the period 2025–2040, Kirchner, Schönhart, and Schmid (2016) confirmed scholars' concern that the new CAP reform may fail to deliver better environmental outcomes than its forerunners.

Finally, among the external factors influencing farms, location plays a fundamental role. Indeed, firms' location and the environmental characteristics of the area in which firms are embedded may determine various differences in farms' performance. The effects of location, clustering, and spatial spillovers across nearby firms are described in the next paragraph.

6.1.3 Spillovers and Geographical Location

In agricultural economics, it is fundamental to take spatial information into consideration when evaluating firms' productivity (Weiss, 1996). Indeed, several authors demonstrated that the existence of networks and the geographical localization of firms have a central role in determining the productivity level of the agricultural sector (Capitanio, Coppola, and Pascucci, 2010; Triguero, Córcoles, and Cuerva, 2013). Agricultural production is characterized by spatial dependence due to geographical phenomenons such as soil characteristics, landscape configurations, climatic conditions, and location-specific attributes such as cost of transportation, distance to the consuming centres, and the directions of local public goods and institutions (Areal, Balcombe, and Tiffin, 2012; Bockstael, 1996). Moreover, an individual's working motivation may be affected by the one of the surrounding farmers and this can result in shared knowledge and similar investment decisions. Thus, farmers working in the same area can emulate each other and a farmer may experience efficiency gains by learning how to use his resources more efficiently from neighbouring farmers (Skevas and Lansink, 2020). Hence, for the agricultural sector, farms' location and spillover effects are particularly relevant features, due to the strong influence of external factors like the natural environment, specific characteristics of the region, and the presence of nearby specialized farms.

In the agricultural economics literature, Foster and Rosenzweig (1995) is one of the first contributions investigating the presence of learning spillovers. In particular, they found evidence of a significant impact of neighbours' experience on rural Indian households' profitability levels. Later on, Wollni and Andersson (2014) demonstrated that farmers having a larger availability of information in their neighbourhood network and acting in cooperation with their neighbours are more likely to adopt new technologies such as organic agriculture. Similarly, Lapple et al. (2017) revealed that farmers take their peers' decisions into account in adopting new technologies. Moreover, they underlined that farmers are influenced by their peers, which in turn affects neighbouring farms, generating a global spatial spillover effect that influences the adoption rates of all neighbours. Likewise, Skevas and Lansink (2020) confirmed the existence of both positive and negative spillover effects across Dutch dairy farms observed over the period 2009–2016. Specifically, the authors found that being surrounded by older farmers negatively influences neighbours while being located close to more intensive producers decreases peers' inefficiency level. This latter result indicates that farmers can improve their efficiency level by learning from neighbours how to use their resources more effectively thanks to emulation and knowledge spillovers. Vidoli et al. (2016), concentrating on the Italian wine industry, highlighted that spatial proximity among wine producers can stimulate productivity, and that Italian wine clusters can be considered communitarian networks that continuously share technical advice in a collaborative environment. Analysing spatial spillovers at the aggregate level and concentrating on the TFP of the Italian agricultural sector over the period 2008-2015, Baldoni and Esposti (2020) found evidence of spatial productive clusters among Italian provinces. In a similar way, Martínez-Victoria, Sánchez-Val, and Arcas-Lario (2018) evidenced strong spatial interactions between nearby Spanish agricultural cooperatives. Martínez-Victoria, Sánchez-Val, and Lansink (2019), also demonstrated that, over the period 2005-2014, the productivity growth of agri-food companies located in Murcia (Spain) was associated with the productivity growth of nearby firms. Similarly, Cardamone (2020), using data on Italian food manufacturers, showed that higher productivity of peers can be beneficial to improve firms' productivity level and compete at the international level. Indeed, interacting with each other and sharing knowledge can foster TFP and can help in creating a successful market.

On the other hand, negative spillover effects were detected by Setiawan, Emvalomatis, and Lansink (2012) examining the relationship between technical efficiency and industrial concentration in the Indonesian food and beverages industry. Estimating technical efficiency using a DEA approach, the authors found that higher industrial concentration negatively influences technical efficiency scores indicating that firms located in highly concentrated areas tend to gain more through cartel and anti-competitive practices rather than from efficiency spillovers. In this framework, also Storm, Mittenzwei, and Heckelei (2014) found that Norwegian farms' survival probabilities from 1999 to 2009 were negatively affected by the presence of economically larger neighbouring farms, generating competition and adverse spatial spillovers.

Despite the acknowledged importance of spatial dependence in affecting the productivity and efficiency level of agricultural producers, to our knowledge, there are no studies evaluating the impact of different typologies of spatial spillover effects on the performance of firms belonging to the agricultural sector, especially for Italy. Therefore, in this chapter, we take advantage of the SDF-CSD model developed in this thesis to investigate the spatial spillover effects influencing Italian farms' productive performance.

6.2 Literature Review of SF Models in the Agricultural Sector

Stochastic frontier models have generally been applied to the agricultural sector since their earliest developments. A comprehensive list of empirical applications using stochastic frontier models to investigate the level of productivity of the agricultural sector can be found in Table 1 of Coelli (1995). In particular, the author lists 38 papers published between 1985 and 1994 based on the agricultural sector distinguishing among contributions using a DEA approach (10) and works applying stochastic frontier methods (28). The most common applications of stochastic frontier models concerning agriculture relate to rice production (11 papers) and to the dairy industry (7 papers).

Considering more recent works, Coelli, Rahman, and Thirtle (2003), using data for 16 regions of Bangladesh, applied a stochastic frontier production function to measure TFP growth, technical efficiency change and technological change in Bangladesh crop agriculture from 1960 to 1992 founding that TFP change depends on the green revolution technology and on agricultural research expenditures. Among other works using aggregate data, Lio and Hu (2009), investigating the relationship between six governance indicators and agricultural efficiency using a sample of 118 countries for the years 1996, 1998, 2000 and 2002 through a SF approach, found that agricultural efficiency of the poorer countries can be enhanced by improvements in the rule of law and by stimulating the respect of citizens for institutions. On the contrary, greater democracy is associated with lower agricultural efficiency levels. Moreover, Auci and Vignani (2020) investigating the impact of climate variability on the Italian regions' efficiency in terms of crop yields in the period 2000–2009 using a SF approach, found a negative effect of summer precipitations and a beneficial effect of spring and autumn rainfalls on crop yields. Considering temperature, regional efficiency is positively affected by an increase in winter and summer minimum temperatures while for autumn the authors found the opposite effect. Similarly, Chambers and Pieralli (2020) analyzed the relationship between US state-level TFP agricultural growth and weather finding that weather-related effects differ across Climate-Hub Regions but are particularly important in the Midwest. Finally, Song and Chen (2019) estimated a translog stochastic frontier production function to analyse the eco-efficiency of grain production and its determinants in China finding that per capita GDP, per capita water supply and the proportion of government expenditures on environmental protection positively affected the Chinese grain production eco-efficiency in the period 1997-2015.

From a macroeconomic point of view, Benedetti, Branca, and Zucaro (2019) measured irrigated crop technical efficiency scores in southern Italy for the year 2016 using a stochastic frontier production function assuming a heteroskedastic inefficiency component. The results of the analysis show that (i) technical efficiency is seriously influenced by individual farms' characteristics (ii) conventional farms tend to be more efficient compared to organic farms (iii) the use of a fertigation system tends to boost the level of technical efficiency of farms. In this framework, also Abunyuwah, Yenibehit, and Ahiale (2019), discussing technical efficiency variations among carrot farmers located in the Ashanti-Mampong municipality of Ghana, found that the socioeconomic characteristics of the farmers such as farm size, access to credit, household labour, age, and years of education are all significant determinants of farms' technical inefficiency. In particular, investigating the relationship between farm size and productivity over a sample of 1300 farms located in Kenya, Muyanga and Jayne (2019) found a U-shaped relationship, indicating that a strong positive relationship between farm size and productivity emerges mainly considering farms sized between 5 to 70 hectares.

Druska and Horrace (2004) is one of the first contributions estimating a SF model that considers spatial dependence occurring between firms belonging to the agricultural sector. Specifically, the authors estimated a panel data model taking cross-sectional correlation in the disturbances into account. Their findings suggest that positive spillovers affect both the level of efficiency of Indonesian rice farms and their ranking. Similarly, Schmidt et al. (2009), analysing spillover effects across farms located in the Center-West region of Brazil, found that ignoring spatial effects leads to different rankings of inefficiencies across agents. In this framework, also Areal, Balcombe, and Tiffin (2012) estimating a spatial stochastic frontier model over a sample of 215 dairy farms located in England and Wales from 2000 to 2005, highlighted that not accounting for spatial dependence may produce biased estimates of the inefficiency distribution. Moreover, Fusco and Vidoli (2013) estimated a SF model using an autoregressive specification of the inefficiency error term to account for cross-sectionally correlated random factors affecting the productivity level of neighbouring firms such as climatic and local features. Focusing on 975 wine companies located in the spatial clusters of Trentino-Alto Adige, Tuscany and Apulia in the year 2009, the authors demonstrated the existence of evident spin-offs between neighbouring farms located inside the same cluster.

Despite the large number of contributions analyzing the productivity and efficiency level of the agricultural sector using spatial and non-spatial SF models, none of the current works has yet considered four different sources of spatial dependence simultaneously. Indeed, using the SDF-CSD model, we are able to capture (i) global productivity spillovers, (ii) local input spillovers, (iii) behavioural correlation in farms' efficiency levels determined by cross-sectionally correlated inefficiency determinants and (iv) environmental correlation depending on unobserved but spatially correlated variables. Identifying the different kinds of spillover effects is essential to public governments and institutions in order to exploit existing spatial interactions in policy interventions aiming at reinforcing the agricultural industry.

6.3 The Empirical Model

In this empirical application, we take advantage of the SDF-CSD model to analyse the performance of the Italian agricultural sector considering four different kinds of spatial effects using RICA data at the NUTS-3 level. This novel spatial estimator results to be particularly suitable for this sector due to the strong importance of unobserved location-specific attributes in the agricultural industry. Indeed, there are many spatially-correlated factors that may not be considered in the model specification which could influence agricultural production (soil quality, climatic and topographic conditions, environmental characteristics, socio-economic aspects, level of infrastructure in the area, availability of input suppliers, quality of transport facilities, etc.). Estimating the SDF-CSD model, it is possible to take into account spatial cross-sectional dependence arising from unobserved factors common to neighbouring areas, which in this sector is highly relevant, thanks to the spatial structure in the random error term. Moreover, the spatial structure related to the determinants of firms' efficiency allows capturing behavioural spatial dependence arising from emulation behaviours of agricultural producers located in nearby areas and from policies and institutions operating at the local level (Areal, Balcombe, and Tiffin, 2012). On the other hand, the spatial structures entering the frontier function relate to productivity and input spillovers. Input spillovers may generate from greater availability of specific products, input suppliers, assets and workers with industry-specific skills in a certain area (Marshall, 1890). Furthermore, farmers' productive performance may be related to the one of neighbours due to the transmission of knowledge and best practices between peers (Cardamone, 2020), collective behaviours such as similar financial decisions resulting from face-to-face relationships, exchange of ideas and learning from others (Skevas and Lansink, 2020), farmers adoption of new similar technologies to face specific techno-economic problems that are common to firms operating in nearby areas (Billé, Salvioni, and Benedetti, 2018), and marketing-related externalities such as positive feedbacks deriving from "protected designation of origin" (PDO) certifications (Vidoli et al., 2016). Indeed, the successful performance of neighbouring producers may generate economic returns also to peers because of the increased reputation of the whole area (i.e. "halo effect" (Beebe et al., 2013)).

We use a Cobb-Douglas specification to model the production function equation, as shown in Eq.(6.1) for $i, j = 1, ..., N \; (i \neq j)$ and $t = 1, ..., T$. Since we include four input variables in the analysis, we prefer a Cobb-Douglas functional form with respect to a Translog specification because it involves the estimation of fewer parameters and thus, it facilitates the interpretation of the results. Moreover, the Cobb-Douglas function is often used to estimate the production function parameters due to its ability to provide more efficient estimates, especially when dealing with small samples (Yao and Liu, 1998).

$$
\begin{aligned}
Y_{it} = {} & \beta_0 + \beta_L L_{it} + \beta_{AA} AA_{it} + \beta_M M_{it} + \beta_{WEF} WEF_{it} + \beta_t t + \rho \sum_{j=1}^{N} w_{ij} Y_{jt} \\
& + \theta_L \sum_{j=1}^{N} w_{ij} L_{jt} + \theta_{AA} \sum_{j=1}^{N} w_{ij} AA_{jt} + \theta_M \sum_{j=1}^{N} w_{ij} M_{jt} + \theta_{WEF} \sum_{j=1}^{N} w_{ij} WEF_{jt} - u_{it} + \widetilde{v}_{it}
\end{aligned}
\tag{6.1}
$$

Specifically, the dependent variable Y_{it} is defined as the logarithm of the total value added generated by the agricultural sector in province i at time t. Following Vidoli et al. (2016), we consider four input variables, all in log-form: total working hours (L_{it}), utilized agricultural area (AA_{it}), machinery (M_{it}), and water, energy, and fuel (WEF_{it}). Moreover, we add the time trend t to the model specification to capture the temporal dynamics, where t has a minimum value of 1 for 2008 and then it increases by 1 for each year reaching a maximum of 11 for 2018. To consider cross-sectional spatial dependence affecting the frontier function we include in Eq.(6.1) the spatial lag of the dependent variable and of the four production inputs. In order to define neighbouring observations, we follow the queen contiguity criteria, identifying neighbours as provinces sharing a common border or vertex. Thus, we build the spatial weight matrix W as a row standardized binary contiguity matrix considering second-order neighbours (i.e. we assign value 1 to neighbouring provinces and to neighbours of neighbours and 0 otherwise).[1] Some robustness checks using different spatial weight matrices are provided afterwards. In particular, w_{ij} refers to a generic spatial weight belonging to the $(N \times N)$ sparse spatial weight matrix having all zeros on the main diagonal. Hence, we are able to detect global spatial dependence through ρ, while the parameters θ_L, θ_{AA}, θ_M, and θ_{WEF} allows capturing local spatial dependence related to the four input variables.

Finally, u_{it} and $\widetilde{v}_{it}$ represent the two error terms. Specifically, the random disturbance is distributed as a multivariate normal random variable with mean 0 and variance-covariance matrix Π equal to $\sigma_v^2 M_\gamma M_\gamma^T$ with $M_\gamma = (I_N - \gamma W)^{-1}$. The random disturbance accounts for unobserved but spatially correlated variables through the inclusion of M_γ. Hence, we are able to capture the remaining spatial dependence resulting from unobserved cross-sectionally correlated spatial features such as climatic conditions, soil characteristics, and local institutional and socio-economic factors affecting the agricultural sector through the parameter γ. On the other hand, the inefficiency error term, defined using the scaling property, can be written as $u_{it} = \widetilde{h}_{it}\widetilde{u}_t$, where $\widetilde{h}_{it}$ is the scaling function defined as in Eq.(6.2) and $\widetilde{u}_t$ is the industry-specific inefficiency error term common to all firms but varying in time following a truncated normal distribution with mean 0 and variance σ_u^2.

$$\begin{aligned} \widetilde{h}_{it} = (I_N - \tau W)^{-1} \exp(&\phi_S Small_{it} + \phi_B Big_{it} + \phi_F Family_{it} + \phi_D Diversified_{it} \\ &+ \phi_H Hired_{it} + \phi_Y Youth_{it} + \phi_W Woman_{it} + \phi_{Sub} Subsidies_{it}) \end{aligned} \tag{6.2}$$

The scaling function shown in Eq.(6.2) is composed by the spatial lag $(I_N - \tau W)^{-1}$ and by a positive function of the determinants of farms' efficiency level. As usual in SF model specifying the inefficiency error term using the scaling function approach, we choose the exponential function to obtain easily interpretable estimates for the ϕ parameters. Indeed, if we define $f(Z, \phi) = \exp(Z\phi)$, the interpretation of the ϕ parameters corresponds to regressing the determinants of firms inefficiency Z on $\log(u)$ as shown in Eq.(3.62a)-(3.62c) in Chapter 3. Moreover, as proposed by Orea and Alvarez (2019), we are able to capture the overall level of spatial dependence associated with the variables that determine cross-sectional inefficiency through the introduction of the spatial lag in the scaling function. Indeed, farms' inefficiency can depend on the inefficiency determinants of neighbours and ignoring this feature can lead to heteroskedasticity issues in the

[1] A second-order matrix compared to a first-order one allows to consider more complex spatial structures and to better identify spatial clusters. Moreover, this matrix is the one that minimizes the loglikelihood function.

inefficiency error term. Hence, through τ we are able to capture the fourth source of spatial dependence, namely behavioural correlation related to the inefficiency determinants.

