The Climate Challenge Needs Billions of Euros: Can Spillover and Hype Effects Fuel Scale-Up in Europe?

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Abstract

Our paper employs a spatial econometric framework to test whether increased funding or a rising valuation of a startup generates indirect effects that benefit similar or proximate firms. The findings reveal positive spillovers across firms belonging to the same industrial and technological domain, as well as within the same geographical region, indicating that increased funding and rising valuations can bolster the success not only of the directly affected firm but also of other firms. Specifically, startups would generate a sort of 'hype' effect benefiting firms that are close on the geographical, industrial and technological spaces, albeit with varying intensities.

1. Introduction

Climate-tech represents a diverse array of technological innovations designed to mitigate carbon emissions and facilitate adaptation to environmental challenges. As the urgency to address climate change grows, the role of technology-driven solutions becomes increasingly central to global sustainability efforts. However, the transition toward a low-carbon economy is not solely a matter of technological feasibility; it also hinges on the ability to scale up investments.

In this context, securing adequate funding for climate-tech startups and emerging technologies is paramount. Some promising ventures exemplify how targeted investments can accelerate the deployment of technological solutions, for example, in energy storage and alternative energy. Moreover, insights gained from breakthrough innovations, such as green steel and next-generation photovoltaic panels, highlight the crucial need to support emerging technologies through financial investment, as they have the potential to reshape the sustainability landscape.

In this regard, venture capital and business angels play a major role in providing the necessary funding and strategic support that startups need to scale and succeed (Winton and Yerramilli, 2008). Nevertheless, they are not alone. The public sector is taking on an increasingly important role, especially as technological progress becomes a crucial tool for overcoming major societal challenges such as climate change. More recently, the banking system has also started to emerge as a key player (Quas et al., 2022). Traditionally, banks have been reluctant to finance high-risk startups, which require flexible and long-term financial support. Bank loans offer vital capital for startups without affecting their ownership structure and often provide more favorable interest rates than equity instruments, particularly in the late stage of a startup's life cycle (Thies et al. 2019; Block et al. 2018). However, with the increasing focus on sustainability and climate change adaptation, some banks are now developing specific financial instruments for green energy and climate technologies, positioning themselves as a critical link between venture capital and more traditional forms of financing (Bauer et al., 2024).

In private markets investors and financial institutions face the difficulty of identifying opportunities, implying that they must rely on observable signals to assess the quality and potential of startups (Spence, 1974, 2022). When a startup secures significant funding or experiences a rising valuation, it sends a positive signal to the market, indicating reliability, growth potential, and reduced risk. As a result, investors and institutions may perceive startups operating in the same industrial sector or leveraging comparable technologies as more attractive investment opportunities. This generates spillovers that, in some ways, mimic a 'hype' effect.

The literature on how physical contiguity can foster the emergence and growth of startups is extensive and well-established. Scholars suggest that investing in a single firm generates positive externalities for neighbouring firms on the geographical space, fostering localized knowledge spillovers and ecosystem growth (Ivkovi and Weisbenner, 2005; Pan and Yang, 2018). This effect is particularly pronounced in climate-tech clusters and startups' ecosystems, where firms share collaborative networks.

In contrast, research on how funding for a startup can generate spillovers benefiting similar or 'nearby' startups, defined in industrial and technological rather than geographical terms, remains relatively scarce and fragmented (Wang and Schøtt, 2020; Schnitzer and Watzinger, 2022). Understanding such spillover dynamics holds significant relevance from both a scientific and policy standpoint and could inform more effective funding strategies for climate-tech innovation. We aim to substantiate the need for a broader perspective beyond mere geographical contiguity and to fill a gap in the empirical literature by proposing non-geographical proximity to measure spillovers among startups.

Our contribution to the literature is threefold. First, we introduce a spatial analysis framework that allows for the investigation of how industrial relatedness and technological adjacency, beyond mere physical contiguity, shape spillover or hype effects (Autant-Bernard, 2012; Marra et al., 2024). Secondly, we are interested in investigating spillovers among startups through funding and valuation: an area that, to our knowledge, has so far been explored only in very specific niches, such as initial coin offerings (ICOs) to raise capital for new ventures (Domingo et al., 2020; Fisch, 2019; Moro et al., 2024). Thirdly, we propose to measure industrial and technological proximity through semantic metrics based on textual data from the indexed content retrievable from queries on the company website via search engines. Such metrics provide a fresh perspective on inter-firm relationships, moving beyond traditional approaches (Nathan and Rosso, 2015; Abbasiharofteh et al., 2024).

The paper is structured as follows. Section 2 introduces the relevant background and presents the two research hypotheses. Section 3 presents the dataset, while Section 4 describes the methodology and focuses on the statistical modelling. Section 5 presents the results, provides robustness checks, and discusses the findings. Finally, Section 6 concludes, addresses limitations and outlines future steps of research.

