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Empirical insights into strategic competition, productivity and resilience of the Italian entrepreneurial system

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To my parents

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Publications

1. V. Pieroni, A. Grassi, N. Lattanzi, Il contributo identitario del Made in Tuscany alla specificità strategica e alla competenza distintiva dell'azienda, in L. Anselmi, N. Lattanzi (a cura di), Il Family Business Made in Tuscany, Franco Angeli, Milano, 2016, pp. 470–492, ISBN 978-88-917-4412-8.
2. V. Pieroni, Azienda familiare e strumenti innovativi di management, in N. Lattanzi (a cura di), Le aziende familiari. Generazioni, società, mercato, Giappichelli, Torino, 2017, pp. 137–173, ISBN/EAN 978-88-9211081-6.
3. V. Pieroni, Ricchezza familiare e soluzioni di investimento per lo sviluppo delle aziende, pages 91-132, and V. Pieroni, F. Cognetta, Il Family Office nella dottrina: una lettura mediante l'analisi di rete bipartita, pages 33-46, in N. Lattanzi (a cura di), Family Office. Scenari e nuove frontiere per la gestione e la valorizzazione del patrimonio-azienda familiare, Giuffrè Editore, Milano, 2019, ISBN 978-88-28-80314-0.
4. V. Pieroni, A. Facchini and M. Riccaboni, (2021). COVID-19 vaccination and unemployment risk: lessons from the Italian crisis. Scientific reports, 11(1), 1-8.
5. S. Amato, V. Pieroni, N. Lattanzi and G. Vitali (2021). Are family firms good neighbours? a spatial analysis of italian technology-intensive firms. Journal of Small Business and Enterprise Development, 29(4), 663-693.

Presentations

1. *AIDEA (Italian Academy of Business Administration and Management) XXXVIII Italian Conference*, Rome, Italy, 2017;
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Abstract

The globalization of economic activities and the acceleration of technological change brought about profound changes in the competitive arena where firms strive to succeed. Enterprises must promptly adapt to change to survive and build a sustainable advantage over their competitors. The need for effective solutions to strengthen the entrepreneurial system and foster a dynamic economy has stimulated the academic and institutional debate on the drivers of firms' competitiveness, productivity, and resilience to sudden shocks. The acknowledged systemic nature of the firm suggests looking beyond its boundaries, at the system of relationships the enterprise is embedded in, to discover the triggers of the firm's development.

OECD and European Union countries soon acknowledged how valuable inter-firm connections are for firms' strategic development, especially when it comes to micro, small and medium-sized enterprises. As a result, policymakers committed to defining a policy agenda to encourage the spontaneous emergence of formal network ties and support the development of localized connections in territorial areas. The first two chapters of this doctoral dissertation are devoted to empirically investigating the triggers of firms' competitiveness and productivity, focusing on the contribution to firms' performance of formal network ties secured by a specific legal regime and localized regional processes (i.e., local spillovers). Chapter 1 assesses the dynamic impact of inter-firm network agreements (introduced by the decree-law n. 5/2009 converted into law n.33/2009) on firms' performance. Our approach to causal inference allows us to estimate heterogeneity-

robust dynamic effects overcoming the issues affecting two-way fixed effects DiD estimates in settings with a staggered treatment rollout. We find that firms participating in formalized networks can reap lasting benefits that keep growing at least until the third year of cooperation, thus improving their revenues, value added and EBITDA. The benefits of formalized networks are even stronger for the subsample of micro-enterprises, especially when they engage with larger partners. Moreover, inter-firm formal networks deliver higher advantages when most members are in the same travel-to-work area. Further insights into the consequences of co-location are discussed in Chapter 2. The study reveals the existence of spatial dependence between nearby firms' productivity, which is supposed to be driven by geographically bounded processes. Using secondary data on Italian technology-intensive manufacturing firms, we exploit spatial econometric models to estimate productivity spillovers across firms. The work brings together family firms and regional studies as it points out whether spatial proximity to family firms is a source of positive or negative externalities. Our findings confirm that proximity to patenting firms is a source of positive externalities. As a second result, we observe that the family's involvement in the ownership and management positions has an overall negative indirect effect on nearby firms' productivity. However, when family firms are innovators, the adverse indirect effect vanishes. The study points out the critical role of innovation in fostering the development of dynamic and fertile regional environments. It also highlights the importance of co-location for public policy initiatives designed to promote economic growth at a local level.

Recently, the entrepreneurial system has been severely hit by the unprecedented shock caused by the outbreak of the COVID-19 pandemic. To curtail the health and socio-economic consequences of the spread of coronavirus (SARS-CoV-2), governments issued several measures, including mobility limitations and interventions to sustain employment (e.g., furlough schemes). Chapter 3 contributes to developing a new research line by analyzing how changes in mobility streams following government restrictions and behavioral adjustments impacted the number of excess deaths and employee furloughs recorded in Italy after the pandemic outbreak. To disentangle the causal effect of mobility restrictions on both dependent variables, we exploited rainfall patterns across Italian administrative regions as a source of exogenous variation in human mobility. We find that a contraction in mobility effectively prevents the most severe consequences of the pandemic, as it leads to a COVID-19 mortality reduction. However, it increases the use of employee furloughs, exacerbating unemployment risk. The Chapter builds on these findings to discuss return-to-work policies and prioritizing policies for administering COVID-19 vaccines in the most advanced stage of the vaccination campaign.

All Chapters focus on the Italian case. Notwithstanding, this dissertation provides insights into widely addressed topics that animate the institutional and academic debate on an international scale.

Disclaimer

This doctoral dissertation is the result of the joint work of the author and co-authors as follows:

1. Chapter 1 is a joint work with Nicola Lattanzi (IMT School for Advanced Studies Lucca) and Massimo Riccaboni (IMT School for Advanced Studies Lucca). Variations have been implemented based on referees' comments. At the time of the final submission of the thesis, the work reproduced in Chapter 1 had been submitted to an academic journal and was under review;

2. Chapter 2 is the reproduction of the paper *Are family firms good neighbours? A spatial analysis of Italian technology-intensive firms* published in the Journal of Small Business and Enterprise Development (Emerald), co-authored with Stefano Amato (IMT School for Advanced Studies Lucca), Nicola Lattanzi (IMT School for Advanced Studies Lucca) and Giampaolo Vitali (CNR-IRCrES, Moncalieri, Italy). DOI 10.1108/JSBED-06-2021-0242. Variations have been implemented based on referees' comments;

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General introduction

The extensive academic and institutional debate on firms' competitiveness and productivity gained new momentum as the challenges posed by the globalization and internationalization of economic activities, the advent of the digital economy and the acceleration of technological change pointed out the need for innovative and farsighted solutions to ensure the survival and growth of enterprises. In the last decades, OECD[1] and European Union member countries have shown a solid commitment to creating favorable conditions for improving the competitiveness of firms, especially micro, small and medium-sized ones (SMEs)[2]. Aware that the structural changes investing global economic landscapes represent a threat to SMEs but also provide the stimulus for a strategic improvement, policymakers have the task of creating a supportive institutional setting to encourage promising and innovative strategic behaviors[3].

The design of a policy agenda aimed at supporting entrepreneurs'

[1] Acronym for Organisation for Economic Co-operation and Development.

[2] In 2000, Ministers and Representatives of governments of OECD member countries adopted the "Bologna Charter on SME", by agreeing on a set of actions aimed at supporting SMEs in a globalized environment. Later, in 2008, EU member countries renewed their commitment by defining an ambitious policy agenda summarized in the "Small Business Act". For further information, please see `https://www.oecd.org/cfe/smes/thebolognacharteronsmepolicies.htm` and `https://ec.europa.eu/growth/tools-databases/sme-best-practices/SBA/index.cfm?fuseaction=welcome.detail`.

[3] Behind this joint effort is the acknowledgment of SMEs' substantial contribution to the growth in value added and employment. In 2019, almost 60% of the increase in value added and 70% of the increase in employment recorded in European Union countries was attributable to SMEs. The data refer to the non-financial business sector (European Commission, Executive Agency for Small and Medium-sized Enterprises, Murphy, et al., 2021).

competitiveness must be grounded on the acknowledgment of the systemic nature of the firm. Firms are typically embedded in a system of relationships and broader social structures (Baù et al., 2019) and are tightly bonded to the territorial surroundings where the economic activity takes place (Dicken and Malmberg, 2001; Grieser et al., 2022). The boundaries delimiting a single organization are not strictly defined and are subject to re-design processes. With the enrichment of the scientific debate on inter-firm relationships (Gulati, 1998; Gulati, Nohria, and Zaheer, 2000) and the ever-growing attention paid to the economic consequences of network participation (Cai and Szeidl, 2018; Laurell, Achtenhagen, and S. Andersson, 2017; Parida, Patel, et al., 2016), the idea that the roots of the competitive advantage do not lie exclusively within the firm was reinforced (Lavie, 2006). Idiosyncratic inter-firm linkages are claimed to be a source of benefits and relational rents since they pave the way for the exchange of valuable relation-specific assets, knowledge and complementary resources (Dyer and H. Singh, 1998). Besides the rationale of economizing on transaction costs (e.g., Williamson, 1991), alliance formation has clear strategic and social implications (Eisenhardt and Schoonhoven, 1996). Firms in weak strategic positions can rely on network ties to acquire new capabilities, especially when the knowledge base of an industry is complex and rapidly expanding (W. W. Powell, Koput, and Smith-Doerr, 1996), improve their strength in the market or enter new markets, share risks and costs (Parida, Westerberg, et al., 2010).

Policymakers soon became aware that inter-firm networks may give enterprises, especially SMEs, the chance to get a stronger competitive stance. From the late 1980s, several countries sponsored networking programmes to foster inter-firm collaborations (e.g. Rosenfeld, 1996). Later, networking initiatives were listed among the pillars of policy agendas for SMEs' competitiveness[4]. In this regard, to transpose the guidelines of the "Small Business Act" into concrete interventions, the Italian policymaker introduced a legal framework[5] to encourage the creation of for-

[4]Refer, again, to the OECD "Bologna Charter on SME" and to the European "Small Business Act".

