

Zhen, Ni; Testa, Giuseppina; Compañó, Ramón

Working Paper

Small-world networks, dynamics and proximity in investment decisions

JRC Working Papers on Corporate R&D and Innovation (CoRDI), No. 2/2025

Provided in Cooperation with:

Joint Research Centre (JRC), European Commission

Suggested Citation: Zhen, Ni; Testa, Giuseppina; Compañó, Ramón (2025) : Small-world networks, dynamics and proximity in investment decisions, JRC Working Papers on Corporate R&D and Innovation (CoRDI), No. 2/2025, European Commission, Joint Research Centre (JRC), Seville

This Version is available at:

<https://hdl.handle.net/10419/322089>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



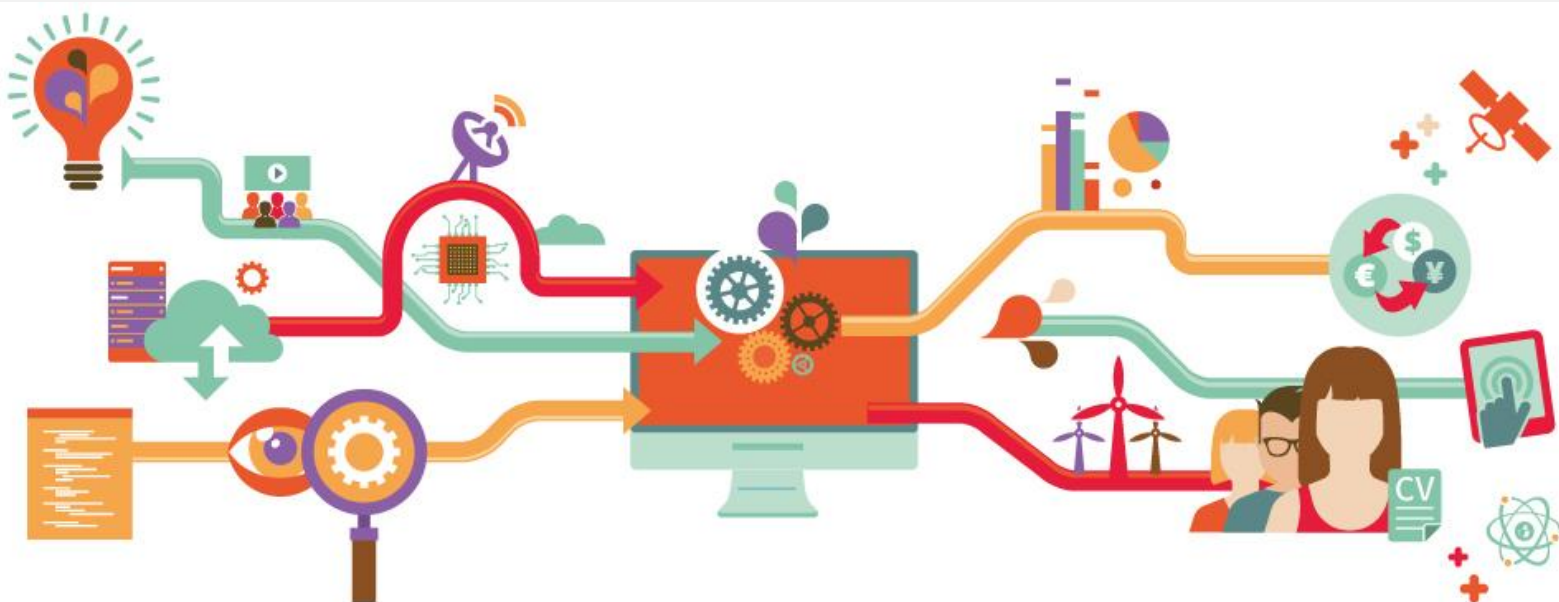
<https://creativecommons.org/licenses/by/4.0/>

Small-World Networks, Dynamics and Proximity in Investment Decisions

JRC Working Papers on Corporate R&D and Innovation (CoRDI)

No 2/2025

Zhen, N., Testa, G., Compañó, R.



This publication is a working paper by the Joint Research Centre (JRC), the European Commission's science and knowledge service. It aims to provide evidence-based scientific support to the European policymaking process.

The contents of this publication do not necessarily reflect the position or opinion of the European Commission. Neither the European Commission nor any person acting on behalf of the Commission is responsible for the use that might be made of this publication. For information on the methodology and quality underlying the data used in this publication for which the source is neither Eurostat nor other Commission services, users should contact the referenced source. The designations employed and the presentation of material on the maps do not imply the expression of any opinion whatsoever on the part of the European Union concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries.

The JRC Working Papers on Corporate R&D and Innovation (CoRDI) address economic and policy questions related to industrial research and innovation and their contribution to the European fair and sustainable competitiveness and growth. They are produced under editorial supervision by the Industrial Innovation & Dynamics (IID) team of Unit B6 Industrial Strategy, Skills and Technology Transfer in the JRC Directorate B Fair and Sustainable Economy of the European Commission.

The CoRDI Working Papers are accessible electronically from the following repositories: RePec (<http://repec.org/>), the JRC Industrial Research and Innovation webpage (<http://iri.jrc.ec.europa.eu/home>), and the JRC Publication Repository (<https://publications.jrc.ec.europa.eu/repository/>).

Editorial Board: The JRC Working Papers on Corporate R&D and Innovation are published under the editorial supervision of Pietro Moncada-Paternò-Castello (Solvay Brussels School of Economics and Management, Université Libre de Bruxelles, Belgium) and Alexander Tübke in collaboration with Fernando Hervás, Koen Jonkers, Francesco Rentocchini at the European Commission – Joint Research Centre, and in cooperation with Sara Amoroso (German Institute for Economic Research, Germany), Michele Cincera (Solvay Brussels School of Economics and Management, Université Libre de Bruxelles, Belgium), Alex Coad (Waseda University, Tokyo, Japan), Enrico Santarelli (University of Bologna, Italy), Daniel Vertesy (International Telecommunication Union, Switzerland – and UNU-MERIT, The Netherlands), Antonio Vezzani (UNCTAD, Switzerland); Marco Vivarelli (Università Cattolica del Sacro Cuore, Italy) and Zoltan Csefalvay (Mathias Corvinus Collegium, Hungary).

Any comments and submissions can be sent by email to: JRC-B6-secretariat@ec.europa.eu.

Contact information

Name: Alexander Tuebke

Email: Alexander.TUEBKE@ec.europa.eu

EU Science Hub

<https://joint-research-centre.ec.europa.eu>

JRC141795

Seville: European Commission, 2025

© European Union, 2025



The reuse policy of the European Commission documents is implemented by the Commission Decision 2011/833/EU of 12 December 2011 on the reuse of Commission documents (OJ L 330, 14.12.2011, p. 39). Unless otherwise noted, the reuse of this document is authorised under the Creative Commons Attribution 4.0 International (CC BY 4.0) licence (<https://creativecommons.org/licenses/by/4.0/>). This means that reuse is allowed provided appropriate credit is given and any changes are indicated.

For any use or reproduction of photos or other material that is not owned by the European Union permission must be sought directly from the copyright holders.

How to cite this report: N, Zhen, G, Testa, R, Compañó, *Small-World Networks, Dynamics and Proximity in Investment Decisions*, European Commission, 2025, Seville JRC141795.

Contents

Abstract.....	2
Acknowledgements.....	3
Executive summary.....	4
1 Introduction.....	5
2 Literature review.....	7
3 Theoretical background and hypothesis.....	9
3.1 Determinants of Investment Decisions in Venture Capital Firms.....	9
3.1.1 The role of cultural proximity.....	9
3.1.2 The role of spatial proximity.....	9
3.1.3 The role of syndication and networks.....	10
3.1.4 Other determinants.....	11
4 Dataset, Network Analysis, and Adjacency Matrix.....	13
4.1 Dataset.....	13
4.2 Network analysis.....	14
5 Econometric modelling, case control and variables.....	17
5.1 Econometric modelling and variables.....	17
5.2 Case control.....	18
6 Descriptive Statistics.....	20
7 Estimation results.....	24
7.1 Main results.....	24
7.2 Robustness check.....	30
8 Conclusion and Policy Implications.....	34
References.....	36
List of tables.....	41
Annexes.....	42
Annex 1. Definition of Variables and Data Sources.....	42
Annex 2. Definitions of Key Concepts in Network Analysis.....	43

Abstract

Using deal-level micro data from the Dealroom database, we construct a dynamic co-investment syndication network to examine the influence of cultural proximity and geospatial proximity between investors and start-ups, as well as the network position of global VC firms on investment decisions in European-based start-ups. By applying a linear probability regression model with high-dimensional fixed effects over the period 2015–2022, we confirm that both cultural and spatial proximity significantly facilitate VC investment. Moreover, our analysis reveals that a prominent network position — characterized by how well-connected (degree centrality) and how influential (Katz centrality) within the co-investment network— substantially enhances VC investments on account of the facilitated sharing of information, contacts, and resources among investors.

Furthermore, our findings reveal that small-world networks, characterized by high clustering coefficients, facilitate investments in distant start-ups, helping to overcome spatial constraints—an aspect largely overlooked in the literature. Small-world syndication networks foster trust among members, complementing each other through differentiation and specialization in industrial knowledge and local markets, potentially altering risk-averse behaviour and enabling investments that transcend geographical boundaries.

Acknowledgements

The authors would like to acknowledge the valuable discussions and comments received from Dario Diodato, Lorenzo Napolitano, Marie Lalanne, Francesco Rentocchini, James Gavigan, Alexander Tübke (European Commission, Joint Research Centre), Francesco Lelli (University of Trento), and Jitse Duijsters (University of Groningen), as well as from participants at the JRC's Industrial Innovation Dynamics (IID) seminar series held in Seville, on December 16, 2024, and at the 37th RSEP International Conference on Economics, Finance and Business, which took place on November 22-23, 2024, at the University of Washington Rome Center, Rome. This research was conducted without specific funding from public, commercial, or not-for-profit sectors. The authors remain responsible for all errors.

Executive summary

The EU faces significant funding gaps in venture capital (VC) investment, as VC firms exhibit local bias and predominantly invest in nearby start-ups. This paper aims to explore factors that facilitate easier access to venture capital, identifying possible targets and policy measures to reduce regional funding gaps. Specifically, we deepen the analysis by investigating the impact of network position of VCs within the syndication network on VC investment decisions, along with closeness of the investor to start-up countries in cultural and legal terms. This paper is among the first to examine VC investment decisions through the lens of small-world networks, highlighting the role of clustering coefficients within small-world investor communities on the ability to overcome spatial constraints and invest in distant start-ups, a factor largely overlooked in the literature to date.

Utilizing deal-level data from the Dealroom database for the period 2015-2022, this study focuses on start-ups headquartered in the EU27, Iceland, Liechtenstein, Norway, Switzerland, and the UK, with global investors from over 110 countries. Based on a linear probability regression model with high-dimensional fixed effects, we find that cultural proximity, spatial proximity, and a prominent network position—measured by degree and Katz centrality within the co-investment network—significantly facilitate VC investments.

In addition, we find that better-positioned investors, in terms of degree and Katz centrality, have less incentive to invest in distant deals. High degree and Katz centrality might not compensate for the lack of established relationships and trust with distant entrepreneurs. Better-networked VCs may prefer local or regional investments to exert more control and influence, to leverage network advantages.

Our findings highlight the influence of high clustering coefficients within small-world investor communities in overcoming spatial constraints to invest in distant start-ups—a factor that has been largely overlooked in the existing literature. Participation in international, closely connected networks enhances trust within the network, potentially altering risk-averse behaviors and transcending geographical boundaries.

The findings of this study have significant policy implications. To address regional funding disparities, policymakers should implement policy instruments to foster venture capital syndication, particularly with well-connected and influential investors. Policymakers should promote familiar, trusted partnerships. Encouraging syndication with global investors in small-world networks can help transcend geographical boundaries, reducing regional funding gaps, fostering a more integrated and collaborative global investment landscape.

1 Introduction

Venture capital (VC) firms are vital sources of funding for emerging companies, new ventures, novel industries, and technology clusters (Giraudo et al., 2019; Gompers and Lerner, 2001; Bertoni et al., 2015; Ghinami and Montresor, 2023). An effective VC market plays an essential role in promoting sustainable economic growth, creating jobs, fostering innovation, developing the entrepreneurial ecosystem, and supporting regional development (Kortum and Lerner, 2000; De la Dehesa, 2002; Chen, 2009; Lutz et al., 2013).

