Spillover Effects in the Innovative Activity of Italian Start-ups: a Spatial Stochastic Frontier Approach

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Abstract

Start-ups play a fundamental role in countries' economic growth since they stimulate inventiveness and market dynamics and in periods of deep transformations, it becomes even more important to understand what contributes to determining their survival in the market. In this framework, innovation is a key factor for favouring incumbent firms' positive performance, survival and competitiveness. Besides internal investments in R&D activity and the presence of skilled and qualified personnel, also the external environment in which incumbent firms are located can represent a key source of new knowledge thanks to knowledge and learning spillovers occurring in innovative clusters. Therefore, in this paper, we evaluate the role of knowledge spillovers in affecting Italian start-ups efficiency level differentiating between spatial effects arising from intangible investments and firms' patenting activity. Moreover, we also consider whether productivity and input spillovers occur across neighbouring start-ups. To achieve these goals, we use georeferenced firm-level data on Italian innovative start-ups in the period 2018-2020 and we estimate a spatial stochastic frontier model that allows considering different sources of spatial dependence. The results of the analysis can help policymakers design plans and policies aimed at favouring start-ups' competitiveness by exploiting firms' interaction and cooperation.

1. Introduction

Start-ups are fundamental for countries' economic growth since they stimulate inventiveness and market dynamics, increase productivity and satisfy new consumers' needs by producing highly technological and up-to-date products (Antonietti, Gambarotto, 2020). In periods of crises and profound transformations, the identification of the sources of start-up's survival in the market is crucial. In Italy, policymakers are paying particular attention to innovative start-ups due to their key role in (re)launching and promoting the national economy. In

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particular, the 'Italian Start-up Act' issued by the Italian government by Decree Law 221/2012 in 2012 recognizes the key role of entrepreneurship and innovation as drivers of sustainable economic growth. Between the different factors affecting entrepreneurs' propensity to start a new business, empirical studies have identified the key role of the context in which new firms originate such as the personality traits of the population, the social acceptance of the entrepreneur status and the regional entrepreneurship culture (Stuetzer *et al.* 2017; Kibler *et al.* 2014; Fritsch, Wyrwich, 2014, 2017; Capello, Lenzi, 2016). However, a large number of start-ups fail within the first three years of activity due to inappropriate technological, market and institutional conditions (Acs *et al.*, 2016).

One of the main engines for start-ups' survival and competitiveness can be identified by firms' innovative activity. Indeed, despite the difficulty of new firms to survive the first years of activity, innovation can play a fundamental role in determining incumbent firms' positive performance. Between internal innovative factors, R&D investments, patents and qualified personnel play a crucial role in shaping start-ups' innovation process. First, R&D activities are characterized by high uncertainty because firms do not know in advance if R&D investments will achieve some positive and exploitable results. Moreover, research activity performed by start-ups is even more risky because incumbent firms often make R&D investments in an informal, non-systematic and non-organic way (Matricano, 2020a, 2020b). However, research activity is a fundamental first step to achieving higher performances (Galizzi, Venturini, 1996; Leiponen, 2000; Avermaete *et al.*, 2004; Frick *et al.*, 2019). A second factor that can allow start-ups to reach superior returns is the presence of qualified personnel such as scientists and engineers (Huiban, Bouhsina, 1998; Leiponen, 2000). Indeed, adequately trained and skilled people can contribute better to R&D activities compared to general technicians and employees thanks to their distinctive competencies (Selznick, 1957). Finally, holding a patent is usually a positive signal of start-ups quality and strength because it allows new ventures to achieve higher returns protecting their innovative efforts thanks to property rights for the newly developed products (Mason, Stark, 2004; Hottenrott *et al.*, 2016; De Rassenfosse, 2012). However, patenting is usually too expensive for incumbent entrepreneurs and bigger companies are more willing to hold patents with respect to small start-ups (Andries, Faems, 2013; Frietsch *et al.*, 2013; Greenberg, 2013).

