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ORIGINAL ARTICLE

Assessing the role of spatial externalities in the survival of Italian innovative startups

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Abstract

The paper provides novel empirical evidence about the effects of spatial externalities on the survival of innovative startups in Italy. Using geocoded firm-level data, we build micro-geographic measures of specialization and diversity that are robust to the modifiable areal unit problem. Estimates of spatial externalities are obtained through survival regression models that assess the relationship between these measures and firms' survival time. The main findings are that the nature and strength of agglomeration externalities depend on the firm's life cycle. In particular, an interesting stylized fact can be deduced: these kinds of external economies have a negative effect on innovative startups' survival at the beginning of their activity, which then reverses to be positive when innovative startups reach a certain maturity.

KEYWORDS
firm survival, geocoded firm-level data, innovative startups, spatial externalities

JEL CLASSIFICATION
C41, D22, R12

1 | INTRODUCTION

Italian *innovative startups*, a particular legal form of new venture recently introduced by the Italian government, have become an interesting case study to empirically assess research hypotheses about the role of innovation in the economy. Indeed, a growing body of literature is devoted to analyzing data pertaining to these peculiar economic activities to make advancements in industrial economics, regional sciences, management sciences, and entrepreneurship studies. Startups dedicated to innovation are interesting because they often achieve better performances (Bandera & Thomas, 2018; Vivarelli & Audretsch, 1998), contribute to creating new employment opportunities and developing new sectors (Acs & Audretsch, 1987; Matricano, 2020a, 2020b; Shearman & Burrell, 1998), and, overall, have an essential role in the improvement of the welfare system (Barboza & Capocchi, 2020; Birch, 2020; Phillips & Kirchhoff, 1989; Rickne & Jacobsson, 1999).

In particular, Barboza and Capocchi (2020) used data from a sample of Italian innovative startup companies to assess the role of knowledge spillover effects (KSE) on employment. Their empirical results show that KSE positively impact regions characterized by a high level of specialization, while simultaneously tend to negatively impact regions characterized by a high level of competition and diversity. Matricano (2020b) used a similar sample to assess the impact of research and development (R&D) investments, highly skilled labor, and patents on employment and capital turnover. Capozza et al. (2020) analyzed data from a survey launched by the Italian Ministry of Economic Development to identify the drivers of innovative startups' propensity to innovate, and hence, inform public policies aimed at improving national competitiveness. Cavallo et al. (2021) studied the spatial proximity between the Italian innovative startups' locations and the industrial districts to investigate the role of small and medium enterprises (SMEs) in entrepreneurial ecosystems. Similarly, Del Bosco et al. (2021) considered the spatial proximity of universities, research centers, and incubators. Finally, Cavallo et al. (2020) used data from Italian innovative startups aggregated at the regional level to examine how agglomeration externalities affect regional innovative startups' entry rate.

Following Cavallo et al. (2020), this study further explores the role of agglomeration economies. In particular, we assess their effects on innovative startups' survival (rather than entry), using firm-level data and survival regression models. Our contribution is twofold. First, we investigate agglomeration economies as determinants of the post-entry performance of firms, which is the role that most of the literature assigns to this form of externality (Beaudry & Schiffauerova, 2009). In this respect, firm survival—unlike productivity or employment growth—is a more robust indicator of performance as it is less sensitive to volatility and short-run shocks (Basile et al., 2017; Bernard & Jensen, 2007). Second, the use of firm-level data, instead of regionally aggregated data, allows for dealing with different sources of bias. On the one hand, it obviously solves the problem of ecological fallacy. On the other hand, it enables exploiting micro-geographic distance-based measures of agglomeration externalities that are robust to the modifiable areal unit problem.

Our findings suggest that the effects of agglomeration externalities are complex and nonlinear with respect to the firm's life cycle and point toward an interesting observation. Agglomeration externalities have a negative impact on innovative startups' survival at the beginning of their activity, which then reverses to be positive when innovative startups reach a certain age (essentially after four years).

The remainder of the paper proceeds as follows. The second section provides an essential overview of the literature on agglomeration externalities and firm survival. The third section illustrates the data and the methodology of our empirical analysis. The fourth section presents the results, while the fifth section concludes the study.