Entrepreneurs often struggle to secure external capital due to information asymmetries and agency issues (Gompers and Lerner, 2001). Specialized equity investors, such as venture capitalists (VCs) and business angels (BAs), are more adept at addressing these asymmetries than traditional financial institutions due to superior screening, monitoring, and staging capabilities (Kaplan and Stromberg, 2001). VCs typically engage in close oversight of the firms they invest in (Lerner, 2022), helping to mitigate financial constraints during the early stages of a firm's development (Clementi and Hopenhayn, 2006; Cooley and Quadrini, 2001; Desai et al., 2003), and contributing to the professionalization of the firm (Hellmann and Puri, 2002; Puri and Zarutskie, 2012). Consequently, companies backed by VCs have lower failure rates within their first five years compared to those without VC financing (Puri and Zarutskie, 2012).

Over the past decade, Europe has overall been witnessing a considerable rise in VC investments. According to the 2022 PitchBook European Venture Report, the volume of VC deals increased from 19.2 billion euros in 2015 to 91.6 billion euros in 2022 ⁽¹⁾. This increase has however been uneven. Start-ups in underdeveloped regions face great challenges in accessing VC resources compared to start-ups in economic hubs. The lack of adequate financing options hinders successful entrepreneurship, especially in Europe, where external equity investors are more risk-averse than their US counterparts (Bertoni et al., 2015).

Regional funding gaps imply an under-representation of VC investments in certain areas, relative to their share of national economic activity (Mason, 2007). These gaps are particularly evident in VC investments (Mason, 2007; Martin et al., 2005, 2002), with the equity gap ranging from 0.7% of GDP in the Netherlands to 13.05% in Romania (McCahery et al., 2016). Cross-border investments within Europe accounted for only 23.1% of total VC activity on average from 2007 to 2020 (Asdrubali, 2023).

In fields where quality and risk is difficult to measure objectively, such as venture capital investment, reputation and influential networks are essential for securing access to resources and rewards (Zava and Caselli, 2024; Fraiberger et al., 2018). Venture capitalists often depend on familiar local networks to mitigate uncertainty by building mutual trust through repeated interactions, and sharing information with other investors, consultants, and accountants (Florida and Kenney, 1988; Florida and Smith Jr, 1993; Mason, 2007). In fact, VCs report that 58% of their deal flow originates from their networks (Zava and Caselli, 2024; Gompers et al., 2016). Therefore, the success of VCs depends on their role within syndication networks, particularly on how well-connected and influential they are.

By and large, VC investment is characterized by local bias (Cumming and Dai, 2010; Zook, 2002; Lutz et al., 2013; Mason, 2007); and clustering patterns (Sorenson and Stuart, 2001; Mason, 2007). Local bias refers to the tendency of VC firms to invest in nearby start-ups, while clustering patterns indicate that VC firms are usually concentrated in major financial centres and high-tech regions

⁽¹⁾ 2022 Annual European Venture Report by PitchBook
https://files.pitchbook.com/website/files/pdf/2022_Annual_European_Venture_Report.pdf.

(Mason, 2007). Local bias primarily stems from the scarcity of publicly available information on new and emerging businesses, as this information is often personal, informal, and difficult to access over long distances (Mason, 2007). Spatial proximity enables investors to select and monitor investee companies more effectively, leading to a concentration of VC investments in core regions while neglecting economically lagging areas (Harrison et al., 2010). Clustering patterns in financial centres provide VC firms with essential access to the knowledge and expertise needed to identify deals, structure investments, and support their portfolio companies. Proximity to other financiers, entrepreneurs, legal, accounting, and consultancy firms also plays a crucial role during the investment process (Mason, 2007). This paper aims to explore factors that facilitate easier access to venture capital, identifying possible targets and policy measures to reduce regional funding gaps. Specifically, we deepen the analysis by investigating the impact of network position of VCs within the syndication network on VC investment decisions, along with closeness of the investor to start-up countries in cultural and legal terms. This issue is policy-relevant, as adequately funded entrepreneurship can contribute to economic development in lagging regions and reduce cross-regional disparities.

The novel contribution of this paper is twofold. First, to our knowledge, this study is among the first to incorporate network analysis into VC investment decisions within a temporal context (Sorenson and Stuart, 2001; Ghinami and Montresor, 2023). Unlike previous studies that primarily focus on US VC samples, this analysis leverages the Dealroom dataset (2015–2022), covering start-ups headquartered in the EU27, Iceland, Liechtenstein, Norway, Switzerland, and the UK, with global investors from over 110 countries. Second, this study is among the first to examine VC investment decisions through the lens of small-world networks, highlighting the role of inherent network structures in shaping investment choices from an empirical perspective. Small-world networks, characterized by short path lengths and high local clustering coefficients, have gained attention as powerful organizing mechanisms that enhance performance by facilitating efficient knowledge transfer, learning, and collaboration (Uzzi et al., 2007). While studied in contexts such as strategic alliances, patenting inventors, co-authorship networks, actors and musicians, small-world networks remain largely unexplored in venture capital co-investment (Uzzi et al., 2007). To our knowledge, this study is the first to identify the distinct impact of high clustering coefficients within small-world investor communities on the ability to overcome spatial constraints and invest in distant start-ups, a factor largely overlooked in the literature to date.

The paper is structured as follows: Section 2 reviews the key literature. Section 3 identifies the relationship between cultural and geospatial proximities, syndication and network on VC investment decisions and postulates several hypotheses. Section 4 provides a summary of data construction and network analysis. Section 5 discusses the econometric model, case control and variable selection. Section 6 presents descriptive statistics. Section 7 presents the estimation results and additional robustness checks. Finally, Section 8 synthesizes the main findings, discusses policy implications, and concludes the study.

2 Literature review

The literature on VC investment decisions is extensive and well-developed (Gompers et al., 2020; Hoenig and Henkel, 2015). Our work closely aligns with research on networks and VC investment. Sorenson and Stuart (2001) seminal study highlights how institutions and social structures influence transaction patterns among economic actors. They demonstrate that social networks within the VC community, established through syndicated investment, facilitate the diffusion of information across boundaries and expanding the spatial radius of exchange. Ghinami and Montresor (2023) examine the role of various dimensions of proximity in predicting successful matches between VC funds and innovative startups seeking finance. Their findings indicate that tangible proximity is important. Additionally, relational proximity, reflected in the professional and investment networks of partners, appears as the strongest predictor of successful matches between VCs and innovative start-ups. Zava and Caselli (2024) also emphasize the significance of reputation and networks of influence in determining access to resources. They find that a company's access to subsequent rounds of funding is positively related to the network of influence of the investors from previous rounds, with the influence effect being more pronounced in early-stage deals.

Bubna et al. (2020) identify characteristics of VC communities, noting that they share similarity in age, the number of connections and functional style but not necessarily in spatial location. Focusing on performance, Hochberg et al. (2007) demonstrate that VCs with central positions in syndication networks benefit from both a higher quantity of deal flow and superior quality of deals. This centrality allows them to access valuable information, including tacit knowledge, which enhances their ability to make informed investment decisions, ultimately improving fund performance. Similarly, Christopoulos et al. (2022) show that investors' strong network ties are associated with sales growth of portfolio companies before and after deals, consistent with both selection and value-added channels.

This study also draws from literature on the influence of organizational structure on VC investment, with an emphasis on social elements such as trust and cultural proximity. Using a hand-collected dataset of European VC deals, Bottazzi et al. (2010) finds that 'generalized trust' among nations positively predicts VC firms' investment decisions but has a negative correlation with successful exits ⁽²⁾. On the basis of their concept of generalized trust, our analysis incorporates a number of features that capture cultural proximity, in particular the common language and common legal system shared by the investor's and investee's countries.

Empirical research has increasingly focused on the distinctive structure of small-world networks, characterized by high local clustering coefficients and short path lengths (Fleming et al., 2007). A widely held prediction is that small-world networks enhance innovative creativity (Verspagen and Duysters, 2004; Schilling and Phelps, 2007; Uzzi and Spiro, 2005; Fleming et al., 2007). First, small-world networks facilitate diverse relationships, providing fresh, non-redundant information and enabling resource pooling (Uzzi and Spiro, 2005; Fleming et al., 2007). Second, small-world networks foster trust and close collaboration within a dense and embedded social context (Schilling and Phelps, 2007). Sociologists such as Coleman (1988) and Granovetter (1992) have argued that densely clustered networks foster trust, transparency, reciprocity norms, and a shared identity. These characteristics promote high levels of cooperation and facilitate collaboration by serving as self-enforcing informal governance mechanisms (Dyer and Singh, 1998; Schilling and Phelps, 2007).

⁽²⁾ Bottazzi et al. (2010) distinguish between two types of trust: generalized trust and personalized trust. Generalized trust refers to a set of beliefs about the behavior of a random member of an identifiable group, often based on generalizations or even stereotypes. In contrast, personalized trust relates to the evolving relationship between two specific individuals. In this paper, we focus on generalized trust.

Third, small-world networks enhance the speed of information flow due to their short path lengths and high clustering (Verspagen and Duysters, 2004; Fleming et al., 2007). The dense connectivity within clusters increases a network's transmission capacity, allowing large volumes of information to spread rapidly (Burt, 2001; Schilling and Phelps, 2007). The close interactions in turn, facilitate the transfer of tacit, embedded knowledge (Hansen, 1999; Zander and Kogut, 1995; Schilling and Phelps, 2007). As a result, clustering supports the exchange of richer and more extensive knowledge (Schilling and Phelps, 2007). While small-world networks have been studied in contexts such as strategic alliances, patenting inventors, co-authorship networks, and creative industries like acting and music (Uzzi et al., 2007), this paper extends the literature by examining their influence on venture capital co-investment.

Another important strand of literature highlights the significance of spatial proximity. Spatial proximity facilitates better oversight, more frequent interactions and a deeper understanding of the local business environment. The agency problem and information asymmetry between VCs and start-up companies become more challenging with increased distance. Lutz et al. (2013) indicate that the probability of a financing relationship decreases by 8% if the journey time increases by one standard deviation, based on data from German portfolio companies over the period 2002-2007. Spatial proximity is particularly crucial for deals involving very small or very large investment sums, and for less experienced venture capitalists and lead investors. Cumming and Dai (2010) find that more reputable VCs (those that are older, larger, more experienced, and have a stronger IPO track record) and VCs with broader networks exhibit less local bias.

3 Theoretical background and hypothesis

3.1 Determinants of Investment Decisions in Venture Capital Firms

The success of a start-up depends on multiple factors: the prosperity of the business itself; the team; the timing and technology adopted; the underlying business model; the industry in which it operates; and sometimes factors beyond control, such as luck (Zava and Caselli, 2024; Gompers et al., 2016). As a matter of fact, only a small percentage of start-ups succeeds: 40% of funded ventures fail during the first year and 90% ceases business leaving losses behind (Zava and Caselli, 2024; Dingee et al., 1990). It is challenging to assess the underlying quality of start-ups. Their unproven business models, untested management teams, nascent technologies and immature market all pose uncertainty for investors (Sorenson and Stuart, 2001; Mason, 2007).

Meanwhile, VCs cannot rely on entrepreneurs for accurate information about the quality of their business plans, who typically overstate the attractiveness of proposals to secure funding (Amit et al., 2022; Sorenson and Stuart, 2001). Venture capital investment is a high-risk business that requires a long-term commitment. Information asymmetry, agency problems, and distrust between investors and entrepreneurs all pose investment barriers (Herrmann et al., 2016; Carpenter and Petersen, 2002; Sorenson and Stuart, 2001).

3.1.1 The role of cultural proximity

In this context, social elements such as trust plays a vital role in investing in young and risky start-ups. As Arrow (1972) put it: "Virtually every commercial transaction has within itself an element of trust." Bottazzi et al. (2010) distinguish between two forms of trust: generalized trust and personalized trust. Generalized trust involves beliefs about the behavior of a typical member of an identifiable group, often shaped by generalizations or stereotypes. Personalized trust, by contrast, develops through the evolving relationship between specific individuals. Individuals who share the same language or legal system are generally more likely to trust one another. In line with Bottazzi et al. (2010), we adopt the concept of generalized trust. 'Cultural proximity' refers to the similarity between investors and start-ups, particularly in terms of language and legal systems. These cultural similarities can influence investment decisions, deal evaluations, structures, and post-investment relationships, largely through the generalized trust.