[5]Decree-law n. 5/2009 converted into law n.33/2009 and subsequent amendments.

mal inter-firm networks and foster long-term strategic cooperation (Arrigo and Tassani, 2016). The framework regulates the establishment of formalized network ties and grants autonomy to the participants in setting up the rules and duties partners must comply with (Massari, Riggio, and Calace, 2015). The legal recognition of inter-frim networks with the provision of a dedicated regime encourages members' commitment and ensures against opportunistic behaviors (Williamson, 1979), which typically lead to the failure of spontaneous aggregations.

Despite inter-firm ties can easily overcome regional boundaries enabled by the growing availability of information and communication technologies (ICT), which are claimed to have a distance-destroying capacity (Morgan, 2004), firms' geographical proximity and spatial embeddedness still matter in explaining the development of economic activities, growth and competitiveness (Du and Vanino, 2021). Firms are inherently spatial and their characteristics are shaped by the local environment they are embedded in (Dicken and Malmberg, 2001). Among the benefits ascribed to firms' co-location is the free-of-charge transmission of knowledge enabled by geographical proximity (Audretsch and Feldman, 2004; Audretsch and Belitski, 2020). Economic geographers, industrial economists and regional economists have shown a growing interest in exploring how the process of knowledge creation and exchange can affect or be affected by the spatial concentration of economic activities (Capello, 2002; Rammer, Kinne, and Blind, 2020). Collective learning processes taking place locally may be facilitated by the existence of relational synergies between co-located firms and a common institutional and technical culture (B. r. T. Asheim, 1996). Labour mobility and stable informal interactions between suppliers and buyers in the *milieu* are among the main channels through which knowledge spillovers occur (Stoyanov and Zubanov, 2012; Bloom et al., 2019). Hence, spatial proximity may reinforce firms' competitive position in that it favors the activation of the dynamics mentioned above, which take place locally and are at the core of productivity spillovers across nearby firms (Cardamone, 2017).

From a policy perspective, the approach to designing effective interventions for firms' competitiveness can't be "place-less", meaning that it can't overlook the existing connections that tie the firm to its spatial surroundings or disregard the spatial externalities stemming from firms' co-location. In this vein, cluster policies could encourage the creation of localized knowledge and its transmission to spur regions' competitiveness and innovativeness (Enright and Ffowcs-Williams, 2002).

Besides the rationale of rectifying market and regulatory failures[6], policymakers are called to take action whenever unprecedented shocks have severe socio-economic consequences.

Recently, the sudden economic crisis following the outbreak of the COVID-19 pandemic highlighted the urgency to enforce supporting measures to mitigate the negative impact of the shock and help firms recover, fueling the discussion on the adequate policy responses to be implemented (Juergensen, Guimón, and Narula, 2020; Besley and Stern, 2020; Acemoglu et al., 2021; F. Alvarez, Argente, and Lippi, 2021). To mitigate the impact of the pandemic and provide support to firms and households, governments rolled out a set of financial and economic measures, including interventions to sustain employment (e.g., furlough schemes) (OECD, 2022; Casarico and Lattanzio, 2022).

This doctoral dissertation is an empirical journey through the exploration of the competitiveness, productivity and resilience of the Italian industrial system. It is made up of three works developed to get new insights on well-debated topics in management and regional studies and examine the socio-economic consequences of the massive shock caused by the recent COVID-19 pandemic. Each study provides several managerial and/or policy implications.

Thesis outline

The first chapter empirically assesses the contribution of Italian network agreements to firms' performance. The legal framework regulating the

[6]As an example, according to the guidelines on cluster policies defined on the occasion of the Bologna Conference in 2000, government interventions towards clusters are justified by reference to market failures. For further information, please refer to https://www.oecd.org/cfe/smes/2010888.pdf.

tool was introduced in 2009 to promote long-term strategic partnerships between enterprises. Our empirical approach is based on recent methodological advances for Difference-in-Differences estimation with multiple periods and variation in treatment timing (Goodman-Bacon, 2021; Callaway and Sant'Anna, 2020; Sun and Abraham, 2020). Specifically, we estimate dynamic treatment effects relying on the contribution by Sun and Abraham (2020). The proposed method delivers unbiased estimates under the hypothesis of network effects heterogeneity across treated cohorts. Besides, it allows for providing new insights into the evolution of network agreements' expected benefits over time. Indeed, although network agreements have immediately raised the interest of scholars and practitioners, we need more evidence on the evolution and persistence of their contribution to member firms' performance. We find that participation in formal inter-firm networks secured by a proper legal framework has a lasting positive impact on firms' revenues, value added and EBITDA (earnings before interest, taxes, depreciation and amortization). On average, dynamic treatment impacts keep growing in magnitude until the third year of exposure to the treatment and persist until the sixth year of cooperation. The analysis shows that network agreements' returns take time to grow and stabilize. Then, we examine whether and how the idiosyncratic combination of partners' profiles induces heterogeneity in network agreements' impacts. We observe that networking benefits micro-enterprises to a greater extent, especially when they connect with larger partners. Moreover, formal network agreements are highly favorable when most network members are located in the same travel-to-work area.

The second chapter investigates the spatial dependence between nearby firms' productivity, working on a sample of Italian technology-intensive manufacturing firms. Relying on the estimation of spatial econometric models, we bridge family firms and regional studies by testing whether geographic proximity to family firms is a source of productivity externalities. The study reveals that firms' productivity is related to neighbouring firms' one, attesting to the existence of spatial spillovers arising from co-location. Moving beyond, we observe that firms' specific characteristics act as a source of heterogeneity in that the magnitude and sign of productivity spillovers vary conditional on neighbours' features. Notably, proximity to patenting firms is beneficial for the productivity of nearby enterprises, while being close to family firms is a source of negative externalities. However, the adverse effect vanishes when family firms are also innovators.

The third and final chapter examines the economic consequences of sudden changes in mobility flows following the outbreak of the COVID-19 pandemic. Our instrumental variable approach exploits rainfall patterns across Italian NUTS3 regions as a source of exogenous variation in human mobility to unveil the causal effect of mobility restrictions on excess deaths and furlough workers. The analysis reveals that the shock in mobility flows induced by restrictive measures and behavioral adjustments was effective in curtailing the contagion since a mobility contraction of 1% was followed by a mortality reduction of 0.6%. However, on the other hand, the drop in mobility affected the risk of unemployment, as shown by the induced increase in the use of wage compensation schemes.

The international reach of the Italian case

All chapters share a common feature: they all focus on the Italian case. For the purpose of the outlined research, Italy represents a good case study for several reasons. The first reason lies in the peculiar composition of Italy's production fabric, where SMEs play a prominent economic and social role. In 2018 micro, small and medium-sized enterprises[7] generated around 66.9% and 78.1% of the overall value added and employment delivered by Italian enterprises in non-financial businesses[8]. Despite showing a good propensity to innovation (European Commission,

[7]Enterprises employing less than 250 people. The threshold has been set by the EU recommendation 2003/361.

[8]In 2020 SMEs' contribution to value added and employment was 64.3% and 76.1% respectively, still above the European average. The figures are released by the European Commission. For further information please refer to the European Commission dedicated webpage.

Executive Agency for Small and Medium-sized Enterprises, Schroder, et al., 2020), SMEs usually suffer from the limited availability of resources (e.g., human and financial) compared to larger counterparts and struggle to compete in rapidly changing globalized markets. Intending to implement the Small Business Act recommendations (Ministero dello Sviluppo Economico, 2011), the Italian legislator has promptly provided a framework to legally recognize and regulate inter-firm networks, aware that networking represents a promising organizational solution to prompt the competitiveness of smaller businesses. The Italian intervention paved the way for a quantitative assessment of the impact of formal agreements on firms' performance (Dickson et al., 2021; Burlina, 2020; Costa, Luchetti, and Romano, 2017; Cisi et al., 2020). The work reproduced in Chapter 1 contributes to the debate by inferring the economic impact over time of participation in formal strategic networks. Policy and managerial implications of establishing legally secured connections for cooperation are discussed.

The second reason lies in Italy's productivity dynamics. Since the second half of the 1990s, the Italian economy has experienced a slowdown in productivity growth[9] (C. Giordano, Toniolo, and Zollino, 2017). In comparative terms, Italy lagged behind other European countries, such as Germany and France, recording lower productivity growth rates both before and after the global financial crisis in 2008 (Bugamelli, Lotti, et al., 2018). Italy's gap in productivity dynamics has been ascribed to the inherent fragmentation of its productive system, widely represented by SMEs that are likely to underinvest in innovation due to the lack of sufficient resources (Bugamelli, Cannari, et al., 2012). This calls for a deeper understanding of the determinants of firms' productivity to get insights and stimulate policy interventions. In this regard, we look for the source of positive productivity spillovers in firms' spatial proximity to innovators or family firms.

Finally, the prompt reaction of the Italian government to the spread of the novel coronavirus (SARS-CoV-2), with the enforcement of several measures to contain the contagion and support the economy (Euro-

[9]Productivity stagnation hit especially non-financial services.

pean Commission, 2021), provided the opportunity to study the health and socio-economic consequences of lockdown policies. Since the first months of 2020, Italy has been severely hit by the pandemic. The government was forced to issue social distancing measures and shut down non-essential activities to curb the contagion. The sudden shock induced a change in mobility patterns with consequences on the risk of unemployment, as shown by the extensive use of wage guarantee schemes by the private sector. The Italian response to the pandemic offered the chance to unveil the causal relationship between mobility contraction and employee furlough, enriching the discussion on the return-to-work policies for the post-lockdown period.

Despite being circumscribed to the Italian case, the results displayed in this doctoral thesis can reach and engage an international audience. The empirical evidence attesting formal inter-firm networks' effectiveness for firms' performance can encourage the implementation of networking policies on an international scale. Foreign economies which committed themselves to the creation of a favorable environment for the ecosystem of SMEs, can draw insights and guidelines from the Italian experience to transpose the principles of the "Bologna Charter" and "Small Business Act" into concrete interventions.