Focusing on the determinants of inefficiency, we model the scaling function by introducing some variables related to the main characteristics of Italian farms at the provincial level. First of all, we consider the average farm dimension in the province introducing two variables (*Small* and *Big*) that respectively measure the proportion of small and big farms in the province. Following the RICA classification, small farms are identified as farms with an economic dimension smaller than €25.000, medium farms are those with an economic dimension ranging between €25.000 and €100.000, while big farms are those reporting an economic dimension bigger than €100.000, where the economic dimension is given by the sum of the standard production of vegetable agricultural activities and breeding carried out in a given year. Besides considering farm size, we also take the organizational type of the farm into consideration including in the model the variable *Family* that equals the proportion of farms run by family members in the province. Another important aspect that can affect farms' inefficiency level is diversification. Indeed, diversification may raise efficiency thanks to reduced risks related to crop loss or diseases. On the other hand, specialisation might boost technical efficiency since it enables farmers to specialize in a few tasks, and therefore it improves management practices. Thus, we include in the scaling function equation the variable $Diversified$ measuring the proportion of diversified farms in the province. Moreover, a further interesting issue concerns the link between technical inefficiency and relying on external factors such as hired labour or rented land. Indeed, hired labour may result in more skilled and educated workers but may imply supervision problems while renting land may incentivize farmers to be more productive in order to pay rentals, but may reduce the aspiration of performing long-term improvements. Hence, we include in the model the variable *Hired* measuring the average percentage of hired land in the province. Furthermore, farmers' characteristics such as age, gender, and education are often considered as a proxy for management practices and social capital. Therefore, we include in the scaling function *Youth* and *Woman* representing the percentage of farms run by young entrepreneurs (with less than 40 years) and by women, respectively. Finally, we investigate if subsidies positively or negatively affect farmers' inefficiency levels. Indeed, they can both lower farmers' motivation to work efficiently or act as a source of credit allowing farmers to innovate and operate more efficiently (Skevas and Lansink, 2020). Thus, we introduce the variable *Subsidies* considering total subsidies received by farms located in each province over total farm income as proposed by Stetter and Sauer (2021).

The estimates of the unknown parameters (β, ρ, θ, ϕ, τ, γ, σ_u^2, σ_v^2) can be obtained maximising the loglikelihood function composed by the partial loglikelihood functions referring to each time period shown in Eq.(3.58) in Chapter 3. It is worth highlighting that we didn't have any problem in simultaneously estimating the four different spatial parameters (two frontier based and two error based) using a constrained numerical maximisation algorithm implemented in Matlab even if our sample numerosity is not very large (107 units and 11 time periods). Besides estimating the SDF-CSD model we also estimated the nested specifications including fewer spatial terms in order to test whether it is better to choose a more comprehensive model considering four different spatial terms or a simpler specification.

Finally, it is well known that the parameters related to the frontier function cannot be considered marginal effects when the spatial lag of the dependent variable is included in the model because they do not represent anymore the first partial derivatives. Therefore, the marginal effects related to the four input variables can be computed starting from Eq.(6.3).

$$\frac{\partial Y}{\partial X} = (I_{NT} - \rho W)^{-1}(I_{NT}\beta_X + W\theta_X) \qquad X = L, AA, M, WEF \tag{6.3}$$

Specifically, the direct effect of the generic input variable X on Y can be computed as the average of the diagonal elements of the matrix resulting from the product on the right-hand side of Eq.(6.3), the indirect effect can be found as the average of the sum of the non-diagonal elements, and the total effect is equal to the sum of the previous two. The related standard error and t-values can be found using the delta method.

6.4 Data and Variables

6.4.1 The RICA Survey

The data used in this empirical application are aggregated data at the NUTS-3 level on the Italian agricultural sector collected through the RICA survey, which is the Italian counterpart of the FADN survey. The Farm Accountancy Data Network (FADN) is an annual sample survey established by the European Economic Commission in 1965 for all the member states of the European Union with the EEC Regulation 79/56 and updated with the EC Reg. 1217/2009 and subsequent amendments. The FADN survey represents the only harmonized source of microeconomic data on the evolution of incomes and on the economic-structural dynamics of farms at the European level. The Italian counterpart of the FADN survey is known as RICA, which stands for "Rete di Informazione Contabile Agraria" and it has been carried out in Italy since 1968. The primary task of the FADN is to satisfy the information needs of the European Union for the definition and evaluation of the Community Agricultural Policy (CAP). The FADN data represent the main source of information both for the European Commission and for the member states in order to evaluate the impact of the proposed changes to the CAP through the simulation of different scenarios concerning economic, environmental, social and innovation issues. The information collected with the FADN also makes it possible to respond to the needs of research and business consultancy services, through a series of variables and indices on the technical, economic, patrimonial, and income characteristics of farms.

The FADN survey does not represent the entire universe of farms surveyed in a given territory, but only those that, due to their economic dimension, can be considered professional and market-oriented. In Italy, starting from 2014, the minimum threshold for inclusion in the RICA observation sample corresponds to a minimum standard gross income of 8,000 euros. The RICA survey is based on the Agricultural Census carried out by the Italian National Institute of Statistics (ISTAT). The Italian FADN sample is selected following a stratified random sampling technique in which the strategic variables used for the allocation of the sample units in the strata are the standard output, the utilized agricultural area, and the adult bovine units. The selection of the units to be surveyed in each stratum is equi-probabilistic, meaning that the extraction of the units under investigation from the reference universe is carried out randomly, strata by strata, thus allowing the possibility of extending the sample results to the corresponding population. The methodology adopted aims to provide representative data on three dimensions: region, economic dimension, and technical-economic order.

For each company in the sample, the FADN survey collects information regarding about 1000 variables while for the RICA the total amount of variables included in the survey is bigger than 2500. The variables detected provide information on physical and structural issues (location, surfaces, consistency of farms, company labour, services offered, etc.); economic issues (revenues from sales, company re-uses, final stocks, purchases of technical means, etc.); and financial and patrimonial matters (debts, credits, public aid, production rights, acquisition and disposal of patrimonial assets, etc.). The information framework of the RICA, which is much broader than the institutional needs of the European Commission, makes it possible to carry out analyses on various themes ranging from the productivity of farms to production costs, from environmental sustainability to the role of the agricultural family. In the time period 2014-2019, the Italian RICA sample is based on average on a sample of about 11,000 companies, structured in order to represent the different types of production and dimensions in the national territory. Moreover, it allows an average national coverage of 95% of the utilized agricultural area, 97% of the standard production value, 92% of the work units, and 91% of the livestock units.

In this empirical application, we consider aggregated data at the NUTS-3 level from the RICA survey in the time period 2008-2018 because for confidentiality reasons it is not possible to know the exact location of each farm in the sample. Moreover, aggregated data at the municipal level do not ensure representative results because in most cases they do not have a minimum required sample numerosity of 5 units per municipality. Thus, the NUTS-3 aggregation results to be the finer aggregation level which also guarantees representative results.

6.4.2 Descriptive Statistics

Table 6.1 describes all the variables considered in the analysis, i.e. output, inputs, and determinants of farms' efficiency. It can be observed that small farms prevail over bigger ones. Indeed, on average, the 24% of farms in our sample are small farms, while big farms represent only the 12% of the sample. All the remaining ones are considered medium-sized farms. Moreover, the majority of farms are managed by family members (53%). Focusing on the characteristics of the farmers, only the 13% of farmers have less than 40 years old, on average, while the average number of farms run by women is equal to 21%. As for the degree of diversification, specialized farms tend to prevail in Italy. Indeed, only 13% of farms use diversification techniques. On the other hand, hiring land is quite common, in fact, on average the 44% of agricultural land is hired. Finally, considering the percentage of total subsidies on farms' income, it can be noticed that, in most cases, subsidies constitute a substantial part of farmers' earnings. Indeed, on average the 28% on total farms' income comes from received subsidies.

Concentrating on the output variable, Figure 6.1 depicts the quantile map for farms' value added in 2018. The most profitable farms are located in the North (and in particular in the North-East) and in the internal provinces of Italy. On the other hand, the less productive areas are located along the Adriatic and the Tyrrhenian coast, in northern Lombardy, in Apulia, in Calabria, and in the two islands. In particular, less productive as well as more productive areas tend to cluster and locate in nearby provinces. To verify if local spatial dependence detected in Figure 6.1 is statistically significant, we provide the LISA significance cluster map for the value-added in 2018. Specifically, Figure 6.2 shows that the North of Italy is characterized by different types of clusters. Indeed, we have high-high and low-high clusters in the eastern provinces, and in two western provinces of Piedmont and Liguria, while all low-low and high-low clusters are located in the northern provinces of Lombardy and Trentino-Alto-Adige, along the border with Switzerland. As for the Centre of Italy, we only detect two high-high clusters, one in Terni and one in the Naples areas. On the other hand, in the South of Italy, we only have low-low and high-low clusters, specifically located in southern Sicily and Sardinia, and in the heel of Calabria. Conditioning the value-added cluster map on the quantiles of *Subsidies*, it can be seen that the North-East, which is one of the most profitable areas of Italy, is among those areas with a lower share of subsidies while the less productive North-West belongs to those areas with a higher share of subsidies over farms income. As for southern Italy, most of the less productive provinces belong to the third quantile of *Subsidies* and in particular, Sardinia is the region with higher values of *Subsidies*. Thus, this preliminary analysis reveals a negative relationship between the share of subsidies received by provinces and the profitability level of the area.

Finally, in Figure 6.3 we investigate the territorial distribution of the determinants of farms' efficiency. While the Centre-North of Italy is characterized by a higher share of big farms and of farms with a higher percentage of hired land, in the North-West and in Southern Italy are principally located smaller farms and farms run by family members as well as farms run by women and by young entrepreneurs. Considering the degree of diversification, the majority of diversified farms are located in the Centre, in the North of Italy and in the Apulia region. Finally, considering subsidies previous insights about the strong difference between the North-East and the rest of Italy are confirmed.

TABLE 6.1: Variables Description

Variable	**Definition**	**Units**	**Min**	**10th Perc.**	**Mean**	**90th Perc.**	**Max**	**SD**
Y	log(Value Added)	€	10.62	13.91	15.49	18.83	17.78	1.18
L	log($WorkingHours$)	num.	8.40	11.26	12.58	13.69	14.41	1.04
AA	log($UtilizedAgriculturalArea$)	km	2.46	6.04	7.63	8.93	10.07	1.16
M	log($Machinery$)	€	3.69	7.82	9.29	10.55	11.49	1.1
WEF	log($Water, Energy, Fuel$)	€	6.91	10.35	12.15	13.72	14.69	1.37
t	Time	num.	1	2	6	10	11	3.16
Small	Perc. Small Farms	%	0.00	0.05	0.24	0.47	0.89	0.16
Big	Perc. Big Farms	%	0.00	0.00	0.12	0.27	0.71	0.12
Family	Perc. Family Farm	%	0 .00	0.19	0.53	0.87	1.00	0.25
Diversified	Perc. Diversified Farms	%	0.00	0.00	0.13	0.34	0.72	0.16
Hired	Perc. Hired Land	%	0.00	0.14	0.44	0.73	0.99	0.23
Youth	Perc. Young Farmers	%	0.00	0.03	0.13	0.27	0.54	0.11
Woman	Perc. Farms Run by Woman	%	0.00	0.05	0.21	0.37	0.56	0.13
Subsidies	Tot. Subsidies/Tot. Income	%	0.01	0.07	0.28	0.59	0.92	1.06

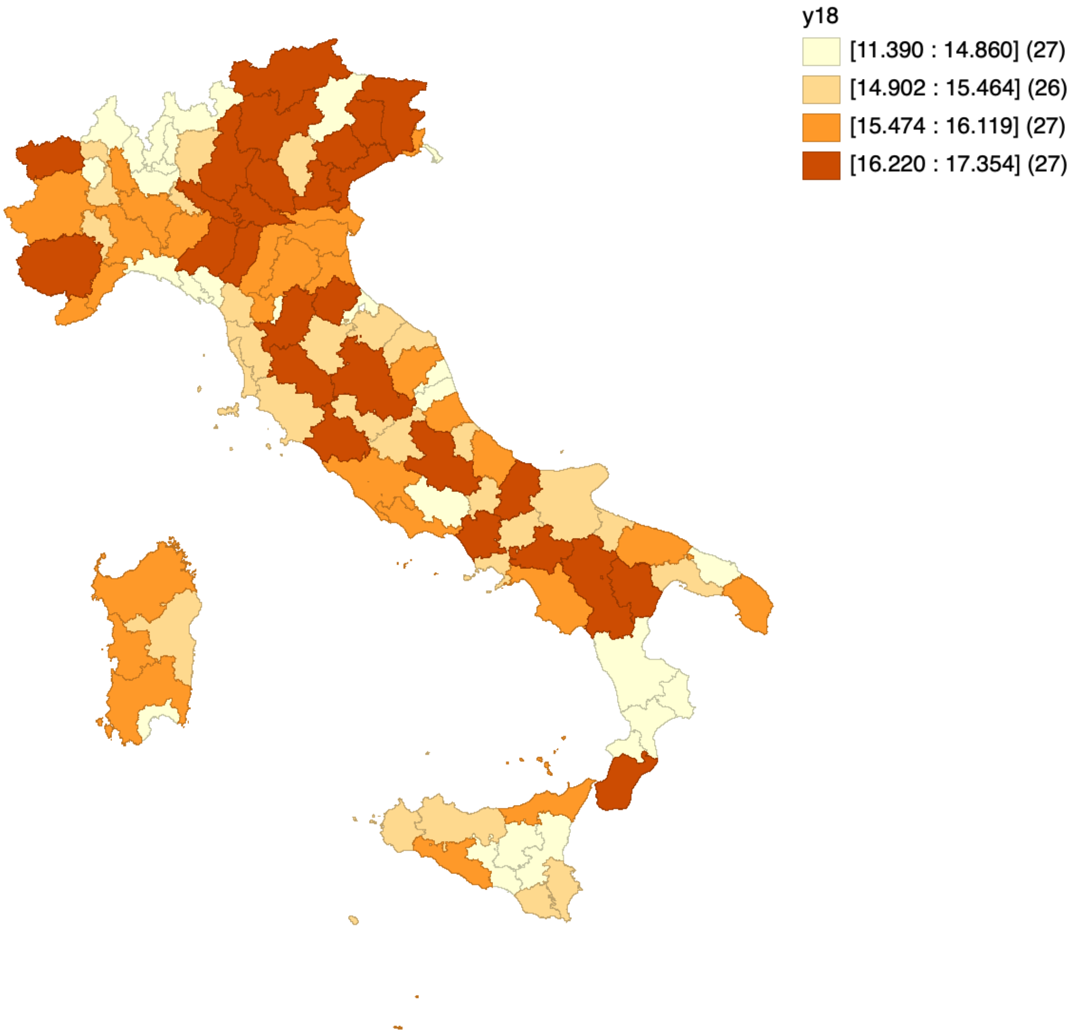

FIGURE 6.1: Quantile Map: Value Added, 2018

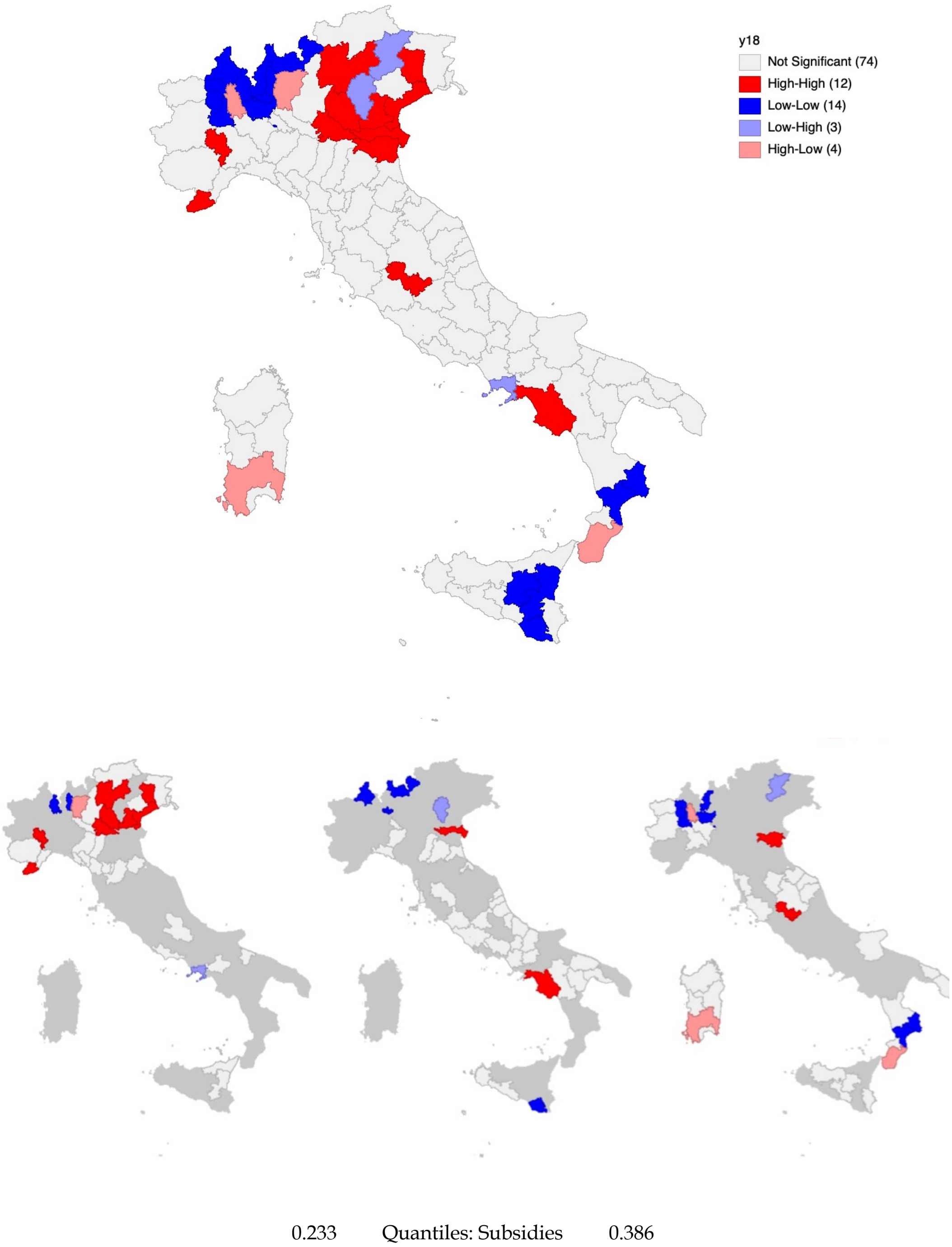

FIGURE 6.2: LISA Significance Cluster Map Conditional on Subsidies: Value Added, 2018