2 | LITERATURE REVIEW

Externalities can play an essential role in a firm's. Since the 1990s, interest in agglomeration externalities has been growing in economics theories (Fazio & Maltese, 2015). The literature on this topic has been developed since the Marshallian studies, and it is common to distinguish between two types of externalities: specialization externalities (also called Marshallian externalities) and diversity externalities (also called Jacobian externalities).

According to Marshall's ideas, proximity is essential for generating the firms' geographical specialization, which in turn favors the transmission of knowledge, reduces transport costs, and creates a more efficient labor market (Beaudry & Schiffauerova, 2009; Marshall, 1890). One of the main ideas of Marshallian externalities is that different producers located in the same local context obtain external local benefits through knowledge spillovers, labor pooling, and proximity to specialized suppliers. A typical example given in the literature is that of the Silicon Valley software industry (Lyn & Rodriguez-Clare, 2011).

Marshall (1890) was the first to distinguish between two types of economies of scale: internal to the firm (driven by a decrease in the average costs) and external to the firm (related to the industrial environment around the firm). Arrow (1962) and Romer (1986) developed Marshall's idea into a model called Marshall-Arrow-Romer (MAR) externalities or localization externalities since they are related to the geographical dimension of economies. Lyn and Rodriguez-Clare (2011) provided insights regarding the effects of external economies on patterns of international trade, gains from trade, and the role of industrial policy. The most relevant results show that Marshallian externalities can account for approximately 35% of the overall gains from trade, thus providing evidence that Marshallian externalities lead to additional gains from trade (Lyn & Rodriguez-Clare, 2011).

An essential component of MAR externalities is represented by knowledge spillovers, which positively affect firms' innovativeness. A single firm usually cannot fully appropriate the knowledge it creates; therefore, this knowledge spills over to other firms. We are referring to tacit knowledge, which is uncodified and can be assimilated via social interaction processes. Spillovers tend to be bounded to the region in which the new knowledge is created. This is one of the main reasons why firms need geographical proximity. In the literature, however, there is no direct proof of this kind of spillover (Beaudry & Schiffauerova, 2009).

Van der Panne and van Beers (2006) analyzed the role of Marshallian and Jacobian externalities in favoring regional innovativeness in the Netherlands. The results show that regions with specialized production structures accommodate more innovators than diversified regions. Innovators engage in extended innovation networks and report increased innovation output, even if they are less inclined to innovate in partnership and introduce less radical innovation.

More recently, economists have focused on the external environment and relations between cities (also called systems of cities), rather than the links between actors within the same city (Burger & Meijers, 2016). In this context, the network dimension is fundamental in studying external economies and urban growth; it explains why research identifies the following two branches of externalities: agglomeration externalities and urban network externalities. The first group refers to the agglomeration benefits, which go beyond agglomeration in the strict sense of the word and are defined as an externality field because its effects are zonal. The second group regards the fact that the performance of cities may become increasingly dependent on their position in urban networks where external economies are increasingly mobile.

Agglomeration externalities can also originate outside of industry. Jacobs discussed the role of these externalities: they are also called urbanization economies because they require urban areas, characterized by a high degree of local diversity, to show their effects (Fazio & Maltese, 2015). Indeed, Jacobs believed in diversity as an engine for innovation. Diversity is more significant in cities; therefore, cities can be an important source of innovation, increasing knowledge externalities (Beaudry & Schiffauerova, 2009).

The growth of cities encourages innovation and catalyzes technology adoption (Beaudry & Schiffauerova, 2009). Urban agglomerations are one of the critical drivers of growth in the twenty-first century since the urban areas' economic benefits are reaped from production and consumption activities in urban spaces that are dynamically diverse, geographically concentrated, and fiercely competitive (De Groot et al., 2016).

There is a large number of empirical estimates of agglomeration externalities reported in the literature. De Groot et al. (2016) systematically reviewed the empirical literature and drew robust conclusions about the role of agglomeration externalities. In particular, they concluded that specialization impacts lower-density places (mid-sized manufacturing-oriented cities) more positively, and diversity externalities positively impact urban growth worldwide, especially in recent years. However, empirical studies give more support to specialization externalities and less to diversity externalities (De Groot et al., 2016).