Similarly, the empirical investigation of productivity spillovers stemming from firms' geographical proximity could guide the design of policy interventions to support regional clusters' development. Despite the ongoing globalization of economic activities, policymakers are aware that the sources of competitive advantage can be localized and can be found in regional productive systems [10]. Spatial proximity can be a crucial ingredient for strengthening regional economies, although it is not the only one (Boschma, 2005; Harris et al., 2019).

Then, finally, upon the gradual spread of the novel coronavirus (SARS-CoV-2), governments around the world issued comparable emergency measures to deal with the pandemic crisis. Massive interventions aimed at supporting households and enterprises complemented lockdowns and

[10] On the international commitment towards cluster policies, please see `https://www.oecd.org/cfe/smes/2010888.pdf`.

mobility restrictions enforced to curtail the contagion (OECD, 2022). The Italian government was not the only one to undertake employment protection programs, as other European countries introduced short-time furlough or wage compensation schemes. For this reason, our work fuels the debate on the socio-economic consequences of mobility restrictions and discusses the most appropriate return-to-work policies while addressing an international audience.

Chapter 1

The Dynamic Impact of Inter-Firm Network Agreements: A Microeconometric Analysis

The content of this chapter is a joint work with Prof. Nicola Lattanzi and Prof. Massimo Riccaboni. Variations have been implemented based on referees' comments.

1.1 Introduction

Networks of inter-firm collaborative agreements represent a widely debated and investigated phenomenon (Riccaboni and Pammolli, 2002; Hoang and Antoncic, 2003; Smith-Doerr and W. W. Powell, 2010). A significant contribution to the theoretical conceptualization of inter-firm network formation comes from the transaction cost economics theory (Williamson, 1979; Williamson, 1991). Revolving around the concept of economizing on transaction costs, the framework has been a reference point in the following scientific debate. However, it leaves largely unexplored the many strategic motivations behind the establishment of cooperative networks (W. Powell, 1990; Granovetter, 1985). Network arrangements can be signed to overcome strategic weaknesses and gain a competitive advantage (Jarillo, 1988; Gulati, Nohria, and Zaheer, 2000). The chance to get rapid access to pivotal assets (tangible or intangible), know-how, capabilities, and technologies while keeping flexibility and autonomy fosters collaborative agreements. It provides strategic advantages that would otherwise be precluded (W. Powell, 1990; Gulati, 1999; Orsenigo, Pammolli, and Riccaboni, 2001; Pammolli and Riccaboni, 2002). Better access to external information and capabilities (Malecki and Veldhoen, 1993) can strengthen network members' market position or ease entry into new market segments (Coviello and Munro, 1995; Laurell, Achtenhagen, and S. Andersson, 2017). Networking firms can also exploit production synergies and pool resources to reach scale and scope economies (Jarillo, 1988; Shan, 1990).

Inter-firm strategic alliances usually take time to deliver substantial benefits, though (Rosenfeld, 1996; Huggins, 2001). The emergence of network outcomes is affected by the speed at which learning occurs. Learning how to manage external know-how and resources is critical to attaining market goals and improving organizational performance (Gibb, 1997; Stuart, 2000). However, firms need time to absorb knowledge and increase their learning capacity (Cohen and Levinthal, 1990; Latham and Le Bas, 2006). Besides, in the post-formation phase of an alliance, value creation is typically hindered by the high coordination costs implied by the complexity of the ongoing activities to be carried out jointly and the interdependence of tasks (Gulati and H. Singh, 1998). Over time, as network members learn how to combine their assets and develop effective coordination routines, the alliance starts delivering increasing value (Dyer, H. Singh, and Hesterly, 2018; Gulati, Wohlgezogen, and Zhelyazkov, 2012).

The relational nature of networks suggests that partners' performance gains are a function of specific assets and capabilities developed within an idiosyncratic relationship (Mesquita, Anand, and Brush, 2008). The unique way partners' attributes combine shapes the identity of the relationship and affects its value creation potential (Dyer and H. Singh, 1998).

A trait that defines a partnership's specificity and is expected to condition the magnitude of its impacts is the interplay between partners' size (Burgers, Hill, and W. C. Kim, 1993). Inter-firm enduring cooperation is deemed to benefit smaller firms in many regards. Despite their pivotal contribution to the economy[1], SMEs suffer from the pitfalls commonly associated with their small size, among which is the limited availability of human, financial, or technical resources (Kelliher and Reinl, 2009). Smaller firms may struggle to access new or broader markets due to the lack of capabilities, resources, or reputation (Y. Kim and Vonortas, 2014). They could be overcome by larger intermediaries in acquiring critical market information and exploiting future opportunities (Van Laere et al., 2003; A. Bonaccorsi, 1993). Then, in competitive contexts where scale and scope are essential to succeed and cost containment practices are a primary source of advantage, SMEs struggle to survive the competition of larger and more efficient enterprises (Gomes-Casseres, 1997; Narula, 2004). When size constraints become too heavy to compete, connecting to external partners in a network-shaped organizational structure may provide SMEs with several benefits (Street and Cameron, 2007). Through recurrent relationships, smaller firms can gain access to valuable resources (Stuart, 2000; Pyke, 1992), integrate diverse competencies (Parida, Westerberg, et al., 2010), increase their knowledge (Inkpen and Tsang, 2005; Beecham and Cordey-Hayes, 1998), improve reputation (Parida, Westerberg, et al., 2010) and acquire information on market and industry trends (O'donnell, 2014). Formal cooperation agreements allow smaller firms to pursue innovation while sharing the related risks (Teng, 2007). However, as smaller firms reap advantages from getting access to partners'

[1]SMEs are the backbone of the European economy. Back in 2018, around 99.8% of total non-financial enterprises operating in European countries fell under the definition of SMEs (Muller et al., 2019). Their contribution to the economy amounted to 56.4% of value added and 66.6% of employment generated in 2018. In 2020, SMEs still represented 99.8% of non-financial European enterprises accounting for 53% of value added and 65.2% of employment (European Commission, Executive Agency for Small and Medium-sized Enterprises, Murphy, et al., 2021). The Italian figures regarding SMEs are even above the European averages. In 2018, Italian SMEs accounted for 99.9% of total enterprises and generated 66.9% of value added and 78.1% of employment produced by the "non-financial business sector" (European Commission, 2019).

complementary resources, the value of an alliance is claimed to depend upon other members' resource profiles (Stuart, 2000). Based on that, large well-endowed partners are plausibly highly valuable ones (Stuart, 2000). Smaller firms can take advantage of larger enterprises' consolidated market position, customer base, financial resources, or reputation (Podolny and Page, 1998) in exchange for their flexibility and innovative potential, especially in technology fields (Narula, 2004; Mitchell and K. Singh, 1996).

Network partnerships' value creation potential is also moderated by participants' geographical location (Enright, 1995; Dyer, 1996). Cooperative agreements among nearby partners can benefit from the activation of spatial spillovers and external economies (Van Oort et al., 2012). Partners' co-location facilitates the exchange of knowledge and information (Audretsch and Feldman, 1996) through recurrent face-to-face interactions (Breschi and Lissoni, 2001a), or spatially-bounded labor mobility flows (Kesidou and Romijn, 2008). Direct communication channels among proximate partners and the ongoing flow of information ease the coordination of complex tasks and accelerate the convergence toward efficient coordination routines (Ring and Ven, 1992; Gulati, Wohlgezogen, and Zhelyazkov, 2012). Then, if connecting to nearby partners, enterprises can benefit from external economies, e.g., they can cut transportation costs or share local infrastructures and facilities (Parr, 2002a). When relying too much on a spatially bounded network of strong ties, firms may fall victim to the lock-in effect, though (Boschma, 2005). Then, they may lose sight of alternative courses of action, missing learning opportunities (Balland, Boschma, and Frenken, 2015).

Despite the many acknowledged advantages of establishing enduring network ties, inter-firm alliances may fail to deliver positive outcomes (Kale, Dyer, and H. Singh, 2002; Miles and Snow, 1992). Network members may adopt opportunistic behaviors and not fully commit themselves to shared strategic purposes (Williamson, 1993), or try to reinforce their bargaining power to claim a larger share of the value created in the partnership (Panico, 2017; Hoffmann et al., 2018). An inaccurate design of the relationship can lead to uneven dynamics (Miles and Snow,

1992) and increase the risk of aggressive misappropriation tactics (Katila, Rosenberger, and Eisenhardt, 2008). Effective control mechanisms are required to deter harmful behaviors and favor partners' strategic alignment (T. K. Das and Teng, 1998). Contractual control secured by an adequate legal framework becomes important in this regard, as it provides stability to the relationship through the formalization of partners' rights, duties, and mutual expectations (Bentivogli, Quintiliani, and Sabbatini, 2013).

Recently, public authorities have shown their commitment by formally recognizing inter-firm networks as a possible response to the challenges posed by the globalization of business, with a special focus on small and medium-sized enterprises (SMEs). The "Bologna Charter on SME policies", adopted in 2000 by OECD member countries[2], and the 2008 "Small Business Act" from the European Commission called for interventions aimed at creating a favorable environment for the growth of small and medium-sized businesses (Ministero dello Sviluppo Economico, 2011).

In this vein, with the aim of stimulating firms' competitiveness and encouraging enduring network relationships (Capuano, Carnazza, and Saracino, 2012), the Italian policymaker introduced in 2009 a legal tool[3], the "network agreement" ("network contract" or "contratto di rete" in the original definition), meant to regulate and secure strategic inter-firm cooperation (Massari, Riggio, and Calace, 2015). The alliance formalized through the agreement is grounded on several long-term oriented objectives set by the participants. The agreement is not subject to strict limitations either in scope or duration (RetImpresa, 2011; RetImpresa, 2012) since it is conceived to answer a strategic need. The tool grants flexibility and autonomy to its members in regulating internal relationships (Arrigo and Tassani, 2016).

[2]For further information see `https://www.oecd.org/cfe/smes/thebolognacharteronsmepolicies.htm`.