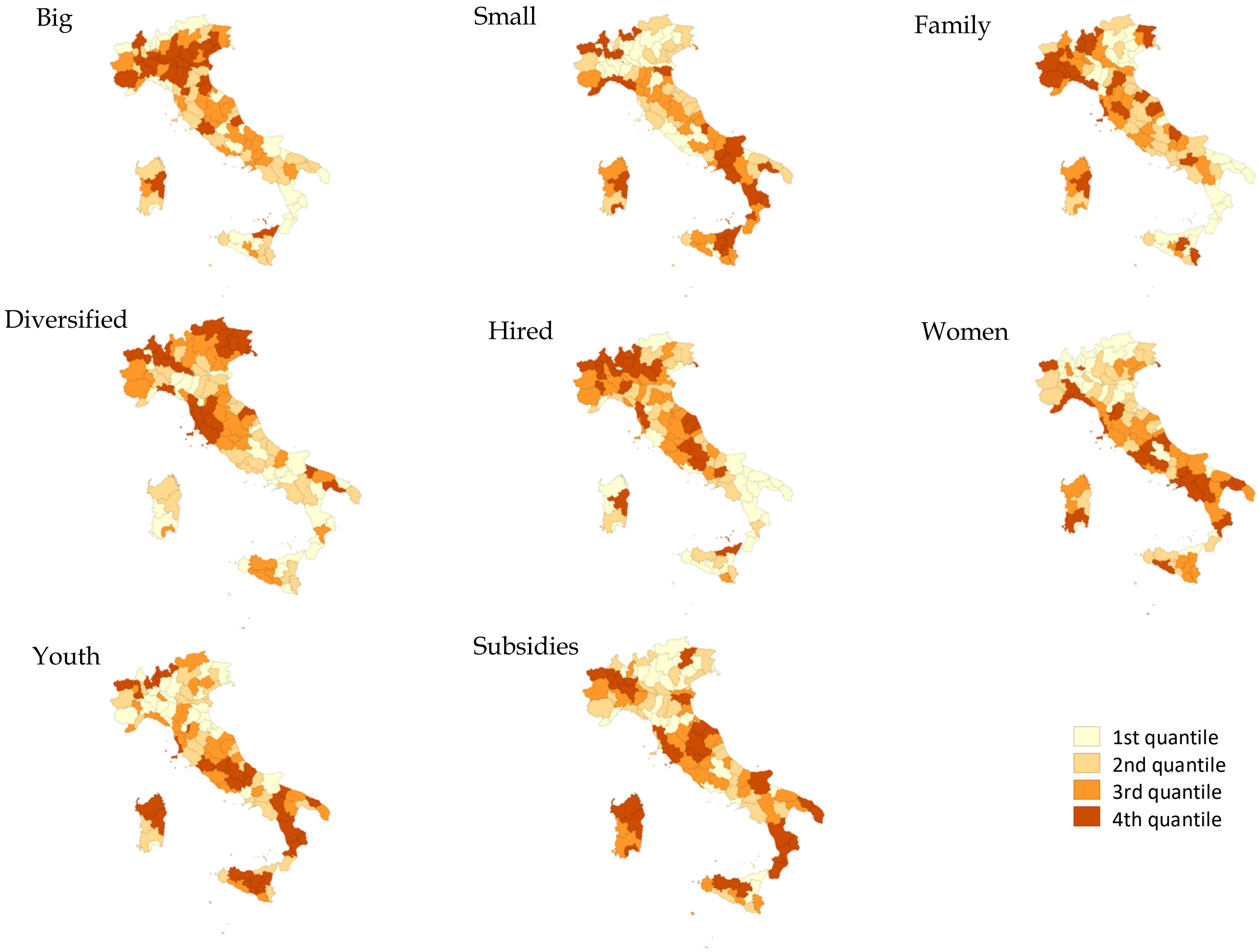

FIGURE 6.3: Quantile Map: Determinants of Farms' Inefficiency, 2018

6.5 Results

6.5.1 Estimation Results and Model Selection

Table 6.2 shows the estimation results of the SDF-CSD model (yxuv model) and of all the nested specifications combining different spatial lags related to the frontier function or to the two error terms. In particular, the u=v model in Table 6.2 indicates a restricted model, also known as spatial error model (SEM) in spatial econometric literature, where the overall error term ε follows a unique spatial process without distinguishing between the inefficiency and the noise term. Accordingly, the yxu=v model represents the general Manski model introducing the spatial lag of Y, X and ε, while the yu=v and the xu=v model are the two nested specifications also known as SARAR and SDEM model, respectively. Indeed, starting from the SDF-CSD it is possible to restrict the model specification in order to capture only specific sources of spatial dependence depending on the economic phenomenon under investigation. As a consequence, the SDF-CSD model leads the way to a number of spatial specifications (such as the yuv model, the yxv model, the yxu model, etc..) never introduced before but that can be very useful in empirical applications.

Comparing the estimation results of the nested models shown in Table 6.2, it can be noticed that the β estimates and the ϕ estimates are quite robust to the different specifications. Nevertheless, as previously described, the β coefficients cannot be interpreted in a meaningful way when the spatial lag of Y is included in the model. As for the ϕ estimates, our results indicate that provinces with a higher percentage of small farms as well as provinces with a lot of farms run by family members tend to be more inefficient while big farms contribute to decreasing the inefficiency level of the agricultural sector at NUTS-3 level. Indeed, as pointed out by Hall and LeVeen (1978), large farms can benefit from the existence of economies of scale and of preferential access to the inputs market. Concerning diversification, we find that the degree of diversification positively affects inefficiency. Indeed, specialisation might boost technical efficiency more than diversification since it enables farmers to specialize in a few tasks, and therefore it improves farmers' management practices (Latruffe, 2010). Moreover, specialisation also avoids conflicts related to crop rotations and prevents difficulties associated with competition for the use of the same resources such as land. Investigating the link between technical inefficiency and the use of external factors, we find a negative effect of the percentage of rented land in the province on technical inefficiency even if *Hired* results to be significant only in some nested specifications. Indeed, a higher percentage of hired land on the farm may incentivize farmers to work efficiently in order to pay rentals (Latruffe, 2010). Considering subsidies, our results confirm the idea that they contribute to decreasing the efficiency level of farms likely due to lowered farmers' motivation and distorted farms' production structure and factor use (Rizov, Pokrivcak, and Ciaian, 2013). Indeed, public policies and regulations can influence farmers' decisions on resource allocation producing several distortions due to increased input waste or inefficient input-output combinations. Finally,

TABLE 6.2: Results

Lag	yxuv		uv		u		v		yx		y		x	
	Coeff.	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*
β_0	3.87***	0.53	4.25***	0.62	4.57***	0.28	3.69***	0.18	3.10***	0.49	3.07***	0.38	4.49***	0.41
β_L	0.61***	0.02	0.63***	0.02	0.64***	0.02	0.61***	0.02	0.62***	0.02	0.61***	0.02	0.61***	0.02
β_{AA}	0.13***	0.02	0.13***	0.02	0.10***	0.02	0.14***	0.02	0.14***	0.02	0.09***	0.02	0.13***	0.02
β_M	0.07***	0.01	0.07***	0.01	0.08***	0.01	0.07***	0.01	0.07***	0.01	0.10***	0.01	0.07***	0.02
β_{WEF}	0.20***	0.01	0.19***	0.01	0.19***	0.01	0.20***	0.01	0.20***	0.01	0.20***	0.01	0.20***	0.01
β_t	-0.01	0.01	-0.01	0.02	-0.03	0.02	-0.01	0.01	-0.01	0.01	-0.01	0.01	-0.02*	0.01
ρ	0.14*	0.08	-		-		-		0.38***	0.07	0.06***	0.02	-	
θ_L	-0.06	0.08	-		-		-		-0.25***	0.07	-		-0.03	0.06
θ_{AA}	-0.25***	0.05	-		-		-		-0.27***	0.05	-		-0.33***	0.04
θ_M	0.02	0.04	-		-		-		0.01	0.05	-		0.05	0.04
θ_{WEF}	0.02	0.05	-		-		-		-0.02	0.07	-		0.13***	0.04
ϕ_S	0.70***	0.18	0.67***	0.17	0.37***	0.11	0.86***	0.22	0.73***	0.19	0.40***	0.11	0.49***	0.14
ϕ_B	-1.72***	0.46	-1.65***	0.41	-1.47***	0.31	-1.70***	0.47	-1.71***	0.59	-1.56***	0.33	-1.54***	0.43
ϕ_F	0.22**	0.11	0.20**	0.1	0.14**	0.07	0.28**	0.13	0.22	0.14	0.13*	0.07	0.23**	0.09
ϕ_D	0.37**	0.15	0.24*	0.14	0.19*	0.11	0.35**	0.17	0.40**	0.16	0.08	0.11	0.31**	0.12
ϕ_H	-0.06	0.11	-0.07	0.1	-0.14*	0.07	-0.01	0.13	-0.03	0.12	-0.17**	0.08	-0.06	0.09
ϕ_{Sub}	0.71***	0.1	0.69***	0.09	0.55***	0.07	0.82***	0.12	0.72***	0.13	0.59***	0.07	0.64***	0.09
ϕ_Y	0.66***	0.2	0.67***	0.19	0.71***	0.15	0.55***	0.22	0.69***	0.23	0.70***	0.15	0.68***	0.17
ϕ_W	0.55***	0.18	0.58***	0.17	0.66***	0.14	0.37*	0.21	0.52**	0.19	0.65***	0.14	0.57***	0.16
τ	0.37***	0.12	0.58***	0.08	0.57***	0.05	-		-		-		-	
γ	0.37***	0.07	0.52***	0.05	-		0.63***	0.04	-		-		-	
σ^2_u	0.05		0.06		0.12		0.03		0.04		0.16		0.08	
σ^2_v	0.09		0.09		0.10		0.09		0.09		0.10		0.10	

Lag	yuv		xuv		yxu		yxv		yu		yv		xu	
	Coeff.	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*
β_0	5.09***	0.64	4.37***	0.59	3.33***	0.46	3.27***	0.49	4.97***	0.52	3.77***	0.55	4.98***	0.61
β_L	0.63***	0.02	0.61***	0.02	0.62***	0.02	0.61***	0.02	0.65***	0.02	0.61***	0.02	0.62***	0.02
β_{AA}	0.13***	0.02	0.13***	0.02	0.14***	0.02	0.14***	0.02	0.10***	0.02	0.14***	0.02	0.13***	0.02
β_M	0.07***	0.01	0.07***	0.01	0.07***	0.01	0.07***	0.01	0.08***	0.01	0.07***	0.01	0.07***	0.01
β_{WEF}	0.19***	0.01	0.20***	0.01	0.20***	0.01	0.20***	0.01	0.18***	0.01	0.20***	0.01	0.20***	0.01
β_t	-0.01	0.02	-0.01	0.02	-0.01	0.01	-0.01	0.01	-0.04**	0.02	-0.01	0.01	-0.02	0.02
ρ	-0.05	0.03	-		0.35***	0.06	0.21***	0.07	-0.02	0.03	0.00	0.03	-	
θ_L	-		0.04	0.09	-0.23***	0.06	-0.12	0.08	-		-		-0.01	0.09
θ_{AA}	-		-0.24***	0.05	-0.26***	0.04	-0.27***	0.05	-		-		-0.28***	0.04
θ_M	-		0.03	0.04	0.01	0.04	0.02	0.04	-		-		0.05	0.04
θ_{WEF}	-		0.05	0.05	-0.03	0.05	0.04	0.05	-		-		0.05	0.05
ϕ_S	0.65***	0.17	0.66***	0.17	0.71***	0.18	0.74***	0.19	0.36***	0.11	0.86***	0.22	0.49***	0.14
ϕ_B	-1.70***	0.42	-1.72***	0.44	-1.72***	0.49	-1.72***	0.46	-1.49***	0.31	-1.70***	0.47	-1.60***	0.45
ϕ_F	0.21**	0.10	0.21*	0.11	0.18	0.12	0.28**	0.13	0.14**	0.07	0.28**	0.13	0.13	0.09
ϕ_D	0.27**	0.14	0.35	0.14	0.40***	0.15	0.39***	0.16	0.20*	0.11	0.35*	0.17	0.36***	0.12
ϕ_H	-0.06	0.10	-0.07***	0.10	-0.04	0.11	-0.06	0.12	-0.14**	0.07	-0.01	0.13	-0.06	0.08
ϕ_{Sub}	0.69***	0.09	0.70***	0.09	0.71***	0.10	0.74***	0.10	0.55***	0.07	0.82***	0.12	0.64***	0.1
ϕ_Y	0.68***	0.19	0.65***	0.19	0.71***	0.22	0.63***	0.21	0.72***	0.15	0.55***	0.22	0.72***	0.18
ϕ_W	0.56***	0.17	0.56***	0.18	0.55***	0.19	0.48***	0.20	0.64***	0.14	0.37*	0.21	0.64***	0.17
τ	0.62***	0.07	0.47***	0.12	0.18	0.15	-		0.59***	0.05	-		0.44***	0.11
γ	0.52***	0.05	0.43***	0.07	-		0.35***	0.08	-		0.63***	0.04	-	
σ^2_u	0.05		0.05		0.05		0.04		0.12		0.03		0.08	
σ^2_v	0.09		0.09		0.09		0.09		0.10		0.09		0.09	

Lag	xv		u=v		yxu=v		yu=v		xu=v		non-spat.			
	Coeff.	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*		
β_0	3.74***	0.49	4.17***	0.29	3.86***	0.53	4.82***	0.69	4.30***	0.59	3.90***	0.19		
β_L	0.61***	0.02	0.63***	0.02	0.61***	0.02	0.62***	0.02	0.61***	0.02	0.62***	0.02		
β_{AA}	0.13***	0.02	0.13***	0.02	0.13***	0.02	0.13***	0.02	0.13***	0.02	0.09***	0.02		
β_M	0.07***	0.01	0.07**	0.01	0.07***	0.01	0.07***	0.01	0.07***	0.01	0.10***	0.01		
β_{WEF}	0.21**	0.01	0.19***	0.01	0.20***	0.01	0.19***	0.01	0.20***	0.01	0.20***	0.01		
β_t	-0.01	0.01	-0.01	0.02	-0.01	0.01	-0.01	0.02	-0.01	0.01	-0.02**	0.01		
ρ	-		-		0.14*	0.08	-0.04	0.03	-		-			
θ_L	0.04	0.09	-		-0.06	0.08	-		0.04	0.09	-			
θ_{AA}	-0.29***	0.05	-		-0.25***	0.05	-		-0.24***	0.05	-			
θ_M	0.03	0.04	-		0.02	0.04	-		0.03	0.04	-			
θ_{WEF}	0.11**	0.05	-		0.02	0.05	-		0.05	0.05	-			
ϕ_S	0.70***	0.19	0.68***	0.17	0.70***	0.18	0.67***	0.17	0.66***	0.17	0.37***	0.11		
ϕ_B	-1.74***	0.48	-1.66***	0.42	-1.72***	0.46	-1.70***	0.42	-1.72***	0.44	-1.57***	0.32		
ϕ_F	0.31**	0.13	0.20**	0.10	0.22**	0.11	0.21**	0.10	0.22**	0.11	0.13*	0.07		
ϕ_D	0.38**	0.16	0.24*	0.14	0.37***	0.15	0.26*	0.14	0.35***	0.14	0.08	0.11		
ϕ_H	-0.08	0.12	-0.06	0.10	-0.06	0.11	-0.06	0.10	-0.07	0.1	-0.17**	0.08		
ϕ_{Sub}	0.74***	0.11	0.70***	0.09	0.71***	0.10	0.71***	0.09	0.70***	0.1	0.59***	0.07		
ϕ_Y	0.61***	0.20	0.66***	0.19	0.66***	0.20	0.66***	0.19	0.65***	0.19	0.71***	0.15		
ϕ_W	0.47**	0.19	0.56***	0.17	0.55***	0.18	0.54***	0.17	0.56***	0.18	0.63***	0.14		
τ	-		0.54***	0.09	0.37***	0.12	0.55***	0.10	0.44***	0.13	-			
γ	0.48***	0.08									-			
σ^2_u	0.04		0.05		0.05		0.05		0.05		0.17			
σ^2_v	0.09		0.09		0.09		0.09		0.09		0.11			

$***$: *pvalue* ≤ 0.01; $**$: *pvalue* ≤ 0.05; $*$: *pvalue* ≤ 0.10

provinces with a higher percentage of farms run by women or by young entrepreneurs tend to be more inefficient than others. In particular, Timothy and Adeoti (2006) attribute the negative effects associated with females to unequal access to agricultural resources while concerning age, as Mathijs and Vranken (2001) explained, older farmers result to be more efficient thanks to increased experience and learning ability.