2. Literature

Startups generate positive spillovers through informal exchanges, collaborations, and employee mobility, which enhance the productivity and innovation of neighbours (Audretsch and Feldman, 1996; Delgado et al., 2014). These spillovers extend beyond existing firms, fostering an environment that attracts new businesses seeking to leverage shared resources such as skilled labour, infrastructure, and networks (Feldman, 2003; Glaeser et al., 2010).

We aim to investigate the spillovers arising from new funding or rising valuations of startups and their benefits to other firms, building on an existing yet fragmented literature (Wang and Schøtt, 2022; Calia et al., 2007; Schnitzer and Watzinger, 2022; Hackober and Bock, 2021). In principle, newly funded or high-profile startups tend to engage more actively with similar or nearby firms, fostering increased interactions and potential knowledge exchange. The channels through which spillovers can spread are diverse, reflecting the complexity of reality (Isenberg, 2010; Stam, 2015; Park et al., 2020). However, many can be traced back to the existence of both real and 'virtual' connections between firms (Feldman, 2003; Spigel, 2017; Balland et al., 2013; Ghinami and Montresor, 2023). Firms engaged in similar activities or employing the same or complementary technologies often interact through formal collaborations, supply chain linkages, or even informal exchanges at industry events. These interactions facilitate the diffusion of best practices, technological advancements, and business strategies. Additionally, digital platforms and professional networks create connections that transcend geographical boundaries, allowing firms to benefit from industry trends, investor attention, and technological breakthroughs. There is no doubt that imitation processes and word-of-mouth within the relevant community are strengthened by the alignment of interests and opportunities fostered by overlapping specializations and reliance on similar technologies. As a result, spillovers cannot be confined exclusively to physical contiguity (Marra et al., 2020; Knoben and Oerlemans, 2006; Santamaria and Breschi, 2025).

Confirming the above, some empirical evidence suggests that new firms and startups' funding generates spillovers and enhances the visibility of their geographical region, industrial specialization, and technological domain. This is particularly pronounced in clusters and technological districts. It can manifest in various ways, from increased investor confidence in a particular sector to a surge in media attention that attracts further funding opportunities (Gompers and Lerner, 2001; Eldar and Grennan, 2024; Lerner et al., 2023). In effect, when a startup secures significant investment or experiences a sharp rise in valuation, it signals potential success to investors, prompting them to seek similar opportunities within the same or similar industrial or technological domain (Nanda and Rhodes-Kropf, 2013). Higher valuations may also attract skilled labour, suppliers, and strategic partnerships, indirectly benefiting proximate firms (Samila and Sorenson, 2011).

The mechanism that comes into play at the investor level is not straightforward. While private investors and financial institutions are prone to providing financial support, broadening the pool of potential stakeholders is constrained by the inherent trade-off between seizing high-reward opportunities and distributing risks among partners (Gompers and Lerner, 2001). Accordingly, many worry that potential returns may decline as more actors become involved (Casamatta, 2003). This reluctance limits the funding of new ventures, delaying the scaling up of critical innovations. At the same time, however, the difficulty of identifying opportunities in private markets implies that investors look for and rely on observable signals to assess the quality and potential of startups (Petty and Gruber, 2011; Zacharakis and Meyer 2000). When a startup secures significant funding or experiences a rising valuation, it sends a signal to the market. As a result, investors perceive that startup as well as all those operating in the same industrial sector or leveraging comparable technologies as more attractive investment opportunities.

The signalling theory provides a useful lens to understand how securing new funding can generate appreciable indirect effects (Spence, 1974, 2022). The study of spillover effects between startups in terms of funding and valuation is an area that still requires further investigation (Domingo et al., 2020; Fisch, 2019; Moro et al., 2024). The existing literature lacks detailed insights into how funding rounds, investor sentiment, and market signals shape the valuation and success of emerging ventures. It is common sense to say that when a startup successfully raises funds, especially from reputable investors, it sends a credible signal to the market about its viability, innovation potential, and growth prospects. This signal not only enhances the perceived legitimacy of the funded startup but can also increase investor confidence in other nearby or similar startups (Kirsch et al. 2009; Plummer et al. 2016). This triggers a self-reinforcing cycle, where heightened investor enthusiasm fosters greater capital inflows, accelerating growth across an entire industrial or technological niche.

In this paper we maintain and test two straightforward hypotheses:

Hp#1: Increased funding for a single startup creates spillover effects that benefit both geographically close firms and those with industrial relatedness and/or technological proximity.

Hp#2: A rising valuation of a given startup creates spillover effects that benefit both geographically close firms and those with industrial relatedness and/or technological proximity.

From a more operational perspective, we define two firms as industrially or technologically proximate when they share similar specializations (e.g., renewable energy, sustainable mobility) or work on related technologies (e.g., EV batteries, carbon capture). The measurement of proximity has evolved significantly in recent years, with an increasing number of studies employing non-geographical metrics to account for spillover effects (Autant-Bernard, 2012; Marra et al., 2024). Among others, Nathan and Rosso (2015) highlight how text data can enhance firm characterization, offering valuable insights into the proximity between firms in digital sectors, Qin et al. (2021) employ topic modelling to measure cognitive proximity in patents, and Marra and Baldassari (2022) employ text-based descriptions to distinguish firms, offering an alternative to traditional NACE codes.