Besides the importance of internal innovative activity, also the external environment in which firms are embedded plays a crucial role in determining new ventures' performance due to the relevance of learning and knowledge spillovers in stimulating incumbent firms' innovative activity (Acs *et al.* 2009; Jacobs, 1969). 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*". Thus, knowledge spreads better within geographical boundaries because of its tacit and uncodified nature (Baptista, 2000). Therefore, also investments in innovative activities performed by other firms and public organizations in the neighbourhood contribute to positively influencing peers (Link, Rees, 1990; Audretsch, Belitski, 2020) and this is particularly true for start-ups due to the importance of external knowledge inputs in the first business stages (Audretsch *et al.*, 2021). In particular, being located in highly innovative areas encourages both start-up formation and subsequent performance because growing and promising clusters attract new businesses, talented entrepreneurs and individuals with relevant skills and new ideas and knowledge tend to spill over stimulating new ventures' innovative activity (Porter, 2000).

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). Crespi *et al.* (2007) 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 closest firms. 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). The intensity at which new knowledge is assimilated depends on the absorptive capacity of firms. According to Yang (2010), absorptive capacity is the most important prerequisite for success because identifying new sources of knowledge, assimilating, and applying them to commercial ends guarantees a successful knowledge transfer.

Despite many studies recognized the importance of spillover effects in shaping start-ups' productive performance, to our knowledge, there are still no studies investigating the role of both internal and external sources of innovation in determining the level of efficiency of incumbent firms. However, both for entrepreneurs and local governments, it would be fundamental to be aware of the role of knowledge spillovers originating from different sources of firms' innovative activity in shaping neighbouring start-ups' performance in order to design plans and programs aimed at supporting start-ups' formation and survival. Therefore, in this paper, we aim at measuring the impact of both internal innovation and spatial effects arising from neighbouring start-ups' innovative activity on incumbent firms' efficiency levels. Specifically, we concentrate on Italian innovative start-ups in the time period 2018-2020 and we estimate the spatial Durbin stochastic frontier model introducing spillover effects in the determinants of firms' efficiency introduced by Galli (2023). Indeed, this novel spatial stochastic frontier model allows evaluating the specific spatial effects arising from each inefficiency determinant introducing the spatial lag of the inefficiency variables. Moreover, besides capturing spillover effects related to firms' efficiency, it also allows to identify productivity and input spillovers affecting neighbouring firms' performance. As a result, clear and distinct insights on the different spatial effects can be obtained distinguishing between spillover effects affecting the level of productivity of firms and spatial effects related to firms' efficiency level.

To sum up, this study extends the current literature on start-ups' performance in different ways. First, to our knowledge, this is the first paper investigating the impact of external sources of innovation on start-ups' efficiency levels. Second, besides considering spillover effects related to firms' innovative activity, we also evaluate spatial effects affecting firms' productivity level, i.e. productivity and input spillovers. Indeed, greater availability of specific products, input suppliers, assets and workers with industry-specific skills in a certain territory may favour input spillovers (Marshall, 1890) while start-ups' productive performance may be influenced by the one of neighbours due to the transmission of best practices between peers, collective behaviours resulting from face-to-face relationships, learning from others, and firms' adoption of new similar technologies (Skevas, Lansink, 2020). The results of our analysis indicate that while positive and significant knowledge spillover generate from neighbouring start-ups' intangible investments, spillover effects related to patents are negative but non-statistically significant. Policymakers can therefore rely on these insights to design proper policies and plan to favour start-ups' innovative activity promoting interaction, cooperation and exchange of ideas between neighbours.

2. Econometric Approach

In order to obtain detailed insights on the different kinds of spatial spillover effects affecting start-ups' productive performance we estimate the spatial stochastic frontier model for panel data introduced by Galli (2023). The first characteristic of this novel spatial specification consists in introducing the spatial lag of each inefficiency determinant, allowing the evaluate the specific spillover effects arising from each variable that contribute to determining the inefficiency level of neighbours. The second characteristic concerns the comprehensiveness of the model specification. Indeed, it introduces three different spatial terms allowing to capture productivity spillovers, input spillovers and spatial effects related to the determinants of firms' inefficiency level. Thus, by estimating this model, it is possible to evaluate whether productivity and input spillovers affect the productive performance of neighbouring start-ups as well as to investigate the role of knowledge spillovers arising from start-ups' innovative activity in shaping peers' inefficiency level. The model specification is defined as in Equations (1-4) with i=1,…,N and t=1,…,T indicating the spatial unit index and the time index.