TABLE 6.3: Model Comparison

Model	LL	Test Statistic	Constraints	P-value	Parameters	AIC	BIC
SDF-CSD	-284.61	Base Model	-	-	23	615.22	731.85
uv	-297.70	26.18	5	0.00	18	631.40	722.67
u	-340.48	111.74	6	0.00	24	728.96	850.66
v	-305.14	41.06	6	0.00	17	644.28	730.48
yx	-296.20	23.18	2	0.00	25	642.40	769.17
y	-366.48	163.74	6	0.00	17	766.96	853.16
x	-319.66	70.10	3	0.00	26	691.32	823.16
yuv	-296.53	23.84	4	0.00	19	631.06	727.40
xuv	-285.73	2.24	1	0.09	27	625.46	762.37
yxu	-295.56	21.90	1	0.00	22	635.12	746.68
yxv	-286.70	4.18	1	0.02	28	629.40	771.38
yu	-340.02	110.82	5	0.00	18	716.04	807.31
yv	-305.13	41.04	5	0.00	29	668.26	815.31
xu	-311.35	53.48	2	0.00	21	664.70	771.19
xv	-290.09	10.96	2	0.00	30	640.18	792.30
u=v	-297.89	26.56	6	0.00	17	629.78	715.98
yxu=v	-284.61	0.00	1	6.30	31	631.22	788.42
yu=v	-297.05	24.88	5	0.00	18	630.10	721.37
xu=v	-285.77	2.32	2	0.16	32	635.54	797.80
non-spatial	-369.50	169.78	7	0.00	16	771.00	852.13

Concentrating on the spatial parameters, we detect positive and significant spatial dependence either at the frontier level or related to the two error terms. Thus, the estimate of ρ indicates that positive global productivity spillovers affect the Italian agricultural sector as well as positive spillover effects related to the determinants of farms' efficiency (τ), and to unobserved environmental factors (γ). Specifically, the degree of global spatial dependence (0.14) estimated using the SDF-CSD model is considerably smaller than the level of behavioural and environmental spatial correlation associated with the two error components (both equal to 0.37) indicating that the Italian agricultural sector is more strongly affected by error-based than by frontier-based spatial dependence. These findings reveal that, in the agricultural industry, the productive performance of the Italian provinces is affected by those of the neighbouring spatial units. In particular, we detect positive spatial dependence in the determinants of farms' efficiency, indicating that farmers located in neighbouring areas may emulate each other and that neighbouring provinces are characterized by similar institutional, cultural, and socio-economic features. Moreover, the positive and significant coefficient associated with γ suggests that there are a number of non-observed potential sources of spatial dependence such as soil quality, climatic conditions, and other location-specific attributes.

To choose the model specification that better fits the data, in Table 6.3 we compare the different nested models using some likelihood ratio tests and information criteria. According to both the LR test and the AIC criteria, the yxu=v model is the preferred one. Indeed, the degree of spatial dependence associated with the inefficiency and the random error term in this case study is the same for both the two error components using the SDF-CSD model. Thus, in this empirical application, it is better to simplify the model specification using a model that considers one unique spatial term referring to the whole error structure. Moreover, in Appendix B we also estimate the SDF-STE model using data on the Italian agricultural sector. Comparing the two spatial stochastic frontier models proposed in this thesis using the Vuong test for non-nested models and the Takeuchi information criteria, we find that the SDF-CSD model outperforms the SDF-STE using these data. The preference for the SDF-CSD model in this empirical application may depend on the importance of unobserved but spatially-correlated variables in this sector that are considered in the SDF-CSD specification but not in the SDF-STE. In addition, the insights on the indirect effects related to the inefficiency determinants resulting from the spatial lags of the Z variables introduced in the SDF-STE model in this case are not particularly appealing since spillovers resulting from the characteristics of the agricultural sector at the provincial level such as the degree of differentiation, farms' size, and the share of farms run by women or young person are not of interest in this application. In sum, the introduction of the spatial lags of the Z variables is not motivated by the objectives of this empirical analysis which is aimed at identifying the different typologies of spillovers (productivity and input spillovers, behavioural and environmental correlation) occurring in the Italian agricultural sector.

6.5.2 Sensitivity to the Spatial Weight Matrix and Marginal Effects

In this subsection, we estimate the SDF-CSD model using different spatial weight matrices. Besides the second-order binary contiguity matrix (W2), we consider a first-order binary contiguity matrix (W) and a dense inverse distance matrix (Wid). According to the results of the Monte Carlo simulations in Chapter 4, when we introduce a dense inverse distance matrix, we associate it only to the spatial lags related to the frontier function while for the two error terms, we use a sparse matrix like W or W2. The estimation results are shown in Table 6.4. In particular, we find that the estimates of the β and of the ϕ parameters are quite robust to different specifications of the spatial weight matrix. On the other hand, we detect some differences in the estimated spatial coefficients. Indeed, the level of global spatial dependence related to the frontier (ρ) is significantly different from zero only when a second-order binary contiguity matrix is associated with the spatial lags of the frontier function. Indeed, in the models considering a first-order contiguity matrix or a dense inverse distance matrix in the frontier function, we do not find evidence of significant global productivity spillovers. On the other hand, the estimates of τ and γ tend to raise in magnitude in the models considering W or Wid in the frontier function

TABLE 6.4: Sensitivity to the Choice of W

SDF-CSD	W2		W		W2,W		W,W2		Wid,W2		Wid,W	
	Coeff.	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*
β_0	3.87***	0.53	4.29***	0.65	3.47***	0.46	3.83***	0.42	6.20***	1.27	6.74***	1.26
β_L	0.61***	0.02	0.59***	0.02	0.61***	0.02	0.60***	0.02	0.63***	0.02	0.63***	0.02
β_{AA}	0.13***	0.02	0.14***	0.02	0.14***	0.02	0.15***	0.02	0.14***	0.02	0.14***	0.02
β_M	0.07***	0.01	0.09***	0.01	0.07***	0.01	0.08***	0.01	0.07***	0.01	0.07***	0.01
β_{WEF}	0.20***	0.01	0.19***	0.01	0.20***	0.01	0.20***	0.01	0.19***	0.01	0.18***	0.01
β_t	-0.01	0.01	-0.02	0.02	-0.01	0.01	-0.01	0.02	-0.02	0.02	-0.03	0.02
ρ	0.14*	0.08	-0.06	0.12	0.29***	0.06	0.01	0.05	0.08	0.18	0.12	0.18
θ_L	-0.06	0.08	0.12	0.09	-0.19***	0.06	0.10**	0.05	-0.23	0.20	-0.26	0.19
θ_{AA}	-0.25***	0.05	-0.15***	0.04	-0.27***	0.04	-0.11***	0.03	-0.67***	0.18	-0.81***	0.16
θ_M	0.02	0.04	0.02	0.03	0.01	0.04	-0.01	0.03	0.37**	0.16	0.44***	0.17
θ_{WEF}	0.02	0.05	0.03	0.03	0.01	0.04	0.01	0.03	-0.04	0.21	-0.11	0.22
ϕ_S	0.70***	0.18	0.51***	0.15	0.73***	0.18	0.65***	0.16	0.75***	0.19	0.73***	0.19
ϕ_B	-1.72***	0.46	-1.57***	0.37	-1.64***	0.46	-1.70***	0.41	-1.64***	0.51	-1.57***	0.54
ϕ_F	0.22**	0.11	0.12	0.08	0.22**	0.11	0.15	0.10	0.29**	0.12	0.30**	0.12
ϕ_D	0.37**	0.15	0.24*	0.13	0.39**	0.15	0.26*	0.14	0.50***	0.14	0.57***	0.14
ϕ_H	-0.06	0.11	-0.11	0.08	-0.03	0.11	-0.11	0.10	0.06	0.10	0.06	0.09
ϕ_{Sub}	0.71***	0.10	0.63***	0.09	0.71***	0.10	0.68***	0.09	0.72***	0.11	0.70***	0.11
ϕ_Y	0.66***	0.20	0.65***	0.17	0.68***	0.20	0.60***	0.19	0.61***	0.20	0.68***	0.20
ϕ_W	0.55***	0.18	0.70***	0.16	0.54***	0.18	0.64***	0.17	0.46***	0.18	0.45***	0.18
τ	0.37***	0.12	0.47***	0.13	0.15	0.12	0.55***	0.08	0.48***	0.10	0.43***	0.09
γ	0.37***	0.07	0.27***	0.09	0.12**	0.05	0.48***	0.06	0.38***	0.06	0.15***	0.05
σ_u^2	0.05	-	0.08	-	0.04	-	0.06	-	0.04	-	0.04	-
σ_v^2	0.09	-	0.09	-	0.09	-	0.09	-	0.09	-	0.09	-
LL	-284.61	-	-314.25	-	-292.08	-	-289.72	-	-285.89	-	-285.31	-

$***: pvalue \leq 0.01$; $**: pvalue \leq 0.05$; $*: pvalue \leq 0.10$

TABLE 6.5: Marginal Effects

Effects		**W2**		**W**		**W2,W**		**W,W2**		**Wid, W2**		**Wid,W**	
		Coeff.	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*	*Coeff.*	*SD*
L	*Direct*	0.61***	0.02	0.59***	0.02	0.61***	0.02	0.60***	0.02	0.63***	0.02	0.63***	0.02
	Indirect	0.03	0.06	0.08**	0.04	-0.01	0.07	0.11**	0.04	-0.19	0.18	-0.21	0.18
	Total	0.64***	0.06	0.67***	0.04	0.59***	0.07	0.71***	0.04	0.44**	0.18	0.42***	0.17
AA	*Direct*	0.13***	0.02	0.14***	0.02	0.13***	0.02	0.15***	0.02	0.14***	0.02	0.13***	0.02
	Indirect	-0.26***	0.05	-0.15***	0.03	-0.32***	0.05	-0.11**	0.04	-0.72***	0.21	-0.91***	0.22
	Total	-0.13**	0.06	-0.01	0.03	-0.19***	0.05	0.04	0.03	-0.59**	0.21	-0.77***	0.22
M	*Direct*	0.07***	0.01	0.09***	0.01	0.07***	0.01	0.08***	0.01	0.07***	0.01	0.07***	0.01
	Indirect	0.04	0.05	0.01	0.03	0.05	0.05	-0.01	0.03	0.41**	0.2	0.51**	0.24
	Total	0.11**	0.05	0.11***	0.03	0.12**	0.05	0.07**	0.03	0.47**	0.2	0.59***	0.24
WEF	*Direct*	0.20***	0.01	0.19***	0.01	0.20***	0.01	0.20***	0.01	0.19***	0.01	0.18***	0.01
	Indirect	0.06	0.05	0.01	0.03	0.09	0.06	0.01	0.03	-0.03	0.19	-0.09	0.21
	Total	0.26***	0.06	0.21***	0.03	0.29***	0.06	0.20***	0.03	0.16	0.2	0.08	0.22

$***: pvalue \leq 0.01$; $**: pvalue \leq 0.05$; $*: pvalue \leq 0.10$

instead of W2. These results confirm previous insights on the greater relevance of error-based spatial spillover effects in the Italian agricultural sector compared to frontier-based spatial spillovers. Thus, the agricultural output of the Italian provinces is mainly affected by positive spatial correlation related to the inefficiency determinants and to unobserved location-specific attributes.

Starting from the estimates of Table 6.4, Table 6.5 shows the corresponding marginal effects. Considering the direct effects of the X variables on Y, we find that they do not vary depending on the choice of the spatial weight matrix. Specifically, the direct effects of the four inputs considered in the analysis are all positive and significant, as expected. In particular, labour results to be the more effective input variable (0.61), followed by water, energy, and fuel (0.20). In line with the results of Fusco and Vidoli (2013), capital inputs such as machinery (0.07) and land (0.13) contribute less to the productive performance of the Italian agricultural sector compared to human resources. Overall, the sum of the elasticities related to the four input variables results to be greater than 1 regardless of the spatial structure considered. Thus, in line with most European countries (Rizov, Pokrivcak, and Ciaian, 2013), the Italian agricultural sector is characterized by increasing returns to scale, indicating that increasing the inputs by 1% would produce more than 1% increase in output.

Considering the indirect effects, they tend to vary depending on the choice of the spatial weight matrix. Indeed, the indirect effect associated with labour is positive and significant only when we consider a first-order contiguity matrix related to the frontier function, while the indirect effect of machinery is positive and significant only using a dense inverse distance spatial weight matrix associated with the frontier function. On the other hand, the indirect effects of the agricultural area and of water, energy and fuel do not change across the different estimated models. Specifically, while the former is always negative and significant, the latter never reports values statistically different from zero in all the different specifications. In sum, we detect positive input spillover effects at the local level in terms of labour while the positive input spillovers related to machinery result to be significant only at the global level. On the contrary, provinces that dispose of larger agricultural areas tend to be located near provinces with fewer lands likely due to the specific territorial conformation and the alternation of more rural provinces with more urbanized ones.

6.5.3 TE Scores

The lower panel of Figure 6.4 shows the time trend of the average TE scores computed using the SDF-CSD model. Specifically, we find that the efficiency level of the Italian agricultural sector sharply decreased from 2009 to 2010, and then it started to rise slowly from 2013 onward, reaching a value of 0.47 in the last year of the analysis. Moreover, the upper panel of Figure 6.4 shows the kernel density plots of the technical efficiency scores computed estimating the SDF-CSD model, the non-spatial SF model, and the uv and xy models, introducing spatial dependence only in the error terms and in the frontier function, respectively. Considering the scale of the distribution, it can be noticed that the TE scores' distribution from the non-spatial model is the closest one to the distribution obtained through the SDF-CSD model. On the other hand, the xy model tends to overestimate the TE scores while the uv model tends to underestimate them. As for the shape of the distribution, the distribution obtained using the SDF-CSD model resembles the one coming from the spatial error model but is mitigated by the quasi-normal shape of the xy model. Thus, the SDF-CSD model allows to accurately combine the main features of the distributions of the TE scores resulting from the uv and xy model. Thus, these findings show that the distribution of the TE scores obtained through non-spatial models is the one that better approaches the one from the SDF-CSD model one while considering spatial dependence only in the frontier function or in the error terms leads to severe distortions both in the scale and in the shape of the distribution. Therefore, it is fundamental to combine frontier-based and error-based spatial effects both to consider different sources of spatial dependence through a comprehensive model and also to obtain consistent estimates of the TE scores.

Moreover, in Table 6.6 we present the efficiency ranking of the 107 Italian provinces for the four different SF models considered in this section (SDF-CSD, uv-model, yx-model, non-spatial SF model) to observe more in detail how both the ranking and the level of the TE scores modify depending on the kind of spatial structure considered. Specifically, the province of Cremona is ranked first in three out of four models, reaching a score of 0.68 using the SDF-CSD model, 0.87 using the yx-model, 0.79 with the non-spatial model, and 0.40 with the uv-model. On the other hand, the less efficient province in terms of agricultural production is Catanzaro, reaching a score of 0.21, 0.13, 0.14, and 0.08 using the xy, the non-spatial, the SDF-CSD, and the uv-model, respectively. Thus, as noticed in the upper panel of Figure 6.4, while the TE scores tend to be overestimated using a spatial SF model considering spatial dependence only in the frontier function, introducing spatial dependence only in the error structure leads to lower efficiency scores. Moreover, we find very dissimilar rankings associated with the different SF models considered. For example, while the province of Rovigo ranks second with the SDF-CSD, it is the first one using the uv-model, the sixth with the yx-model, and the tithe with the non-spatial SF model. Thus, both not considering spatial dependence and introducing it only in the frontier function or in the error components lead to a biased inefficiency ranking.