As shown in Fazio and Maltese (2015), there is a large body of literature about the impact of externalities on the productivity of Italian firms, which represent an interesting case, considering the country's particular geographical and industrial characteristics. Empirical studies mainly confirm the role of the spatial effects of specialization and the impact of market structure, endowment, and factor accumulation in the pattern of externalities (Cainelli & Leoncini, 1999).

Observing 784 Italian local labor systems[1] and 34 manufacturing and service sectors, Paci and Usai (1999) found that local employment tends to be negatively affected by specialization. At the same time, it seems to benefit from a diversified and competitive environment composed chiefly of small firms.

Cainelli and Lupi (2011) conducted one of the few micro-level studies on Italian firms and suggested that localization economies are positive but decrease with distance. In contrast, diversity economies are negative for shorter distances and become positive for greater distances, that is when the reference areas considered are larger.

Fazio and Maltese (2015) analyzed the role of spatial agglomeration externalities on the productivity of SMEs in Italy. While Marshallian economies positively influence the level of productivity, Jacobian and Porter externalities do not have the same effect. This could result from technological or pecuniary externalities at work so that firms located in highly specialized areas tend to acquire the ability to efficiently combine the factors of production and their benefits in terms of input sharing and labor-market pooling.

While the literature has focused extensively on the effects of agglomeration externalities on firm entry, growth, and productivity, relatively few studies have examined the impact on firm survival (Audretsch & Mahmood, 1995; Fotopoulos & Louri, 2000; Gémar et al., 2016). Most of the pertinent studies are based on a national or sectorial limited view (Audretsch & Mahmood, 1995; Fotopoulos & Louri, 2000; Howell et al., 2018; Renski, 2015), except for a few exceptions (Ferragina & Mazzotta, 2014) that consider a large panel of firms by sector within a time series approach. In the survival analysis, it is common to consider many dimensions of agglomeration (Howell et al., 2018) since they may have different effects on new firm survival. Renski (2011) found that regions with higher industrial specialization are characterized by a relatively lower risk of new firms' failure in more than half of the analyzed industries. We argue that the relationship between localization and firm should be studied more extensively as it is crucial for implementing good policies (Falk, 2015; Gémar et al., 2016; Howell et al., 2018; Serio, 2020).

3 | MATERIALS AND METHODS

3.1 | Data and variables

The study exploits data pertaining to the business demography of Italian innovative startup firms collected from the business register held by the Italian Chambers of Commerce. According to a national law (known as the Startup Act of 2012) designed to incentivize the birth and growth of a startup ecosystem, innovative startups are a specific kind of firm that, among other things, have fewer than 249 employees, an annual turnover of less than 5 million euros, and do not distribute dividends. Moreover, they have to meet at least one of the following requisites: i) at least 15% of the highest value between the operating costs and the revenue is expended on research and development every year; ii) at least one-third of employees are Ph.D. students or Ph.D. graduates, or at least two-thirds of the entire workforce hold a master's degree; iii) own or lease a patent, a brand, or registered software. The Startup Act allows firms that meet this legal definition of an innovative startup to have some convenient bureaucratic, legal, and economic benefits (Finaldi Russo et al., 2016).

The set of innovative startup firms used for the empirical analysis concerns the 5,434 manufacturing and services activities started during 2012 to 2016. The database is entirely georeferenced, meaning that for each unit, the point location, in terms of longitude and latitude coordinates, is available.

[1]According to Italy's National Institution of Statistics [*Instituto Nazionale di Statistica*] (ISTAT), local labor systems are "sub-regional areas where the bulk of the labour force lives and work and where establishments can find the main part of the labour force necessary to occupy the offered jobs." For further information see https://www.istat.it/en/labour-market-areas

TABLE 1 List of variables.

Variable	Description
Specialization	Based on an inverse function of the spatial distance of a given firm from all the other firms in the same industry
Diversity	Based on an inverse function of the spatial distance of a given firm from all the other firms in different industries
Size	Average annual sales grouped into tertiles: • Small (reference category): First tertile (€0–3,820) • Medium: Second tertile (€3,821–50,102) • Large: Third tertile (€50,103–5,043,585)
Ownership	Two categories: • Concentrated ownership (reference category) • Diffuse ownership
Stability	Two categories based on the ROA indicator: • Negative average ROA (reference category) • Positive average ROA
Entry year	Four categories based on the cohort of entry in the market: • Firm founded before 2014 (reference category) • Firm founded in 2014 • Firm founded in 2015 • Firm founded in 2016
Sector	Based on the one-digit NACE rev. 2 classification of economic sectors
Region	Based on the NUTS 2 classification of European territorial units