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

$$v_{it} \sim i.i.d. N\left(0, \sigma_v^2\right) \quad [2]$$

$$u_{it} \sim i.i.d. N^{+}\left(\mu_{it}, \sigma_u^2\right) \quad [3]$$

$$\mu_{it} = Z_{it}\phi + \sum_{j=1}^{N} w_{ij} Z_{jt} \quad [4]$$

Specifically, Y_{it} indicates the productive output of the i-th firm at time t, X_{it} represents a $(1\times k)$ vector including the k production inputs used by firm i at time t with related parameter vector β $(k \times 1)$, ρ is the scalar parameter associated with the spatial lag of the dependent variable, allowing to capture global spatial spillovers, w_{ij} refers to the generic element of the block diagonal spatial weight matrix W $(NT \times NT)$ containing positive spatial weights to identify neighbouring spatial units (indexed by j=1,…,N) and zero elements on the main diagonal, θ is the parameter vector $(k \times 1)$ referring to the spatial lag of the input variables capturing exogenous local input spillovers. Following the classical specification for the error term ε_{it} as being composed by two independent components (Aigner *et al.*, 1977), v_{it} represents the random error and it is assumed to follow a normal distribution with zero mean and variance σ_v^2 as shown in Equation (2) while u_{it} is the inefficiency error term identifying the distance from the productive output of each firm given the level of inputs to the optimal frontier due to technical inefficiency and, in this framework, it is usually assumed to follow a truncated normal distribution with mean u_{it} and variance σ_v^2 as shown in Equation (3). Finally, following the modelling approach introduced by Battese and Coelli (1995) and modified in order to capture spatial effects related to the inefficiency determinants, the mean u_{it} of the inefficiency term u_{it} in Equation (4) is modelled as function of m exogenous variables (Z_{it}) representing the inefficiency determinants with associated parameter vector ϕ ($m\times1$) and of their spatial lag with related parameter vector δ ($m\times1$), allowing to identify spatial dependence arising from the determinants of technical inefficiency of nearby firms.

To estimate the model in Equations (1-4) the two variance parameters should be reparametrized as $\sigma^2 = \sigma_u^2 + \sigma_v^2$, $\lambda = \sigma_u^2/\sigma^2$ and consistent parameter estimates can be found by implementing a likelihood-based approach. In particular, being the two error terms independent, the joint probability density function of v_{it} and u_{it} can be obtained as the product of the two marginal distributions (i.e. normal and truncated normal, respectively). Subsequently, substituting in the joint probability density function of v_{it} and u_{it} and u_{it} the expression v_{it} and $v_{it}=\varepsilon_{it}-u_{it}$, the joint probability density function of u_{it} and ε_{it} can be obtained. Then, the joint probability density function of ε can be found integrating out u_{it} and multiplying all the marginal distributions of ε_{it} for with i=1,…,N and t=1,…,T. Starting from the joint probability density function of ε, the likelihood function can be obtained as the product of $f_\varepsilon(\varepsilon)$ and the determinant of the Jacobian of the transformation from ε_{it} to Y_{it} in order to take the endogeneity deriving from the inclusion of the spatial lag of the dependent variable into account. The parameter estimates can be found maximising the loglikelihood function using numerical algorithms implemented in standard statistical software. More details on the underlying modelling assumptions and the estimation technique can be found in Galli (2023).

However, in spatial models introducing the spatial lag of the dependent variable, the β estimates cannot be interpreted as marginal effects because changes in the generic regressor X_r of firm i also affect the production output of firm j (Elhorst, 2014). Therefore, also in this case, the marginal effects have to be computed separately, and in particular, they are contained in the matrix on the right-hand side of Equation (5) representing the first partial derivative of Y with respect to the generic regressor X_r (r=1,…,k).

$$\frac{\partial Y}{\partial X_r} = (I_{NT} - \rho W)^{-1}(I_{NT}\beta_r + W\theta_r) \qquad [5]$$

In order to summarize the information contained in that matrix, LeSage and Pace (2009) proposed to compute the marginal effects of the independent variable X_r on Y differentiating among direct, indirect and total effects. In particular, they proposed to identify the direct effect of the X_r on Y as the average of the diagonal elements of the matrix on the right-hand side of Equation (5), the indirect effect as the average of the sum of the non-diagonal elements of that matrix, and the total effect as the sum of the direct and the indirect effects.