Figure 6.5 maps the TE scores resulting from the SDF-CSD model for the 107 Italian provinces, comparing the years 2008 and 2018. Overall, provinces located in the North of Italy result to be much more efficient than those located in the South and this gap has remarkably increased in the past eleven years. Specifically, the large efficiency cluster in the Po Valley is strengthening over time while Sardinia, Calabria, the Southern Apulia, and the Northern provinces at the border with Switzerland are achieving lower and lower efficiency scores. Besides highlighting a severe North-South divide that is increasing with time, Figure 6.5 shows that Italian provinces are characterized by strong spatial concentration considering the efficiency level of the agricultural sector.

Aiming at quantifying the level of spatial dependence related to the efficiency level of the Italian agricultural sector, we follow the method proposed by Glass, Kenjegalieva, and Sickles (2016) to compute direct, indirect, and total relative efficiencies. In particular, by multiplying the TE scores for the spatial lag of the dependent variable, it is possible to obtain total technical efficiency scores $TE_{it}^{Tot} = (I_N - \rho W)^{-1}\, TE_{it}$, including both direct and indirect effects. Instead of computing relative direct, indirect, and total efficiency scores with respect to the best-performing unit in the sample as proposed by Glass, Kenjegalieva, and Sickles (2016), we follow the method introduced by LeSage and Pace (2009) to compute the marginal effects to disentangle the direct, indirect, and total technical efficiency scores. Specifically starting from the matrix $\epsilon = (I_N - \rho W)^{-1}\, (I_N \cdot TE_{it})$, direct TE scores ($TE_{it}^{Dir}$) corresponds to the elements on the main diagonal of ϵ, indirect TE scores (TE_{it}^{Ind}) are the row sums of the non-diagonal elements, and the total TE scores previously defined equals $TE_{it}^{Tot} = TE_{it}^{Dir} + TE_{it}^{Ind}$. The distribution of the resulting direct, indirect, and total TE scores is reported in Figure 6.6. Specifically, it can be observed that the distribution of TE_{it}^{Dir} highly reflects the one of TE_{it}, while the distribution of TE_{it}^{Ind} takes smaller values and it is much more concentrated around the mean value. Moreover, the average direct TE score (ADTE) equals 0.50, the average indirect TE score (AITE) equals 0.08, and the average total TE score (ATTE) equals 0.58. Thus, efficiency mostly depends on internal and controllable factors and on average, the 13.79% of provinces' overall efficiency level comes from positive spillover effects resulting from neighbours.

6.5.4 Robustness Check

Similarly to the previous application on the Italian accommodation sector, also in this case, non-spatial unobserved individual-specific effects and endogeneity related to the

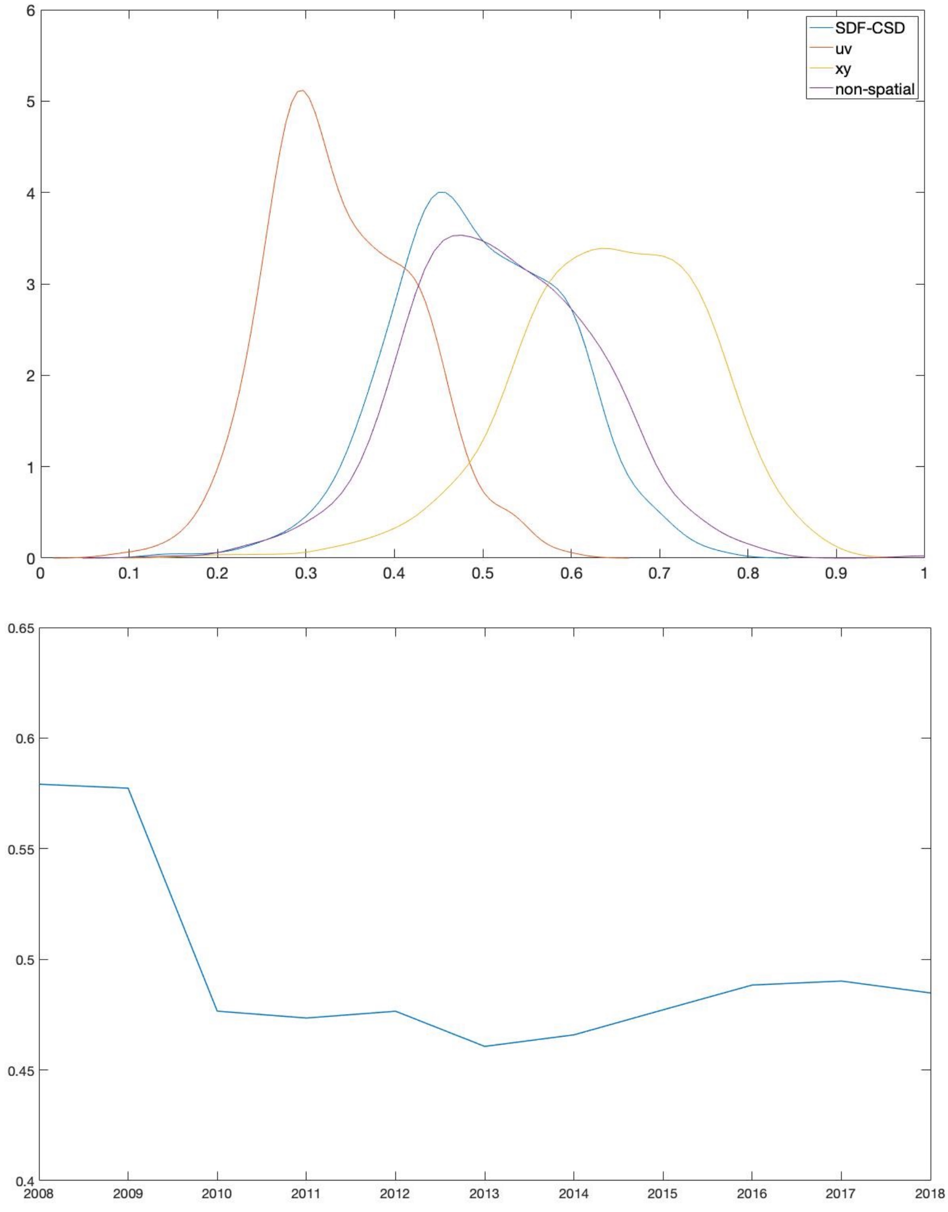

FIGURE 6.4: TE Scores: Kernel Density Plot and Time Trend

TABLE 6.6: Efficiency Scores Ranking, Year 2018

	SDF-CSD		uv-model		yx-model		non-spatial model	
Ranking	Provinces	TE	Provinces	TE	Provinces	TE	Provinces	TE
1	Cremona	0.68	Rovigo	0.49	Cremona	0.87	Cremona	0.79
2	Rovigo	0.66	Cremona	0.48	Pavia	0.82	Lodi	0.73
3	Brescia	0.65	Pordenone	0.48	Brescia	0.81	Pavia	0.72
4	Parma	0.64	Brescia	0.47	Lodi	0.81	Brescia	0.71
5	Verona	0.63	Verona	0.46	Parma	0.8	Messina	0.69
6	Pordenone	0.63	Venezia	0.46	Rovigo	0.8	Pistoia	0.69
7	Lodi	0.63	Treviso	0.46	Pistoia	0.79	Parma	0.68
8	Pavia	0.62	Padova	0.46	Messina	0.79	Verbano-Cusio-Ossola	0.68
9	Pistoia	0.62	Parma	0.46	Reggio Emilia	0.78	Bergamo	0.68
10	Venezia	0.62	Lodi	0.45	Bergamo	0.78	Rovigo	0.68
11	Reggio Emilia	0.62	Gorizia	0.45	Verona	0.78	Reggio Emilia	0.67
12	Mantova	0.62	Trento	0.45	Prato	0.77	Pordenone	0.67
13	Treviso	0.62	Vicenza	0.45	Mantova	0.77	Ravenna	0.66
14	Padova	0.61	Mantova	0.44	Pordenone	0.77	Verona	0.66
15	Bergamo	0.61	Reggio Emilia	0.44	L'Aquila	0.77	Mantova	0.66
16	Trento	0.61	Pistoia	0.44	Ravenna	0.76	Gorizia	0.65
17	Ravenna	0.6	Bergamo	0.44	Venezia	0.76	Forlì-Cesena	0.64
18	Vicenza	0.6	Pavia	0.43	Trento	0.76	L'Aquila	0.64
19	Prato	0.6	Ravenna	0.43	Forlì-Cesena	0.76	Trento	0.64
20	Gorizia	0.6	Modena	0.43	Treviso	0.75	Padova	0.64
21	Modena	0.59	Udine	0.42	Piacenza	0.75	Venezia	0.63
22	Forlì-Cesena	0.59	Piacenza	0.41	Teramo	0.75	Piacenza	0.63
23	Piacenza	0.59	Forlì-Cesena	0.41	Padova	0.74	Vicenza	0.63
24	Messina	0.59	Prato	0.41	Gorizia	0.74	Treviso	0.62
25	L'Aquila	0.58	Bologna	0.39	Verbano-Cusio-Ossola	0.74	Cuneo	0.62
26	Teramo	0.56	Bolzano	0.39	Vicenza	0.74	Teramo	0.62
27	Verbano-Cusio-Ossola	0.55	Belluno	0.39	Modena	0.73	Modena	0.61
28	Latina	0.55	L'Aquila	0.39	Latina	0.73	Rimini	0.6
29	Udine	0.55	Verbano-Cusio-Ossola	0.38	Catania	0.72	Vercelli	0.58
30	Bologna	0.55	Messina	0.38	Cuneo	0.72	Caserta	0.58
31	Rimini	0.55	Rimini	0.38	Caserta	0.72	Viterbo	0.58
32	Caserta	0.55	Teramo	0.37	Rimini	0.72	Bologna	0.57
33	Bolzano	0.54	Lucca	0.37	Matera	0.71	Latina	0.57
34	Catania	0.53	Latina	0.37	Viterbo	0.71	Udine	0.57
35	Vercelli	0.53	Vercelli	0.36	Vercelli	0.7	Catania	0.57
36	Viterbo	0.53	Alessandria	0.36	Bologna	0.69	Alessandria	0.56
37	Cuneo	0.53	Caserta	0.36	Napoli	0.69	Fermo	0.55
38	Alessandria	0.53	Cuneo	0.36	Alessandria	0.69	Matera	0.55
39	Savona	0.52	Savona	0.36	Savona	0.68	Lucca	0.55
40	Lucca	0.52	Viterbo	0.35	Bolzano	0.68	Milano	0.55
41	Napoli	0.52	Trieste	0.35	Udine	0.67	Savona	0.55
42	Belluno	0.52	Catania	0.34	Fermo	0.67	Torino	0.55
43	Fermo	0.5	Milano	0.34	Barletta-Andria-Trani	0.67	Napoli	0.54
44	Torino	0.5	Ferrara	0.34	Lucca	0.66	Bolzano	0.54
45	Caltanissetta	0.49	Torino	0.34	Caltanissetta	0.66	Macerata	0.53
46	Roma	0.49	Napoli	0.34	Torino	0.66	Belluno	0.52
47	Matera	0.49	Fermo	0.33	Trapani	0.65	Prato	0.52
48	Barletta-Andria-Trani	0.49	Firenze	0.33	Oristano	0.65	Avellino	0.52
49	Campobasso	0.48	Asti	0.33	Roma	0.65	Arezzo	0.51
50	Benevento	0.48	Arezzo	0.33	Avellino	0.64	Caltanissetta	0.51
51	Asti	0.48	Roma	0.32	Campobasso	0.64	Barletta-Andria-Trani	0.51
52	Milano	0.48	Caltanissetta	0.32	Asti	0.64	Campobasso	0.51
53	Trapani	0.48	Macerata	0.32	Macerata	0.64	Benevento	0.51
54	Macerata	0.48	Massa-Carrara	0.32	Benevento	0.64	Asti	0.51
55	Avellino	0.48	Campobasso	0.32	Ragusa	0.64	Oristano	0.5
56	Arezzo	0.48	Perugia	0.31	Belluno	0.63	Roma	0.5
57	Isernia	0.47	Monza e della Brianza	0.31	Bari	0.63	Perugia	0.49
58	Ragusa	0.47	Lecco	0.31	Ascoli Piceno	0.63	Nuoro	0.49
59	Ascoli Piceno	0.47	Isernia	0.31	Arezzo	0.62	Firenze	0.49
60	Oristano	0.47	Pesaro Urbino	0.31	Isernia	0.62	Pesaro Urbino	0.49
61	Perugia	0.47	Ascoli Piceno	0.31	Pesaro Urbino	0.62	Ragusa	0.49
62	Ferrara	0.47	Benevento	0.31	Reggio Calabria	0.62	Trapani	0.49
63	Firenze	0.47	Siena	0.31	Perugia	0.62	Isernia	0.49
64	Pesaro Urbino	0.46	Trapani	0.31	Sud Sardegna	0.61	Ascoli Piceno	0.48
65	Trieste	0.46	La Spezia	0.31	Nuoro	0.61	Bari	0.48
66	Chieti	0.45	Barletta-Andria-Trani	0.31	Milano	0.61	Massa-Carrara	0.47
67	Salerno	0.45	Ragusa	0.3	Salerno	0.6	Salerno	0.47
68	Bari	0.45	Avellino	0.3	Firenze	0.6	Siena	0.47
69	Nuoro	0.45	Chieti	0.3	Chieti	0.6	Biella	0.47
70	Siena	0.44	Livorno	0.3	Agrigento	0.59	Monza e della Brianza	0.47
71	Massa-Carrara	0.44	Imperia	0.3	Imperia	0.59	Chieti	0.47
72	Agrigento	0.44	Terni	0.29	Terni	0.59	Trieste	0.47
73	Sud Sardegna	0.44	Oristano	0.29	Potenza	0.58	Livorno	0.46
74	Imperia	0.44	Biella	0.29	Siena	0.58	Imperia	0.46
75	Lecco	0.44	Agrigento	0.29	Siracusa	0.58	Reggio Calabria	0.46
76	Terni	0.44	Ancona	0.29	Livorno	0.58	Ancona	0.46
77	La Spezia	0.44	Matera	0.29	Monza e della Brianza	0.57	Terni	0.46
78	Monza e della Brianza	0.44	Pisa	0.29	Ferrara	0.57	Como	0.45
79	Siracusa	0.44	Salerno	0.29	Foggia	0.57	Ferrara	0.45
80	Livorno	0.43	Como	0.29	Massa-Carrara	0.57	Agrigento	0.45
81	Ancona	0.42	Siracusa	0.28	Trieste	0.56	Siracusa	0.44
82	Biella	0.42	Varese	0.28	Ancona	0.56	Sud Sardegna	0.44
83	Pescara	0.42	Nuoro	0.28	Lecco	0.56	Potenza	0.44
84	Foggia	0.42	Pescara	0.28	Pescara	0.56	Cagliari	0.43
85	Frosinone	0.41	Bari	0.28	La Spezia	0.56	Lecco	0.43
86	Potenza	0.41	Sud Sardegna	0.28	Biella	0.55	Pescara	0.43
87	Pisa	0.41	Frosinone	0.27	Sassari	0.55	Foggia	0.43
88	Sassari	0.4	Foggia	0.27	Cagliari	0.53	La Spezia	0.43
89	Cagliari	0.39	Novara	0.26	Frosinone	0.53	Pisa	0.43
90	Palermo	0.39	Grosseto	0.26	Pisa	0.52	Varese	0.4
91	Varese	0.38	Sassari	0.26	Taranto	0.52	Frosinone	0.4
92	Como	0.38	Palermo	0.26	Palermo	0.52	Sassari	0.4
93	Grosseto	0.38	Cagliari	0.26	Lecce	0.51	Palermo	0.39
94	Taranto	0.37	Potenza	0.25	Brindisi	0.51	Grosseto	0.39
95	Brindisi	0.37	Sondrio	0.25	Grosseto	0.51	Taranto	0.39
96	Novara	0.37	Rieti	0.24	Cosenza	0.51	Novara	0.39
97	Lecce	0.37	Aosta	0.24	Como	0.49	Sondrio	0.37
98	Rieti	0.36	Taranto	0.23	Rieti	0.48	Lecce	0.36
99	Reggio Calabria	0.36	Lecce	0.22	Varese	0.48	Cosenza	0.36
100	Cosenza	0.35	Brindisi	0.22	Novara	0.47	Aosta	0.35
101	Aosta	0.34	Enna	0.22	Enna	0.44	Rieti	0.35
102	Sondrio	0.34	Cosenza	0.2	Aosta	0.43	Brindisi	0.32
103	Enna	0.33	Genova	0.2	Sondrio	0.42	Enna	0.32
104	Genova	0.27	Reggio Calabria	0.18	Crotone	0.4	Genova	0.29
105	Crotone	0.26	Crotone	0.14	Vibo Valentia	0.39	Vibo Valentia	0.27
106	Vibo Valentia	0.24	Vibo Valentia	0.12	Genova	0.34	Crotone	0.25
107	Catanzaro	0.14	Catanzaro	0.08	Catanzaro	0.21	Catanzaro	0.13