Past studies have mainly focused on economies that are geographically widely dispersed but culturally quite homogenous, such as those of the US or Canada (Brander et al., 2002). In this paper, however, we focus on start-ups located in Europe, a continent where significant cultural diversity emerges within a relatively short distance. For instance, European countries frequently share borders, yet they may not share a common language or legal system. Therefore, we propose our first hypothesis:

Hypothesis 1: The probability of closing an investment increases with cultural proximity between VC investors and start-ups.

3.1.2 The role of spatial proximity

VC investments require a quite deal of trust between investors and investee. Traditionally, the most effective way of trust building is via physical contact. Building trust through videoconferences rather than in-person interactions has been a subject of discussion, particularly with the rise of remote work and the increased reliance on virtual meetings due to the COVID-19 pandemic.

Videoconferences and other IT tools can enable trust-building, but they are not as effective as

physical contact for several reasons. First, in-person interactions provide a wealth of non-verbal cues that contribute to trust-building, such as eye contact, body language, and physical proximity. Second, sharing experiences, like a handshake or a spontaneous conversation before or after a meeting, can contribute significantly to building trust. Such personal connections can foster a sense of camaraderie and a personal connection that is hard to replicate online. Proximity reduces communication costs and facilitates trust and transparency. Most of time, the effective information exchange occurred between investors and investees during “unplanned encounters at restaurants or coffee shops, opportunities to confer in the grandstands during Little League baseball games or at soccer matches, or news about a seminar or presentation all happen routinely ...” (Powell et al., 2002; Mason, 2007). In-person meetings remain therefore a prime asset to create trust and confidence between investors and investees, despite the current IT advancements.

Previous studies at the micro level have identified a significant role of geographical proximity in affecting the probability of making an investment. The primary explanation of this is that VC firms rely on access to personal networks and face-to-face contacts for finding, evaluating, and monitoring investment opportunities. VC investment typically involves at least at the beginning, regular face-to-face visits to meet with management in the portfolio companies to oversee firm performance. Some scholars believe the effective geographical radius within which VC firms prefer to make investments may be restricted to one to two hours’ travel time from their office (Mason and Harrison, 1994). VCs may spend an average of four to five hours per month on-site at each of the companies in which they play a lead role (Gorman and Sahlman, 1989). Geospatial proximity helps mitigate information asymmetry and agency problems. Physical closeness facilitates both pre- and post-investment activities for venture capital investments, such as acquiring information on potential investment opportunities, evaluating their quality, and monitoring and advising new ventures (Sorenson and Stuart, 2001). Therefore, we propose our second hypothesis:

Hypothesis 2: The probability of making an investment decreases with geographical distance between VC investors and start-ups.

3.1.3 The role of syndication and networks

In fields where it is challenging to measure quality objectively, reputation and networks are crucial for securing access to resources and rewards (Zava and Caselli, 2024; Fraiberger et al., 2018). Venture capitalists often rely on familiar local networks to overcome uncertainty by sharing information with other investors, consultants, and accountants, with whom trust is built through repeated interactions (Florida and Kenney, 1988; Florida and Smith Jr, 1993; Mason, 2007). As a matter of fact, venture capitalists report that 58% of their deal flow originates from personal networks (Zava and Caselli, 2024; Gompers et al., 2016). The network position of VC firms—specifically their centrality within a co-investment syndication network—is a crucial factor in determining the likelihood of making successful investments.

Venture capitalists (VCs) often syndicate their investments with other VCs rather than investing alone (Lerner, 1994; Hochberg et al., 2007). VC co-investors are often selected from existing network members or based on their reputation in the VC market. One reason to involve of multiple VCs in the same funding round is to reduce the costs, e.g. expenditures for due diligence, and the risks associated with the investment (Hochberg et al., 2007). VCs co-invest with the expectation of future reciprocity (Lerner, 1994). VC networks can leverage past experiences to select better investments when the viability and return potential of proposals are uncertain (Lerner, 1994; Wilson, 1968; Sah and Stiglitz, 1984). Additionally, syndication facilitates the sharing of information, contacts, and resources across sector boundaries, expanding the spatial radius of

exchange and allowing investors to diversify their portfolios (Bygrave, 1992; Sorenson and Stuart, 2001). VC firms that are centrally positioned within co-investment networks are more likely to access and evaluate high-quality investment opportunities. Both the quantity and quality of connections are crucial in determining the network position of a venture capital (VC) firm. Therefore, we propose the following hypothesis:

Hypothesis 3: The probability of making an investment increases with the prominence of a VC's position within the syndication network.

Blau (1977) observed that social space influences interaction patterns similarly to physical space. In the absence of publicly available investment information, particularly for early-stage start-ups, interpersonal networks become a primary and reliable source of insight (Mason, 2007). These networks shape the flow and dissemination of information and knowledge through connections. Dependence on personal and professional networks, often referred to as 'Rolodex power', underscores the significance of social networks in investment decisions (Mason, 2007). This flow of information is typically personal and informal, making it challenging to manage over long distances (Mason, 2007).

VC networks play a vital role in facilitating the transmission of information and the exchange of knowledge among key actors (Ghinami and Montresor, 2023). A VC firm with a central position in this network is more likely to transcend geospatial boundaries, overcoming the limitations imposed by distance. Each new investor brings about unique information, expertise, services, and their own relationships and networks (Sorenson and Stuart, 2001). Social ties based on trust and reliability, whether direct or mediated through common co-investors, provide a preferred channel for information exchange (Uzzi, 1996; Ghinami and Montresor, 2023).

In this context, we explore scenarios where VC firms may overcome geographical constraints and show a greater propensity to invest in distant start-ups. As Sorenson and Stuart (2001) observed, syndication networks facilitate the diffusion of information across sectors and geospatial boundaries, thereby expanding the spatial radius of exchange and mitigating local biases. Accordingly, we propose the following hypothesis:

Hypothesis 4: Better-networked VCs are more likely to invest in distant start-ups.

We specifically anticipate that this hypothesis applies to VCs with high local clustering coefficients. Small-world networks, characterized by short path lengths and high local clustering coefficients, inherently facilitate rapid access to information, efficient information transmission, and exchange from diverse and novel sources (Sullivan and Tang, 2012). While firms generally adopt an exploitative approach and prioritize local searches (March, 1991; Sullivan and Tang, 2012), those with access to novel information flows are better positioned to evaluate distant business opportunities. As a result, these firms are more likely to engage in exploratory learning by pursuing new ideas and opportunities (March, 1991; Sullivan and Tang, 2012).

3.1.4 Other determinants

VC experience plays a crucial role in investment decisions. First, experienced venture capitalists develop competence in drafting effective contracts to mitigate agency problems and identifying early warning signs within their portfolio companies. As they assess more business plans and observe more companies, they become increasingly efficient in evaluating business proposals, investment opportunities, and entrepreneurs (Fried and Hisrich, 1994). In our current analysis, in view of the limitations on VC age (e.g. a young VC firm may be highly experienced compared to an

older, but less active VC firm), we account for the total number of deals made by each VC by the investment year, as well as their experience in specific industries and stages.

The literature also indicates that the effects of a VC firm's experience on investment decisions vary depending on the stage of company development. In the early stages, the prior experience of VCs is crucial to assess and monitor investment opportunities, as early-stage start-ups lack a proven track record. In contrast, later-stage companies may require less intensive monitoring due to their established success records (Gompers, 1996).

4 Dataset, Network Analysis, and Adjacency Matrix

4.1 Dataset

This paper uses Dealroom, a commercial database covering start-ups, scale-ups, growth and tech companies from 2015 to 2022. The study focuses on start-ups headquartered in the EU27 countries, along with Iceland, Liechtenstein, Norway, Switzerland, and the UK, while global investors are located across 110 countries. We specifically examine equity financing rounds classified as Angel, Seed, Early VC, and Late VC ⁽³⁾. Other deal types such as acquisitions, buyouts, non-VC growth equity, IPOs, media for equity, mergers, private placement VC, secondary deals, SPAC IPOs, debt financing, grants, and convertibles are excluded from the analysis ⁽⁴⁾. Additionally, crowdfunding firms are excluded based on the variable investor type. The final sample consists of venture capital (VC) investors, including business angels, government venture capital investors, corporate investors and investment banks ⁽⁵⁾. Approximately 83.86% of the deals are classified as Angel, Seed, or Early VC rounds.

The final dataset comprises 40,556 deals involving 20,221 investors from 110 countries, who have invested in 25,687 European start-ups across the EU-27, as well as Iceland, Liechtenstein, Norway, Switzerland, and the UK. It is important to note that investors are global and free to form syndications without distinguishing between EU and non-EU countries. The number of deals per annum rises steadily from 3,384 in 2015 to 6,691 in 2022, nearly doubling over eight years and underscoring the growing importance of the VC industry.

On average, a VC firm invests in 3.5 companies and participates in 1.6 rounds, with the considerable variation. Noteworthy examples include Bpifrance, which invested in 693 start-ups during the period from 2015 to 2022. Investors like Bpifrance, Battery Ventures (US-based), and Goldman Sachs are active across all investment stages, including Angel, Seed, Early VC, Growth Equity VC, and Late VC, covering Series A through Series G rounds.

Out of the 40,556 total, 21,761 involve solo investors, while 46.34% of the deals are syndicated. On average, 2.2 investors participate in each deal, with the largest syndication involving 44 investors. It is important to note that larger VC syndicates are not always advantageous. Co-investment can introduce syndication costs, including information asymmetry, agency issues, and coordination frictions among members. Larger syndicates often face diverging incentives, slower consensus-building, and reduced strategic agility (Brander et al., 2002). Additionally, VCs vary in reputation among entrepreneurs, from being “entrepreneur-friendly” to “quick to pull the trigger” (Nanda and Rhodes-Kropf, 2018; Brander et al., 2002). The choice of initial investors within a syndicate has lasting consequences, as their decision not to reinvest may signal risk to potential follow-up financiers, significantly affecting a start-up’s success. Therefore, selecting syndication partners wisely is crucial—balancing the benefits of collaboration while carefully managing associated costs and risks.

⁽³⁾ The seed stage is defined as rounds labeled as ‘seed’. The angel stage is defined as rounds labeled as ‘angel’. Early VC is defined as rounds labeled as ‘early VC’ or ‘series A’. Late VC encompasses rounds labeled as ‘growth equity VC’, ‘late VC’, or ‘series B’ through ‘series I’. Since the VC is identified based on the ‘round’ variable rather than the investor type, seed accelerators are also included in the sample.

⁽⁴⁾ Definitions for these terms are available via Dealroom’s taxonomy at: <https://dealroom.co/blog/glossary-definitions>.

⁽⁵⁾ Venture capital refers to independent, professionally managed funds dedicated to equity or equity-linked investments in privately held, high-growth companies (Gompers and Lerner, 2001).

4.2 Network analysis

Dealroom data contains deal-level information with identifiable deal IDs linking to start-ups, investors, and co-investors. This allows for the identification and tracking of co-investment relationships within a year, facilitating the construction of syndication networks.

The construction procedure is established as follows: the dataset is first split on an annual basis. A binary matrix M is then constructed to indicate the relationships among all investor IDs and all deal IDs in a given year. The matrix elements take the value 1 if there is an investment from a specific investor to a specific deal, and 0 otherwise. By applying the rule MM' , a weighted adjacency matrix is created, where each matrix element indicates the number of co-investments between two investors in a given year. The analyzed network is represented by an undirected adjacency matrix due to the absence of data on the lead role played by specific VC firms. Consequently, there is no differentiation between the originator and the receiver in terms of investment direction.

Networks are dynamic entities, with new syndications forming and terminating over time (Hochberg et al., 2007). The temporal dimension is crucial due to the dynamic nature of investments, as the start-up ecosystem continuously evolves with emerging technologies and trends (Zava and Caselli, 2024). Syndication networks should incorporate the evolving relationships among investors along with all market developments (Zava and Caselli, 2024). In order to capture the temporal dimension, we constructed eight annual adjacency matrices from 2015 to 2022. Annual networks effectively represent the dynamism of co-investment formation and evolution. In a VC co-investment syndication network, nodes represent venture capital firms, while edges denote co-investment relationships within a specific year. A distance of 2 indicates an indirect link through a mutual co-investor, and a distance of 3 implies a connection through two intermediary co-investors. The greater the distance between two investors, the weaker their connection.

Network position represents how centrally positioned an investor is relative to other investors in the network. We use a variety of centrality measures, including degree centrality, Katz centrality, and clustering coefficients. Each highlights different facets of economic roles of a VC firm within the syndication network and interactions with other entities. Our analysis employs *nwcommands*, an efficient Stata package for network calculations (Grund and Hedstrom, 2015).