Table 1 reports the list of variables used as covariates in the regression analysis. The first two variables—*specialization* and *diversity*—are firm-level measures to assess MAR and Jacobs externalities, respectively. Knowing the exact point-level geographical locations of all the startup firms under study allows us to define firm-level measures of agglomeration externalities instead of using the more common regional-based indices such as the location quotient, the Gini index, or the Ellison–Glaeser index (Ellison & Glaeser, 1997). Unlike regional-based measures, the firm-level ones have the advantage of not being affected by the modifiable areal unit problems bias (Arbia, 1989). Indeed, the former are computed on regionally aggregated variables according to arbitrary partitions of the geographical space (such as provinces, regions, or municipalities). In reviewing the extensive literature on agglomeration externalities, Beaudry and Schiffauerova (2009) found that the occurrence and strength of these phenomena depend strictly on the chosen level of spatial aggregation.

The first two variables, *specialization* and *diversity*, were developed by adopting the approach of Arbia et al. (2015) as described below. Let S_i denote the set of startup firms belonging to the same industry, as startup firm i, and S_i^c denote the set of startup firms belonging to different industries as that of startup i. Let c_{ij} denote a binary dummy variable such that $c_{ij} = 1$ if startup j was active when i entered the market, and 0 otherwise. We measured *specialization* and *diversity* as follows:

$$Specialization_i \equiv \sum_{j \in S_i} c_{ij} \phi_{ij}(d_{ij}) \tag{1}$$

$$Diversity_i \equiv \sum_{j \in S_i^c} c_{ij} \phi_{ij}(d_{ij}) \tag{2}$$

where d_{ij} represents the geographical distance between i and j and quantifies the level of spatial interaction of the i^{th} startup firm with the other contemporary startup firms in the same industry (Equation 1) and with the contemporary startup firms in different industries (Equation 2), respectively. In harmony with the idea that an observed unit's level of spatial interaction with the other observed units should negatively depend on the distances between them, these measures were derived by specifying the appropriate functional form for the spatial interaction term $\phi_{ij}(\cdot)$. Several of the most commonly used functions were considered, including $\phi_{ij}(d) = 1/d$, $\phi_{ij}(d) = 1/d^2$, $\phi_{ij} = 1/(1+d)$, $\phi_{ij} = 1/\left(1+d^2\right)$. Preliminary analyses revealed that measures including interactions of the form $\phi_{ij} = 1/\left(1+d^2\right)$ led to models with a better fit in terms of the likelihood. Therefore, in this case, Equations (1) and (2) with interactions of the form $\phi_{ij}(d) = 1/\left(1+d^2\right)$ define proper micro-founded spatial measures of *specialization* and *diversity*, respectively. A positive statistical association between firm survival and *specialization* (or *diversity*) would provide evidence of MAR (or Jacobs) externalities. Both variables were introduced in the regression model through dummy variables according to the quartiles to assess potential nonlinear effects.

Firm *size*, measured using average annual sales, is a control variable that accounts for the fact that bigger firms can usually introduce more actions to resist economic downturn and maintain survival and resilience. This variable was introduced in the regression model through dummies according to the tertiles to explore the effect of different sizes (that is, small, medium, and large) on survival probability.

The variable *ownership* identifies the firm's shareholder structure. In particular, it is a binary variable indicating whether a startup has a concentrated or diffuse ownership structure. Its inclusion in the model aimed at controlling for the (expected) more substantial commitment of major shareholders to firm survival.

Another relevant factor of firm survival that may confound the genuine effect of spatial externalities is financial stability. To control for that, we included the variable *stability*, an indicator variable that equals 1 if the firm has a positive average return on asset (ROA) balance sheet index.

Finally, the regression model included a full set of year of entry dummies to control for time-specific economic shocks shared by all startup firms of the same annual cohort, and sectoral and regional dummies to control for all other factors that are external to the firm, and related to the industry and the local economic environment.