As for the β estimates, also the ϕ estimates related to the inefficiency determinants cannot be interpreted as marginal effects due to the introduction of the spatial lag of the dependent variable. Thus, the marginal effects can be computed starting from the matrix on the right-hand side of Equation (6) representing the first derivative of the inefficiency level with respect to the generic determinant Z_r with r=1,…,m.

$$\frac{\partial u}{\partial Z_r} = \left(I_{NT} - \rho W\right)^{-1}\left(I_{NT}\,\phi_r + W\delta_r\right) \quad [6]$$

Starting from that matrix and following LeSage and Pace (2009), the marginal effects of Z_r on u can be computed as before. Thus, the direct effect of Z_r on u can be computed as the average of the diagonal elements of the matrix on the right-hand side of Equation (6), the indirect effect as the average of the sum of the non-diagonal elements of that matrix, and the total effect as the sum of the direct and the indirect effects. Finally, in order to compute the related standard errors or t-values, it is possible to simulate the distribution of the direct, indirect and total effects based on the variance-covariance matrix obtained from the estimation procedure or, alternatively, they can be computed using the delta method.

Starting from the estimated coefficients, the technical efficiency scores can be computed following the method proposed by Battese and Coelli (1998) as $TE = E(exp\left(-u_{it}\right) \mid \varepsilon_{it})$. In particular, technical efficiency scores equal to zero will indicate fully inefficient firms while fully efficient firms will obtain a value of 1.

3. Data and Empirical Model

The data used in this paper are collected from the AIDA Bureau Van Dijk database, being the only one that provides information both on the consolidated accounts of Italian companies and on their geographical location. In particular, we considered all data on Italian innovative start-ups in the time period 2018-2020, where innovative start-ups are defined by Decree Law 221/2012 as those firms operating for at least 48 months, owned directly for at least 51% by physical subjects, with a turnover rate fewer than 5 million euros and with the social aim of developing innovative products and/or services with a high technological content (Colombelli, 2016). Overall, our final sample consists of 1301 firms observed over three years.

The specification of the empirical model is shown in Equations (7-8) for i=1,…N and t=1,…T. The frontier function in Equation (7) is modelled as a Cobb-Douglas function following a production function approach.

$$Y_{it} = \beta_0 + \rho\sum_{j=1}^{N} w_{ij}Y_{jt} + \beta_L L_{it} + \beta_K K_{it} + \beta_t t + \sum_{j=1}^{N} w_{ij}L_{jt}\theta_L + \sum_{j=1}^{N} w_{ij}K_{jt}\theta_K + v_{it} - u_{it} \quad [7]$$

Specifically, Y_{it} represents the productive output of firm i at time t and it is measured as the logarithm of the value added; the two input variables L_{it} and K_{it} are defined respectively as the logarithm of total salaries paid to the staff and of fixed capital; t represents the time trend and takes value 1 for the year 2018, 2 for 2019 e 3 for 2020. We include in the model specification both the spatial lag of the dependent variable and the spatial lag of the inputs to capture respectively productivity and input spillovers through ρ, θ_L and θ_K. While ρ measures the overall global level of spatial dependence related to firms' productivity level, the θ parameters identify local spatial dependence arising from input variables. To identify neighbouring start-ups we define the spatial weight matrix W as a row-standardized inverse distance matrix truncated at 50 kilometres. Thus, the spatial weights w_{ij}, before row-normalization, take positive values equal to $1/d_{ij}$ where d_{ij} indicates the distance between each pair of spatial units i, j and zero values in the main diagonal and for spatial units that are more than 50km away. Indeed, spillover effects are usually assumed to occur at the local level because firms' interaction and emulation need face-to-face contact, local cooperation and individual contact (Griliches, 1992). Finally, v_{it} is the random error component being distributed as a normal random variable with zero mean and variance σ_v^2 while u_{ij} represents the inefficiency error component and following Battese and Coelli (1995) it is assumed to follow a truncated normal distribution with mean μ_{ij} and variance σ_u^2. The mean of the inefficiency error term is modelled as a function of some exogenous inefficiency determinants as shown in Equation (8).