3. Data

We collected data on climate-tech firms and startups from Dealroom.co, a commercial database that integrates machine learning and data engineering with user-submitted information and verification processes, in October 2024 (Dealroom, 2024). More specifically, the database provides information on more than nine thousand operational companies active in the European territory.

Using hyperlinks to corporate websites, we collected text data on company websites to measure proximity. For the statistical models, we focused on a sample of 745 companies, with all available data on funding, valuation, business model, number of employees, age, and type of investors.

The sample was constructed to ensure a proper investigation of spillovers in the climate-tech in Europe (Autant-Bernard and LeSage, 2011). The selected sample is representative of the entire population in terms of geographical distribution, valuation (Table 1) and sectoral coverage (Table 2).

Table 1 about here

Table 2 about here

4. Methodology

4.1. Textual analysis

We leverage web data to profile companies based on their industrial specializations and adopted technologies (Marra et al., 2024).

The construction of the proximity matrix follows a structured methodology (Marra and Baldassari, 2022). First, we retrieve indexed content from company websites via search engine queries and apply text mining to extract an initial set of keywords or ‘entities.’ Next, we use the Latent Dirichlet Allocation (LDA) algorithm for topic modeling, identifying additional keywords or ‘topics’ to assign to each company. Finally, where necessary, we semantically refine and enhance the keyword list to ensure more comprehensive and coherent company profiles.

Each firm is assigned a final vector of tokens, which is used to calculate the cosine similarity for each pair of firms.

4.2. Adjacency matrices

Then, we convert the cosine similarity’s linear relationships into an inverted-U shaped curve, meant to replicate the chance of spillovers and competitive effects in the industrial and technological spaces (Ben Letaifa and Rabeau, 2013; Marra et al, 2024).

The industrial and technological adjacency matrices ($\boldsymbol{W}$) are constructed according to a hyperbola: if two firms present very low or very high cosine similarity, adjacency is zero; higher values of the cosine similarity may have a more pronounced impact on the extent of proximity. This hyperbolic curve suggests that the probability of spillovers is highest at median levels of proximity and decreases at the extremes. Therefore, adjacency value is expected to increase up to the maximum if the cosine similarity grows towards the median.

The rationale behind this transformation lies in the fact that positive dynamics can foster a self-reinforcing cycle in which financial resources, talent, and strategic partnerships concentrate around specific domains, increasing the likelihood of similar and nearby startups securing funding and accelerating their growth (Spigel, 2017; Stam and Spigel, 2016). At the same time, however, negative spillovers may also arise, such as intensified competition for capital and talent, potentially crowding out smaller startups or creating speculative pressures that make it more difficult for early-stage ventures to secure funding on reasonable terms (Samila and Sorenson, 2011; Gornall and Strebulaev, 2020).

We build spatial econometric models using $\boldsymbol{W}$ based, respectively, on specializations, technologies and geographical spaces. The first two (semantic) matrices, the industrial and technological ones, are assumed as exogenous. The geographical space is treated as usual in spatial econometrics field. Starting from the physical distance between the firms' coordinates, the geographical matrix is constructed as a standard nearest neighbour one (Harris et al. 2011; LeSage, 2015).

4.3. Statistical models

We aim at explaining firms' capacity to attract new funding and attain higher valuations, using not only their intrinsic characteristics, but also their neighbours' peculiarities. The neighbourhood is defined in different ways, according to the three adjacency matrices presented above.

Before modelling the interaction between firms using spatial econometric specifications, we define two basic ordinary least square (OLS) models as:

$$y_i = \alpha + x_i^t \beta + \varepsilon_i \qquad [1]$$

where the dependent variables differ according to two specifications.

In one model, y_i is the logarithm of valuation in thousands of euros ($Valuation$), for the $i = 1 \dots N$ firms. In the second specification, y_i represents the total funding in millions of euros ($Total\_funding$) obtained by the $i = 1 \dots N$ firms.

In both models, α is the intercept, β is the parameters' vector related to each of the covariates, ε_i is the error term. The $r = 1 \dots P$ variables included in the matrix X are: a variable indicating if the firm operates as a business to business or not ($B2B$) to capture the increased likelihood of interacting with other businesses (Cappelli and Cucculelli, 2024); regarding the firms' intangible or intellectual resources, we use the number of employees as a proxy for knowledge exchange and spillovers ($Employees$), in line with Balsmeier et al. (2014) and Marra et al. (2024); the variable Age is intended as the difference between 2024 and the year of foundation, to distinguishing if the firm is an early stage startup or a more mature one (Guerrero et al., 2023). Additionally, we include three dummy variables, which account, respectively, if the firm has received funding from venture capitals ($Venture$), public funding ($Public$) or business angels ($Angel$), as their relevance has been addressed in Croce et al. (2018) and Islam et al. (2018). In the specification where the dependent variable is $Valuation$, the variable $Total\_funding$ is added to the set of covariates. All the explanatory variables are not collinear, as stressed from the correlation coefficients, which are all restricted within the interval (0; 0.18].