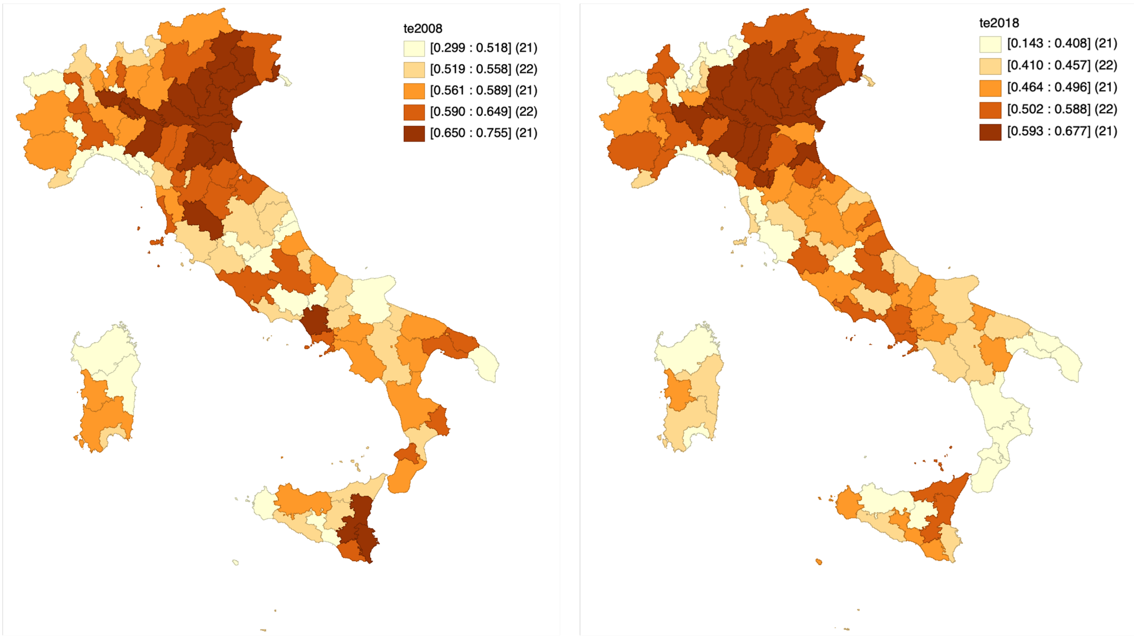

FIGURE 6.5: TE Scores Quantile Map, Years 2008 and 2018

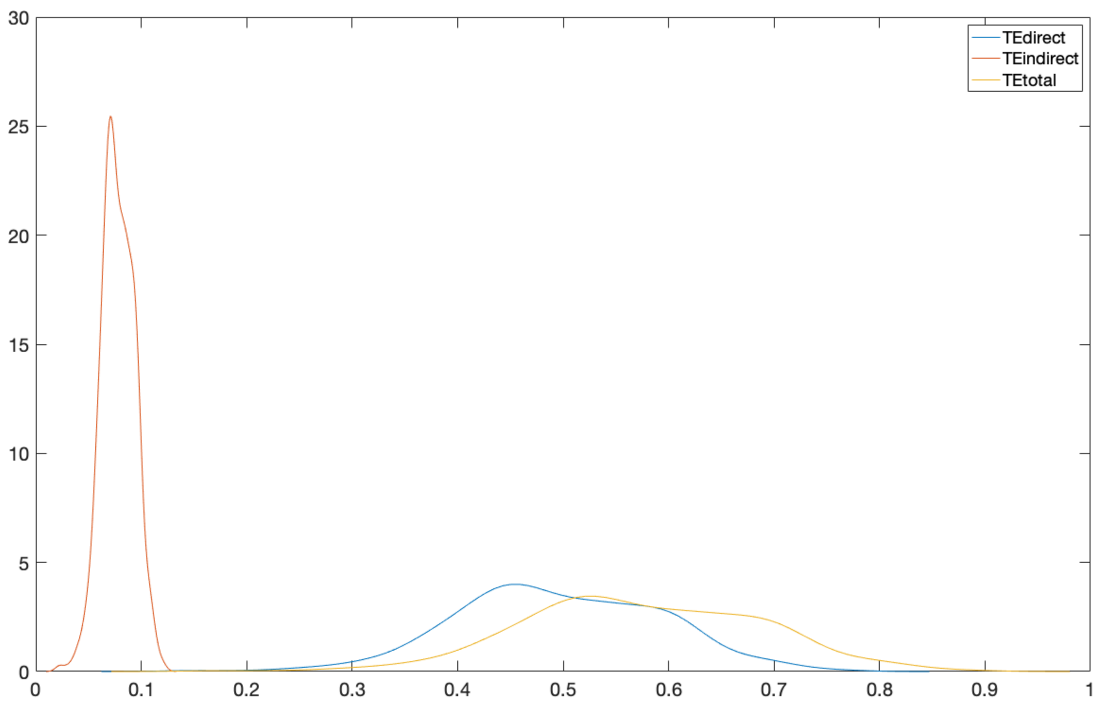

FIGURE 6.6: Direct, Indirect, and Total TE Scores: Kernel Density Plot

TABLE 6.7: Robustness Check

	SF		**FE**		**Lag-1**	
	Coeff	*SD*	*Coeff*	*SD*	*Coeff*	*SD*
β_0	2.83***	0.18	2.41***	0.17	3.92***	0.25
β_L	0.61***	0.02	0.66***	0.02	0.60***	0.03
β_{AA}	0.08***	0.01	0.09***	0.01	0.07***	0.02
β_M	0.09***	0.01	0.07***	0.01	0.06***	0.02
β_{WEF}	0.28***	0.01	0.23***	0.01	0.26***	0.02
β_t	-0.01***	0.01	-0.01***	0.01	-0.01***	0.01
σ_u^2	0.01	-	0.01	-	0.43	-
σ_v^2	0.34	-	0.29	-	0.45	-

	Lag-2		**FE and Lag-1**		**FE and Lag-2**	
	Coeff	*SD*	*Coeff*	*SD*	*Coeff*	*SD*
β_0	4.62***	0.32	3.75***	0.27	4.63***	0.35
β_L	0.60***	0.04	0.63***	0.03	0.63***	0.04
β_{AA}	0.08***	0.03	0.10***	0.02	0.11***	0.03
β_M	0.04**	0.02	0.04**	0.02	0.03**	0.02
β_{WEF}	0.23***	0.03	0.22***	0.02	0.19***	0.03
β_t	-0.01*	0.01	-0.01**	0.01	-0.01*	0.01
σ_u^2	0.61	-	0.42	-	0.61	-
σ_v^2	0.48	-	0.41	-	0.44	-

$***: pvalue \leq 0.01$; $**: pvalue \leq 0.05$; $*: pvalue \leq 0.10$

input variables can have a distorting effect on the estimation results. Indeed, unobserved individual factors such as soil types, average managerial abilities, environmental conditions, land quality, feeds, labour conditions, and different technologies across provinces are likely relevant for the agricultural sector's performance (Demirdogen, Olhan, and Hasdemir, 2021). Moreover, when the variables used in the analysis are collected from farm accounting data, the production data can reflect the optimizing behaviour of the farmers, meaning that farmers typically chose the level of the inputs and outputs with an objective in mind, which makes inputs and output choice variables economically endogenous. As depicted by Lien, Kumbhakar, and Alem (2018, p.53) "*The economic endogeneity in almost all the cases leads to econometric endogeneity in which the choice variables are correlated with the composite error term in the production function*". However, to date, in stochastic frontier literature, there are no current available methods dealing together with spatial heterogeneity, individual heterogeneity and endogeneity. Therefore, more research has to be done to fill this gap.

To test whether our findings are robust to unobserved individual heterogeneity and to endogeneity issues, in this section we compare our non-spatial estimates with those of the non-spatial true fixed effect stochastic frontier model introduced by Greene (2005a) and we partially attempt to control for possible endogeneity using lagged variables as proposed by Castiglione and Infante (2014) and de Vries and Koetter (2011). As shown in Table 6.7, our non-spatial estimates are robust to the fixed-effect model specification and to simultaneity issues related to the input variables. Moreover, in the last two columns of Table 6.7 we control for both individual fixed effects and for endogeneity using lagged variables. Overall, the estimation results are in line with our baseline estimates, confirming that distortions arising from individual unobserved effects and endogeneity are typically small (Drucker and Feser, 2012; Ellison, Glaeser, and Kerr, 2010; Koo and Lall, 2007; Rice, Venables, and Patacchini, 2006).

6.6 Final Remarks

Evaluating the SDF-CSD model from a practical perspective, in this section we find that the main advantage resulting from estimating the SDF-CSD model in practice concerns the possibility of also evaluating a number of nested specifications never introduced before. Indeed, starting from the SDF-CSD and making some LR tests for nested models, it is possible to test whether it is better to simplify the model specification considering only specific spatial lags or if a comprehensive spatial SF model is required. Thus, it is possible to precisely assess which kind of spatial effect is more appropriate for studying the phenomenon under investigation without making a priori assumptions on the spatial structure of the data.

Moreover, we showed that the SDF-CSD model allows obtaining more accurate technical efficiency scores, mixing together the main distributional features resulting from spatial SF models that only include frontier-based or error-based spillovers. Indeed, we found that the efficiency scores resulting from both non-spatial SF models and simpler spatial SF models result to be biased, generating inconsistent efficiency rankings across units. Specifically, the efficiency scores from spatial SF models considering spatial cross-sectional dependence only in the frontier function tend to be upwardly biased while those coming from spatial SF models introducing only error-based spatial cross-section dependence tend to be underestimated.

Considering the main findings of this empirical application on the productive performance of the Italian agricultural sector, we showed that this sector is highly affected by spatial spillover effects both related to the frontier function and to the two error terms. Specifically, using the SDF-CSD model we find that both sources of spatial dependence positively and significantly influence neighbouring provinces, even if behavioural correlation in the inefficiency determinants and environmental correlation associated with unobserved spatially correlated variables exceed the level of frontier-based global spatial dependence. Thus, the Italian provinces mainly benefit from the existence of positive agglomeration economies in terms of agricultural production resulting from common practices and similar unobserved features characterising neighbouring areas.

From a practical perspective, the empirical evidence on the existence of significant agglomeration externalities originating from various channels has important implications for policymakers dealing with the Italian agricultural sector. Indeed, strategic plans and programs aimed at improving the Italian agricultural sector's performance may take advantage of positive spillovers by strengthening the cohesiveness of the networks, providing more opportunities for farmers to learn from each other, stimulating cooperation and networking, and encouraging local farmers associations as well as knowledge dissemination on the use of new equipment and new management practices. Exploiting existing spatial interactions by creating a collaborative environment can be an effective strategy for policymakers to overcome the technological backwardness of most Italian farmers and thus, boost the productivity of the Italian agricultural sector.

In future extensions of this work, it would be interesting to evaluate the effectiveness of CAP subsidies from an environmental perspective aiming to evaluate whether they really contribute to environmental sustainability, good maintenance of agricultural land and natural resources, and to a balanced development of rural areas.

Conclusion

Final Remarks

After presenting the concepts of industrial clustering, agglomeration externalities, and spatial spillover effects in Chapter 1 and previous spatial stochastic frontier models in Chapter 2, in this thesis, two extensions of existing spatial stochastic frontier models have been developed in Chapter 3. The first spatial model, i.e. the SDF-STE, extends the spatial SF model proposed by Glass, Kenjegalieva, and Sickles (2016) adding some exogenous determinants of firms' efficiency and their spatial lags. Thus, besides considering productivity and input spillovers, this model introduces the possibility to evaluate whether the determinants of technical inefficiency of nearby firms contribute to shaping the efficiency level of neighbours. This is the first model that allows considering detailed and distinct insights on the indirect effects originating from each inefficiency determinant of neighbouring producers. The second model developed in this thesis, i.e. the SDF-CSD, extends the spatial SF model developed by Orea and Alvarez (2019) introducing a further spatial structure related to the frontier function. Indeed, while Orea and Alvarez (2019) consider spatial cross-sectional dependence related to the random error term and to the inefficiency component, we also include the possibility to evaluate productivity and input spillovers including the spatial lag of the dependent variable and of the input variables in the same fashion as Glass, Kenjegalieva, and Sickles (2016). To our knowledge, this is the first spatial stochastic frontier model considering four different kinds of spatial effects, two related to the frontier function and two related to the error components. Thus, this is the only specification that allows controlling for both error-based and frontier-based spatial spillover effects. In Chapter 4 we tested the final sample properties of the two proposed specifications. The results of the simulations indicate that the SDF-STE model performs well also considering small samples while to estimate the SDF-CSD model without bias it is better to consider sparse spatial structures related to the spatial lag of the inefficiency component. In Chapters 5 we applied the SDF-STE model to firm-level data on the Italian accommodation sector while in Chapter 6 we estimated the SDF-CSD model using NUTS3 level data for the Italian agricultural sector. Empirical results from these two applications demonstrate the empirical relevance of both models. Indeed, applying the SDF-STE model to hotel data allows to precisely disentangle the specific indirect effects associated with R&D activity, human capital investments, and patents and trademarks filing performed by neighbouring spatial units. In particular, we find that while the indirect effects associated with intangible and human capital investments positively spread over the territory, spillover effects related to patents and trademarks are negative. Thus, patents and trademarks play an effective role in protecting innovative hotels' productive advantage. On the other hand, estimating the SDF-CSD model using RICA data sheds light on the different sources of spatial dependence occurring across neighbouring provinces in terms of agricultural production. Specifically, we find that the Italian agricultural sector is more strongly affected by error-based than by frontier-based spillovers. Moreover, we show that the SDF-CSD model allows to more accurately estimate the technical efficiency scores, mixing together the main distributional features resulting from spatial SF models that only include frontier-based or error-based spillovers. In conclusion, the SDF-STE and the SDF-CSD models can be useful for a variety of works on economic topics in the fields of regional science, productivity and efficiency analysis, firm-level microdata applications and in general for several kinds of analyses dealing with spatial networking and agglomeration. On one hand, the SDF-STE model is suitable for studies in which the specific spatial spillovers affecting neighbouring firms' efficiency levels are the main focus of the investigation. On the other hand, the SDF-CSD model can be a useful starting point for different kinds of analyses in which no prior assumptions on the kind of spatial structure to be included in the model can be made. Indeed, starting from the SDF-CSD model it is possible to select the spatial specification that best fits the data testing different restrictions through likelihood ratio tests. Thus, the SDF-CSD model leads the way to a number of spatial specifications never introduced before but that can be very useful in empirical applications.

Limits and Further Developments

Recent advancements in stochastic frontier models literature have primarily focused on two different directions: (i) introducing some spatial components in order to consider cross-sectional spatial dependence (Areal and Pede, 2021; Glass, Kenjegalieva, and Sickles, 2016; Orea and Alvarez, 2019; Tsukamoto, 2019); (ii) controlling for non-spatial individual heterogeneity (Belotti and Ilardi, 2018; Greene, 2005a, 2005b; Kutlu, Tran, and Tsionas, 2020b; Wang and Ho, 2010) or for possible sources of endogeneity (Amsler, Prokhov, and Schmidt, 2016; Kutlu, Tran, and Tsionas, 2019). Up to now, to our knowledge, there are no contributions controlling together for both spatial and non-spatial individual heterogeneity, while the only work developing a SF model considering both a spatial autoregressive term and endogeneity due to the correlation of the inefficiency term and the two-sided error term is Kutlu (2020). In this thesis, positioning in the first strand of literature described above, we focus on the spatial dimension. However, given the relevant role of both individual effects and endogeneity issues, in Chapter 5 and 6 we compared our results to other non-spatial SF approaches that allow considering individuals-specific effects or that control for possible endogeneity issues to test the robustness of our estimates. The results obtained controlling for unobserved individual heterogeneity or for possible endogeneity issues are in line with our baseline estimates, showing that distortions arising from individual unobserved effects and endogeneity are small. Thus, according to Drucker and Feser (2012), Ellison, Glaeser, and Kerr (2010), Koo and Lall (2007), and Rice, Venables, and Patacchini (2006) we do not expect that endogeneity issues or individual heterogeneity could have a relevant and distorting impact on our findings.

In a further extension of this work, a model that combines the main features of both spatial specifications introduced in this thesis could be proposed. In particular, starting from the SDF-CSD, it would be possible to drop the spatial lag related to the whole inefficiency error term and add the specific spatial lags of the inefficiency determinants in the same fashion as the SDF-STE model in order to control for the specific spatial effects related to each determinant of firms' efficiency level besides capturing productivity spillovers, input spillovers and environmental correlation. Further extensions of the models presented in this thesis could aim at controlling for endogeneity using an instrumental variables approach extending Kutlu (2020) estimator in order to account for endogeneity issues while considering different sources of spatial dependence as proposed in this thesis. In addition, it would be interesting to introduce a fixed or random effect estimator to take unobserved individual heterogeneity into account. In particular, starting from Wang and Ho (2010) within transformed or first difference non-spatial estimator, it would be possible to add different spatial terms in order to control for both spatial dependence and fixed effects. Moreover, the inefficiency error term in the SDF-CSD model could be extended in order to vary both across time ad individuals by using a Bayesian approach for the estimation to deal with non-closed forms for the loglikelihood function.