$$\mu_{it} = \phi_0 + \phi_{Int} Int_{it} + \phi_{Pat} Pat_{it} + \phi_{Size} Size_{it} + \phi_{Years} Years_{it} + \\ \phi_{Man} Man_{it} + \phi_{ST} ST_{it} + \phi_{IC} IC_{it} + \sum_{j=1}^{N} w_{ij} Int_{jt} \delta_{Int} + \sum_{j=1}^{N} w_{ij} Pat_{jt} \delta_{Pat} \qquad [8]$$

Specifically, we investigate how start-ups' innovative activity influences incumbent firms' efficiency level considering in the inefficiency model intangible investments and patent filling. In particular, we measure the share of investments in intangible capital as the ratio between investments in immaterial capital over total investments (*Int*). Intangible assets may be identified as a proxy for firms' innovative activity because they represent the value of a firm's information and communication technology, organizational capital, and investments in R&D (Bernini, Galli, 2022). Therefore, companies' competitiveness and success may be strongly associated with intangible investments because they allow new knowledge acquisition and process improvements (Montresor, Vezzani, 2016). Moreover, we measure start-ups' patenting activity through the dummy variable *Pat* which takes a value of 1 if the firms registered at least one patent in the time period considered and 0 otherwise. Patents are a very commonly used indicator of firms' innovative activity because patenting allows innovative start-ups to protect the newly developed product as trade secrets, granting the innovative firm a competitive advantage (Nelson, 2009). Besides considering how start-ups' internal innovation affects their efficiency level directly, we also consider spillover effects arising from innovative activity performed by neighbours. Indeed, incumbent firms may take advantage of knowledge originating from the external environment through emulation, cooperation and exchange of ideas with neighbouring firms. Therefore, we include in the model specification also the spatial lag of ***Int*** and ***Pat*** to evaluate whether investments in intangible capital performed by neighbours and having innovative firms that have registered patents as peers influence start-ups' efficiency level through knowledge spillovers.

In order to consider start-ups' heterogeneity we include in the inefficiency model also some control variables such as ***Size*** and ***Years*** where the former measures the start-ups' size as the logarithm of the number of employees and the latter captures the age of the head. Finally, we also take the three main sectors of activity into account including three dummy variables to identify those start-ups working in the manufacturing sector (*Man*), in the scientific and technological sector (*ST*), and in the information and communication sector (*IC*). We do not include the spatial lag of the control variables in the inefficiency model since the focus of the analysis is on start-ups' innovation and spillover effects arising from innovative activity performed by neighbours.