To move from an OLS to a spatial econometric frame, we need to test if, according to the selected $\boldsymbol{W}$, the residuals of the OLS model present spatial autocorrelation. At this scope, we use the Moran's *I* test, based on the Moran's statistic (King, 1981). The null hypothesis of this test is the absence of spatial autocorrelation. Under this hypothesis, the expected value of the Moran's *I* is: $E(I) = 1/(N-1)$. Accordingly, high values of this statistic lead to the rejection of the no correlation hypothesis in favour of the presence of positive spatial autocorrelation.

If, according to the Moran's test, the introduction of spatial models is justified, we follow a structured selection process, as suggested by Pace and LeSage (2010) and Elhorst (2010). As a first step, the best specification to start with is the Spatial Durbin Model (SDM), since it may overcome the bias related to omitted variables. More specifically, the SDM nests both the Spatial Lag Model (SLM) and the Spatial Lag of X (SLX). In fact, in a second step, should be tested if the SDM can be reduced to a SLM or SLX model. Considering that these two specifications are nested in the SDM, a likelihood ratio test (LR-test; Elhorst, 2014) could be performed to establish which is the best specification.

A LR-test takes the following form:

$$-2(LogL_{res} - LogL_{unres}) \quad [2]$$

where $LogL_{res}$ is the log-likelihood of the simpler (restricted) model. In our case this model is the SLM or the SLX, compared with the $LogL_{unres}$, that is the log-likelihood of the most general (unrestricted) model (that is, the SDM). The null hypothesis of LR-tests is that the unrestricted model does not outperform the simpler and restricted one, which is then advisable. This statistic follows a Chi-squared distribution, with degrees of freedom equal to the number of restrictions imposed.

The SDM is defined as:

$$y_i = \alpha + x_i^t \beta + \rho \sum_{j=1}^{N} w_{ij} y_j + \sum_{r=1}^{P} \sum_{j=1}^{N} w_{ij} x_{jr} \theta_r + \varepsilon_i \quad with\, j \neq i \qquad [3]$$

where ρ is the parameter which considers the spatial autocorrelation between the dependent variables, while the vector of parameters θ, for $r = 1 \dots P$, measures the influence of the covariates on the neighbours' dependent variables.

Imposing the restriction $\rho = 0$, this model nests the SLX, which can be written as:

$$y_i = \alpha + x_i^t \beta + \sum_{r=1}^{P} \sum_{j=1}^{N} w_{ij} x_{jr} \theta_r + \varepsilon_i \qquad [4]$$

while, if we impose the restrictions $\theta_1 = \theta_2 = \cdots = \theta_P = 0$, from the SDM is obtained the SLM, which takes the form:

$$y_i = \alpha + x_i^t \beta + \rho \sum_{j=1}^{N} w_{ij} y_j + \varepsilon_i \qquad [5]$$

Regarding the interpretation of parameters, in the SLX direct impacts are represented by β coefficients, while θ_r parameters are the indirect effects (Elhorst, 2014). Instead, both in SDM and SLM cases, the coefficients are not directly interpretable, but we need to estimate direct and indirect impacts. Therefore, we calculate the partial derivatives matrix of the expected value of y with respect to the r^{th} explanatory variable (LeSage and Pace, 2010). On the diagonal of this matrix, we find the direct effects. The off-diagonal elements capture spatial spillovers in the form of indirect effects, that are the impacts due to a change in the explanatory variables in one unit over a neighbouring one. The sums of these two are the total impacts.

5. Results and discussion

To evaluate the importance of geographical proximity between firms, an OLS regression is first estimated for both specifications presented in the previous section. The results, reported in Table 3, confirm the significant relevance of all variables. More specifically, in the model where funding is the dependent variable, B2B, firm age, number of employees, venture capital, and business angels are all statistically significant. In the model with valuation as the dependent variable, all variables become statistically significant, with the sole exception of firm's age. Notably, public funding also attains statistical significance in this specification.

Table 3 about here

The OLS estimation is followed by a Moran's I test on the residuals to assess if there is autocorrelation according to the spatial wights matrices proposed (King, 1981). Results are presented in Table 4.

Table 4 about here

All the tests yield a result significantly greater than zero, leading to the rejection of the null hypothesis in favour of the presence of positive spatial autocorrelation (similar and nearby firms, according to the chosen $\boldsymbol{W}$, trend to assume similar values).

Once established the relevance of the spatial dimensions, it comes the selection of the best econometric models. To identify the most suitable spatial specification between SDM and its nested SLM and SLX, it is performed a likelihood ratio (LR) test between all models estimated via maximum likelihood (ML). The results are summarized in Table 5, where it is shown that the SDM outperform the SLX (the values of the test are always significant with a 5% confidence), while the null hypothesis that the SLM is preferrable to the unrestricted

(SDM) model cannot be rejected in all cases according to 5% confidence. This circumstance let us to choose the SLM configuration to estimate the spatial spillovers.