We focus on start-ups from the EU 27, plus Iceland, Liechtenstein, Norway, Switzerland, and the UK. Global investors are free to form syndications without distinguishing between EU and non-EU countries. Moreover, centrality measures vary over time as networks are updated annually. Therefore, each VC firm exhibits different centrality measurements across years.

Weighted Degree Centrality: Degree centrality assesses the number of direct connections a VC firm maintains. This fundamental measure indicates the structural significance of a VC firm within the network. A high degree centrality suggests that a VC firm is well-connected, implying substantial activity and influence within the network. If such a firm exits, many others would lose a significant co-investor. Firms with numerous connections may rely less on any single VC for information or deal flow, potentially offering access to a broader range of expertise, contacts, and capital pools (Hochberg et al., 2007).

Since our analysis involves an undirected, weighted adjacency matrix, we calculate weighted degree centrality, which reflects the intensity of cooperation through the frequency of co-investments annually. The weighted degree represents not just the count of connections but the total co-investment activities within a year with all co-investors. To ensure temporal comparability, we normalize the weighted degree by dividing by the total number of nodes in the network (i.e., $N - 1$).

In this context, we refer to “isolated investors” as those who do not syndicate with any other VC firms within a given year, effectively remaining outside the network. Conversely, “solo investors” are those who do not co-invest in specific deals. According to Brander et al. (2002), isolated investors may signal highly promising projects, where the need for additional opinions is minimal, and they may be reluctant to share potentially lucrative deals with other VCs. On the other hand, moderately promising projects are often syndicated. Empirical evidence generally supports the value-added hypothesis, with syndicated projects yielding higher returns than isolated investments.

Katz Centrality: Katz centrality evaluates both the quantity and quality of a node’s connections. It measures a node’s relative influence in the network by considering its neighbours’ connections and applying an attenuation factor to distant connections. This means that nodes farther away contribute less to the centrality measure. Katz centrality captures different aspects of information or knowledge transfer. A VC firm with high Katz centrality is influential not only due to its direct connections but also through its indirect connections to other influential actors. This measure reflects the firm’s overall importance in the network, accounting for both direct and extended connections. There is a strong correlation between Katz centrality and degree centrality, with a correlation coefficient of 0.9823.

The attenuation factor for Katz centrality ensures that the influence of a vertex decreases with distance. This factor should be strictly less than the inverse of the largest eigenvalue of the adjacency matrix, which, in our case, is 57.0793 ⁽⁶⁾. We focus on the Giant Connected Component for both descriptive statistics and estimation results with Katz centrality. Due to the complex nature of the network, annual networks often contain multiple disconnected components. To ensure comparability, we focus on the largest connected subgraph (GCC) within each network, as the Katz centrality of nodes in different disjoint subgraphs cannot be directly compared. Connected components are subgraphs where nodes can be reached from each other through network edges (Coscia, 2021). We present an overview of component distribution in Table 1. The Giant Connected Component comprises about 50% of the sample, whereas observations for the second-largest component are limited ⁽⁷⁾. Thus, we focus on the Giant Connected Component for describing and estimating Katz centrality. Katz centrality considers the overall network structure, and focusing on the Giant Connected Component provides a solid basis for comparison.

Table 1. Network Component Distribution Over Time

Year	No. Observations	No. Giant Connected Component	No. Second Largest Component	% Giant Connected Component	% Second Largest Component
2015	3205	1593	4	49.70%	0.12%
2016	3920	1875	1	47.83%	0.03%
2017	5102	2597	11	50.90%	0.22%

⁽⁶⁾ Consequently, the attenuation factor should be less than $1/57.0793=0.01752$, and slightly below the given threshold, accordingly, the attenuation factor is set as 0.01.

⁽⁷⁾ Giant Connected Component refers to the largest connected subgraph within a network.

2018	4766	2490	3	52.25%	0.06%
2019	4300	2466	3	57.35%	0.07%
2020	5134	3081	1	60.01%	0.02%
2021	8342	5502	2	65.96%	0.02%
2022	9126	6160	9	67.50%	0.10%

Source: JRC analysis

Clustering Coefficient: The local clustering coefficient of a node quantifies how close its neighbours are to form a clique (every two distinct vertices in the clique are adjacent). The clustering coefficient measures the degree to which nodes in a network cluster together, often summarized by an old adage, '*The friend of my friend is my friend*'. In the context of a VC co-investment network, a high clustering coefficient suggests the presence of a small-world network, highlighting the likelihood that two co-investors of a particular VC firm are also co-investors with each other. This metric serves as a proxy for the level of information sharing within highly-connected communities. In such small-world networks, deal flow information is perceived as more reliable as referrals carry reputational risks. Moreover, the dense connectivity facilitates extensive exchanges of deal flow opportunities, industry expertise, valuable contacts, and financial resources that VC firms can leverage (Hochberg et al., 2007; Watts, 1999; Uzzi et al., 2007).

In addition, networks with high clustering coefficients foster learning and knowledge creation, enabling firms to evaluate investment opportunities beyond. While firms often rely on local searches, close connections provide access to novel insights, promoting exploratory learning and innovation (March, 1991). The combination of trusted collaboration and fresh, nonredundant information improves investment decision-making, enabling firms to transcend local biases and geographic constraints (Sullivan and Tang, 2012; Schilling and Phelps, 2007).

We assume that centrality measures from annual networks are comparable despite differences in the number of nodes and network structure (Barbour and Reinert, 2003). Exact comparability would require network matching or alignment methods to identify corresponding nodes and subnetwork matches, though exact graph matching is NP-hard, and approximate methods are often computationally intensive and yield limited alignment (Barbour and Reinert, 2003). Combining annual networks into a single comprehensive network would increase disconnected components, making Katz centrality comparisons impractical.

To facilitate network comparisons, we focus on the relative ranking of nodes based on centrality measures within each network. To standardize these measures across years, we apply min-max scaling to normalize all measures to the range [0,1]. It is worth noting that while degree and clustering coefficients are node-specific properties, Katz centrality reflects the structure of the entire network.

5 Econometric modelling, case control and variables

5.1 Econometric modelling and variables

Our objective is to explain the likelihood of establishing an investment relationship between a specific VC investor and a start-up. The unit of analysis is the sample of the potential matches (realized and unrealized) between an individual start-up and an individual VC firm. We estimate the probability of investment decision with the following econometric model:

$$\text{Deal}_{is,t} = \alpha + \beta_1 \text{Cultural_Proximity}_{is} + \beta_2 \text{Geospatial_Proximity}_{is} + \beta_3 \text{Network}_{i,t} + \gamma X_{is,t} + \delta_i + \mu_s + \lambda_t + \epsilon_{is,t} \quad (1)$$

Where i indexes investor and s indexes start-ups. The dependent variable $\text{deal}_{is,t}$ is a dummy variable that takes the value 1 if investor i finances start-up s . We examine the impact of cultural proximity, spatial proximity and network position of investors within co-investment networks on the investment decision, along with other control variables. Cultural proximity is measured by two factors—common language and common legal system—which vary at the country-dyadic level between investor and start-up, and invariant to time. The common language variable is a dummy variable that takes the value 1 if the investor and start-up countries share an official language. Similarly, the common legal variable is a dummy variable that takes the value 1 if the investor and start-up countries share the same legal family or framework.

For common language, we use the ‘World Languages’ dataset from the University of Groningen, which records all official languages in each country as of 2015. For the common legal framework between country pairs, we draw on the dataset by Porta et al. (2008), which identifies two primary legal traditions: common law and civil law, along with several sub-traditions, including French, German, socialist, and Scandinavian.

Geospatial proximity refers to the logarithmic value of the geodesic distance between the investor and start-up’s locations in kilometers, calculated as the shortest path between two points on the Earth’s surface. Missing values are supplemented using data from the Crunchbase database, which provides longitude and latitude for investors and start-ups. This geospatial distance varies at the investor-company pair level. Network position, which is investor-specific and time-varying, captures the annual centrality and interconnectedness of VC investors within the co-investment syndication network. The vector $X_{is,t}$ includes a set of control variables. More specifically, $X_{is,t}$ includes control variables that vary at the country-dyadic level, such as GDP-difference between the investor and investee countries. GDP difference denotes the difference in the logarithmic value of annual GDP per capita between the investor and start-up countries, using data from the World Bank.

In addition, $X_{is,t}$ includes control variables that vary at the investor-start-up pair level, such as industry fit, which measures the degree to which the investment aligns with the investor’s industry focus. In particular, it is calculated by the average percentage of deals made by the VC in the same industry as the start-up. In addition, stage fit measures the degree to which the investment aligns with the investor’s preferred stage of firm development, which is calculated by the average percentage of deals at the same round as the start-up. It is worth noting that industry fit refers to the percentage of deals made by the VC in the same industry as the start-up over all time. Therefore, it is time-invariant, in contrast to variable such as log GDP-difference which is time varying.

Lastly, $X_{is,t}$ encompasses variables that vary across investors and start-ups, respectively. In terms of VC-specific factors, we control for VC experience captured by the total number of deals by each

investor by the investment time ⁽⁸⁾. In terms of start-up-specific factors, we control for start-up age and investment stage. Age represents the current year minus the launch year of start-ups. We only retain those start-ups aged between 0 to 10 years from Dealroom. The investment stage categorizes deals into Angel, Seed, Early VC, and Late VC based on the variable 'round'.

To control for systematic differences across investors and start-ups, the most appealing way is to incorporate investors and start-ups level individual effects. The investor fixed-effects take care of any systematic differences across investors, such as screening and monitoring capability, risk preferences. The start-ups level individual effects control for company characteristics, such as capacity to write compelling business proposals, seek external funding and engage in a trust-based relationship. $\epsilon_{is,t}$ represents the idiosyncratic errors that are identically and independently distributed across deals between start-ups and investors over time.

The approach of the 'rare event logit' proposed by King and Zeng (2001) is particularly useful for binary outcomes with rare events, correcting for the underestimation of probabilities. However, it has limitations, including a static setting. To tackle unobservable investor and company's characteristics, we aim to incorporate a set of investor fixed effects and start-up fixed effects. The introduction of excessive fixed effects in the logit model can lead to the incidental parameter problem and biased estimates (Greene, 2004).

In order to afford daunting amounts of fixed effects on the level of investors and start-ups, given the large number of fixed effects, we employ linear probability regression models with high-dimensional fixed effects accordingly (Guimaraes and Portugal, 2010). The dimensionality refers to the quantity of fixed effects included in the analysis. Specifically, we account for two high-dimensional fixed effects in the linear regression model—start-ups and investors by examining both realized and unrealized deals to assess the influencing factors of VC investment decision. In particular, Guimaraes and Portugal (2010) partition the estimation equation between explanatory variables and dummies, then use zigzag algorithm or the GaussSeidel algorithm as discussed in Smyth (1996) for the partitioned equation to produce slow but stable exact least square solutions. In the framework of the rare event model, linear probability model with fixed effects produces more accurate estimates and predicted probabilities than conditional logit and logit with dummies, when the dependent variables has less than 25% of ones (Timoneda, 2021).

5.2 Case control

Our unit of analysis is the sample of the potential (realized and unrealized) matches between an individual start-up and an individual VC firm. The dependent variable is a dummy variable that takes the value 1 for an effective deal and 0 for a case-control.

Ideally, we identify all VC candidates that evaluate a start-up and decide not to make the investment. In reality, as this information is unavailable we can only "make up" non-events (King and Zeng, 2001). When the occurrence of the case is rare in the population, considerable resources in data collection can be saved by randomly selecting within categories of dependent variable (King and Zeng, 2001). This is known in econometrics as choice-based or endogenous stratified sampling or case-control design in epidemiology (Breslow, 1996; King and Zeng, 2001). The effective strategy of case-control design of rare events is to collect all rare cases and a random selection of observations of non-events. In other words, in order to make valid inferences, more efficient sampling designs exist such as sampling all available events and a tiny fraction of non-events, compared to commonly used data collection strategies (King and Zeng, 2001).

⁽⁸⁾ It should be distinguished from the total number of deals by each investor over the period 2015-2022.

We implement the case control based on Sorenson and Stuart (2001) and King and Zeng (2001), by pairing VC firms that funded a start-up in a given quarter of a calendar year with a start-up funded by a different venture capitalist in that same quarter. This method of case-control design guarantees the random selection of observations of non-events. The dataset is therefore split into 32 subsamples based on year quarters. Within each quarter, investors and start-ups are re-matched, incorporating relevant investor-level and start-up-level information for that period.