3.2 | Survival analysis

Survival analysis is the proper statistical approach to empirically assess the determinants of firm's survival time, that is, the time passed between a firm's entry into a market and its exit. This approach is essentially based on regression models that adequately deal with censored observations that occur when the study time is shorter than the time needed to observe a firm's exit.

An important concept in survival analysis is the hazard function $\lambda_i(t)$ that, in this empirical circumstance, can be defined as the instantaneous failure rate for firm *i* surviving until time *t*. Another concept related to the hazard function is the hazard rate, $\lambda_i(t)dt$, representing the probability that the firm's failure will occur at time *t* conditional on the firm surviving until time *t*. Survival regression models assess the relationship between explanatory variables and the hazard function; therefore, the underlying distribution of $\lambda_i(t)$ must be specified. If no prior information about the form of the hazard function is available, it is possible to use the so-called Cox proportional hazards model (Cox, 1972), which does not require the formulation of any distributional assumptions. The model can be described as follows:

$$\lambda_i(t) = \lambda_0(t) exp(\beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_k x_{ki}) \tag{3}$$

where $\lambda_0(t)$ is the baseline hazard, $x_1, x_2, \ldots, x_k$ are the explanatory variables, and $\beta_1, \beta_2, \ldots, \beta_k$ are the corresponding unknown regression parameters, which can be estimated through the partial maximum likelihood estimator (Cox, 1975) with Efron's approximation (Efron, 1977) to deal with tied survival times.

Under the assumption that $\lambda_0(t)$ is the same for all firms, then its functional form does not need to be specified. Indeed, the ratio between the hazards of two generic *i* and *l* firms is equal to

$$\frac{\lambda_i(t)}{\lambda_l(t)} = \frac{\lambda_0(t)exp(\beta_1 x_{1i} + \ldots + \beta_k x_{ki})}{\lambda_0(t)\,(\beta_1 x_{1l} + \ldots + \beta_k x_{kl})} = exp[\beta_1(x_{1i} - x_{1l}) + \ldots + \beta_k(x_{ki} - x_{kl})] \tag{4}$$

that is, it is independent of both $\lambda_0(t)$ and t.

Although the model is distribution-free, it does, however, require the hazards to be proportional. The validity of the proportional hazards assumption can be verified by means of the Grambsch–Therneau test (Grambsch & Therneau, 1994).

4 | RESULTS

4.1 | Regression estimates

As a preliminary analysis of the potential effects of agglomeration externalities on firm survival, we examined how survival probability over time changes across the different levels of specialization and diversity. In particular, using the Kaplan–Meier estimator (Kaplan & Meier, 1958), we estimated the firm survival probabilities at each month from entry into the market for separate groups of startups belonging to different quartiles of the *specialization* and *diversity* variables, respectively. Figure 1 depicts the resulting survival curves, which do not provide evidence to support the occurrence of positive spatial externalities. On the contrary, since for both *specialization* and *diversity* the survival curves for the startups in the fourth quartile tend to be the lowest, these results suggest that agglomeration may negatively affect firm survival.

To shed more light on the relationship between firm survival and spatial externalities, while controlling for the confounding effects of the structural characteristics of startups, we estimated a Cox proportional hazard model including all the variables representing the potential predictors of firm survival. To deal with the fact that firms