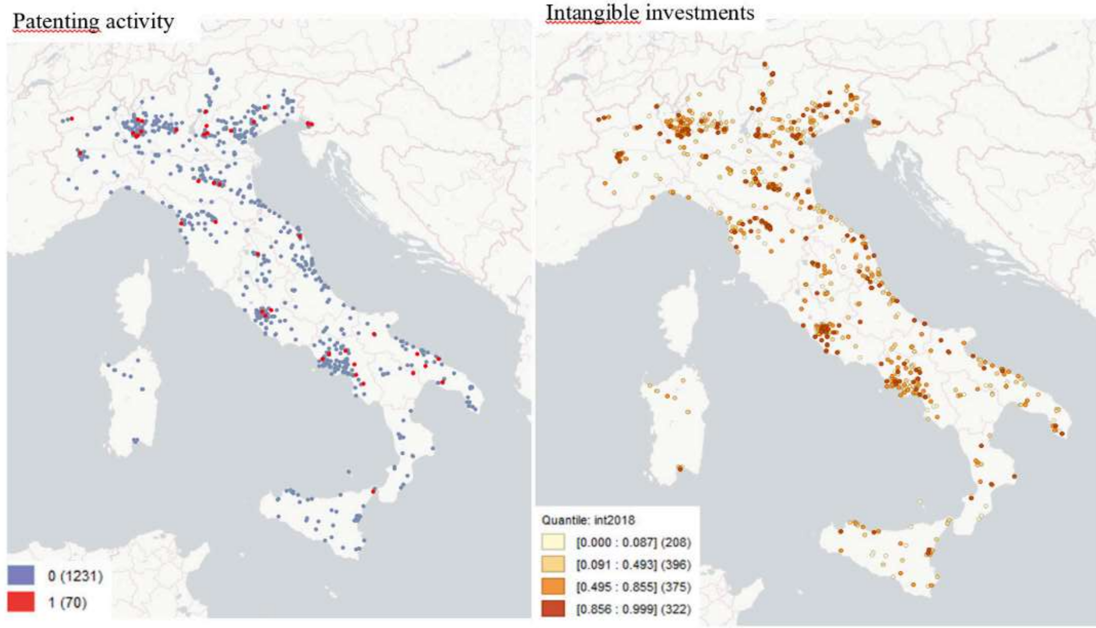
More details on the variables used in the analysis and some descriptive statistics are provided in Table 1. Moreover, some insights on the innovative activity performed by Italian start-ups can be found in Figure 1. In particular, it can be observed that only 70 firms over 1301 have developed at least one patent in the time period considered and these firms tend to be located in the main

Table 1 – Variables and Descriptive Statistics

Variables	*Definition*	*Min*	*Mean*	*Max*	*SD*
Y	Log(valueadded)	0	3.33	6.87	1.77
L	Log(totalsalaries)	0	2.04	6.81	2.02
K	Log(fixedcapital)	0	1.55	6.80	1.71
t	1 if 2018; 2 if 2019; 3 if 2020	1	2	3	0.82
Int	Share of intangible investments over total investments	0	0.48	0.99	0.37
Pat	1 if the firm has registered at least one patent in the time period; 0 otherwise	0	0.04	1	0.19
Size	Log(numberofemployees)	0	0.55	3.09	0.70
Age	Log(age)	3.13	3.81	4.44	0.25
Man	1 if in manufacturing sector; 0 otherwise	0	0.14	1	0.34
IC	1 if in information and communication sector; 0 otherwise	0	0.48	1	0.50
ST	1 if in scientific and technological sector; 0 otherwise	0	0.26	1	0.44

Source: Authors' elaboration

Figure 1 – Start-ups' Innovative Activity



Source: Authors' elaboration

Italian metropolises such as Rome, Milan, Naples, Bologna, Turin, etc. Considering start-ups' intangible investments, the right panel of Figure 1 shows that investments in intangible assets tend to prevail in firms belonging to innovative clusters rather than in firms located in isolated locations.

4. Estimation Results, Marginal Effects and Efficiency Scores

The results in Table 2 indicate that Italian innovative start-ups' are affected globally by positive and significant productivity spillovers. Indeed, the estimate

Table 2 – Estimation Results

	Coeff	*SD*
B_0	6.45 ***	0.23
B_L	0.57 ***	0.02
β_K	0.24 ***	0.01
β_t	0.05 ***	0.00
θ_L	0.02	0.04
θ_K	0.01	0.05
ρ	0.04 *	0.03
ϕ_0	5.46 ***	0.41
ϕ_{Int}	-0.45 ***	0.07
ϕ_{Pat}	-0.03	0.13
ϕ_{Age}	0.01 ***	0.00
ϕ_{Size}	0.07 **	0.06
ϕ_{Man}	0.04	0.08
ϕ_{IC}	-0.15 ***	0.08
ϕ_{ST}	-0.31 ***	0.09
δ_{Int}	-0.49 ***	0.18
δ_{Pat}	0.15	0.31
σ^2	1.42	-
λ	0.39	-
Min TE	0.01	
Mean TE	0.16	
Max TE	0.64	

Notes: ***: p-value < 0.01; **: p-value < 0.05; *: p-value < 0.10

Source: Authors' elaboration

of ρ equals 0.04 and is significant at a 5% significance level. Therefore, having productive firms as neighbours positively affects the productivity level of peers. However, due to the introduction of the spatial lag of the dependent variable, we cannot interpret the β and the ϕ estimates in a meaningful way because they do not coincide with the first partial derivatives of Y with respect to X and Z, respectively. Thus, marginal effects have to be computed separately.