Appendix A

CES, Cobb-Douglas and Trans-Log Production Functions

From the CES to the Cobb-Douglas Function

The CES (constant elasticity of substitution) function, introduced by Arrow et al. (1961) in their study "*Capital-Labor Substitution and Economic Efficiency*", was developed to overcome the limitation of the Cobb-Douglas function of imposing an elasticity of substitution between inputs of exactly 1. The elasticity of substitution is a measure of the extent to which one input substitutes for another along an isoquant. In particular, if inputs do not substitute, the elasticity of substitution equals zero and isoquants forms a right angle, while if inputs are perfect substitutes for each other it approaches infinity and isoquants consist of lines with no curvature. In the Cobb-Douglas case, a percentage change in the ratio of the use of two inputs x_1 and x_2 along an isoquant makes the marginal rate of substitution change of the exact same percentage (i.e. the elasticity of substitution equals 1). Therefore, the CES function was developed to avoid assuming a priori unitary elasticity of substitution between inputs and to estimate it using data. The main features of the CES function are: (i) the elasticity of substitution between two inputs can vary between zero and infinity; (ii) for a given set of parameters, the elasticity of substitution is constant at any point along the same isoquant, regardless of the ratio of inputs used. The name "constant elasticity of substitution (CES) production function" comes from this second property.

Considering labour (L) and capital (K) as the only two factors influencing the level of output Y, the CES function can be written as in Eq.(A.1),

$$Y = a(\alpha K^{-\rho} + (1-\alpha)L^{-\rho})^{-\frac{\nu}{\rho}} \tag{A.1}$$

where $a \in [0, \infty[$ represents TFP, $\alpha \in [0, 1]$ determines the optimal distribution of the two inputs, $\rho \in [-1, 0[\cup]0, \infty[$ is the substitution parameter and ν represents the homogeneity degree. In particular, $\nu = 1$ corresponds to the case of constant returns to scale; $\nu > 1$ corresponds to the case of increasing returns to scale and $\nu < 1$ corresponds to the case of decreasing returns to scale. The elasticity of substitution can be obtained as $\sigma = \frac{1}{1+\rho}$.

It can be demonstrated that, imposing $\nu = 1$, when $\rho \to 0$ (and therefore $\sigma \to 1$) the CES function reduces to a Cobb-Douglas production function. In particular, we refer to the logarithmic form of Eq.(A.1) and we compute the limit for $\rho \to 0$. This limit leads to an indeterminate form of type $\frac{0}{0}$, thus, we apply de l'Hôpital rule as shown in Eq.(A.2c) to obtain the log-form of the Cobb-Douglas production function with constant returns to scale in Eq.(A.2d).

$$\lim_{\rho\to 0} \log Y = \lim_{\rho\to 0} \left(\log a - \frac{1}{\rho} \log(\alpha K^{-\rho} + (1-\alpha)L^{-\rho}) \right) \tag{A.2a}$$

$$= \log a + \lim_{\rho\to 0} \frac{-\log(\alpha K^{-\rho} + (1-\alpha)L^{-\rho})}{\rho} \tag{A.2b}$$

$$= \log a + \lim_{\rho\to 0} \frac{-\left(-\alpha K^{-\rho} \log K - (1-\alpha)L^{-\rho} \log L\right)}{\alpha K^{-\rho} + (1-\alpha)L^{-\rho}} \tag{A.2c}$$

$$= \log a + \alpha \log K + (1-\alpha) \log L \tag{A.2d}$$

The CES function can therefore be used to represent different substitution possibilities and related isoquant patterns, but also this function has two relevant limits. Indeed, like the Cobb-Douglas, the CES function can represent only the second stage of production for both inputs (i.e. concentric or oval isoquants are not allowed), meaning that production is characterized by decreasing but positive marginal returns. Moreover, even if the CES can include more than two inputs, the elasticity of substitution is a single parameter. Therefore, the same elasticity value must apply to all input pairs. All these limits can be overcome using a Trans-Log production function. Indeed, the Trans-Log function allows the marginal rate of substitution to vary from one point to another along the same isoquant. Moreover, partial elasticities of substitution can be calculated for each pair of inputs.

The Trans-Log Function

The Trans-Log function, developed by Christensen, Jorgenson, and Lau (1971, 1973), can be derived as an approximation of the CES function using a second-order Taylor polynomial at $\rho = 0$. In particular, starting from the log-form of the CES function previously defined, the Taylor series expansion around $\rho = 0$ is shown in Eq.(A.3a)-(A.3b).

$$\log Y = \log a + \nu\alpha \log K + \nu(1-\alpha) \log L - \frac{\rho\nu}{2}\alpha(1-\alpha) \log K^2$$
$$- \frac{\rho\nu}{2}\alpha(1-\alpha) \log L^2 + \rho\nu\alpha(1-\alpha) \log L \log K \tag{A.3a}$$

$$= \log a + \nu\alpha \log K + \nu(1-\alpha) \log L - \frac{\rho\nu}{2}\alpha(1-\alpha)(\log L - \log K)^2 \tag{A.3b}$$

The Trans-Log function considering only labour and capital as inputs can be written as in Eq.(A.4) with $\alpha_0 = \log a$, $\alpha_K = \nu\alpha$, $\alpha_L = \nu(1-\alpha)$, $\alpha_{LL} = \alpha_{KK} = -\frac{\rho\nu}{2}\alpha(1-\alpha)$, $\alpha_{LK} = \rho\nu\alpha(1-\alpha)$ and satisfying the conditions in Eq.(A.5)-(A.6).

$$\log Y = \alpha_0 + \alpha_K \log K + \alpha_L \log L + \alpha_{KK} \log K^2 + \alpha_{LL} \log L^2 + \alpha_{KL} \log L \log K \tag{A.4}$$

$$\alpha_K + \alpha_L = \nu \tag{A.5}$$

$$\rho\nu\alpha(1-\alpha) = \alpha_{KL} = -2\alpha_{LL} = -2\alpha_{KK} \tag{A.6}$$

As shown in Eq.(1.5) in Chapter 1, the Trans-Log function can be generalized including any number of inputs. Moreover, when $\rho = 0$ (i.e. when $\sigma = 1$), the Trans-Log function reduces to the Cobb-Douglas function.

To determine the elasticity of substitution for a Trans-Log function, we can follow Allen's approach (Allen, 1938). In particular, it is necessary to know the parameters of the production function as well as to be aware of the precise point on the isoquant for which the elasticity of substitution is to be estimated and of the input ratio $\frac{x_1}{x_2}$ for that point. Indeed, unlike the Cobb Douglas and the CES function, the Translog production function does not have constant elasticities of substitution and thus, the percentage change in the input ratio divided by the percentage change in the marginal rate of substitution is not constant all along the isoquant but varies from one point to another. The elasticity of substitution between two generic inputs x_i and x_j can be expressed as

$$\begin{aligned} \sigma_{ij} &= \frac{\left(x_i \frac{\partial Y}{\partial x_i} + x_j \frac{\partial Y}{\partial x_j}\right)}{x_i x_j} \frac{\frac{\partial Y}{\partial x_i}\frac{\partial Y}{\partial x_j}}{\left(2\frac{\partial^2 Y}{\partial x_i \partial x_j}\frac{\partial Y}{\partial x_i}\frac{\partial Y}{\partial x_j} - \frac{\partial^2 Y}{\partial^2 x_i}\left(\frac{\partial Y}{\partial x_i}\right)^2 - \frac{\partial^2 Y}{\partial^2 x_j}\left(\frac{\partial Y}{\partial x_j}\right)^2\right)} \\ &= \frac{\left(x_i \frac{\partial Y}{\partial x_i} + x_j \frac{\partial Y}{\partial x_j}\right)}{x_i x_j} \frac{\frac{\partial Y}{\partial x_i}\frac{\partial Y}{\partial x_j}}{|H|} \end{aligned} \tag{A.7}$$

where

$$H = \begin{bmatrix} 0 & \frac{\partial Y}{\partial x_i} & \frac{\partial Y}{\partial x_j} \\ \frac{\partial Y}{\partial x_i} & \frac{\partial^2 Y}{\partial^2 x_i} & \frac{\partial^2 Y}{\partial x_i \partial x_j} \\ \frac{\partial Y}{\partial x_j} & \frac{\partial^2 Y}{\partial x_i \partial x_j} & \frac{\partial^2 Y}{\partial^2 x_j}. \end{bmatrix} \tag{A.8}$$

If a production function has more than two inputs, the partial elasticities of substitution for each pair of them can be computed.

Appendix B

Model Comparison

In stochastic frontier model literature, the likelihood ratio test is the more commonly used tool in order to compare nested competing specifications. However, due to the recent development of several extensions of standard SF models based on different underlying distributions for the inefficiency error term or on different modelling approaches in order to include some inefficiency determinants, simple LR tests for nested specifications may no longer be sufficient. Thus, in order to compare non-nested model specifications two different tools can be adopted: the Takeuchi information criteria and the Vuong test on the closeness of two competing models to the true data generating process. In both cases, the model selection is based on the Kullback-Leibler information criterion (KLIC), providing information on the loss obtained by approximating the true probability distribution of the data with a given probability distribution. Specifically, given the true probability density $h(y|s)$ and the parametric family of SF model with conditional probability density $f(y|s;\theta_f)$, the KLIC is defined as

$$KLIC(h(y|s), f(y|s;\theta_f)) = E_h(ln(h(y|s))) - E_h(ln(f(y|s;\theta_f^*))) \tag{B.1}$$

where E_h is the expectation with respect to the true distribution $h(y|s)$ and θ_f^* is the pseudo-true value of the unknown parameter θ_f. Given that the first term on the right hand side of Eq.(B.1) does not depend on the choice of the model, the KLIC corresponds to choosing the model specification that maximises the second term of Eq.(B.1) and thus, that minimizes the information loss. A straightforward estimator of this second term is given by:

$$lnL_n^f(\hat{\theta}_f) = \frac{1}{n}\sum_{i=1}^{n} ln(f|s;\hat{\theta}_f) \tag{B.2}$$

where $\hat{\theta}_f$ is the maximum likelihood estimator[1] of the unknown parameter θ_f given the model F_{θ_f}, the data $(y_i, s_i)_{i=1}^n$, and conditional log-likelihood function $lnL_n^f(\hat{\theta}_f)$.

[1]The maximum likelihood estimator is a consistent estimator for θ_f^* (Vuong, 1989; White, 1982)

Akaike and Takeuchi information criteria

As suggested by Akaike (1973), the expression in Eq.(B.2) is a biased estimator of $E_h(ln(f(y|s;\theta_f^*)))$. Thus, the author suggested $lnL_n^f(\hat{\theta}_f) - d_f$ as a bias corrected estimator of the second term of Eq.(B.1), where d_f is the number of parameters of the model F_{θ_f}. This expression is valid under the assumption that the model is correctly specified, i.e. $h(y|s)$ is nested in $f(y|s;\theta_f)$. Starting from this proposed estimator, the Akaike information criteria is then defined as in Eq.(B.3).

$$AIC = -2lnL_n^f(\hat{\theta}_f) + 2d_f \tag{B.3}$$

Therefore, by easily substituting the value of the log-likelihood function in Eq.(B.3), it is possible to obtain a measure of the relative distance between the estimated model and the true data generating process. As a consequence, when different competing nested models are compared, a model with a smaller AIC has to be preferred.

Generalizing the AIC information criteria for non-nested models, Takeuchi (1976) proposed the following information criteria:

$$TIC = -2lnL_n^f(\hat{\theta}_f) + 2tr(H(\hat{\theta}_f)I(\hat{\theta}_f)^{-1}) \tag{B.4}$$

where $I(\hat{\theta}_f)$ and $H(\hat{\theta}_f)$ are respectively the sample analogue of the Fisher information matrix and of the expected outer product of the score function, defined as shown in Eq.(B.5)-(B.6).

$$H(\hat{\theta}_f) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\partial lnf(y|s;\hat{\theta}_f)}{\partial\theta_f}\frac{\partial lnf(y|s;\hat{\theta}_f)}{\partial\theta_f^T}\right) \tag{B.5}$$

$$I(\hat{\theta}_f) = -\frac{1}{n}\sum_{i=1}^{N}\frac{\partial^2 lnf(y|s;\hat{\theta}_f)}{\partial\theta_f\partial\theta_f^T} \tag{B.6}$$

In the case of nested models, $tr(H(\hat{\theta}_f)I(\hat{\theta}_f)^{-1}) = d_f$ and the TIC information criteria reduces to the AIC.

LR and Vuong test

We now consider a competing alternative model G_{θ_g} nested to F_{θ_f}. The likelihood ratio test is based on the idea that the preferred model is the one that is closer to the true conditional distribution, i.e. it is the one that minimizes the KLIC. Thus, if the model F_{θ_f} is preferred to G_{θ_g}, we have that:

$$KLIC(h(y|s), f(y|s;\theta_f^*)) < KLIC(h(y|s), g(y|s;\theta_g^*)) \tag{B.7}$$

and therefore,

$$E_h(ln(f(y|s;\theta_f^*))) > E_h(ln(g(y|s;\theta_g^*))) \tag{B.8}$$

or

$$E_h\left(ln\frac{f(y|s;\theta_f^*)}{g(y|s;\theta_g^*))}\right) > 0. \tag{B.9}$$

Hence, if we want to compare two different nested models F_{θ_f} and G_{θ_g}, the choice can be based on the sign of Eq.(B.9). Specifically, the test is based on the null hypothesis "the two models are equivalent (i.e. given that the nested model G_{θ_g} is simpler than F_{θ_f}, G_{θ_g} is better than F_{θ_f})", against the alternative hypothesis "F_{θ_f} is better than G_{θ_g}". The test statistic can therefore be based on the sample counterpart of Eq.(B.9) shown in Eq.(B.10).

$$\frac{1}{n}\sum_{i=1}^{n}\left(ln\frac{f(y|s;\hat{\theta}_f)}{g(y|s;\hat{\theta}_g))}\right) = \frac{1}{n}(lnL_n^f(\hat{\theta}_f) - lnL_n^g(\hat{\theta}_g)) \tag{B.10}$$

Specifically, the likelihood ratio test statistic for nested models is given in Eq.(B.11) and under H0 it is distributed as a chi-squared distribution with $d_f - d_g$ degrees of freedom.

$$LR(\hat{\theta}_f, \hat{\theta}_g) = 2(lnL_n^f(\hat{\theta}_f) - lnL_n^g(\hat{\theta}_g)) \tag{B.11}$$

However, when the competing model G_{θ_g} is non-nested to F_{θ_f}, the LR test is no more applicable. Therefore, Vuong (1989) proposed an alternative test based on the test statistics shown in Eq.(B.12) in order to compare non-nested specifications. The null hypothesis of the test is that the two models are equally close to the true data generating process without giving any more a clear information on the model that has to be preferred, since there is no more a simpler and a more complex specification. The alternative hypothesis remains unchanged and states "F_{θ_f} is better than G_{θ_g}". The test statistic of the Vuong test is shown in Eq.(B.12) and under H0, it is asymptotically distributed as a standardized normal random variable.

$$V(\hat{\theta}_f, \hat{\theta}_g) = \frac{n^{-\frac{1}{2}}LR(\hat{\theta}_f, \hat{\theta}_g)}{\hat{\sigma}_{LR}} \tag{B.12}$$

In particular, $\hat{\sigma}_{LR}$ is the estimator of the variance of $E_h\left(ln\frac{f(y|s;\theta_f^*)}{g(y|s;\theta_g^*))}\right)$ and it can be calculated as shown in the following equation.

$$\hat{\sigma}_{LR} = \frac{1}{n}\sum_{i=1}^{n}\left(ln\frac{f(y|s;\hat{\theta}_f)}{g(y|s;\hat{\theta}_g)}\right)^2 - \left(\frac{1}{n}\sum_{i=1}^{n}ln\frac{f(y|s;\hat{\theta}_f)}{g(y|s;\hat{\theta}_g)}\right)^2 \tag{B.13}$$

Examples

In this section, the two models developed in this thesis are compared based on the data on the Italian accommodation sector and on the Italian agricultural sector respectively used in Chapter 5 and Chapter 6.