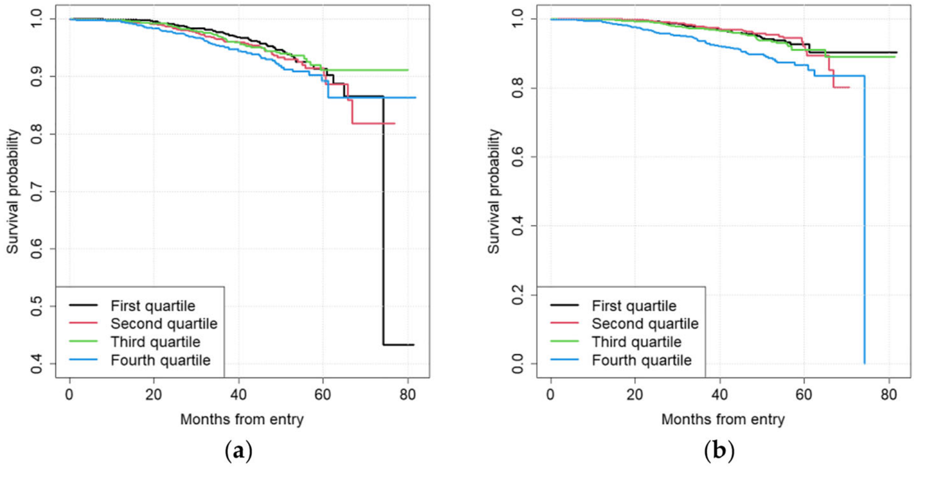

FIGURE 1 Kaplan–Meyer estimates of the survival probability of 5,434 manufacturing and services startups that entered the market during 2012–2016. *Note:* The x-axis reports the time (in number of months) from when a company entered the market, defined as first registration in the Italian business register. The y-axis reports the cumulative survival probability. Panel A shows firm survival curves by specialization; panel B shows firm survival curves by diversity.

located in the same area (such as a province) may have correlated survival times, thus violating the independence assumption, we estimated the province-level clustered standard errors of model parameters using the robust estimator by Lin and Wei (Lin & Wei, 1989).

Model 1 in Table 2 provides the estimates of the baseline model, which confirm the conclusion suggested by the survival curves. Indeed, for both *specialization* and *diversity*, the model parameters associated with the higher quartiles are significantly greater, implying that startups located in relatively more specialized and diversified local environments tend to have a lower chance of survival in the market. More specifically, for example, startups in the fourth quartile of *specialization* have an estimated risk of failure that is 18 times higher ($exp(2.899) = 18.156$) than that of the startups in the respective first quartile. At the same time, startups in the fourth quartile of *diversity* have a 140 times higher risk of failure ($exp(4.973) = 144.460$) than the startups in the respective first quartile.

These estimates, however, may be biased because of the violation of the proportional hazards assumption. The Grambsch–Therneau test applied to Model 1 is indeed significant ($\chi^2 = 49.686$; p-value $= 0.040$) and indicates that

TABLE 2 Results from the Cox proportional hazard models.

	Model 1	Model 2
Specialization – Quartile 2	1.487*** (0.498)	1.330*** (0.548)
Specialization – Quartile 3	2.910*** (0.626)	3.369*** (0.689)
Specialization – Quartile 4	2.899*** (0.638)	3.029*** (0.705)
Diversity – Quartile 2	1.457* (0.583)	−0.126 (0.677)
Diversity – Quartile 3	2.415*** (0.661)	1.239 (0.711)
Diversity – Quartile 4	4.973*** (0.776)	3.922*** (0.787)
$\boldsymbol{g(t)}$		−18.846*** (2,711)
Specialization – Quartile 2 $\times g(t)$		−2.014* (1.168)
Specialization – Quartile 3 $\times g(t)$		−3.605*** (1.246)
Specialization – Quartile 4 $\times g(t)$		−3.848*** (1.382)
Diversity – Quartile 2 $\times g(t)$		2.535*** (1.317)
Diversity – Quartile 3 $\times g(t)$		1.085 (1.350)
Diversity – Quartile 4 $\times g(t)$		−1.480 (1.621)
Size – Medium	−0.080 (0.295)	−0.026 (0.295)
Size – Large	−1.069*** (0.385)	−1.140*** (0.410)
Ownership – Diffuse	4.237*** (0.283)	4.104*** (0.304)
Stability – Positive	−0.597* (0.345)	−0.387 (0.364)
Entry year – 2014	1.356*** (0.423)	1.723*** (0.471)
Entry year – 2015	2.155*** (0.478)	1.710** (0.537)
Entry year – 2016	2.608*** (0.611)	2.362** (0.692)
Sector dummies	Yes	Yes
Region dummies	Yes	Yes
Observations	4,818	4,818
Log-likelihood	−391.992	−356.185
PH test	49.686**	41.000

Note: Coefficients and standard errors (in parentheses) are reported for each explanatory variable used in the model. The sample size for the regression analysis was reduced because of missing values of some covariates due to non-systematic inconsistencies. Therefore, the model estimates were not biased by sample selection.
*p-value < 0.01.**p-value < 0.05.***p-value < 0.01.