Table 5 about here

A robustness analysis is conducted over all the model estimated. To notice that the impacts and parameters estimated using SDM and SLX are comparable in terms of signs and magnitudes with those of the SLM, proving the robustness of our results to the model selection (Lu and White, 2014). Concerning the robustness of coefficients estimated via ML, possible endogeneity could arise due to the presence of the lagged dependent variable in the SLM model. We control for this circumstance by estimating the same models with also a spatial two stage least square (S2SLS) procedure, which confirms the ML estimations. These results are available in the Appendix (Tables 1A, 2A, 3A, 4A, 5A and 6A).

The instruments implied are with WX, W^2X, and W^3X, as recommended by the literature (Kelejian and Prucha, 1998; Baltagi et al. 2014), where W^2 and W^3 are, respectively, the second and the third spatial lag.

In the following tables are summarized all the direct and indirect impacts obtained using each one of the three spatial matrices (Geographical, Industrial and Technological) for both the specification proposed: with $Total\_funding$ as dependent variable (Table 6, Table 7 and Table 8) and with $Valuation$ as dependent variable (Table 9, Table 10 and Table 11).

Table 6 about here

Table 7 about here

Table 8 about here

Table 9 about here

Table 10 about here

Table 11 about here

The results indicate that most covariates have a statistically significant and positive direct effect, confirming their relevant role in the OLS and in the spatial econometric models. The interpretation of the results and the sign of the coefficients align with both expectations and the literature (Balsmeier et al., 2014; Marra et al., 2024; Guerrero et al., 2023; Croce et al., 2018; Islam et al., 2018).

Within the spatial econometric framework, the emergence of largely expected indirect impacts indicates that these effects extend to and benefit neighbouring firms.

Business angels generate positive indirect effects in both models (funding and valuation) with geographical and industrial proximity (Table 6 and Table 7; Table 9 and Table 10), highlighting their role in fostering broader entrepreneurial ecosystems (Croce et al., 2018). Unlike institutional investors, business angels often engage closely with startups, sharing industry-specific expertise and facilitating connections within their professional networks. This hands-on involvement enhances the capabilities of not only the funded startup but also nearby firms and firms operating in the same industrial domain: their investments signal credibility, attracting further funding and talent to the local ecosystem. As a result, business angels contribute to regional innovation clusters, reinforcing industrial specialization and stimulating broader economic growth.

Public funding, even if not directly significant, generates positive indirect effects by fostering a supportive environment for innovation and investment. Government-backed capital reduces financial constraints for startups, enabling them to develop technologies and business models that, in turn, create spillovers benefiting industrially and technologically proximate firms (Table 7 and Table 8). These spillovers enhance investor confidence in ventures in the same industrial or technological domains and attract private investment.

Venture capital contributes to positive spillovers in the funding model of geographical and technological proximity by fostering innovation clusters and facilitating the emergence of technological opportunities. VC-backed firms often become anchors of local entrepreneurial networks, attracting talent, suppliers, and additional investment. The knowledge transfer and mentorship provided by venture capital further benefit nearby firms with similar technological expertise, accelerating industry-wide advancements. Additionally, the presence of VC investment signals market potential, encouraging further funding and business activity (Table 6 and Table 8). The evidence above strengthens the notion that a diverse mix of financial sources can amplify ecosystem-wide effects (Islam et al., 2018).

In the valuation model of geographical and technological proximity, total funding, number of employees (linked to knowledge exchange and spillovers, in line with Tubiana et al., 2022), and venture capital exhibit positive indirect effects (Islam et al., 2018), indicating that well-funded and growing firms tend to uplift their neighbours through knowledge diffusion, resource sharing, or hype effects (Table 9 and Table 11).

However, some findings present greater challenges in interpretation. For instance, in the industrial proximity models (for funding and valuation) firms' age exhibits a negative indirect effect, indicating that firms receive fewer spillovers when their (industrially) proximate neighbours are more mature (Table 7 and Table 10). This may stem from negative indirect effects arising from counterproductive dynamics, where firms competing within the same industrial specialization cannibalize each other's funding and business opportunities (Ben Letaifa and Rabeau, 2013; Samila and Sorenson, 2011; Gornall and Strebulaev, 2020). This result would suggest that older firms have a diminished capacity to generate spillovers and create hype that benefit similar firms or are less actively involved in knowledge diffusion (Marra et al., 2024). Alternatively, the result can also be interpreted as younger firms benefiting more from dynamic, innovative environments (Martin-Rios et al., 2022; Spigel, 2017; Stam and Spigel, 2016).