Our case control results in approximately 87,617,723 additional potential deals. It represents a random fraction of possible deals that are likely to happen. Compared to 40,556 effective deals, it qualifies the actual dataset as rare events. To illustrate, there are 1026 start-ups along with 1034 investors in the first quarter of 2015. Pairing start-ups with investors independently without regard to VC experience, investment history in industry, and geospatial distribution would result in 1026×1034 possibilities, whereas the effective deals are around 1037. Therefore, we inflate our sample by a factor of around 1000.

6 Descriptive Statistics

Table 2 provides an overview of the descriptive statistics for the full sample, including both case-control and effective deals. The network measures are constructed based on the effective deals and represent investor-specific characteristics that are rematched with start-ups during the case-control procedure. Compared to the effective deal sample, the full sample tends to over-represent global investors. As a result, the full sample, in contrast to the effective deals, is characterized by longer geodesic distances, less commonalities in language and legal systems, greater GDP differences, lower degrees and Katz centrality, and higher clustering coefficients. This is particularly due to the case controls re-matching with non-EU investors, such as those from China and the rest of the world, who are associated with higher clustering coefficients.

Table 2. Summary Statistics of Full and Effective Deal Samples

	Full Sample Mean	Effective Deal Mean
Firm age	3.25	3.33
Log distance	7.12	5.05
Common legal	0.28	0.73
Common language	0.22	0.70
GDP difference	0.05	0.03
Industry fit	0.07	0.37
Stage fit	0.27	0.51
Degree	0.03	0.08
Katz centrality	0.000033	0.000066
Clustering	0.44	0.38
Observations	87,703,908	86,185

Source: JRC analysis

Table 3 provides descriptive statistics for investors from various global regions, including EU, the US, China, and the rest of the world (ROW) based on effective deals ⁽⁹⁾. The data reveals a clear pattern in network centrality: the EU exhibits the highest degree, followed by the US, China, and finally, the ROW. The Katz degree follows a similar distribution across these regions, underscoring the highly central and influential role of the EU within the network. In contrast, the clustering coefficients exhibit an inverse pattern, with China showing the highest level of clustering, indicative of a strong community-based investing approach where co-investors frequently collaborate,

⁽⁹⁾ EU27, Iceland, Liechtenstein, Norway, Switzerland and the UK.

followed by the US, ROW, and the EU. In addition, China demonstrates the highest industry fit (0.6), while ROW exhibits the highest stage fit (0.66), indicating more focused investment strategies ⁽¹⁰⁾. The US and China also tend to have more co-investors per deal and larger deal sizes ⁽¹¹⁾.

Table 3. Summary Statistics by Region (EU, US, China, ROW)

	EU	US	China	ROW
Firm age	3.33	3.39	3.80	3.20
Log distance	4.00	8.90	9.04	8.24
Common legal	0.82	0.44	0.30	0.44
Common language	0.79	0.45	0.00	0.30
GDP difference	0.01	0.39	-1.47	-0.49
Industry fit	0.32	0.50	0.60	0.56
Stage fit	0.49	0.54	0.60	0.66
No. of deals per investor	32.45	15.40	6.34	10.05
Degree	0.09	0.07	0.06	0.03
Katz centrality	0.000071	0.000055	0.000049	0.000032
Clustering	0.35	0.51	0.54	0.48
No. of co-investors	3.54	5.16	5.14	4.39
Amount in EUR million	11.55	30.90	33.78	20.59
Stage	2.61	2.79	2.95	2.65

Source: JRC analysis

Table 4 summarizes key characteristics of top investors as measured by different network centrality. ‘Top Degree’ refers to the most connected investors, defined as those with degree centrality above the 90th percentile in the annual network. ‘Top Katz’ identifies the most influential investors with Katz centrality above the 90th percentile within the annual network’s Giant Connected Component (GCC). ‘Top Clustering Coefficient’ highlights investors whose clustering

⁽¹⁰⁾ For general comparison purposes, we do not restrict the sample to cases where the annual number of deals involving at least two investors exceeds one.

⁽¹¹⁾ Variables such as isolate and number of co-investors are excluded from the estimation due to their high correlation with the centrality measures. Additionally, the amount variable refers to the total deal volume; however, in cases of syndication, the actual investment amount is uncertain due to the unclear distribution of funds among co-investors.

coefficient ranks above the 90th percentile in the annual network, limited to cases where the annual number of deals involving at least two investors exceeds one.

Table 4. Summary Statistics for Investors with Top Degree Centrality, Katz Centrality, and Clustering Coefficients

	Top Degree	Top Katz (GCC)	Clustering Coefficients = 1
Number of total deals	241.82	268.83	19.19
Number of investors	4.54	4.63	4.82
Deal amount (EUR million)	24.15	26.93	22.12
Number of industries	21.86	22.60	5.80
Number of observations	8467	6856	4992
Number of distinct investors	132	91	1777

Source: JRC analysis

A notable finding is that different centrality measures capture distinct aspects of network structure. Investors with the highest Katz centrality demonstrate the largest number of total deals per investor over the period 2015-2022 (268.83), followed by top-degree investors (241.82), over ten times the corresponding number for the top investors in the small-world networks (19.19). Top degree and top Katz investors also engage in a wide range of industries (21.86 and 22.6 industries, respectively). Conversely, investors with high clustering coefficients tend to focus on specialized sectors (5.8).

Moreover, top degree and top Katz investors consist of a small number of distinct investors over the period 2015-2022 (132 and 91, respectively). It implies a high persistence in top network positions over the period 2015-2022, comparing to a more diverse representation in the top clustering coefficient group (1,777). The group of top clustering coefficient investors, totalling 1,777, still represents only a small fraction (8.7%) of the 20,221 investors overall. The comparison suggests that the components of top investors with the greatest influence and connections remain stable, whereas the top investors with the highest clustering coefficients fluctuate over time. This table illustrates how network structure influences investment strategy. Investors with broad, extensive networks (high degree and Katz centrality) tend to participate more deals and engage in larger deals, on account of central position to access to a wide information exchange. In contrast, those within small-world networks (high clustering coefficient) may focus on limited investments, prioritize collaborative, long-term, trust-based relationships.

Regarding effective deals, long-distance transactions (characterized by above-average geodesic distances) are predominantly driven by VC investors from the US (67.23%), Singapore (3.96%), China (2.84%), and Japan (2.37%). Table 5 lists the top 10 countries involved in these long-distance deals.

Table 5. Top 10 Countries for Long-Distance Deals

Country	Frequency	Percent	Cumulative
United States	12,987	67.23	99.85
Singapore	765	3.96	26.95
China	549	2.84	9.16
Japan	457	2.37	19.14
Canada	423	2.19	5.59
Hong Kong	420	2.17	13.73
Australia	314	1.63	2.31
United Arab Emirates	252	1.30	31.79
Israel	248	1.28	16.62
India	241	1.25	15.11

Source: JRC analysis

7 Estimation results

7.1 Main results

Table 6 presents the estimation results based on the linear probability regression model with high-dimensional fixed effects over the period 2015–2022. The estimation is based on the Stata command *reghdfe*, which implements linear models with two-dimensional fixed effects (Correia, 2016). We include individual fixed effects at both the investor and start-up levels and use heteroscedasticity-consistent standard errors (Huber-White sandwich estimators).

In Column 1 we report the results of degree centrality, and in Column 2 we report the results from Katz centrality. It is worth noting that Katz centrality is dependent on the specific network structure. In order to facilitate comparison, we focus on the subsample of Giant Connected Component for the estimation. Accordingly, there is a sharp decline in terms of observation in the column 2.

Table 6. Regression Results Based on the Linear Probability Model with High-Dimensional Fixed Effects (2015–2022)

	Deal	Deal
log distance	-0.00159*** (0.000011)	-0.00170*** (0.000013)
commonlegal	-0.000195*** (0.000009)	-0.000140*** (0.000012)
commonlan	0.00159*** (0.000016)	0.00172*** (0.000020)
degree	0.0105*** (0.000233)	
katz		13.30*** (0.356213)
age	0.0000952*** (0.000008)	0.000124*** (0.000011)

GDP difference	-0.000341***	-0.000575***
	(0.000083)	(0.000112)
industry fit	0.00942***	0.0104***
	(0.000049)	(0.000063)
stage fit	0.00405***	0.00432***
	(0.000022)	(0.000028)
number deal by investor	-0.0000299***	-0.0000318***
	(0.000001)	(0.000001)
Stage and Year Dummies	YES	YES
N	87620565	60051050

Standard errors in parentheses

*p < 0.05, ** p < 0.01, *** p < 0.001

Source: JRC analysis

Notably, geospatial distance exerts negative and significant impact on the probability to make VC investment. This clearly supports the Hypothesis 2 that the VC is a highly localized activity. The coefficient -0.000159 indicates that a 1% increase in geodesic distance reduces the probability of reaching a deal by 0.0000159. Moreover, we find that the coefficients on the commonality of official languages are positive and significant at the 0.1% level across all specifications, validating the hypothesis 1 that cultural proximity facilitates the VC investment. The coefficient in column 1 indicates that, sharing common official languages is estimated to increase the probability of engaging in a deal by about 0.00159, *ceteris paribus*. The negative and significant sign of GDP per capita implies that increased economic discrepancy would reduce the probability of VC investment. More specifically, 1% increase in GDP per capita discrepancy between investor and investee country is estimated to reduce the probability of reaching a deal by 0.00000341, *ceteris paribus*. Both degree centrality and Katz centrality exhibit positive and significant impact on the probability to make a deal, which validate Hypothesis 3. A one-unit increase in the normalized degree centrality increases the probability of investment by 0.0105, while one-unit increase in the normalized Katz degree increases the probability of investment by 13.3, *ceteris paribus*. In addition, the coefficients on the industry fit and stage fit are positive and significant at the 0.1% level across all specifications. It provides evidence that VC experience facilitates investment decision in the same industry and same stage. This shows that specialization is important for VC market, start-ups need to fit into investor's strategic preferences to attract investments (Bottazzi et al., 2010). The

coefficients for the number of deals show a significant negative effect, likely due to their positive correlation with network positions. As experience accumulates, VCs expand network through VC co-investors and industry companies, which grants privileged access to information about promising investment opportunities. VC fund managers can expand their networks within the VC community and among entrepreneurs across various industries (Hochberg et al., 2007).

Table 7 displays the estimation results based on the linear probability regression model with high-dimensional fixed effects, including interaction terms between degree centrality and Katz centrality with distance. The negative and significant sign of the interaction term indicates that better-positioned firms, in terms of degree and Katz centrality, have less incentive to invest in distant deals. This implies that well-networked VCs with high degree and Katz centrality may not alter their risk-averse behaviours regarding distant deals. High degree and Katz centrality might not compensate for the lack of established relationships and trust with distant entrepreneurs. Better-networked VCs may prefer local or regional investments to exert more control and influence, to leverage network advantages, this is consistent with empirical findings that European VC investors exhibit higher risk aversion compared to their US counterparts (Bottazzi et al., 2010).

Table 7. Estimation Results Based on the Linear Probability Model with High-Dimensional Fixed Effects, Including Interaction Terms between Degree Centrality, Katz Centrality, and Distance (2015-2022)

	Deal	Deal
log distance	-0.00126*** (0.000012)	-0.00127*** (0.000016)
Commonlegal	-0.000183*** (0.000009)	-0.000133*** (0.000012)
commonlan	0.00161*** (0.000016)	0.00175*** (0.000020)
degree	0.0624*** (0.001313)	
degree # log distance	-0.00754*** (0.000179)	
katz		82.49*** (1.976921)

katz# log distance	-10.12***	
	(0.271277)	
age	0.0000978***	0.000119***
	(0.000008)	(0.000011)
GDP difference	-0.000264**	-0.000565***
	(0.000083)	(0.000112)
industry fit	0.00942***	0.0104***
	(0.000049)	(0.000063)
stage fit	0.00405***	0.00431***
	(0.000022)	(0.000028)
number deal	-	-
by investor	0.0000286***	0.0000297***
	(0.000001)	(0.000001)
Stage and Year Dummies	YES	YES
N	87620565	60051050

Standard errors in parentheses

*p < 0.05, ** p < 0.01, *** p < 0.001

Source: JRC analysis

Table 8 reports the estimates involving clustering coefficients and the interaction term between clustering coefficients and distance. By definition, investors who participate in a single deal with at least two co-investors achieve the highest clustering coefficient, as all co-investors are part of the same deal, which forms a clique. For example, consider a VC firm that completes eleven deals in 2015—ten as solo investments and one involving three co-investors. This deal structure automatically results in the highest clustering coefficient but fails to capture the tendency of multiple investors from different deals to overlap, co-invest and form a clique. To better reflect the local clustering coefficient and characteristics of small-world networks, the estimation sample is

restricted to cases where an investor participates in more than one deal per year involving at least two co-investors, which explains the sharp decline in observations.