[3]The legal framework regulating network agreements has been introduced by the decree-law n. 5/2009 converted into law n.33/2009, then integrated and modified by the decree-law n. 83/2012 converted into law n. 134/2012, by the decree-law n. 179/2012 converted into law n. 221/2012 and by the law n. 154/2016.

Early empirical evidence reveals that participation in network agreements is positively associated with firms' performance (Burlina, 2020; Dickson et al., 2021; Cisi et al., 2020). Smaller firms reap higher benefits from networking concerning value added per unit of sales (Cisi et al., 2020; Aiello et al., 2023), and turnover growth (Costa, Luchetti, and Romano, 2017). Due to the recent introduction of the tool, we still have a paucity of evidence on the persistence of network impacts in the medium-long run. Most importantly, only a few studies provide a dynamic assessment of network agreement effects (Costa, Luchetti, and Romano, 2017), and still, they cover a narrow time frame. Firms usually have high expectations for the benefits they could attain in the short term from formal cooperation (Rosenfeld, 1996). Then, if networks' value creation potential takes time to reach maturity (Gulati, Wohlgezogen, and Zhelyazkov, 2012), firms may show disappointment and lower their commitment (Huggins, 2001). Deepening the knowledge of network agreements can help to better understand their potential from a dynamic perspective. Moreover, further evidence is needed to unveil whether and how the interplay between partners' attributes, specifically firms' size (Cantele and Vernizzi, 2015) and geographical location (Cisi et al., 2020; Rubino and Vitolla, 2018), conditions network agreements' value creation potential and induces heterogeneity in causal impacts. Especially when interested in the moderating role of size, the empirical literature on network agreements is mostly devoted to exploring how firms' own features make them able to reap the most from networking, neglecting the way partners' attributes combine and shape the relationship.

Working on a sample of Italian manufacturing and service enterprises, we contribute to filling this gap by performing a causal inference on the impact participation in network agreements has on firms' revenues and operating income. Our work adds novelty as we provide a dynamic assessment of network agreements' causal effects over time, estimating dynamic causal impacts until the seventh year of networking. Our empirical approach allows for coping with the pitfalls of two-way fixed effects Diff-in-Diff estimations in settings with multiple time periods and variations in treatment timing across units (Goodman-Bacon, 2021). Firms are deemed to be treated from the moment they sign an agreement, and since they enter the agreement at different points in time, a staggered design was best suited to model our data. We implemented an event study relying on the estimation method proposed by Sun and Abraham (2020), which returns robust estimates under the hypothesis of heterogeneous effects across treatment cohorts. We formally addressed firms' self-selection into the treatment by selecting a proper counterfactual group through propensity score matching (PSM) (Rosenbaum and Rubin, 1983). To the best of our knowledge, the extant empirical literature on network agreements does not explicitly address the issues affecting difference-in-differences treatment effect estimates in a setting with staggered treatment adoption. Besides, only a few studies adopt a causal inference approach to deliver a causal interpretation of network agreements' effects on firms' performance.

Comparing sub-samples of treated firms, we moved the discussion forward by providing insights into heterogeneity in causal impacts elicited by the idiosyncratic combination of partners' profiles, with a focus on network members' size diversity and spatial proximity. Instead of limiting our analysis to unveiling whether firms reap stronger or weaker advantages from formal networks based on their own attributes, we studied how the fit between partners' profiles can generate a synergistic effect, moderating formal networks' value-generation potential (Dyer and H. Singh, 1998; Stuart, 2000; Y. Luo, 1997). Our attention shifts from the single participant to the configuration of the network relationship.

Our findings reveal that network agreements positively and significantly affect revenues, value added, and operating margins (EBITDA), reinforcing previous evidence. Formal strategic networks are found to yield increasing benefits that keep growing in magnitude until the third year of exposure to the treatment and tend to stabilize afterward. Network effects persist over time until the sixth year in the agreement, then lose statistical significance, probably due to the limited number of observations. As expected, micro-enterprises employing less than ten workers are found to reap most of the gains from network participation. We reveal, however, that micro-enterprises experience greater benefits when they establish a contractual relationship with at least one medium-sized or large partner.

Concerning network members' geographical proximity, we employed a functional geography[4] to define network agreements' spatial concentration and unveil heterogeneity in causal effects. When comparing treatment effects experienced by firms in networks with at least 60% of members in the same travel-to-work area (TTWA) to those recorded by firms in networks involving less than 60% of participants from the same TTWA, dynamic impacts follow a similar path in both subgroups (especially when concerning revenues and EBITDA). However, when we isolate the 25% of networking firms involved in the most and less concentrated agreements, the advantages of building formal connections within highly connected geographical areas become evident.

Our findings allow for drawing policy and managerial implications. Inter-firm alliances formalized through the network agreement yield persistent benefits over time, confirming the strategic and long-term oriented nature of cooperation. The economic impact of network agreements, however, takes time to grow and stabilize. Hence, adequate communication is needed to let potential entrants mature the right expectations of the tool's effectiveness. From a managerial perspective, this research sheds new light on the importance of formalized strategic inter-firm networks in stimulating participating firms' performance over the years. We bring new insights into the contribution of formal network policies to firms' competitiveness in a setting characterized by a high frequency of micro and small enterprises struggling to survive in globalized markets under strong competitive pressure. Our results further support formal networking initiatives as a promising managerial practice. Concerning network formation, partners' selection must be carried out carefully based on the expected synergies between firms' resource profiles.

The remainder of this work is organized as follows. Section 1.2 provides the theoretical background and develops the main hypotheses. Sub-

[4]Please, refer to paragraph 1.5.1 for further information.

section 1.2.2 describes the main features of the Italian policy on network agreements and subsection 1.2.3 presents an overview of networking policies sponsored by public authorities. Section 1.4 outlines the econometric approach while our results are discussed in section 1.5. Finally, in section 1.6, we draw the main conclusions, discussing policy implications, managerial implications, and possible avenues for future research.

1.2 Theoretical background

1.2.1 Inter-firm networks and firm performance

The emergence of inter-firm networks has given rise to a rich academic debate (Smith-Doerr and W. W. Powell, 2010; Anderson, Håkansson, and Johanson, 1994; Podolny and Page, 1998). In the attempt to shed light on the complex mechanisms underlying network formation and explore the strategic implications of cooperative agreements, networking has been widely examined from different perspectives and several disciplinary approaches (Grandori and Soda, 1995; Gulati, 1998). Organizational studies have addressed the phenomenon, conceptualizing the network as a hybrid solution to manage transactions and governance costs (Williamson, 1975; Williamson, 1991). In this theoretical perspective, the establishment of networks is justified by the specific nature of economic transactions (Williamson, 1979), and it is subject to an accurate assessment of its properties and implied costs compared to alternative governance structures. Yet, the transaction-cost theory does not properly address the social (Granovetter, 1985) and the strategic implications of inter-firm relationships.

Firms typically engage in sustained relationships that imply repeated interactions and require reciprocal commitment. Inter-firm links can be established to govern the transfer of goods and services, to use pooled resources or to favor the joint application of complementary resources (e.g., professional know-how) to perform complex tasks (Grandori, 1997). Theoretical arguments grounded on the resource-based view (Wernerfelt, 1984; J. Barney, 1991) suggest that the exchange of focal assets (e.g., physical equipment, capabilities or knowledge) enabled by long-lasting connections can be a source of sustained competitive advantage. The idea that firms can only benefit from proprietary assets kept within their boundaries is challenged. As firm performance is strongly affected by partners' tangible and intangible assets, resource accessibility becomes critical to achieve a competitive advantage (Lavie, 2006). Hence, besides the rationale of transaction cost minimization, partnership formation is prompted by both strategic and social factors (Eisenhardt and Schoonhoven, 1996). Given the systemic nature of firms which are typically embedded in a set of network ties (Gulati, Nohria, and Zaheer, 2000), competitive behaviors and firms' performance (Kumar, Liu, and Zaheer, 2022) can be better understood by adopting a relational rather than an atomistic approach (Dyer and H. Singh, 1998).

Through network alliances, firms can manage and exploit their complementarities to overcome limited endowments (Nohria and Garcia-Pont, 1991; W. Powell, 1990). Inter-firm partnerships enable learning and facilitate knowledge flows (Goerzen and Beamish, 2005; Darr and Kurtzberg, 2000; Inkpen and Tsang, 2005). Stable connections favor the exchange of information via formal and informal interactions stimulating competitiveness and innovation (Malecki and Veldhoen, 1993; Goerzen, 2007). Much emphasis has been placed on the benefits firms can acquire on the side of learning when engaging in strategic alliances (Stuart, 2000), especially in rapidly changing high-technology fields (W. W. Powell, Koput, and Smith-Doerr, 1996).

The gradual accumulation of external information and capabilities enabled by network participation can improve firms' market position on both national and international scales (Coviello and Munro, 1995; Zhou, Wu, and X. Luo, 2007). Companies can rely on network resources to gain the experience and credibility required to expand their market share or enter new domestic or foreign markets (Rubino, Vitolla, and Garzoni, 2019; Laurell, Achtenhagen, and S. Andersson, 2017). Marketing networks provide access to better market information and may activate distribution alliances or client procurement mechanisms (Lechner and Dowling, 2003). When partnerships involve firms operating at the same stage of the supply chain, the partners can share their client base or enhance their market power by acting jointly. Firms can reach a more stable and advantageous position if the agreement is established with regular clients instead. Downstream partnerships, involving direct customers, provide access to a better knowledge of existing market needs and enable faster discovery of emerging needs (Parida, Westerberg, et al., 2010).

On the reputational side, affiliation to a group led by a company or organization endowed with considerable legitimacy could in turn bring about an improvement of other members' status and reputation on the market (Podolny and Page, 1998; Baum and Oliver, 1991).

Firms can find great support in inter-oganizational networks, especially when operating in emergent and growth-stage markets (Hambrick, MacMillan, and Day, 1982; Eisenhardt and Schoonhoven, 1996). Emergent markets are highly uncertain and may take a long time to become visible, thus, companies may need to rely on external resources (e.g. financial ones) to survive and improve their position. Dynamic growth-stage markets instead require firms to keep a degree of flexibility, ensured by network-shaped organizational forms as opposed to vertically integrated ones. Moreover, as already stated, networks provide access to skill-based resources shortening the time needed for their acquisition. Hence, when embedded in a strong web of ties, networking firms are given a chance to strengthen their market position (Hagedoorn, 1993) with expected benefits as regards turnover.