6. Conclusions

This study highlights the importance of expanding the traditional notion of proximity beyond mere geographical contiguity, introducing non-geographical dimensions to assess indirect effects among startups in terms of funding and valuation. The analysis sheds light on spillover and hype effects, where heightened expectations surrounding emerging technologies drive investment inflows and increased valuation, sometimes beyond startups' intrinsic value and actual performance. Even though hype-driven investments may result in temporary overvaluation, the intrinsic characteristics of the private markets should contain speculative risks. Moreover, the growing role of private investors and financial institutions, combined with more rigorous due diligence, ensures that capital is allocated to startups with strong prospects and fundamentals, tempering excessive exuberance.

Our contribution to the literature has been threefold. First, we introduce a spatial analysis framework that accounts for industrial relatedness and technological adjacency, broadening the perspective on spillover effects. Second, we extend the empirical investigation of spillovers to funding and valuation between startups, a relatively underexplored area. Third, we propose a novel approach to measuring industrial and technological proximity using semantic metrics derived from web-based textual data, offering a fresh perspective on inter-firm relationships beyond traditional classification methods.

The findings confirm that increased funding and rising valuations generate positive spillovers, benefiting startups across multiple proximity dimensions. However, the magnitude of these spillovers varies: public funding facilitates spillovers across both industrial and technological spaces, business angels primarily drive spillovers within industrial proximity due to their sector-specific expertise, while venture capital exerts a stronger influence in technological proximity, channelling resources and opportunities across firms within the same technological domain.

Even if banks have traditionally played a key role in financing the later stages of a startup's life cycle, they are expanding this role in the scale-up process beyond simply facilitating venture capital: as startups require larger sums of capital and more stable financial support, traditional loans and alternative financial instruments become increasingly appropriate. Given their expertise in debt financing, banks are well-positioned to offer alternative capital sources, such as customized loan products or structured financing solutions. Furthermore, regulators may encourage further investment through tax breaks for banks that fund startups and scale-ups, particularly in sectors like climate-tech. A larger involvement of the baking system would help diversify the capital sources available to startups as they move from early-stage ventures to larger, more sustainable businesses.

This study presents several limitations. A key challenge remains the limited number of variables inherent to startup dynamics, a phenomenon that is difficult to track accurately, which may affect model specification and general validity. Additionally, our propositions have been tested exclusively within the climate-tech sector, while these would require further sectoral applications to strengthen the findings and its implications.

Future research will advance in three key directions to deepen our understanding of spillover effects in startup ecosystems. First, refining the analysis by exploring alternative functional forms will help better capture the nuances of how spillovers and hype propagate across startups. Second, integrating virtual and physical adjacency matrices will enable a more comprehensive modeling of multi-dimensional proximity, incorporating both industrial and technological linkages alongside the geographical one. Finally, applying network analysis will offer valuable insights into the diffusion patterns of spillovers, shedding light on how interconnected startup ecosystems influence funding dynamics and valuation trends.

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Appendix

Table 1A about here

Table 2A about here

Table 3A about here

Table 4A about here

Table 5A about here

Table 6A about here

Tables

Table 1. Distribution of firms by valuation, in millions of Euros (sample vs population)

Quartile	Sample	Population
Min	0.075	0.065
25%	6.000	6.060
50%	17.250	17.560
75%	55.000	54.659
Max	8181.818	8181.818
Mean	88.128	87.093

Table 2. Distribution of firms by sub-industry (sample vs population)

Sub-Industries	Sample	Population
clean energy	39.73%	40.87%
energy efficiency	26.13%	25.12%
energy storage	8.38%	8.15%
energy providers	6.57%	6.13%
waste solution	3.85%	3.39%
water	2.95%	3.48%
maintenance & vehicle production	2.42%	1.96%
oil & gas	1.74%	1.72%
mobility	1.36%	1.47%
real estate software	1.36%	1.28%
agritech	0.91%	1.03%
others	4.61%	5.40%

Table 3. Estimation of OLS models with, respectively, Valuation and Funding as dependent.

Variables	OLS Funding	OLS Valuation
$Intercept$	3.7180***	0.1478***
$B2B$	0.5083**	0.3424*
$Total\_funding$		0.0029***
Age	0.0703***	0.0208
$Employees$	0.0035***	0.0021***
$Venture$	3.6865***	1.2340***
$Public$	0.3440	0.7406**
$Angel$	0.7262***	0.4533***

Note: *p<0.1, **p<0.05, ***p<0.01.

Table 4. Moran's I statistic for the three different adjacency matrices

W matrix	Moran's I statistic	Expectation	p-value
Industrial	0.036	-0.001	0.002
Technological	0.051	-0.01	0.000
Geographical	0.058	-0.001	0.000

Table 5. LR-tests of SDM against SLX and SLM

Dependent variable	W matrix	SDM vs SLM (p-value)	SDM vs SLX (p-value)
Valuation	Industrial	0.104	0.042
	Technological	0.730	0.005
	Geographical	0.679	0.002
Funding	Industrial	0.054	0.021
	Technological	0.580	0.037
	Geographical	0.830	0.029

Table 6. Estimated impacts of SLM model on Total_funding dependent variable with the Geographical adjacency matrix.