Column 1 shows that clustering coefficients have a negative and significant effect on the probability of making a deal. This aligns with the observation that investors in small-world networks—characterized by high local clustering coefficients—tend to focus on fewer investments, prioritizing close collaboration and long-term, trust-based relationships (Uzzi et al., 2007). Interestingly, we find that the coefficient on the interaction term between the clustering coefficients and distance is positive and significant at the 0.1% level. In contrast to degree and Katz centrality, investors with higher clustering coefficients in the co-investment network demonstrate a higher propensity to transcend spatial boundaries and invest in distant start-ups. Small-world networks facilitate the rapid flow of information, enabling efficient dissemination and exchange from a variety of novel sources (Sullivan and Tang, 2012). While firms generally prioritize exploitation and conduct searches within familiar domains (March, 1991; Sullivan and Tang, 2012), access to diverse and new information allows them to better assess distant business prospects. As a result, these firms are more likely to engage in exploratory learning, seeking out new ideas and opportunities (March, 1991; Sullivan and Tang, 2012).

It is worth emphasizing that small-world networks are not necessarily local. They can be highly interconnected on an international scale. The potential syndication between non-local and local investors is crucial in facilitating long-distance deals (Wright and Lockett, 2003; Manigart et al., 2006; Mason, 2007). As Florida and Kenney (1988) suggest that “investment syndication is perhaps the crucial ingredient in the geography of the venture capital industry.” In a small-world network, every actor is interconnected and cooperates closely, with deal flow information carrying greater trust due to the higher reputational risk associated with referrals in a small network. By evaluating each other’s willingness to invest in distant opportunities, VCs can pool correlated signals, leading to more informed investment decisions in uncertain situations (Wilson, 1968; Sah and Stiglitz, 1986; Hochberg et al., 2007). The signalling effect or ‘four-eyes principles’ ensures good investment decisions (Christopoulos et al., 2022).

Table 8. Estimation Results with Clustering Coefficients, Including Interaction Terms between Clustering Coefficients, and Distance (2015-2022)

	Deal	Deal
log distance	-0.00205*** (0.000018)	-0.00275*** (0.000029)
commonlegal	-0.000242*** (0.000018)	-0.000246*** (0.000018)
commonlan	0.00219*** (0.000030)	0.00222*** (0.000030)

clustering	-0.00115*** (0.000052)	-0.0157*** (0.000419)
clustering# log distance		0.00214*** (0.000058)
age	0.000187*** (0.000015)	0.000185*** (0.000015)
GDP difference	-0.000621*** (0.000156)	-0.000280 (0.000157)
industry fit	0.0122*** (0.000094)	0.0122*** (0.000094)
stage fit	0.00576*** (0.000044)	0.00576*** (0.000044)
number deal by investor	-0.0000363*** (0.000001)	-0.0000364*** (0.000001)
Stage and Year Dummies	YES	YES
N	35904729	35904729

Standard errors in parentheses

* p < 0.05, ** p < 0.01, *** p < 0.001

Source: JRC analysis

Highly interconnected VCs often possess investment expertise that is both sector-specific and location-specific (Hochberg et al., 2007). Different VC may represent distinct pools of expertise, complementing each other through differentiation and specialization in industry knowledge and

local markets (Goldfarb et al., 2007; Sorenson and Stuart, 2001; Bubna et al., 2020). Small-world networks and familiar partners facilitate learning by fostering a better understanding of partners' norms and processes (Gertler, 1995; Porter, 2000; Bubna et al., 2020). Incomplete contracting theories, which highlight the impossibility of foreseeing all contingencies, also suggest a preference for familiar, trusted partners. This familiarity can enhance trust and reciprocity, leading to better outcomes (Guiso et al., 2004; Bottazzi et al., 2010; Bubna et al., 2020). Leading VC investors are increasingly making investments across various global regions without geographic concerns. This trend is evident as many leading VC firms have co-investors located in different countries, which enables them to operate effectively without being confined to a specific geographic area.

7.2 Robustness check

In order to rule out the possibility that investors from China and the US—who have relatively high clustering coefficients and are geographically distant from EU-based start-ups—are driving the conclusion, we conduct robustness checks using subsample analyses of investors headquartered in Europe, the US, China, and the Rest of the World.

Table 9 presents the estimated results of linear probability regression model with high-dimensional fixed effects on the subsample. The model includes separate effects for degree centrality and Katz centrality. Consistent across all regions, both degree and Katz centrality play a positive, significant role in facilitating investment. Given that no EU country shares a legal framework or language with China, these variables are excluded from the models. The notably higher coefficients of Katz centrality for China and the Rest of the World suggest that, being influential within the syndication network is particularly crucial for Chinese investors and those from the RoW when investing in Europe-based start-ups.

Table 9. Robustness Check: Regression Results Based on the Linear Probability Model with High-Dimensional Fixed Effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	EU	US	China	ROW	EU	US	China	ROW
log_distance	-0.00174*** (0.000013)	-0.00113** (0.000382)	0.00473 (0.004280)	-0.00456*** (0.000221)	-0.00186*** (0.000016)	-0.00128* (0.000504)	0.00728 (0.005705)	-0.00446*** (0.000290)
commonlegal	-0.000483*** (0.000013)	0 (.)		-0.000260*** (0.000034)	-0.000437*** (0.000016)	0 (.)		- 0.000154*** (0.000046)
commonlan	0.00157*** (0.000020)	0 (.)		0.000520*** (0.000053)	0.00173*** (0.000026)	0 (.)		0.000386*** (0.000073)
degree	0.0107*** (0.000277)	0.00966*** (0.000488)	0.0155*** (0.002876)	0.0130*** (0.000907)				
katz					12.93*** (0.417929)	14.52*** (0.750110)	32.26*** (5.487164)	21.47*** (1.640808)

GDP_difference	-0.000594*** (0.000103)	0.000743 (0.000405)	0.00106 (0.001684)	0.000804*** (0.000210)	-0.000936*** (0.000138)	0.000652 (0.000570)	-0.000251 (0.002372)	0.00156*** (0.000322)
industry_fit	0.00983*** (0.000061)	0.00835*** (0.000096)	0.00949*** (0.000484)	0.00928*** (0.000155)	0.0110*** (0.000080)	0.00926*** (0.000121)	0.00968*** (0.000624)	0.00977*** (0.000208)
stage_fit	0.00409*** (0.000027)	0.00395*** (0.000050)	0.00481*** (0.000263)	0.00379*** (0.000069)	0.00435*** (0.000033)	0.00423*** (0.000060)	0.00502*** (0.000339)	0.00400*** (0.000091)
number_deal_by_investor	- 0.0000302*** (0.000001)	- 0.0000259*** (0.000002)	- 0.0000901*** (0.000018)	- 0.0000514*** (0.000006)	- 0.0000318*** (0.000001)	- 0.0000268*** (0.000002)	- 0.000129*** (0.000022)	- 0.000111*** (0.000010)
age	0.000106*** (0.000009)	0.0000359 (0.000019)	0.000159 (0.000118)	0.0000480 (0.000027)	0.000137*** (0.000013)	0.0000343 (0.000028)	0.000425 (0.000175)	0.000185*** (0.000050)
Stage and Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES
N	63038537	16451770	695778	7434476	43629365	11593069	439645	4388523

Standard errors in parentheses
^{*} $p < 0.05$, ^{**} $p < 0.01$, ^{***} $p < 0.001$
Source: JRC analysis

Table 10 presents the estimation results based on the inclusion of the interaction term between distance between start-up and investors. For EU investors, these interaction terms exhibit a significant negative impact, supporting our conclusion that highly central EU investors tend to be sensitive to investment distance. This pattern may reflect a more risk-averse approach. Investors may not alter their risk-averse behaviours regarding distant deals despite their central network advantage. This finding aligns with empirical evidence that European VC investors are generally more risk-averse and well-networked VCs may prefer local or regional investments to exert more control and influence. By contrast, being influential within the syndication network in other regions, such as the Rest of the World may enable VC firms to pursue distant investments more actively.

Table 10. Robustness Check: Regression Results Based on the Linear Probability Model with High-Dimensional Fixed Effects, Including Interaction Terms between Degree Centrality, Katz Centrality, and Distance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	EU	US	China	ROW	EU	US	China	ROW
log_distance	-0.00135*** (0.000014)	-0.000930* (0.000392)	0.00463 (0.004249)	-0.00461*** (0.000225)	-0.00136*** (0.000019)	-0.00106* (0.000524)	0.00732 (0.005666)	-0.00461*** (0.000300)
commonlegal	-0.000467*** (0.000013)	0 (.)		-0.000260*** (0.000034)	-0.000428*** (0.000016)	0 (.)		-0.000155*** (0.000046)
commonlan	0.00161***	0		0.000520***	0.00178***	0		0.000386***

	(0.000020)	(.)		(0.000053)	(0.000026)	(.)		(0.000073)
degree	0.0643*** (0.001342)	0.0762*** (0.016532)	0.0571 (0.111115)	-0.0120 (0.018331)				
degree# log_distance	-0.00866*** (0.000200)	-0.00746*** (0.001850)	-0.00459 (0.012266)	0.00282 (0.002063)				
katz					84.54*** (2.010540)	84.70** (26.382451)	15.96 (187.930915)	-50.13 (27.045632)
katz# log_distance					-11.58*** (0.299965)	-7.865** (2.955387)	1.801 (20.791636)	8.164** (3.084141)
GDP_difference	-0.000653*** (0.000103)	0.000761 (0.000405)	0.00108 (0.001688)	0.000802** (0.000210)	-0.000920*** (0.000138)	0.000657 (0.000570)	-0.000255 (0.002374)	0.00150*** (0.000322)
industry_fit	0.00983*** (0.000061)	0.00835*** (0.000096)	0.00949*** (0.000484)	0.00928*** (0.000155)	0.0110*** (0.000080)	0.00926*** (0.000121)	0.00968*** (0.000624)	0.00977*** (0.000208)
stage_fit	0.00408*** (0.000027)	0.00395*** (0.000050)	0.00481*** (0.000263)	0.00379*** (0.000069)	0.00435*** (0.000033)	0.00423*** (0.000060)	0.00502*** (0.000339)	0.00400*** (0.000091)
number_deal_ by_investor	- 0.0000285*** (0.000001)	- 0.0000261*** (0.000002)	- 0.0000891*** (0.000018)	- 0.0000523*** (0.000006)	- 0.0000303*** (0.000001)	- 0.0000270*** (0.000002)	-0.000129*** (0.000022)	-0.000114*** (0.000010)
age	0.0000987*** (0.000009)	0.0000359 (0.000019)	0.000158 (0.000118)	0.0000498 (0.000027)	0.000127*** (0.000012)	0.0000345 (0.000028)	0.000425* (0.000174)	0.000188*** (0.000050)
Stage and Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES
N	63038537	16451770	695778	7434476	43629365	11593069	439645	4388523

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: JRC analysis

Table 11 displays the results based on clustering coefficients, including interactions with distance. The main effects of clustering coefficients reveal universally negative impacts across regions, consistent with previous findings that investors in small-world networks prefer limited investments, close collaboration, and trust-based relationships. Moreover, the interaction terms imply that our original conclusion holds strongly for investors in the EU and the US. The positive, significant coefficients of interaction term between clustering coefficients and distance suggest that high clustering coefficients indeed promote distant investments for the EU and US investors. Our conclusion that high clustering coefficients enhance the capacity of VC firms to invest in distant start-ups is not driven by the presence of investors from China and the US, who tend to have high clustering coefficients and are geographically distant from EU-based start-ups.