Networking firms can also benefit from production synergies and are able to adopt cost-containment practices. As the effect of resource pooling, companies share risks and can reach economies of scale, typical of joint production agreements, and scope, enabled by the joint utilization of equipment and knowledge (Shan, 1990; Jarillo, 1988; Oughton and Whittam, 1997). By going hybrid, firms that lack the resources to integrate can experience the benefits usually associated with a larger size and exploit inter-firm complementarities (Ménard, 2012). Moreover, with respect to vertically integrated units where several steps of the value chain are internalized, a network-based organization can bring the benefit of economies of specialization and experience (Grandori and Soda, 1995).

Supported by enduring connections, firms, by pooling resources, can afford the expensive and continuous development of new products with a short life-cycle or can secure the supply of complementary inputs and services under favorable conditions (W. Powell, 1990). Given the opportunity to reach cost economies and cost savings while cooperating in input activities (Oughton and Whittam, 1997), firms are expected to undergo an improvement in operating income, as proxied by value added and EBITDA (earnings before interest, taxes, depreciation and amortization).

As a possible counterbalancing effect, since networks imply the establishment of binding long-term relationships within a circle of selected partners, networking firms may find themselves committed to unproductive alliances missing the chance to connect to other valuable firms (Gulati, Nohria, and Zaheer, 2000). Cooperation can be curbed by the lack of strategic or organizational fit among the participants (Kale, Dyer, and H. Singh, 2002) or because of the inability to manage conflicts (Doz and Hamel, 1998). Firms engaging in strategic alliances find themselves exposed to the so-called relational risk (T. Das and Teng, 1996). It is the risk that network members do not fully commit themselves to a shared strategic purpose and pursue their own interest by adopting opportunistic behaviors[5] (Williamson, 1993). For instance, firms may seek to steal partners' superior knowledge and technology at the cost of their counterparts (Hagedoorn, 1993; Panico, 2017). Entrepreneurs may be forced to share proprietary assets (Shan, 1990), lowering their expected returns and exposing themselves to the risk of a possibly damaging misappropriation by their partners (Katila, Rosenberger, and Eisenhardt, 2008). Effective control mechanisms are therefore required to deter opportunism and align partners' behaviors in accordance with mutual expectations and common goals in a long-term perspective (T. K. Das and Teng, 1998). Contractual control is suited for the purpose. At the same time, given the inherent complexity of strategic inter-firm relationships and the high uncertainty of future contingencies and outcomes (Cafaggi, 2011), formal

[5] For further details, please, refer to paragraph 1.2.2.

enforceable contracts should be flexible enough to secure lasting connections and adapt to the specific needs of the parties[6].

The risk of opportunistic behaviors and aggressive appropriation tactics is not the only threat to inter-firm alliances. Even a full commitment to the agreement does not guarantee the achievement of the network's objectives. Indeed, the so-called performance risk involves the probability of not meeting the alliance's strategic goals (T. Das and Teng, 1996), at least in the short term, possibly due to the intrinsic uncertainty and complexity of the shared activities (Tether, 2002). Inter-firm alliances devoted to strategic purposes are, by nature, time-related phenomena. As such, they may fail to deliver noticeable results in the short term (Rosenfeld, 1996). Relationships take time to consolidate as firms' confidence in partner cooperation matures gradually from the interplay of formal control mechanisms and trust (T. K. Das and Teng, 1998). The gradual emergence of network outcomes over time is strongly affected by the speed at which learning takes place. Mutual learning enabled by the acquisition of partners' know-how is among the engines of firms' alliances (Stuart, 2000; Gibb, 1997). The acquisition of external technological know-how creates the opportunity to enter new market segments (Mitchell and K. Singh, 1996), expand on international markets at lower risks (Zhou, Wu, and X. Luo, 2007), and introduce incremental organizational advancements with subsequent efficiency gains (Haned, Mothe, and Nguyen-Thi, 2014). However, learning is expected to deliver effects beyond the short-term horizon (Huggins, 1998). Knowledge takes time to be absorbed and, given its cumulative nature, is associated with increasing returns over time (Latham and Le Bas, 2006). The act of learning favors itself a more efficient accumulation of external knowledge through subsequent periods (Cohen and Levinthal, 1990). This implies an incremental improvement of firms' capabilities in managing performance-enhancing technologies and innovations over time (Dyer and H. Singh, 1998).

Partners' experience, gained as the result of a continuous learning process, can be exploited to improve inter-firm coordination (Reuer and Ariño, 2007). Network members only gradually converge to the opti-

[6] Please, refer to paragraph 1.2.2 for more details.

mal coordination of the activities they are committed to (Gulati, Wohlgezogen, and Zhelyazkov, 2012). In the post-formation phase of an alliance, network members must generally face high coordination costs, due to the complexity of the tasks and strong interdependencies implied by the strategic nature of cooperation (Gulati and H. Singh, 1998). The more partners' complementary resources are interdependent, the higher the degree of organizational complexity permeating the relationship (Thompson, 1967), and the greater the subsequent costs. Right after a network formation, participants may still have to learn about their partners' attributes, and their joint tasks' coordination requirements (Gulati, Wohlgezogen, and Zhelyazkov, 2012; Reuer, Zollo, and H. Singh, 2002). Hence, the partnership takes more time to reach fruition and create value (Dyer, H. Singh, and Hesterly, 2018). As the partners develop a more accurate understanding of other members' resources, capabilities, structural idiosyncrasies and reciprocal interdependencies, they undertake organizational adjustments to improve the efficiency and effectiveness of coordination mechanisms inducing performance enhancements (Zollo, Reuer, and H. Singh, 2002). Better coordination could be attained over time by revising the division of labor (Reuer, Zollo, and H. Singh, 2002), developing joint problem-solving routines (Faems et al., 2008), or improving communication channels (Stuart, 1998). As the partners invest in relation-specific assets and coordination routines to enhance compatibility, the strategic cooperation starts delivering increasing value (Dyer, H. Singh, and Hesterly, 2018).

Empirical evidence on network initiatives sponsored by public authorities[7] supports the hypothesis that strategic networks yield delayed returns (Rosenfeld, 1996; Huggins, 2001).

Based on the aforementioned arguments, we posit the following hypotheses:

> Hypothesis 1a: *participation in formal networks positively affects firms' revenues and operating income*

[7] Further information on international networking policies is provided in paragraph 1.2.3.

Hypothesis 1b: *formal networks' benefits tend to emerge and grow over time*

The intrinsic relational nature of inter-firm networks suggests the idea that idiosyncratic relationships are the fundamental engine of firms' competitive advantage (Dyer and H. Singh, 1998; Mesquita, Anand, and Brush, 2008). The uniqueness of dyadic or multiple interactions developed within a network is deemed to drive the chance to reap relational rents (Dyer and H. Singh, 1998). The mere fact of belonging to a network couldn't be enough to understand its potential. The singularity and specificity of enduring connections, as well as their subsequent outcomes, are conditioned by partners' peculiar characteristics and how they combine (Stuart, 2000). Hence, potential network impacts are expected to show a degree of heterogeneity depending on the interplay between partners' specific profiles, starting from their size (Burgers, Hill, and W. C. Kim, 1993).

Smaller firms, curbed by resource constraints, have sought to exploit collaboration with external partners to face an increasing level of inter-firm and cross-boarded competition (Narula, 2004). The growing importance of networking to sustain small firms' competitiveness has also raised policymakers' awareness and soon became a widely debated topic[8]. Such commitment is well understood if we consider small and medium-sized enterprises' contribution to European economic development[9] (European Commission, Executive Agency for Small and Medium-sized Enterprises, Murphy, et al., 2021). Despite their critical role (European Commission, Executive Agency for Small and Medium-sized Enterprises, Schroder, et al., 2020), SMEs generally suffer from limited human, structural and financial resources if compared to larger firms. This makes them more vulnerable to external shocks like the one triggered by the 2008 financial crisis (OECD, 2009) or by the recent COVID-19 pandemic (Juergensen,

[8]Refer to `https://www.oecd.org/cfe/smes/thebolognacharteronsmepolicies.htm`.

[9]In 2019, almost 61% of the increase in value added and 70% of the increase in employment recorded in EU countries' non-financial business sector was delivered by SMEs. In 2020 micro, small and medium-sized enterprises accounted for 99.8% of all enterprises based in EU countries active in the non-financial business sector.

Guimón, and Narula, 2020).

When stand-alone smaller firms fail to differentiate and operate in a context where economies of scale or scope are crucial to succeed, they struggle to survive the competition of larger and more efficient enterprises (Gomes-Casseres, 1997). Larger firms, endowed with resources that secure a sustainable competitive advantage (J. Barney, 1991), can create entry barriers to prevent smaller ones from competing in the market. To ground their strength on the availability of superior resources, SMEs can rely on networking practices. In so doing, small firms concerned with retaining and strengthening their market position can access complementary resources (Stuart, 2000), integrate diverse skills, share risks (Tether, 2002) and improve their revenue potential (Parida, Westerberg, et al., 2010). Inter-firm connections can provide SMEs with additional production capacity and cash (Gomes-Casseres, 1997). Network ties are also a channel to acquire information on new technologies and manage technological change to keep up with larger enterprises (Julien, 1995).

It is not always the case that smaller firms need to improve their scale and scope by joining network alliances. Indeed, the urgency of connecting to reach cost economies depends on the context in which firms operate and on the nature of competition (Gomes-Casseres, 1997). Nevertheless, even when the scale of operations is not a primary concern, SMEs can reap relevant benefits from inter-firm networks to integrate their knowledge, capabilities and the endowment of technological, physical and financial resources (Martin, Romero, and Wegner, 2019).