Table 3 shows the marginal effects of both the input variables and the inefficiency determinants. Starting from the direct effects related to labour and capital, we find that both inputs have a positive and significant effect on start-ups' productive performance as expected, but labour (0.57) contributes more to shaping incumbent firms' productivity level compared to capital (0.24). Indeed, in the first phases of a business, capital investments may be still limited and start-ups' competitiveness may primarily depend on labour forces. Considering the indirect effects originating from labour and capital of neighbouring producers, we find evidence of positive but non-significant input spillovers. Thus, in the early stages of a firm's activity, being located in areas with a high endowment of assets and workers may not be such influential due to the key role of internal investments.

Passing to the marginal effects of the inefficiency determinants, we find that both internal intangible investments and patenting activity contribute to decreasing firms' inefficiency level but while the former effect is highly negative in

Table 3 – Marginal Effects of the Input Variables and of the Inefficiency Determinants

Inputs:	*Direct effect*	*Indirect effect*
L	0.57 ***	0.05
K	0.24 ***	0.02
Inefficiency Determinants:		
Int	-0.45 ***	-0.52 ***
Pat	-0.03	0.16
Size	0.07 **	-
Age	0.01 **	-
Man	0.04	-
IC	-0.15 ***	-
ST	-0.31 ***	-

Notes: ***: p-value < 0.01; **: p-value < 0.05; *: p-value < 0.10

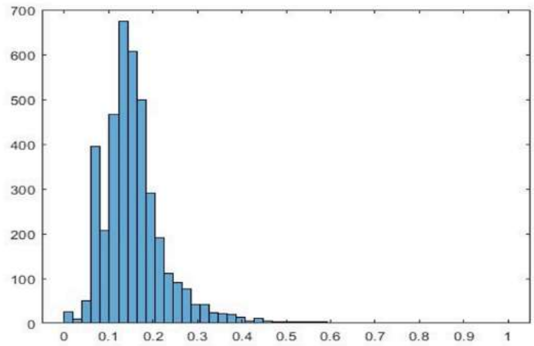
Source: Authors' elaboration

magnitude (-0.45) and significant, the direct effect related to registered patents results to be negative but non-significant (-0.03). Indeed, innovative activity performed through ICT and R&D investments can allow start-ups to develop new competitive products and services and to improve business processes and operations while patenting activity can help protect the newly developed products thanks to property rights that prevent other firms to commercialize them (Helmers, Rogers, 2011). However, the direct effect of patents may result to be non-significant since very few start-ups registered at least one patent in the years of analysis (only 4% of firms in our sample). Indeed, patenting is usually too expensive for incumbent firms (Andries, Faems, 2013; Frietsch *et al.*, 2013). Considering the indirect effects arising from neighbouring start-ups' innovative activity, we find that while positive and significant knowledge spillovers originate from intangible investments performed by peers, neighbours' registered patents have a negative indirect effect on the efficiency level of neighbouring producers even if it appears to be non-significant. Indeed, investments in ICT and R&D performed by neighbours tend to decrease the inefficiency level of peers (-0.52) while the indirect effect of patents on inefficiency results to be positive (0.16). Thus, we find evidence of positive knowledge spillovers originating from highly innovative clusters while patents registered by neighbours result to have an effective blocking function with respect to the newly developed products even if it is not statistically significant.