Application to the Italian Accommodation Sector

In Chapter 5 the SDF-STE model was estimated using data on the Italian accommodation sector in order to evaluate the different spatial effects arising from the inefficiency determinants of Italian hotels. Starting from this first application, we estimate the empirical specification shown in Eq.(5.1)-(5.2) using the SDF-CSD model. The resulting specification is shown in Eq.(B.14)-(B.15). In particular, it can be noticed that while the Translog specification for the frontier function remains unchanged with respect to the SDF-STE model, the inefficiency model is completely different. Indeed, while using the SDF-STE model the mean μ_{it} of the inefficiency error term u_{it} is modelled as a linear function of some inefficiency determinants, using the SDF-CSD model, the Z variables are related to the scaling function $\widetilde{h}_{it}$ and consequently, they refer to the variance-covariance structure of the inefficiency component. Moreover, considering the spatial structure of u_{it}, while in the SDF-STE model the spatial lag of all the inefficiency determinants is added to the inefficiency equation, using the SDF-CSD model, the overall level of spatial correlation associated with the Z variables is detected thought the spatial parameter τ. Finally, also the structure of the random component v_{it} changes. Indeed, in the SDF-STE model v_{it} follows a truncated normal distribution with mean 0 and variance σ_v^2 while using the SDF-CSD model $v_{it} \sim MVN\,(0, \Pi)$, where $\Pi = \sigma_v^2 (I_N - \gamma W)^{-1}((I_N - \gamma W)^{-1})^T$. Therefore, using the SDF-CSD model, it is possible to capture through γ also the level of spatial dependence related to unobserved but spatially correlated variables.

$$\begin{aligned} Y_{it} &= \beta_0 + \beta_L L_{it} + \beta_K K_{it} + \beta_{LL} L_{it}^2 + \beta_{KK} K_{it}^2 + \beta_{LK} L_{it} K_{it} + \beta_t t + \beta_{2t} t^2 + \beta_{tL} t L_{it} \\ &\quad + \beta_{tK} t K_{it} + \rho \sum_{j=1}^{N} w_{ij} Y_{jt} + \theta_L \sum_{j=1}^{N} w_{ij} L_{jt} + \theta_K \sum_{j=1}^{N} w_{ij} K_{jt} - u_{it} + v_{it} \end{aligned} \tag{B.14}$$

$$\begin{aligned} \widetilde{h}_{it} &= (I_N - \tau W)^{-1} \exp(\phi_{hum} Hum_{it} + \phi_{Int} Int_{it} + \phi_{pat} Pat_{it} + \phi_{trad} Trad_{it} + \phi_{size} Size_{it} \\ &\quad + \phi_{dsize} DSize_{it} + \phi_{city} City_{it} + \phi_{cult} Cult_{it} + \phi_{sea} Sea_{it} + \phi_{lake} Lake_{it} + \phi_{mou} Mou_{it} \\ &\quad + \phi_{csea} CSea_{it} + \phi_{cmou} CMou_{it} + \phi_{more} More_{it} + \phi_{nocat} Nocat_{it} + \phi_{notur} Notur_{it}) \end{aligned} \tag{B.15}$$

The estimation results using both models are shown in Table B.1. In particular, it can be noticed that the β estimates are quite robust to the different model specifications. Moreover, the degree of global spatial dependence (ρ) slightly increases using the SDF-CSD model (0.40) with respect to the SDF-STE (0.35). Considering the inefficiency model, we find different magnitudes of the ϕ estimates due to the different modelling approach of the Z variables in the two proposed specifications. However, the sign associated with each parameter is preserved indicating that the direction of the effect of each Z variable does not change dependent on the model specification. Finally, comparing the two competing models using the Vuong test and the Takeuchi information criteria, it results that the SDF-STE model in this empirical application has to be preferred with respect to the SDF-CSD. Indeed, the null hypothesis that two models are equivalent is rejected against the alternative hypothesis that the SDF-STE is better than the SDF-CSD using a 1% significance level. Moreover, a smaller TIC is associated with the SDF-STE compared to the SDF-CSD. Thus, the SDF-STE model results to be more appropriate to analysing the spatial spillover effects affecting neighbouring hotels located in Italy.

Furthermore, in Table B.2 we report the indirect effects computed using the two different spatial SF models. The main insight from Table B.2 concerns the different sources of spatial dependence that can be identified by the two proposed specifications. Indeed, while both models allow to evaluate the spillover effects related to the input variables, the spatial effects detected through the inefficiency model are completely different. In particular, through the SDF-STE it is possible to consider the indirect effects associated with each inefficiency determinant, while using the SDF-CSD, the focus moves to the overall level of spatial dependence associated with the Z variables (behavioural correlation) and to the remaining spatial dependence related to the random error term (environmental correlation). Thus, from a practical perspective, the choice of the preferred specification primarily depends on the economic assumptions made by the researcher, on the aim of the analysis, and on the policy directions that need to be achieved.

Considering the results in Table B.2, we find that positive and significant input spillovers occur between neighbouring hotels using both models. However, the magnitude of the indirect effects associated with labour and capital increases using the SDF-CSD model due to the higher level of global spatial dependence detected by this model. Considering the inefficiency equation, while the SDF-STE allows determining the specific spatial effects arising from human capital exploitation, intangible investments, patents and trademarks filing, and hotels' size as extensively discussed in Chapter 5, the SDF-CSD model only shows the existence of a strong, positive and significant level of spatial correlation related to the inefficiency determinants (0.37). On the other hand, the SDF-CSD also reveals that the random error term is characterized by some positive and significant residual spatial correlation (0.30), indicating that the Italian accommodation sector is affected by remaining positive spatial dependence related to unobserved location-specific factors.

TABLE B.1: Application to the Accommodation Sector: Estimation Results

SDF-STE Model			SDF-CSD Model		
	Coeff.	*t-stat*		*Coeff.*	*t-stat*
β_0	5.467***	13.71	β_0	3.064***	16.97
β_L	0.662***	84.87	β_L	0.680***	41.98
β_K	0.077***	17.20	β_K	0.138***	15.21
β_{LL}	0.057***	40.57	β_{LL}	0.071***	25.21
β_{KK}	0.010***	22.5	β_{KK}	0.011***	13.38
β_{LK}	-0.029***	-29.00	β_{LK}	-0.045***	-13.38
β_t	-0.005	-1.09	β_t	-0.022	-1.19
β_{2t}	-0.001*	-1.25	β_{2t}	-0.014***	-2.69
β_{tL}	0.004***	5.00	β_{tL}	0.003**	2.24
β_{tK}	0.001***	3.00	β_{tK}	0.001**	2.25
ρ	0.351***	18.3	ρ	0.400***	8.90
θ_L	-0.216***	-11.33	θ_L	-0.119**	-1.76
θ_K	0.006	0.78	θ_K	0.094***	2.99
ϕ_0	5.251***	13.23	ϕ_{hum}	-0.247***	-34.36
ϕ_{hum}	-0.647***	-208.58	ϕ_{Int}	-0.073***	-13.94
ϕ_{Int}	-0.115***	-29.54	ϕ_{pat}	-0.026***	- 4.30
ϕ_{pat}	-0.054***	-9.53	ϕ_{trad}	-0.019***	-2.70
ϕ_{trad}	-0.038***	-5.78	ϕ_{size}	0.005*	1.43
ϕ_{size}	-0.037***	-10.57	ϕ_{dsize}	0.039***	2.18
ϕ_{dsize}	0.081***	5.66	ϕ_{city}	-0.012	-1.22
δ_{hum}	0.160***	7.31	ϕ_{cult}	0.014*	1.49
δ_{Int}	-0.072***	-2.71	ϕ_{sea}	-0.024***	-3.82
δ_{pat}	0.099***	2.80	ϕ_{lake}	-0.018*	-1.57
δ_{trad}	0.039	0.97	ϕ_{mou}	0.021**	1.71
δ_{size}	-0.013	-0.7	ϕ_{csea}	-0.032***	-5.06
δ_{dsize}	-0.358***	-3.85	ϕ_{cmou}	0.008**	1.95
ϕ_{city}	-0.064***	-5.94	ϕ_{more}	-0.001	-0.19
ϕ_{cult}	0.016*	1.43	ϕ_{nocat}	0.029***	3.06
ϕ_{sea}	-0.095***	-8.89	ϕ_{notur}	0.028	1.00
ϕ_{lake}	-0.139***	-9.06	τ	0.368***	23.74
ϕ_{mou}	-0.007	-0.45	γ	0.298***	9.13
ϕ_{csea}	-0.085***	-8.12	σ_u^2	0.962	-
ϕ_{cmou}	-0.065***	-5.04	σ_v^2	0.871	-
ϕ_{more}	-0.047***	-3.77			
ϕ_{nocat}	0.052***	4.71			
ϕ_{notur}	0.015	0.48			
σ^2	0.199	-			
λ	0.879	-			
LL	-29861.9		LL	-48120.6	
V	Base Model		V	8.65***	
TIC	59719.5		TIC	95561.2	

$*\!*\!*: pvalue \leq 0.01$; $*\!*: pvalue \leq 0.05$; $*: pvalue \leq 0.10$

TABLE B.2: Application to the Accommodation Sector: Indirect Effects

Model	SDF-STE		SDF-CSD	
Indirect Effects	*Coeff.*	*SD*	*Coeff.*	*SD*
Labour	0.07***	0.01	0.23***	0.04
Capital	0.08***	0.01	0.22***	0.02
Human Capital	-0.10***	0.02	-	-
Int	-0.17***	0.02	-	-
Patents	0.12***	0.03	-	-
Trademarks	0.04*	0.03	-	-
Size	-0.04***	0.01	-	-
Behavioural Corr.	-	-	0.37***	0.02
Environmental Corr.	-	-	0.30***	0.03

$***: pvalue \leq 0.01$; $**: pvalue \leq 0.05$; $*: pvalue \leq 0.10$

Application to the Italian Agricultural Sector

In Chapter 6, the SDF-CSD model was applied to the Italian agricultural sector using RICA data. In this section, we estimate the empirical model specified in Eq.(6.1)-(6.2) also using the SDF-STE model in order to compare the estimation results and the estimated spatial effects. In particular, the frontier function shown in Eq.B.16 does not change with respect to the one specified for the SDF-CSD, while the inefficiency model in Eq.B.17 completely changes. Indeed, estimating the SDF-STE model we refer to the mean μ_{it} of the technical inefficiency error term instead of the variance-covariance structure to account for the effect of some inefficiency determinants and we add to the inefficiency equation the spatial lag of each variable. Thus, the δ estimates allow capturing the specific spatial effects affecting the efficiency level of neighbouring provinces arising from each Z variable.

$$\begin{aligned} Y_{it} &= \beta_0 + \beta_L L_{it} + \beta_{AA} AA_{it} + \beta_M M_{it} + \beta_{WEF} WEF_{it} + \beta_t t + \rho \sum_{j=1}^{N} w_{ij} Y_{jt} \\ &\quad + \theta_L \sum_{j=1}^{N} w_{ij} L_{jt} + \theta_{AA} \sum_{j=1}^{N} w_{ij} AA_{jt} + \theta_M \sum_{j=1}^{N} w_{ij} M_{jt} + \theta_{WEF} \sum_{j=1}^{N} w_{ij} WEF_{jt} - u_{it} + \widetilde{v}_{it} \end{aligned} \tag{B.16}$$

$$\begin{aligned} \mu_{it} &= \phi_S Small_{it} + \phi_B Big_{it} + \phi_F Family_{it} + \phi_D Diversified_{it} + \phi_H Hired_{it} + \phi_Y Youth_{it} \\ &\quad + \phi_W Woman_{it} + \phi_{Sub} Subsidies_{it} + \delta_S \sum_{j=1}^{N} w_{ij} Small_{jt} + \delta_B \sum_{j=1}^{N} w_{ij} Big_{jt} + \delta_F \sum_{j=1}^{N} w_{ij} Family_{jt} \\ &\quad + \delta_D \sum_{j=1}^{N} w_{ij} Diversified_{jt} + \delta_H \sum_{j=1}^{N} w_{ij} Hired_{jt} + \delta_Y \sum_{j=1}^{N} w_{ij} Youth_{jt} + \delta_W \sum_{j=1}^{N} w_{ij} Woman_{jt} \\ &\quad + \delta_{Sub} \sum_{j=1}^{N} w_{ij} Subsidies_{jt} \end{aligned} \tag{B.17}$$

Table B.3 shows the estimation results of the two competing specifications using RICA data on the Italian agricultural sector. First, it can be noticed that the β estimates are robust to the different specifications while the ϕ estimates, as in the previous case, maintain the same significance and sign across the two different models even if the magnitudes tend to change. Moreover, considering the overall level of spatial dependence detected through ρ, we find a higher degree of global spatial dependence using the SDF-STE compared to the SDF-CSD model. However, as we will show in the next paragraph, the estimated input spillovers are approximately the same. Comparing these two non-nested specifications using the Vuong test and the Takeuchi information criteria, we find that the SDF-CSD model has to be preferred to the SDF-STE in this empirical application. Indeed, we reject at a 5% significance level the null hypothesis that the two models are equivalent against the alternative hypothesis that the SDF-CSD is better than the SDF-STE. Moreover, the TIC information criteria confirms a better fit of the SDF-CSD compared to the SDF-STE. Thus, due to the importance of error-based spatial dependence in the Italian agricultural sector, the SDF-CSD model has to be preferred to the SDF-STE.

Finally, Table B.4 shows the indirect effects estimated using the two different spatial SF models introduced in this thesis. Considering input spillover effects, the SDF-STE model and the SDF-CSD highly agree on the existence of negative and significant spillovers related to the use of agricultural land. Moreover, using both models, the spatial spillover effects related to machinery and to water, energy, and fuel are positive but not significantly different from zero. Labour spillovers represent the only exception. Indeed, while they are not significant using the SDF-CSD model, the indirect effect associated with labour is positive and statistically significant at a 10% significance level using the SDF-STE. Considering the inefficiency determinants, we find a positive and significant overall level of behavioural spatial correlation using the SDF-CSD (0.37), while estimating the SDF-STE we are able to distinguish the specific spatial effects related to each Z variable. In particular, we find that the spatial spillovers related to small, big, and family farms positively influence the efficiency level of neighbouring provinces, while the spatial spillover effects related to the percentage of hired land, subsidies, young entrepreneurs and farms run by women are negative and significant. On the other hand, the indirect effect related to the use of diversification techniques is not statistically significant. Finally, only the SDF-CSD model is able to detect some positive and significant remaining spatial correlation related to the random error component (0.37).

TABLE B.3: Application to the Agricultural Sector: Estimation Results

SDF-CSD Model			SDF-STE Model		
	Coeff.	*t-stat.*		*Coeff.*	*t-stat.*
β_0	3.867***	7.29	β_0	2.447***	7.85
β_L	0.614***	26.82	β_L	0.640***	32.00
β_{AA}	0.135***	8.53	β_{AA}	0.131***	9.56
β_M	0.072***	5.03	β_M	0.078***	6.14
β_{WEF}	0.200***	14.29	β_{WEF}	0.190***	15.97
β_t	-0.011	-0.83	β_t	0.010***	3.70
ρ	0.137**	1.78	ρ	0.366***	7.55
θ_L	-0.060	-0.80	θ_L	-0.180***	-3.25
θ_{AA}	-0.246***	-5.21	θ_{AA}	-0.233***	-7.19
θ_M	0.025	0.58	θ_M	0.010	0.31
θ_{WEF}	0.022	0.43	θ_{WEF}	-0.067**	-1.99
ϕ_S	0.703***	4.01	ϕ_0	0.184***	18.40
ϕ_B	-1.722***	-3.75	ϕ_S	0.321***	7.20
ϕ_F	0.218**	1.95	ϕ_B	-0.614***	-0.65
ϕ_D	0.367***	2.51	ϕ_F	0.131***	32.75
ϕ_H	-0.062	-0.58	ϕ_D	0.334***	7.46
ϕ_{Sub}	0.711***	7.39	ϕ_H	0.021	0.51
ϕ_Y	0.655***	3.33	ϕ_{Sub}	0.152***	3.01
ϕ_W	0.546***	3.00	ϕ_Y	0.353***	7.88
τ	0.371***	3.08	ϕ_W	0.142***	14.20
γ	0.368***	5.29	δ_S	-0.471***	-5.11
σ_u^2	0.047		δ_B	-0.543***	-5.73
σ_u^2	0.090		δ_F	-0.275***	-39.29
			δ_D	-0.014	-0.11
			δ_H	0.231***	38.50
			δ_{Sub}	0.680***	4.13
			δ_Y	0.407***	2.47
			δ_W	0.051***	12.75
			σ^2	0.071	
			λ	0.154	
LL	-284.61		LL	-539.27	
V	Base Model		V	2.21**	
TIC	569.24		TIC	1056.10	

$***: pvalue \leq 0.01$; $**: pvalue \leq 0.05$; $*: pvalue \leq 0.10$

TABLE B.4: Application to the Agricultural Sector: Indirect Effects

Model	SDF-CSD		SDF-STE	
Indirect Effects	*Coeff.*	*SD*	*Coeff.*	*SD*
Labour	0.03	0.06	0.08*	0.06
Land	-0.26***	0.05	-0.28***	0.05
Machinery	0.04	0.05	0.06	0.05
Water, Energy, Fuel	0.06	0.05	0.01	0.05
Small	-	-	-0.54***	0.14
Big	-	-	-1.17***	0.40
Family	-	-	-0.35***	0.03
Diversified	-	-	0.17	0.15
Hired	-	-	0.36***	0.04
Subsidies	-	-	1.12***	0.27
Youth	-	-	0.82***	0.26
Woman	-	-	0.16***	0.03
Behavioural Corr.	0.37***	0.07	-	-
Environmental Corr.	0.37***	0.05	-	-

$***: pvalue \leq 0.01$; $**: pvalue \leq 0.05$; $*: pvalue \leq 0.10$

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