A partnership's value-creation potential can be better understood by examining the idiosyncratic interplay of network members' features and resources (Dyer and H. Singh, 1998) without confining the analysis to the single participating firm. Indeed, if access to tangible and intangible resources is one of the main reasons why smaller firms engage in network alliances, we expect that partners' specific characteristics affect the strategic potential of the relationship and condition the value of an alliance portfolio. Thus, well-endowed firms, like larger ones or those showing extensive market coverage, are eligible to be highly valuable partners (Stuart, 2000). Associates with a more consolidated market position and a significant revenue stream can facilitate entry into market niches or share their customer base delivering enhanced benefits to smaller firms. Larger firms often have well-developed marketing, sales, distribution and financial resources that they can share with smaller partners (S. A. Alvarez and J. B. Barney, 2001). SMEs do not need to increase their size or make expensive investments to reach international markets or experience the advantages of volume manufacturing (Doz, 1987). Mimicking the typical patterns of industrial districts, focal firms (usually larger ones) establish enduring connections with smaller units and share superior information on market trends or act as a customer themselves (Boari, 2001). Smaller firms are stimulated by larger partners and challenged to escape inertia and change their strategy if needed.

Connecting with well-known larger partners also brings a reputation gain (Podolny and Page, 1998). The choice by a prominent firm to start a stable partnership with another enterprise acts as a quality endorsement, which is especially useful for smaller firms in a weaker competitive position.

Network diversity driven by partners' characteristics and identity enables the exchange of diverse knowledge, competencies and experiences for the benefit of all participants, especially in high-technology fields (W. W. Powell and Grodal, 2005). Firms can compete globally through the exploitation of dissimilar but complementary skills and resources (Goerzen and Beamish, 2005) combined with non-redundant information (Rauch et al., 2016). Through contact with diverse partners, firms can expand their boundaries and embrace development-oriented strategic paths (Parida, Westerberg, et al., 2010). Excessive diversity could become too costly to manage, though (Lavie, Haunschild, and Khanna, 2012). Small firms in particular may lack the basic resource endowments or managerial capacity to acquire and assimilate the assets provided by larger partners (Parida, Patel, et al., 2016). Then, SMEs may struggle with the high search, coordination and monitoring costs entailed by a complex organizational structure (Goerzen and Beamish, 2005).

Moreover, when connecting to larger enterprises, smaller firms may take on more of the risk implied by the cooperation (Street and Cameron, 2007). In high-technology alliances, with smaller firms providing specialized technological competencies in exchange for larger firms' market and financial support, uneven dynamics are raised by the different rates at which smaller and larger firms can imitate or learn about their partners' resources (S. A. Alvarez and J. B. Barney, 2001). Indeed, while larger firms can learn about the new technologies developed by their partners, smaller firms can't easily imitate large firms' organizational resources and capabilities, including their market stance. However, larger firms' capabilities may be overrated: they may not be capable of commercializing new technologies, causing the alliance to fail to deliver positive returns (Doz, 1987). SMEs tend to be concerned about losing control over their technologies and resources (Narula, 2004). Proprietary technologies made available by smaller firms could be exploited in ways that are not agreed in advance (Gomes-Casseres, 1997), increasing the risk that much of the value stemming from cooperation is appropriated by larger firms (Sulej, Stewart, and Keogh, 2001). Besides, informal control mechanisms and poor governance of the relationship can lead to an uneven distribution of the gains yielded by networks (Gomes-Casseres, 1997). These issues can be exacerbated by the lack of strategic overlap. Firms can be moved by divergent strategic purposes dictated by heterogeneous needs, and the lack of mutual understanding brought about by communication breakdowns can make it hard to achieve mutual benefits (Doz, 1987). The employment of enforceable formal agreements which can flexibly discipline cooperation through a clear definition of partners' rights, duties, mutual obligations, and shared goals provides a solution to mitigate the drawbacks of network partnerships between larger and smaller enterprises (S. A. Alvarez and J. B. Barney, 2001).

Hence, despite the potential difficulties raised by firms' diverse managerial styles or by their unbalanced value appropriation capacity (Lavie, 2007), legally secured connections to larger partners provide smaller firms with competitive and efficiency advantages that outweigh the additional costs of heterogeneity.

Given the aforementioned arguments, we develop the following hypotheses:

> Hypothesis 2a: *smaller firms experience stronger positive effects from participating in formal networks than larger enterprises*

> Hypothesis 2b: *smaller firms engaging in a formal network relationship with at least one larger partner experience stronger positive effects than smaller enterprises with no larger partner*

The unique identity of the relationship and its potential contribution to firms' performance are also determined by the network's geographical concentration and the resulting proximity of network partners (Dyer and H. Singh, 1998; Dyer, 1996; Enright, 1995). Regional scholars have widely discussed the importance of spatial proximity in shaping firms' activity and competitiveness (Lychagin et al., 2016; Morgan, 2004), grounding their arguments on pioneering studies about agglomeration economies (Marshall, 1890). Although the spread of information and communication technologies (ICT) has eased inter-firm cooperation on a broader geographical scale, firm performance is found to be still affected by localized relationships (Amato, Pieroni, et al., 2021).

Co-location is assumed to condition the outcome of cooperation agreements among nearby firms as it triggers the activation of spatial externalities and external economies (Van Oort et al., 2012). First, partners' location in the same geographical area enables information flows and knowledge spillovers (Enright, 1995).

Knowledge spillovers facilitated by geographical proximity represent a primary source of location advantages for nearby enterprises (Audretsch and Feldman, 1996). The intentional and unintentional knowledge flows enabled by geographical closeness and facilitated by face-to-face recurrent interactions (Breschi and Lissoni, 2001a; Harabi, 1997), foster the diffusion of new ideas or improvements and affect co-located firms' performance (Van Oort et al., 2012). Learning processes and knowledge exchanges are eased by proximate partners' positive attitude towards collaboration animated by prior knowledge of one another and mutual esteem (Mellewigt, Madhok, and Weibel, 2007) and the activation of direct communication channels (B. r. T. Asheim, 1996). Informal and recurrent contacts among firms may also encourage the exchange of market information, which in turn allows firms to serve their customers better and consolidate their market position (Parr, 2002b). Labour mobility is regarded as one of the main channels through which knowledge diffuses across enterprises (Kesidou and Romijn, 2008). Workers' mobility reinforces social cohesion between plants and consolidates social ties, thus favoring the transfer of knowledge and information (Eriksson, 2011; Dahl and Pedersen, 2004).

Frequent contacts and exchanges among nearby partners allow for better managing the organizational and coordination complexities permeating strategic alliances (Ring and Ven, 1992). The high interdependence of networking firms' joint activities exacerbates coordination costs and requires a constant exchange of information, especially in the post-formation phase of the alliance (Gulati, 1998). Direct communication channels activated within highly-connected communities and firms' prior knowledge of their neighbours can mitigate the problem and favor the convergence toward efficient coordination routines (Enright, 1995; Gulati, Wohlgezogen, and Zhelyazkov, 2012; Mellewigt, Madhok, and Weibel, 2007). Cooperation between proximate firms can be enforced by informal mechanisms based on personal esteem, shared values, and vision, which typically binds members of regional communities together (Rinaldi and Cavicchi, 2016; Huggins, 2000).

Concerning the acquisition and employment of resources, the spatial concentration of partnering firms' activities may bring the advantages ascribed to agglomeration economies (Parr, 2002a). When cooperating to perform different steps of the production process, geographically proximate firms can reach economies in transportation costs or cut inventory costs by agreeing on implementing a just-in-time system (Parr, 2002b). Moreover, nearby enterprises can economize on acquiring inputs from specialized local suppliers (e.g., warehousing services or specialized business services) and share local infrastructures and facilities (Puga, 2010).

Hence, proximate firms could leverage their geographical closeness to reinforce the expected benefits of networking. However, on the other hand, if the enterprise relies excessively on a network of nearby firms, the benefits of co-location could be counterbalanced by the threats of the spatial lock-in effect (Boschma, 2005). When part of an inward-looking community, companies may lose sight of new opportunities and their learning capacity may be weakened (Pouder and St. John, 1996). Extra-territorial connections can be conducive to economic growth since firms are naturally embedded in economic systems which operate on a much broader scale (Lagendijk, 2002). Inter-firm ties overcoming regional boundaries can sustain intense and profitable interactions (Oinas and Lagendijk, 2017).

A mixture of local and non-local ties can help address the disadvantages of getting stuck in a "blind spot" (Oerlemans and Meeus, 2005). Firms engaging in both intra and inter-regional relationships were found to outperform those from the same industry as regards innovation and sales growth (Oerlemans and Meeus, 2005). Intra-regional connections alone, empowered by firms' development potential, support firms' competitiveness, yet, a good balance between regional and external connections is claimed to be a source of significant advantages brought by novel and diversified knowledge (Kaufmann and Todtling, 2000; Sternberg and Arndt, 2001; B. T. Asheim and Isaksen, 2002).

Given the aforementioned competing arguments supporting the relevance of both local connections and inter-regional ties, we cannot formulate a unique hypothesis regarding the consequences of partnering firms' geographical proximity.

1.2.2 The Italian inter-firm network policy

As previously mentioned, despite being a potential source of advantages for participating firms, networks may fail to yield positive effects (Kale, Dyer, and H. Singh, 2002). The mismanagement of inter-firm connections and the wrong design of the network relationships can lead to uneven dynamics that benefit just a few partners at the expense of others (Miles and Snow, 1992).

Competitive dynamics often arise even when firms engage in cooperative relations (Hoffmann et al., 2018). The fear of opportunistic behaviors can induce enterprises to adopt aggressive strategies to claim their control over strategic resources and capture most of the value created through the partnership (Panico, 2017). Network members could leverage dependence asymmetries to strengthen their bargaining power and prevail over their partners. The competitive tension contaminating strategic partnerships may be exacerbated by the lack of a common background and trust between enterprises, hindering network sustainability (Huggins, 2000). As the threat of opportunism hampers inter-firm relationships, the implementation of organizational structures secured by contractual safeguards and enforcement mechanisms is a valuable option to restrict adversarial tactics. The legal setup of network members' rights and duties protects against aggressive value-capture tactics by prominent partners. As anticipated, the relational risk triggered by non-cooperative behaviors comes along with a performance risk (T. Das and Teng, 1996). To mitigate the latter issue, contracts must serve as a coordinating device, favoring the alignment of goals and the harmonization of individual efforts (Mellewigt, Madhok, and Weibel, 2007). The strategic nature of network agreements makes them suitable to serve this purpose.