Variables	Direct impacts		Indirect impacts	
$B2B$	0.5002	*	0.3384	**
Age	0.0669	***	0.0453	**
$Employees$	0.0034	***	0.0023	***
$Venture$	3.7381	***	2.5287	***
$Public$	0.2822		0.1909	
$Angel$	0.7647	***	0.5173	***
Rho	0.4080	***		

Note: *** p<0.01; ** p<0.05; * p<0.1

Table 7. Estimated impacts of SLM model on Total_funding dependent variable with the Industrial adjacency matrix.

Variables	Direct impacts		Indirect impacts	
$B2B$	0.4727	***	0.4026	
Age	0.0805	***	-0.1882	***
$Employees$	0.0034	***	0.0005	
$Venture$	3.6483	***	-0.9520	
$Public$	0.1968		4.2811	**
$Angel$	0.6995	***	1.5928	**
Rho	0.1862	**		

Note: *** p<0.01; ** p<0.05; * p<0.1

Table 8. Estimated impacts of SLM model on Total_funding dependent variable with the Technological adjacency matrix.

Variables	Direct impacts		Indirect impacts	
$B2B$	0.4337	**	0.6250	
Age	0.0690	***	0.1426	
$Employees$	0.0035	***	0.0018	
$Venture$	3.2286	***	3.8262	*
$Public$	0.2563		7.9824	***
$Angel$	0.6820	***	0.4476	
Rho	0.4691	***		

Note: *** p<0.01; ** p<0.05; * p<0.1

Table 9. Estimated impacts of SLM model on Valuation dependent variable with the Geographical adjacency matrix.

Variables	Direct impacts		Indirect impacts	
$B2B$	0.3324	*	0.1844	
$Total\_funding$	0.0026	***	0.0015	**
Age	0.0192		0.0107	
$Employees$	0.0020	***	0.0011	**
$Venture$	1.2800	***	0.7101	**
$Public$	0.7269	**	0.4032	
$Angel$	0.4794	**	0.2659	*
Rho	0.3640	***		

Note: *** p<0.01; ** p<0.05; * p<0.1

Table 10. Estimated impacts of SLM model on Valuation dependent variable with the Industrial adjacency matrix.

Variables	Direct impacts		Indirect impacts	
$B2B$	0.3016		0.2320	
$Total\_funding$	0.0028	***	0.0049	
Age	0.0324	*	-0.1765	***
$Employees$	0.0019	***	-0.0012	
$Venture$	1.1599	***	-1.2282	
$Public$	0.5591	*	2.5420	
$Angel$	0.4356	***	1.7035	***
Rho	0.2923	***		

Note: *** p<0.01; ** p<0.05; * p<0.1

Table 101. Estimated impacts of SLM model on Valuation dependent variable with the Technological adjacency matrix.

Variables	Direct impacts		Indirect impacts	
$B2B$	0.3476	*	0.2788	
$Total\_funding$	0.0028	***	0.0022	**
Age	0.0180		0.0145	
$Employees$	0.0020	***	0.0016	**
$Venture$	1.1529	***	0.9246	*
$Public$	0.6358	*	0.5099	
$Angel$	0.4403	***	0.3532	
Rho	0.4480	***		

Note: *** p<0.01; ** p<0.05; * p<0.1

Table 1A: Robustness check. Direct and indirect impacts of model 1 (SDM), model 2 (SLX), and model 3 (SLM estimated via 2SLS). Total_funding as dependent, Industrial adjacency.

	Model 1	Model 2	Model 3
Direct Impacts			
$B2B$	0.4708**	0.4831**	0.4421*
Age	0.0814***	0.0807***	0.0668**
$Employees$	0.0034***	0.0034***	0.0032***
$Venture$	3.6528***	3.6740***	3.220***
$Public$	0.1767	0.2105	0.2190*
$Angel$	0.6920***	0.7053***	0.6192***
Indirect impacts			
$B2B$	0.2568	0.4056	0.4004
Age	-0.1709***	-0.1615***	-0.1910**
$Employees$	-0.0002	0.0005	0.0001
$Venture$	-1.4114	-0.6096	-0.8223
$Public$	3.5456*	4.1040***	4.0513**
$Angel$	1.2135*	1.3960***	1.2412*
Rho	0.16**		0.18***

Note: *** p<0.01; ** p<0.05; *p<0.1.

Table 2A: Robustness check. Direct and indirect impacts of model 1 (SDM), model 2 (SLX), and model 3 (SLM estimated via 2SLS). Total_funding as dependent, Technological adjacency.

	Model 1	Model 2	Model 3
Direct Impacts			
$B2B$	0.5457**	0.5403**	0.4221*
Age	0.0735**	0.0821***	0.0169**
$Employees$	0.0041***	0.0050***	0.0032***
$Venture$	3.1196***	3.5180***	3.220***
$Public$	0.2331	0.1664	0.6790*
$Angel$	0.4354***	0.4553***	0.6129***
Indirect impacts			
$B2B$	0.5531	0.2137	0.4454
Age	0.1212	0.1173	0.1102
$Employees$	0.0014	0.0012	0.0012
$Venture$	3.7550*	4.0101**	3.8021**
$Public$	6.9651***	6.6110**	6.0513**
$Angel$	0.3150	0.3710	0.2431
Rho	0.44***		0.46***

Note: *** p<0.01; ** p<0.05; *p<0.1.