Table 11. Robustness Check: Regression Results Based on the Linear Probability Model with High-Dimensional Fixed Effects with Clustering Coefficients, Including Interaction Terms between Clustering Coefficients, and Distance.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	EU	US	China	ROW	EU	US	China	ROW
log_distance	-0.00221*** (0.000021)	-0.00133 (0.000768)	0.0257** (0.009644)	-0.00536*** (0.000412)	-0.00306*** (0.000034)	-0.00278*** (0.000820)	0.0261* (0.010976)	-0.00533*** (0.000481)
commonlegal	-0.000535*** (0.000023)	0 (.)		- 0.000384*** (0.000083)	-0.000540*** (0.000023)	0 (.)		- 0.000384*** (0.000083)
commonlan	0.00217*** (0.000036)	0 (.)		0.000654*** (0.000128)	0.00220*** (0.000036)	0 (.)		0.000653*** (0.000129)
clustering	-0.00111*** (0.000057)	-0.00141*** (0.000140)	-0.0289*** (0.004034)	-0.00162*** (0.000248)	-0.0178*** (0.000458)	-0.0243*** (0.005014)	-0.0259 (0.039641)	-0.000904 (0.004882)
clustering#log_distance					0.00260*** (0.000067)	0.00256*** (0.000560)	-0.000334 (0.004357)	- 0.0000859 (0.000576)
GDP_difference	-0.00135*** (0.000184)	0.000245 (0.000933)	-0.00243 (0.005137)	0.00323*** (0.000533)	-0.00120*** (0.000184)	0.000235 (0.000933)	-0.00243 (0.005142)	0.00324*** (0.000534)
industry_fit	0.0128*** (0.000113)	0.0104*** (0.000194)	0.00953*** (0.001146)	0.0120*** (0.000383)	0.0129*** (0.000113)	0.0104*** (0.000194)	0.00953*** (0.001146)	0.0120*** (0.000383)
stage_fit	0.00575*** (0.000051)	0.00566*** (0.000105)	0.00805*** (0.000773)	0.00534*** (0.000166)	0.00575*** (0.000051)	0.00566*** (0.000105)	0.00805*** (0.000772)	0.00534*** (0.000166)
number_deal_by_investor	- 0.0000365*** (0.000001)	- 0.0000264*** (0.000002)	- 0.000455*** (0.000059)	- 0.000115*** (0.000011)	- 0.0000365*** (0.000001)	- 0.0000264*** (0.000002)	- 0.000455*** (0.000059)	- 0.000115*** (0.000011)
age	0.000202*** (0.000017)	0.0000458 (0.000044)	0.00482*** (0.000713)	0.000279** (0.000091)	0.000198*** (0.000017)	0.0000451 (0.000044)	0.00482*** (0.000713)	0.000277** (0.000092)
Stage and Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES
N	28116971	5646296	171583	1967403	28116971	5646296	171583	1967403

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: JRC analysis

8 Conclusion and Policy Implications

This study investigates the impact of cultural proximity, geospatial proximity, and network position on the investment decisions of global venture capital (VC) firms in EU startups, utilizing deal-level data from the Dealroom database for the period 2015-2022. By employing a linear probability regression model with high-dimensional fixed effects, we find that cultural proximity, spatial proximity, and a prominent network position—measured by degree and Katz centrality within the co-investment network—significantly facilitate VC investments.

The most connected investors (high degree centrality) and the most influential investors (high Katz centrality) are typically involved in a large number of deals, higher deal volumes, a greater number of co-investors, and a broader range of industries. In contrast, investors in small-world networks—characterized by high local clustering coefficients—tend to concentrate on fewer investments with specialized sectors, prioritizing close collaboration and long-term, trust-based relationships.

In addition, we find that investors with higher degree of Katz centrality may not alter their risk-averse behaviours regarding distant deals. This finding aligns with empirical evidence that European VC investors are generally more risk-averse compared to their US counterparts (Bottazzi et al., 2010). Well-networked VCs may prefer local or regional investments to exert more control and influence, thus maximizing the advantages of their network position.

Our findings highlight the influence of high clustering coefficients within small-world investor communities in overcoming spatial constraints to invest in distant start-ups—a factor that has been largely overlooked in the existing literature. Participation in international, closely connected networks enhances trust within the network, potentially altering risk-averse behaviors and transcending geographical boundaries.

Meanwhile, we acknowledge that syndication may also bring about disadvantages, such as information asymmetry, agency costs, and coordination frictions within VC syndicates. Larger syndicates often entail different incentives and objectives, slower decision-making processes to reach consensus, and reduced strategic responsiveness (Brander et al., 2002; Nanda and Rhodes-Kropf, 2018). VCs also have varying reputations among entrepreneurs regarding their approach, ranging from being ‘entrepreneur-friendly’ to being ‘quick to pull the trigger’ (Nanda and Rhodes-Kropf, 2018). The selection of initial VC investors within syndicates is crucial, as their decision not to reinvest can send adverse signals to potential follow-up financiers and significantly impact the success of start-up. Thus, the wise selection of syndication partners is essential, balancing the benefits of syndication while remaining mindful of the associated costs and risks.

The findings of this study have significant implications for our understanding of VC investment decisions. However, it is essential to note that our results show conditional associations but do not necessarily imply causal effects. Therefore, caution is warranted when interpreting our findings, and further research is needed to confirm the causal relationships between the variables of interest. Policies should be designed and implemented with discretion, taking into account the potential risks and unintended consequences of syndication.

In light of these findings, policymakers may consider implementing policy instruments to foster venture capital syndication, particularly with well-connected and influential investors. Policymakers may promote familiar, trusted partnerships. To improve outcomes in VC syndicates, it is crucial to encourage the formation of small-world networks where familiarity and trust can be built. Policymakers may provide incentives for VCs to engage in repeated interactions through events, training sessions, and collaborative projects. This can help mitigate the risks associated with incomplete contracting and enhance the reciprocity necessary for successful long-term partnerships.

Moreover, encouraging syndication with global investors in small-world networks can help transcend geographical boundaries, reducing regional funding gaps, fostering a more integrated and collaborative global investment landscape. It is vital to encourage regional and sectoral networks of VCs. Policymakers could support the creation of specialized syndication platforms where VCs can collaborate based on industry expertise and regional knowledge. By fostering these connections, VCs can leverage their sector-specific and location-specific insights, leading to more informed investment decisions and better outcomes for start-ups. This approach can also facilitate knowledge sharing among VCs with complementary skills, enhancing the overall efficiency and effectiveness of the syndication process.

In conclusion, this study sheds light on the role of cultural proximity, spatial proximity, and a prominent network position—characterized by how well-connected (degree centrality), how influential (Katz centrality), and the extent of clustering (clustering coefficients) within the co-investment network—in shaping VC investment decisions.

While our findings provide valuable insights for both investors and policymakers, it is crucial to recognize the limitations of our study and the need for further research to confirm the causal relationships between the variables of interest. By leveraging network positions, investors can more effectively navigate the investment landscape, and policymakers can develop strategies to address regional funding gaps, which are particularly pronounced in VC investments for Europe-based start-ups.

By leveraging network positions, investors can more effectively navigate the investment landscape, while policymakers can develop strategies to address regional funding gaps, which are particularly pronounced in VC investments for Europe-based start-ups. This research contributes equally to the academic discourse on venture capital and provides practical insights for both investors and policymakers.

References

- Amit, R., Glosten, L., and Muller, E. (2022). Entrepreneurial ability, venture investments, and risk sharing. In *Venture Capital*, pages 135–148. Routledge.
- Arrow, K. J. (1972). Gifts and exchanges. *Philosophy & Public Affairs*, pages 343–362.
- Asdrubali, P. (2023). P. of cross-border venture capital flows in europe.
- Barbour, A. D. and Reinert, G. (2003). Small world networks. *Dynamical Stochastic Modeling in Biology*, page 4.
- Bertoni, F., Colombo, M. G., and Quas, A. (2015). The patterns of venture capital investment in europe. *Small business economics*, 45:543–560.
- Blau, P. M. (1977). A macrosociological theory of social structure. *American journal of sociology*, 83(1):26– 54.
- Bottazzi, L., Da Rin, M., and Hellmann, T. (2010). The importance of trust for investment: Evidence from venture capital. *Review of Financial Studies*, 23(9):3189–3220.
- Brander, J. A., Amit, R., and Antweiler, W. (2002). Venture-capital syndication: Improved venture selection vs. the value-added hypothesis. *Journal of Economics & Management Strategy*, 11(3):423–452.
- Breslow, N. E. (1996). Statistics in epidemiology: the case-control study. *Journal of the American Statistical Association*, 91(433):14–28.
- Bubna, A., Das, S. R., and Prabhala, N. (2020). Venture capital communities. *Journal of Financial and Quantitative Analysis*, 55(2):621–651.
- Burt, R. S. (2001). Bandwidth and echo: Trust, information, and gossip in social networks. *Networks and markets*, 30:37–38.
- Bygrave, W. (1992). Venture capital at the crossroads.
- Bygrave, W. D. (1988). The structure of the investment networks of venture capital firms. *Journal of Business Venturing*, 3(2):137–157.
- Carpenter, R. E. and Petersen, B. C. (2002). Capital market imperfections, high-tech investment, and new equity financing. *The economic journal*, 112(477):F54–F72.
- Chen, C. J. (2009). Technology commercialization, incubator and venture capital, and new venture performance. *Journal of Business research*, 62(1):93–103.
- Chen, J., Cao, R., Song, Y., Hu, A., and Ding, Y. (2024). A dataset of venture capitalist types in china (1978–2021): A machine-human hybrid approach. *Scientific Data*, 11(1):1255.
- Christopoulos, D., Koppl, S., and Koppl-Turyna, M. (2022). Syndication networks and company survival: evidence from european venture capital deals. *Venture Capital*, 24(2):105–135.
- Clementi, G. L. and Hopenhayn, H. A. (2006). A theory of financing constraints and firm dynamics. *The Quarterly Journal of Economics*, 121(1):229–265.
- Coleman, J. S. (1988). Social capital in the creation of human capital. *American journal of sociology*, 94:95–S120.

- Cooley, T. F. and Quadrini, V. (2001). Financial markets and firm dynamics. *American economic review*, 91(5):1286–1310.
- Correia, S. (2016). reghdfe: Estimating linear models with multi-way fixed effects. In *2016 Stata Conference*, number 24. Stata Users Group.
- Coscia, M. (2021). The atlas for the aspiring network scientist. *arXiv preprint arXiv:2101.00863*.
- Cumming, D. and Dai, N. (2010). Local bias in venture capital investments. *Journal of empirical finance*, 17(3):362–380.
- De la Dehesa, G. (2002). *Venture capital in the United States and Europe*. Number 65. Group of Thirty.
- Desai, M. A., Gompers, P., and Lerner, J. (2003). Institutions, capital constraints and entrepreneurial firm dynamics: Evidence from europe.
- Dingee, A., Smollen, L., and Timmons, J. (1990). New venture creation: Entrepreneurship in the 1990s.
- Dyer, J. H. and Singh, H. (1998). The relational view: Cooperative strategy and sources of inter-organizational competitive advantage. *Academy of management review*, 23(4):660–679.
- Fleming, L., King III, C., and Juda, A. I. (2007). Small worlds and regional innovation. *Organization Science*, 18(6):938–954.
- Florida, R. and Kenney, M. (1988). Venture capital and high technology entrepreneurship. *Journal of Business Venturing*, 3(4):301–319.
- Florida, R. and Smith Jr, D. F. (1993). Venture capital formation, investment, and regional industrialization. *Annals of the Association of American Geographers*, 83(3):434–451.
- Fraiberger, S. P., Sinatra, R., Resch, M., Riedl, C., and Barabasi, A.L. (2018). Quantifying reputation and success in art. *Science*, 362(6416):825–829.
- Fried, V. H. and Hisrich, R. D. (1994). Toward a model of venture capital investment decision making. *Financial Management*, 23(3):28–37.
- Gertler, M. S. (1995). “Being there”: proximity, organization, and culture in the development and adoption of advanced manufacturing technologies. *Economic geography*, 71(1):1–26.
- Ghinami, F. and Montresor, S. (2023). Tangible and intangible proximities in the access to venture capital: evidence from italian innovative start-ups. *SocArXiv*. November, 28.
- Giraudo, E., Giudici, G., and Grilli, L. (2019). Entrepreneurship policy and the financing of young innovative companies: Evidence from the italian startup act. *Research Policy*, 48(9):103801.
- Goldfarb, B., Kirsch, D., and Miller, D. A. (2007). Was there too little entry during the dot com era? *Journal of Financial Economics*, 86(1):100–144.
- Gompers, P., Kaplan, S. N., and Mukharlyamov, V. (2016). What do private equity firms say they do? *Journal of Financial Economics*, 121(3):449–476.
- Gompers, P. and Lerner, J. (2001). The venture capital revolution. *Journal of economic perspectives*, 15(2):145–168.