Finally, we find that the direct effect of size is positive (0.07) and significant and thus, bigger start-ups tend to be more inefficient than smaller ones. This insight is not uncommon in the literature since, greater firm size requires major monitoring and coordination costs (Liang *et al.*, 2008) and it can slow down managers' competitive moves and agreements on firms' strategy (Hambrick *et al.*, 1996; Iaquinto, Fredrickson, 1998) making communication, coordination, and decision making more difficult and inefficient, especially in the early stages of a business (Matricano *et al.*, 2022). Moreover, our results indicate that the age of the head positively affects inefficiency indicating that younger managers tend to run businesses more efficiently compared to elderly people. Finally, we find that while start-ups in the manufacturing sector tend to be more inefficient than others, the most efficient start-ups are those belonging to the information and communication sector (-0.31) and the scientific and technological sector (-0.15).

Considering the technical efficiency scores, the last three rows of Table 2 show some insights on the minimum, mean and maximum levels of efficiency of Italian innovative start-ups. In particular, we find that, in the time period considered, the average level of technical efficiency of Italian start-ups is very low and equal to 0.16. The histogram in the upper panel of Figure 2 confirms this finding, showing a distribution of the TE scores very concentrated around the low values, with very

Figure 2 – Technical efficiency scores



Source: Authors' elaboration

few firms reaching scores higher than 0.4. Moreover, the lower panel of Figure 2 shows some insights on the geographical distribution of the TE scores, highlighting that more efficient start-ups tend to be located in neighbouring locations in the areas of Milan, Rome, Naples, Bologna and Padua. On the other hand, less efficient start-ups are mostly located isolated in space and in the internal areas of Italy.

5. Conclusion

In this paper, we investigate the productive performance of Italian innovative start-ups in the time period 2018-2020 taking spatial effects occurring across neighbouring firms into account. In particular, we consider spillover effects influencing both firms' productivity and efficiency levels by estimating the comprehensive spatial stochastic frontier model introduced by Galli (2023) including three different kinds of spatial effects. Indeed, besides considering productivity and input spillover related to the frontier function, this model specification allows capturing the specific spatial effects arising from each inefficiency determinant and influencing start-ups' efficiency levels. Thus, considering start-ups' innovative activity as one of the main sources of (in)efficiency, we analyse both the effect of internal innovation on the efficiency level of Italian incumbent firms and whether neighbouring firms' innovative activity also contributes to boosting peers' performance. To reach this goal, we use georeferenced firm-level data from the AIDA Bureau Van Dijk database on Italian innovative start-ups in the time period 2018-2020.

The results from our analysis indicate that internal intangible investments performed by start-ups significantly contribute to reducing the level of inefficiency of firms. Moreover, also investments in intangible capital of neighbouring producers tend to positively and significantly affect start-ups located in neighbouring areas likely due to knowledge spillovers. Indeed, being embedded in highly innovative clusters positively influences all firms belonging to the cluster thanks to knowledge transfer, innovation sharing and transmission of ideas. Considering patents, we find that while they contribute to decreasing firms' inefficiency level from an internal point of view, negative spillover effects generate across neighbouring units due to their protecting and blocking function with respect to the newly developed products. However, both the direct and indirect effects of patent results to be non-significant since most of the Italian start-ups did not register any patent in the time period considered.

Findings from this paper are relevant both from a theoretical and a practical perspective. Indeed, despite the importance of knowledge spillovers for start-ups formation and survival is highly recognized in economic literature from a theoretical point of view, we provide empirical evidence on the close link between start-ups' innovative activity, neighbouring start-ups' innovation, and incumbent firms' productive performance. In designing plans and policies to support entrepreneurial activity, policymakers can therefore rely on insights from this work in order to strengthen start-ups' performance by promoting internal innovative activity as well as firms' cooperation, networking, and exchange of ideas. Therefore, in order to support and sustain Italian innovative start-ups, governments should design ad hoc policy interventions at the local level as suggested by Capello and Lenzi (2013) aiming at strengthening the linkages and collaboration between inventors, skilled people and entrepreneurs to facilitate knowledge and innovation sharing that in turn can lead to higher industrial performances and finally to increased employment and economic growth (Antonietti, Gambarotto, 2020).

In future extensions of this work, it could be interesting to run this kind of analysis for a longer time span taking into consideration start-ups entering and leaving the sample over time by using an econometric approach suited for unbalanced panel data. However, to date, there are no available methods dealing with both spatial effects and unbalanced panel data in a stochastic frontier setting.

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