Table 3A: Robustness check. Direct and indirect impacts of model 1 (SDM), model 2 (SLX), and model 3 (SLM estimated via 2SLS). Total_funding as dependent, Geographical adjacency.

	Model 1	Model 2	Model 3
Direct Impacts			
$B2B$	0.4588**	0.4771*	0.5001*
Age	0.0682***	0.0707***	0.0612***
$Employees$	0.0033***	0.0034***	0.0034***
$Venture$	3.7929***	3.7711***	3.5811***
$Public$	0.2611	0.2775	0.2912
$Angel$	0.7832***	0.7223***	0.7012***
Indirect impacts			
$B2B$	0.3170	0.1262	0.2448
Age	-0.0434	0.0121	0.0363*
$Employees$	-0.0001	0.0003	0.0018**
$Venture$	7.6838**	4.0016***	2.5287***
$Public$	5.2134**	2.1410*	0.0209
$Angel$	1.3531	1.1162	0.3273**
Rho	0.32***		0.40***

Note: *** p<0.01; ** p<0.05; *p<0.1.

Table 4A: Robustness check. Direct and indirect impacts of model 1 (SDM), model 2 (SLX), and model 3 (SLM estimated via 2SLS). Valuation as dependent, Industrial adjacency.

	Model 1	Model 2	Model 3
Direct Impacts			
$B2B$	0.3513	0.3096	0.3204
$Total\_funding$	0.0029***	0.0028***	0.0026***
Age	0.0241	0.0325*	0.0222
$Employees$	0.0020***	0.0020***	0.0012***
$Venture$	1.1850**	1.1900***	1.560***
$Public$	0.6412*	0.5717*	0.5230*
$Angel$	0.4224***	0.4446***	0.4454***
Indirect impacts			
$B2B$	0.1421	0.2470	0.1323
$Total\_funding$	0.0012**	0.0042*	0.0090
Age	0.0097	-0.1512***	-0.1555**
$Employees$	0.0008**	-0.0008	0.0011
$Venture$	0.4792*	-1.0950	-1.3801
$Public$	0.2593	2.4050	1.9220
$Angel$	0.1708*	1.4910***	1.6003***
Rho	0.19***		0.23***

Note: *** p<0.01; ** p<0.05; *p<0.1.

Table 5A: Robustness check. Direct and indirect impacts of model 1 (SDM), model 2 (SLX), and model 3 (SLM estimated via 2SLS). Valuation as dependent, Technological adjacency.

	Model 1	Model 2	Model 3
Direct Impacts			
$B2B$	0.3497	0.3460*	0.5012*
$Total\_funding$	0.0028***	0.0028***	0.0016**
Age	0.0185	0.0192	0.0019
$Employees$	0.0021***	0.0021***	0.0032***
$Venture$	1.1496***	1.1580***	1.030***
$Public$	0.6351**	0.6604*	0.5990*
$Angel$	0.4354***	0.4243***	0.4154***
Indirect impacts			
$B2B$	-0.5223	-0.4437	0.0244
$Total\_funding$	0.0059	0.0053**	0.0039**
Age	0.1232	0.0672	0.0102
$Employees$	0.0004	0.0002	0.0020*
$Venture$	2.3705	2.0150	0.8101**
$Public$	3.5681	3.6060*	0.0552
$Angel$	0.5105	0.4370	0.1249
Rho	0.32***		0.40***

Note: *** p<0.01; ** p<0.05; *p<0.1.

Table 6A: Robustness check. Direct and indirect impacts of model 1 (SDM), model 2 (SLX), and model 3 (SLM estimated via 2SLS). Valuation as dependent, Geographical adjacency.

	Model 1	Model 2	Model 3
Direct Impacts			
$B2B$	0.3144	0.312	0.3244
$Total\_funding$	0.0026***	0.0026***	0.0016**
Age	0.01989	0.0216	0.0022
$Employees$	0.0019***	0.0019***	0.0012**
$Venture$	1.3827***	1.290***	1.260***
$Public$	0.7297**	0.774**	0.5290*
$Angel$	0.4997***	0.497***	0.4954**
Indirect impacts			
$B2B$	-0.2569	-0.230	0.0144
$Total\_funding$	-0.0005	-0.0012	0.0009*
Age	-0.1057	-0.0730	0.0202
$Employees$	-0.0012	-0.0006	0.0012
$Venture$	7.4662***	5.71***	0.8701**
$Public$	3.4483	3.92**	0.0432
$Angel$	1.5404	1.27**	0.2444*
Rho	0.31***		0.33***

Note: *** p<0.01; ** p<0.05; *p<0.1.