- Gompers, P. A. (1996). Grandstanding in the venture capital industry. *Journal of Financial Economics*, 42(1):133–156.
- Gompers, P. A., Gornall, W., Kaplan, S. N., and Strebulaev, I. A. (2020). How do venture capitalists make decisions? *Journal of Financial Economics*, 135(1):169–190.
- Gorman, M. and Sahlman, W. A. (1989). What do venture capitalists do? *Journal of business venturing*, 4(4):231–248.
- Granovetter, M. (1992). Problems of explanation in economic sociology. *Networks and organizations: Structure, form and action*. Harvard Business School Press.
- Greene, W. (2004). Fixed effects and bias due to the incidental parameters problem in the tobit model. *Econometric reviews*, 23(2):125–147.
- Grund, T. and Hedstrom, P. (2015). Social network analysis using stata. In *Proceedings of the United Kingdom Stata Users' Group Meeting*.
- Guimaraes, P. and Portugal, P. (2010). A simple feasible alternative procedure to estimate models with high-dimensional fixed-effects. *Stata Journal*, 10(4):628–649.
- Guiso, L., Sapienza, P., and Zingales, L. (2004). The role of social capital in financial development. *American economic review*, 94(3):526–556.
- Hansen, M. T. (1999). The search-transfer problem: The role of weak ties in sharing knowledge across organization subunits. *Administrative science quarterly*, 44(1):82–111.
- Harrison, R., Mason, C., and Robson, P. (2010). Determinants of long-distance investing by business angels in the UK. *Entrepreneurship and Regional Development*, 22(2):113–137.
- Hellmann, T. and Puri, M. (2002). Venture capital and the professionalization of start-up firms: Empirical evidence. *The journal of finance*, 57(1):169–197.
- Herrmann, J., Avdeitchikova, S., and Hjertstrom, A. (2016). The influence of functional and relational proximity on business angel investments. *International Journal of Entrepreneurship and Small Business*, 29(3):468–490.
- Hochberg, Y. V., Ljungqvist, A., and Lu, Y. (2007). Whom you know matters: Venture capital networks and investment performance. *The Journal of Finance*, 62(1):251–301.
- Hoening, D. and Henkel, J. (2015). Quality signals? The role of patents, alliances, and team experience in venture capital financing. *Research Policy*, 44(5):1049–1064.
- Kaplan, S. N. and Stromberg, P. (2001). Venture capitalists as principals: Contracting, screening, and monitoring. *American Economic Review*, 91(2):426–430.
- King, G. and Zeng, L. (2001). Logistic regression in rare events data. *Political Analysis*, 9(2):137–163.
- Kortum, S. and Lerner, J. (2000). Assessing the contribution of venture capital to innovation, 31 *rand j. Econ*, 674:682.
- Lerner, J. (1994). The syndication of venture capital investments. *Financial Management*, 23.
- Lerner, J. (2022). Venture capitalists and the oversight of private firms. In *Venture capital*, pages 267–284. Routledge.

- Lutz, E., Bender, M., Achleitner, A.-K., and Kaserer, C. (2013). Importance of spatial proximity between venture capital investors and investees in germany. *Journal of Business Research*, 66(11):2346–2354.
- Manigart, S., Lockett, A., Meuleman, M., Wright, M., Landström, H., Bruining, H., Desbrières, P., and Hommel, U. (2006). Venture capitalists' decision to syndicate. *Entrepreneurship Theory and Practice*, 30(2):131–153.
- March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization science*, 2(1):71– 87.
- Martin, R., Berndt, C., Klagge, B., and Sunley, P. (2005). Spatial proximity effects and regional equity gaps in the venture capital market: evidence from germany and the united kingdom. *Environment and Planning A*, 37(7):1207–1231.
- Martin, R., Sunley, P., and Turner, D. (2002). Taking risks in regions: the geographical anatomy of Europe's emerging venture capital market. *Journal of Economic Geography*, 2(2):121–150.
- Mason, C. (2007). Venture capital: a geographical perspective. *Handbook of Research on Venture Capital*, Edward Elgar, Cheltenham, pages 86–112.
- Mason, C. M. and Harrison, R. T. (1994). Informal venture capital in the UK. University of Illinois at Urbana Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship.
- McCahery, J. A., Vermeulen, E. P., et al. (2016). Venture capital 2.0: From venturing to partnering. *Annals of Corporate Governance*, 1(2):95–173.
- Nanda, R. and Rhodes-Kropf, M. (2018). Coordination frictions in venture capital syndicates. Technical report, National Bureau of Economic Research.
- Porta, R. L., Lopez-de Silanes, F., and Shleifer, A. (2008). The economic consequences of legal origins. *Journal of economic literature*, 46(2):285–332.
- Porter, M. E. (2000). Location, competition, and economic development: Local clusters in a global economy. *Economic development quarterly*, 14(1):15–34.
- Powell, W. W., Koput, K. W., Bowie, J. I., and Smith-Doerr, L. (2002). The spatial clustering of science and capital: Accounting for biotech firm-venture capital relationships. *Regional Studies*, 36(3):291–305.
- Puri, M. and Zarutskie, R. (2012). On the life cycle dynamics of venture capital and non-venture-capital financed firms. *The Journal of Finance*, 67(6):2247–2293.
- Sah, R. and Stiglitz, J. (1986). The architecture of economic systems: Hierarchies and polyarchies. *The American Economics Review*.
- Sah, R. K. and Stiglitz, J. E. (1984). The architecture of economic systems: Hierarchies and polyarchies. Technical report, National Bureau of Economic Research.
- Schilling, M. A. and Phelps, C. C. (2007). Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. *Management Science*, 53(7):1113–1126.
- Smyth, G. K. (1996). Partitioned algorithms for maximum likelihood and other non-linear estimation. *Statistics and Computing*, 6:201–216.

- Sorenson, O. and Stuart, T. E. (2001). Syndication networks and the spatial distribution of venture capital investments. *American journal of sociology*, 106(6):1546–1588.
- Sullivan, B. N. and Tang, Y. (2012). Small-world networks, absorptive capacity and firm performance: Evidence from the US venture capital industry. *International Journal of Strategic Change Management*, 4(2):149–175.
- Timoneda, J. C. (2021). Estimating group fixed effects in panel data with a binary dependent variable: How the lpm outperforms logistic regression in rare events data. *Social Science Research*, 93:102486.
- Uzzi, B. (1996). The sources and consequences of embeddedness for the economic performance of organizations: The network effect. *American sociological review*, pages 674–698.
- Uzzi, B., Amaral, L. A. N., and Reed-Tsochas, F. (2007). Small-world networks and management science research: A review. *European Management Review*, 4(2):77–91.
- Uzzi, B. and Spiro, J. (2005). Collaboration and creativity: The small world problem. *American journal of sociology*, 111(2):447–504.
- Verspagen, B. and Duysters, G. (2004). The small worlds of strategic technology alliances. *Technovation*, 24(7):563–571.
- Watts, D. J. (1999). Small worlds: The dynamics of networks between order and randomness. Princeton University Press.
- Wilson, R. (1968). The theory of syndicates. *Econometrica*, pages 119–132.
- Wright, M. and Lockett, A. (2003). The structure and management of alliances: syndication in the venture capital industry. *Journal of management studies*, 40(8):2073–2102.
- Zander, U. and Kogut, B. (1995). Knowledge and the speed of the transfer and imitation of organizational capabilities: An empirical test. *Organization science*, 6(1):76–92.
- Zava, M. and Caselli, S. (2024). Who brings investments? Venture capital through reputation, networks, and influence. *Venture Capital through reputation, networks, and influence (March 12, 2024)*.
- Zook, M. A. (2002). Grounded capital: venture financing and the geography of the internet industry, 1994–2000. *Journal of economic geography*, 2(2):151–177.

List of tables

Table 1. Network Component Distribution Over Time	15
Table 2. Summary Statistics of Full and Effective Deal Samples	20
Table 3. Summary Statistics by Region (EU, US, China, ROW)	21
Table 4. Summary Statistics for Investors with Top Degree Centrality, Katz Centrality, and Clustering Coefficients	22
Table 5. Top 10 Countries for Long-Distance Deals	23
Table 6. Regression Results Based on the Linear Probability Model with High-Dimensional Fixed Effects (2015-2022)	24
Table 7. Estimation Results Based on the Linear Probability Model with High-Dimensional Fixed Effects, Including Interaction Terms between Degree Centrality, Katz Centrality, and Distance (2015-2022)	26
Table 8. Estimation Results with Clustering Coefficients, Including Interaction Terms between Clustering Coefficients, and Distance (2015-2022)	28
Table 9. Robustness Check: Regression Results Based on the Linear Probability Model with High-Dimensional Fixed Effects	30
Table 10. Robustness Check: Regression Results Based on the Linear Probability Model with High-Dimensional Fixed Effects, Including Interaction Terms between Degree Centrality, Katz Centrality, and Distance.	31
Table 11. Robustness Check: Regression Results Based on the Linear Probability Model with High-Dimensional Fixed Effects with Clustering Coefficients, Including Interaction Terms between Clustering Coefficients, and Distance	33

Annexes

Annex 1. Definition of Variables and Data Sources

Variable	Definition	Data Source
Deal	A dummy variable that takes the value 1 if an effective deal and 0 for case control	Dealroom, case control
Age	Current year minus launch year of start-ups, only retaining start-ups with ages between 0 to 10	Dealroom
log _distance	Logarithmic value of the shortest path between two points along the Earth's surface	Calculated from longitude and latitude coordinates from Dealroom and Crunchbase
GDP difference	The log difference of annual GDP per capita between the investor and start-up countries	World Bank
Common legal	Dummy variable that takes the value 1 if the investor and start-up countries belong to the same legal family or share common legal frameworks	Porta et al. (2008).
Common language	Dummy variable that takes the value 1 if the investor and the start-up country share common official languages	World Languages. University of Groningen (2016). The data set includes all the official languages spoken per country in 2015
Industry fit	The percentage of deals made by the VC in the same industry as the start-up	Dealroom
Stage fit	The percentage of deals made by the VC in the same round as the start-up	Dealroom
Number of deals	The total number of deals by each investor by the end of the year	Dealroom
Stage	Angel, Seed, Early VC (round = EARLY VC or SERIES A), Late VC (round = GROWTH EQUITY VC)	Dealroom

Annex 2. Definitions of Key Concepts in Network Analysis

Variable	Definition
Degree Centrality	In the context of complex networks, degree centrality is defined as the number of connections incident to a node.
Katz Centrality	Katz centrality measures the influence of a node considering both the number and the depth (distance) of its connections. It takes into account not just direct neighbors but also indirectly connected nodes, applying a decay factor for longer paths to prioritize closer connections.
Clustering Coefficient	The clustering coefficient quantifies the degree to which nodes in a network cluster together. A high clustering coefficient indicates that a node's neighbors are highly interconnected, forming small-world networks.
Isolated Investors	Investors that do not syndicate with any other VC firms within a given year, effectively remaining outside the network.
Giant Connected Component	This term refers to the largest connected subgraph within a network.

Getting in touch with the EU

In person

All over the European Union there are hundreds of Europe Direct centres. You can find the address of the centre nearest you online (european-union.europa.eu/contact-eu/meet-us_en).

On the phone or in writing

Europe Direct is a service that answers your questions about the European Union. You can contact this service:

- by freephone: 00 800 6 7 8 9 10 11 (certain operators may charge for these calls),
- at the following standard number: +32 22999696,
- via the following form: european-union.europa.eu/contact-eu/write-us_en.

Finding information about the EU

Online

Information about the European Union in all the official languages of the EU is available on the Europa website (european-union.europa.eu).

EU publications

You can view or order EU publications at op.europa.eu/en/publications. Multiple copies of free publications can be obtained by contacting Europe Direct or your local documentation centre (european-union.europa.eu/contact-eu/meet-us_en).

EU law and related documents

For access to legal information from the EU, including all EU law since 1951 in all the official language versions, go to EUR-Lex (eur-lex.europa.eu).

EU open data

The portal data.europa.eu provides access to open datasets from the EU institutions, bodies and agencies. These can be downloaded and reused for free, for both commercial and non-commercial purposes. The portal also provides access to a wealth of datasets from European countries.

Science for policy

The Joint Research Centre (JRC) provides independent, evidence-based knowledge and science, supporting EU policies to positively impact society



EU Science Hub

[Joint-research-centre.ec.europa.eu](https://joint-research-centre.ec.europa.eu)