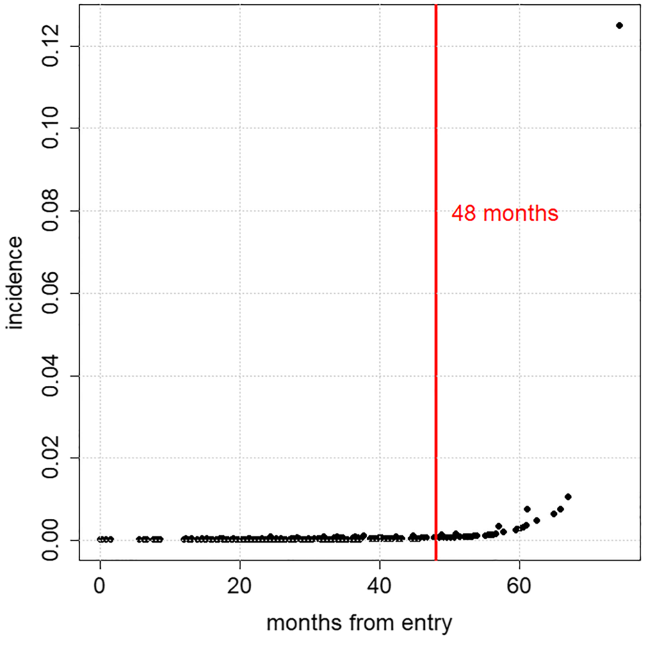

FIGURE 2 Incidence rate of firm failure. *Note:* The x-axis reports the time (in number of months) from when a company enters the market, defined as first registration in the Italian business register. The y-axis reports the incidence rate.

the proportional hazards assumption is not respected. This occurs because the effect of one or more covariates on the risk of failure is not constant over time. The problem can be easily overcome, without resorting to parametric models that require assumptions about the data-generating process, by extending the model with the inclusion of interaction terms between one or more regressors and some function of time (Cox, 1972). In order to choose the proper function of time, we analyzed the behavior of the incidence rate[2] over time (see Figure 2). The plot clearly shows that the risk of exit from the market varies with the "age" of the firm; in particular, the incidence rate is fairly constant and low within the first 48 months (four years) of activity, while it drastically increases after that. Therefore, a proper function of time to address time-varying hazards in the model is

$$g(t) = \begin{cases} 1, & \text{if } t > 48 \\ 0, & \text{if } t \leq 48 \end{cases}. \tag{5}$$

Model 2 in Table 2 provides the estimates of a model that includes $g(t)$, *specialization* $\times$ $g(t)$, and *diversity* $\times$ $g(t)$ as further regressors. This model allowed us to assess the effect of *specialization* and *diversity* both before and after the age of 48 months, and hence, respects the proportional hazards assumption; indeed, the Grambsch–Therneau test when applied to it is not significant ($\chi^2 = 41.000$; p-value $= 0.384$).

Concerning the role of *specialization*, Model 2 offers straightforward indications about the effects of *specialization* on innovative startups' survival. The coefficients associated with this variable are still positive, significant, and increasing along with the quartiles. On the other hand, the coefficients associated with *specialization* $\times$ $g(t)$ are negative, significant, decreasing along with the quartiles, and with comparatively higher orders of magnitude. Therefore, we have evidence that, generally, when an innovative startup enters the market, the competition of other

[2]Calculated as the ratio between the number of firm failures during a given time period and the number of firms at risk during the same time period.

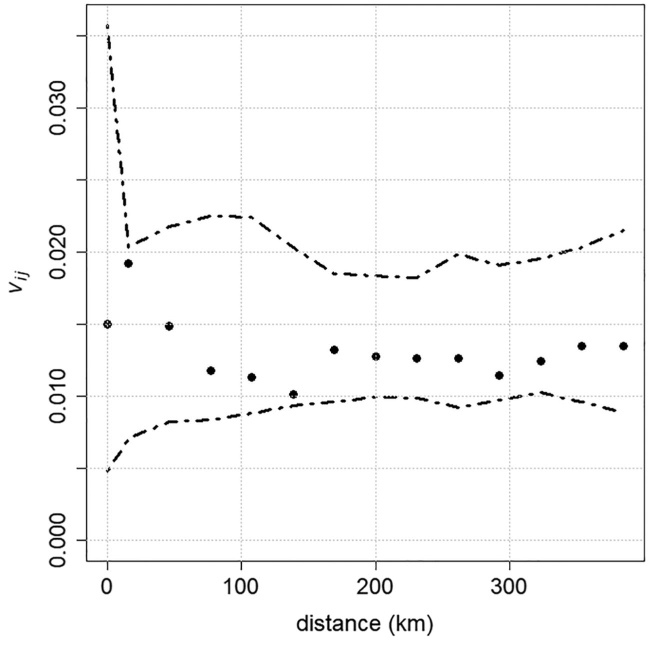

FIGURE 3 Empirical variogram of Model 2 Martingale residuals (circles) and corresponding Monte Carlo envelopes (dashed lines).