The Italian legal framework introducing network agreements has provided a solution to formalizing long-lasting inter-firm connections while granting autonomy to the members in regulating their relationships. The discipline of network agreements sets up a broad frame, then, network participants can establish the rules each of them must comply with to fulfill the collaborative duties (Massari, Riggio, and Calace, 2015). Such flexibility allows network members to cope with the high uncertainty affecting inter-firm cooperation (potentially due to non-verifiable contractual behaviors and the impossibility of foreseeing future actions and states of the world), which hampers the establishment of complete contracts regulating behaviors under all possible contingencies (Cafaggi, 2011). The rules that structure network agreements can be completed and integrated as needed.

The policy is an effort to regulate an emerging real-world phenomenon. It is designed to answer the needs of the enterprises engaging in strategic agreements and it is a formal acknowledgment of growing managerial practices (Arrigo and Tassani, 2016).

The Italian legislator recognized the importance of inter-firm networks as a solution to overcome competitive weaknesses affecting Italian enterprises, especially SMEs, in a highly competitive environment (Bugamelli, Cristadoro, and Zevi, 2009; Calligaris et al., 2016), and thus designed a specific legal regime to formalize and encourage long-term network-shaped partnerships (Capuano, Carnazza, and Saracino, 2012).

As stated by law (decree-law n. 5/2009 converted into law n.33/2009 and subsequent amendments), Italian entrepreneurs can formalize cooperative agreements aimed at fostering their innovativeness and competitiveness on national and international markets. In this regard, network participants must declare their commitment and agree on a long-term-oriented plan. The forms of interdependence managed through a network agreement can be based on the exchange of information and inputs and on the integration of reciprocal competencies to perform economic activities jointly (RetImpresa, 2011). Entrepreneurs can sign a network contract regardless of their respective nature, hence, a wide spectrum of legal entities, from individual entrepreneurs to companies and public actors, are allowed to take part in the agreement. The regulation of network agreements allows contracting firms to choose the desired degree of formalization and complexity for the organizational structure and governance (Pastore, Ricciardi, and Tommaso, 2020). Contracting firms have broad negotiating autonomy. Participants can opt for arm's length weak ties (*"rete contratto"*), with a joint body and a joint capital fund, or for strong ties through an agreement with legal status (*"rete soggetto"*). While weak agreements are not required to have structured network governance (albeit still an option), a joint managing body must be set up whenever the agreement requires legal recognition[10]. The framework regulating network contracts allows participants to reach a high degree of integration without the need to establish ownership ties or relocate property rights.

Regardless of the degree of formalization chosen by the entrepreneurs,

[10]Please, see also `https://contrattidirete.registroimprese.it/reti/`.

the network contract must always specify the strategic goals pursued and the set of rights and duties which regulate inter-firm relationships (Angelone, 2013).

Network members are required by law[11] to identify a set of strategic objectives as a formal recognition of the steps needed to achieving higher levels of competitiveness and innovativeness. A clear statement of common goals is geared toward guiding the participants in the governance of common activities and interdependencies.

The legal regime regulating the establishment of contract networks allows setting the duration of the agreement without a clear indication of either a minimum or a maximum term. This mirrors the intention expressed by the policymakers to formally recognize an emerging behavior moved by a strategic purpose. From a possible interpretation of the legal provision, an agreement's duration should be functional to achieving the strategic aim pursued by the participants (RetImpresa, 2012). Again, the realization of a common objective drives the definition of the organizational structure surrounding joint economic activities.

In this, the network agreement departs from other aggregation models provided by Italian law. Among the most widely used coordination modes based on multilateral contracts, there are consortia and temporary associations of enterprises (Bentivogli, Quintiliani, and Sabbatini, 2013). In a consortium[12], several entrepreneurs can set up a common organization for the governance of different stages of their respective businesses. Consortia pursue the aim of favoring member companies leading to economic benefits like cost savings. Through the coordination of common activities, they have the chance to grasp the advantages of cooperation while retaining their autonomy. Though close to network agreements, consortia lack a long-term common plan, and thus they are not motivated by a declared strategic intention or driven by a shared competitive goal[13].

[11] Article 3 of the decree-law n. 5/2009 and subsequent amendments.

[12] The legal framework regulating consortia is provided by the Italian Civil Code. Article 2602, paragraph 1, formulates the definition of the consortium contract.

[13] Article 2603 of the Italian Civil Code indicates the essential elements of the consortium contract. While the contract must include the object and duration of the consortium and

The temporary association of enterprises is another way to formalize inter-firm partnerships, however, this is characterized by a limited scope since it regulates occasional cooperation usually aimed at carrying out large private or public works or participating in public tenders[14]. For this reason, its duration is determined by the time needed to complete the work identified by the participants, hence it is not intended to manage long-term partnerships established for strategic purposes. Both consortia and temporary associations of enterprises are constrained by a limited scope. They are purpose-related aggregations focused on the achievement of a particular target (e.g., cost economies, participation in public contracts) or the management of specific operations (Massari, Riggio, and Calace, 2015). As such, they both lack a strategic coordination function.

The flexibility of network agreements distinguishes them from European Economic Interest Groups (EEIG)[15] as well. Though EEIGs members are not required to be entrepreneurs, they must be based in at least two countries within the European Union. Firms can sign a network contract regardless of their geographical location (Camere di Commercio, 2017). Network-shaped formalized partnerships can be entirely based in the same geographical unit or span across several regions with the purpose of connecting firms located in different territorial settings.

Hence, the strategic nature of the network agreements emerges as the peculiar feature which differentiates them from alternative multilateral coordination modes. The network contract structures long-term oriented partnerships and outlines the essential elements that fuel cooperation, among which are strategic objectives, the tasks to be accomplished, individual responsibilities, decision rights and mutual expectations (Mellewigt, Madhok, and Weibel, 2007). Conceived to enhance the competitive power and innovative capacity of its members, network

the obligations assumed by each member, there is no explicit reference to the establishment of common strategic goals and a program as required in the case of network agreements. Please, see also `http://www.vt.camcom.it/Pb/Filez/1339575761K948820.pdf`.

[14] In the Italian legal system, temporary associations of enterprises represent atypical contracts.

[15] The legal framework of the EEIG is provided by the EC Regulation n. 2137/85. Then, the implementation of some provisions was deferred to EU member states.

agreements pursue the objectives typically ascribed to lasting strategic cooperation, e.g., providing access to tangible and intangible resources (Grandori, 1997), triggering learning processes (Inkpen and Tsang, 2005), enhancing legitimacy on the market (Zhou, Wu, and X. Luo, 2007), sharing risks and costs (Oughton and Whittam, 1997).

Although strategic cooperation can also be pursued through a lower degree of formalization of the partnership, self-enforcement mainly driven by trust, reputation and reciprocity does not guarantee the sustainability of cooperation in the long run (Cafaggi, 2011). Network agreements secure lasting strategic interactions by serving as a control and coordinating device (Mellewigt, Madhok, and Weibel, 2007).

1.2.3 Empirical evidence on networking policies

The Italian policy on network agreements has been designed to transpose the guidelines of the Small Business Act into concrete interventions. This is a clear recognition of SMEs' importance for the Italian economy given their contribution to employment and GDP[16] (Ministero dello Sviluppo Economico, 2011; Ministero dello Sviluppo Economico, 2016). The Italian legislator promptly addressed the emerging phenomenon of inter-firm networks by introducing a regulation dedicated to encouraging strategic inter-firm cooperation.

However, several business network programmes had been introduced over recent decades before the European Commission renewed its commitment to supporting SMEs growth through the Small Business Act. Among the first interventions, we recall the Danish programme started in 1989, an initiative sponsored by the Industry Ministry and delivered through the Danish Technological Institute (Chaston, 1995). Network formation was facilitated by a team of trained brokers, and each established network received financial support for specific projects. Drawing on this experience, similar interventions were implemented in Norway (the programme covered a period of eight years to 1998), Australia (started in 1995 and sponsored by AusIndustry[17]) (Porras, Clegg, and

[16] Acronym for gross domestic product.

[17] AusIndustry is the Australian Government's business program de-

Crawford, 2004) and Canada (lasting three years to 1998 and ran by several business associations led by the Canadian Chamber of Commerce). Most of these policies were driven by the needs of small and medium-sized companies.

As pointed out in the mid-term evaluation of the Danish network programme (Gelsing and Knop, 1991), around 75% of surveyed participants stated to have increased their competitiveness after joining a network, while 42% of firms reported higher revenues and 19% declared cost savings.

Similar policies were also set up in the United States. In the '90s, the Oregon Economic Development Department sponsored a network initiative modeled on the Danish programme with the goal to "encourage firms to join together to solve mutual problems, cut costs, and access new markets" (Rosenfeld, 1996, p. 252). Grants were awarded to groups of firms cooperating on a common project. From an early evaluation of the program, time constraints and the failure to realize benefits in a short time emerged as the major obstacles faced by network participants (Rosenfeld, 1996). This suggests that inter-firm networks need time to consolidate lasting relationships and yield observable results. Oregon's policy was compared to another program sponsored in 1990 by the Northwest Area Foundation (Minnesota). The initiative was meant to encourage network formation and inter-firm cooperation for the economic development of rural areas. The program's evaluation[18], carried out over three years, collected the opinions of participant firms: the majority claimed to have experienced a growth in sales, employment, and domestic market share since the program started. However, due to the lack of proper tools to estimate network impacts, the respondents were careful not to attribute the entire benefit to inter-firm cooperation. Nevertheless, after two years of networking, one out of five respondents had reduced their operating costs. On the other hand, daily business pressure

livery division in the Department of Industry, Innovation, Science, Research and Tertiary Education. For further information, please see `https://www.industry.gov.au/policies-and-initiatives/ausindustry-services-for-australian-businesses-and-industry`

[18]Survey-based evaluation.

and the failure to realize benefits in the short term were seen as barriers to collaboration.