closely located startups in the same industry generates negative spillover effects. If, however, a startup survives for at least four years then it learns to benefit from the advantages of spatial spillovers, due to the proximity of similar firms, which become a positive factor in survival. As a matter of fact, the nature and effect of MAR externalities on a startup's survival depend on where it is in its life cycle. At the beginning of the firm's life cycle (the first four years), spatial spillovers have a negative effect; however, operating in an industrially specialized local context becomes beneficial after the firm reaches a certain maturity.

In contrast, even controlling for the firm's life cycle stage, the model coefficients associated with the higher quartiles of *diversity* are not significantly lower than zero. Therefore, we still did not find evidence of a positive effect of *diversity* on firm survival, and hence, we cannot support the Jacobs's externalities hypothesis.

4.2 | Robustness check

The inclusion of spatially micro-founded measures of specialization and diversity in the Cox proportional hazard model allowed us to deal with spatial dependence among neighboring firms' survival times. However, there is no guarantee that spatial dependence was captured entirely; some unobserved spatial dependence could still affect the model's residuals. If that is the case, the estimates of the model parameters could be biased, and the inferential results may be unreliable.[3]

We detected residual spatial independence by examining the empirical variogram of the model's residuals (Diggle & Ribeiro, 2007). The variogram is a geostatistical tool that assesses spatial autocorrelation by relating the

[3]The sample size for the regression analysis was reduced because of missing values of some covariates due to non-systematic inconsistencies. Therefore, the model estimates were not biased by sample selection.

dissimilarity between pairs of sample units and the distance separating them. In this circumstance, the empirical variogram ordinates were given by

$$v_{ij} = \frac{1}{2}(r_i - r_j)^2 \tag{6}$$

where r_i and r_j are the Martingale residuals of the estimated Cox proportional hazard model of the startup firms *i* and *j*, respectively. Plotting v_{ij} against the distance between *i* and *j*, together with Monte Carlo simulation-based envelopes for the null hypothesis of no spatial dependence, allowed us to formally detect residual spatial autocorrelation. The simulation envelopes were obtained from 999 independent random permutations of the Martingale residuals, holding their locations fixed, with values averaged across distance ranges.

Figure 3 reports the empirical variogram of Model 2 Martingale residuals along with the Monte Carlo simulation-based envelopes. For ease of visualization, the v_{ij}-values are averaged within distance intervals. The graph shows that all the empirical variogram ordinates fall inside the envelopes, which indicates that there is no significant residual spatial autocorrelation. Therefore, we concluded that our results are robust to the violation of the independence assumption.

5 | CONCLUSION

In conclusion, this study provided novel evidence about how spatial externalities affect the survival chances of Italian innovative startups, which represent an interesting kind of new venture dedicated to innovation. Using geocoded firm-level data and survival regression models, we could disentangle the genuine effects of spatial spillovers from the structural characteristics of firms' locations. Moreover, to the best of our knowledge, this is the first empirical assessment of the impact of agglomeration on firm survival that deals explicitly with the mediating effect of the firm's age. In particular, we found that the kind of impact that spatial externalities exert strongly depends on the firm's life cycle: younger firms tend to be negatively affected; in contrast, more mature firms can benefit from them. This empirical evidence provides an important policy implication for policymakers. Indeed, it suggests that policies favoring agglomeration externalities are more likely to lead to a net overall positive benefit in markets with a relatively mature supply side. On the other hand, in contexts dominated by very young firms, policies that attempt to foster the clustering of economic activities may have undesirable effects on firm survival. While this finding is certainly important and helpful, in order to draw more meaningful policy implications, it is necessary to assess the causal mechanism that sees more mature startups benefit from spatial externalities. Further research is needed in this direction.

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