Using a quantitative approach and objective measures, Schoonjans, Van Cauwenberge, and Vander Bauwhede (2013) provide empirical evidence on the PLATO network program, an initiative subsidized by the Flemish government and organized by a professional association of Flemish companies, the VOKA. The program addressed small and medium-sized companies and was designed to stimulate the exchange of knowledge, experience and establish long-lasting connections through regular meetings. This approach aimed at building trust and motivation to improve the relational embeddedness of participating firms. Firms involved in the PLATO program were found to have higher net assets and value added growth, suggesting that networking was positively correlated with their economic development.

Mixed findings come, instead, from the evaluation of networking initiatives promoted in the United Kingdom. New inter-firm network formation was encouraged in the UK by the Training and Enterprise Councils (TECs) and their partner organizations (Business Links, and regional development agencies). The initiatives were set up to further the generation of both informal networks (to facilitate the share of knowledge, information and skills through informal interactions) and contract-based formal networks to carry out joint activities. From a survey-based evaluation of the interventions, mixed results emerge (Huggins, 2001): only 23% of the respondents reported to have experienced even a moderate benefit on the side of sales and market shares with 44% of the firms indicating no perceived gain (66% of respondents if we isolate formal network participants). This could be partially due to the fact that enterprises seem to be disappointed when gains are not realized in the short term, contrary to expectations. Participating companies rather perceived an improvement in learning capabilities. While 43% of firms declared that network participation had not helped them become more competitive, around half of the firms who had established fairly intensive interactions found that the network experience had improved their performance. Hence, the intensity of the engagement and the commitment of the participants over a sustainable period are found to play a role in affecting network outcomes. Firms committed to a formal network claimed to have experienced a decrease in operating costs. Formal sustained relationships boosted and sustained by trust-based informal intensive interactions seemed to provide a valuable contribution to the economic development of participating firms (Huggins, 2000; Huggins, 1998).

This overview, albeit non-exhaustive, reveals that inter-firm networks sponsored by public authorities or private foundations yield positive results at least under specific conditions. However, we must point out that most of the aforementioned empirical evidence from surveys may have been affected by the subjective perceptions of the respondents.

The Italian intervention, designed to comply with the best practice from the Small Business Act, does not rely on a group of brokers but introduces a legal tool to encourage the establishment of spontaneous and stable aggregations providing a clear regulation of internal relationships. Notwithstanding its recent introduction, the policy has already caught the attention of scholars and representatives of private and public institutions.

Italian network agreements are found to have a positive impact on participant firms' turnover growth (Burlina, 2020) and employment growth (Dickson et al., 2021; Cisi et al., 2020).

Membership in a network agreement was found to be positively associated with firms' gross margin ratio (value added per unit of sales) and export propensity (Cisi et al., 2020). Empirical studies on networking firms' profitability unveiled a complex picture with no significant association, on average, between ROA and participation in formal agreements (Cisi et al., 2020). However, when the focus turned to network members only, firms' ROA was found to be related to agreements' size and composition (Rubino and Vitolla, 2018). Then, early descriptive studies already suggested a potentially positive association between network agreement participation and EBITDA (Foresti, Mangolini, and Ferrero, 2014).

Despite the growing interest raised by the Italian policy among scholars and practitioners, the persistence of network agreements' impacts remains largely unexplored, partly due to the recent introduction of the policy, which did not allow observation of treatment effects in the long run. Most studies investigating the performance gap between firms in a network agreement and firms never joining an agreement rely on observational data going no further than 2015 (Cisi et al., 2020; Rubino, Vitolla, and Garzoni, 2019; Costa, Luchetti, and Romano, 2017; Foresti, Mangolini, and Ferrero, 2014; Dickson et al., 2021). As few units signed an agreement before 2012, this implies that the vast majority of enterprises in a network agreement are observed for no more than three full years into the treatment.

Moreover and most importantly, we have a paucity of evidence on the evolution of network agreements' effects over time. Early insights come from Costa, Luchetti, and Romano (2017), who claim that network impacts on revenues and employment growth tend to increase with the length of exposure to the treatment. Still, the analysis covers a limited time frame (firms first treated in 2011 are observed for at most four years into the treatment), and more insights are needed to highlight networks' implications over time.

Early empirical insights on network agreements seem to suggest a higher gap in operational efficiency and revenue growth between networking and non-networking firms when it comes to smaller firms. SMEs with less than 50 employees are found to display a greater increase in value added per unit of sales compared to larger SMEs (Cisi et al., 2020). Consistently, another study claimed that family-owned firms showed higher value added per unit of sales when in a network agreement, with the magnitude of the effect decreasing as the size of the firm increases (Aiello et al., 2023). Then, participation in network agreements has been shown to have stronger impacts on micro-enterprises revenue growth compared to medium-sized enterprises (Costa, Luchetti, and Romano, 2017). Conversely, the increase in export share associated with membership in a network agreement is found to be lower for smaller SMEs compared to larger ones (Cisi et al., 2020). We are mentioning average estimates that do not account for the attributes of smaller firms' partners, though.

To the best of our knowledge, we still have a paucity of evidence on the heterogeneity of network impacts driven by partners' size diversity. An early examination of the relationship between network size diversification and performance carried out on networking firms only does not allow for inferring heterogeneity in causal effects (Cantele and Vernizzi, 2015). Further evidence is needed in this regard.

The empirical investigation of the Italian network policy shed light on the relationship between networks' structural features and the performance of participating firms. Network size, i.e. the number of units involved in the agreement, is among the main drivers of member firms' performance (Cisi et al., 2020; Burlina, 2020; Cantele and Vernizzi, 2015). The geographical openness, or dispersion, of network agreements has been found to negatively affect participating firms' performance (Cisi et al., 2020; Rubino and Vitolla, 2018) although, the impact of networking firms' spatial location on financial outcomes has not always turned out to be statistically significant (Cantele and Vernizzi, 2015).

In exploring the implications of network agreements' geographical dispersion, most empirical works confine the estimation sample to the treated group only, namely the set of firms taking part in a network agreement (Rubino and Vitolla, 2018; Cisi et al., 2020; Cantele and Vernizzi, 2015). The analyses study how networking firms' performance varies as a function of networks' geographical dispersion, but further assessments are needed to provide a causal interpretation of the results. Furthermore, network agreements' spatial concentration is assessed based on the geography of administrative units (NUTS1, NUTS2 or NUTS3 areas). A territorial partition defined on a functional basis is assumed to better capture the benefits of co-location ascribed to spatial externalities. The functional geography of travel-to-work areas[19] (TTWAs) seems to be suited for the purpose[20].

Our work contributes to the empirical literature on network agreements by providing insights into the evolution and persistence of formal strategic partnerships' causal effects on firms' performance. In addition,

[19]Please, refer to `https://www.istat.it/en/labour-market-areas`.
[20]For further details, please, refer to paragraph 1.5.1.

we unveil whether and how the expected benefits of formal network agreements change in magnitude depending on the idiosyncratic combination of partners' profiles.

1.3 Data

To perform our analysis we rely on two main data sources. Network agreements' data are provided by Unioncamere (Italian Union of Chambers of Commerce, Industry, Handicrafts and Agriculture), the public institution representing all Italian Chambers of Commerce[21]. The dataset lists all the contracts signed until March 2015, including both agreements with and without legal status. We focus on the latter group since it comprises most of the contracts signed at the time: just 222 out of the 1,960 agreements included in the sample have legal status. Besides, the selection of network agreements without legal status allows us to build a treated group that is subject to the same regulation and accounting rules[22].

For each contract, we observe the starting date as well as the year of each subsequent modification of the original legal act. Then, we have the list of all participants along with further information on their main location (province - NUTS 3 region - and municipality), economic activity (industry according to the ATECO 2007 classification), and identity number (tax code). The database comprises 1,960 network agreements (1,738 soft agreements without legal status) involving 10,270 firms in total.

Accounting firm-level data have been drawn from AIDA - Bureau Van Dijk[23] database, a source providing information on the population of Italian private companies required by law to disclose their financial

[21]Raw network contracts' data have been collected by Infocamere and pre-processed by Unioncamere, leading to a well-structured database which has been our reference point throughout the empirical analysis. Infocamere is the IT company that supports the Italian Chambers of Commerce managing all digital content and providing technological services.

[22]Our choice allows us to assure treated units are subject to a homogeneous legal regime. There are, indeed, some minor differences in the accounting rules firms in network agreements with and without legal status must comply with. For further information, please refer to Antonello (2014)

[23]For further information see `https://www.bvdinfo.com/en-gb/`

statements.

For the purpose of this study we collected data for a set of Italian manufacturing and service firms, ending up with an initial sample comprising around 1 million units[24]. We obtained an unbalanced panel including observations for the period 2010-2018.

We followed some data cleaning procedures, specifically excluding the observations falling in the upper and lower one percent of the distribution of firms' revenues, EBITDA (earnings before interest, taxes, depreciation and amortization) and value added[25], namely, the main target variables employed in the analysis. In addition, we removed from the sample all the units showing negative revenues (strictly lower than zero), to avoid potential anomalies. We narrowed down the sample by selecting the firms that were still active at the end of 2018 (the last period covered by the panel) or later.

Our analysis focuses just on the agreements signed between 2011 and 2014 so that, for each we have accounting data for at least one year before and four years after their start. A shorter time horizon would not have allowed us to observe the effects induced by the contract on firm performance (Rosenfeld, 1996; Foresti, Mangolini, and Ferrero, 2014).

Since the dataset by Unioncamere includes statistics on network contracts updated until March 2015, we checked this against Infocamere's datasets (updated to June 2019[26]) to ensure that the sample only contained the units that signed a contract in the period 2011-2014 and were still in a network at the end of 2018. This allows us to have a setting with an absorbing treatment (Sun and Abraham, 2020).

[24]Since AIDA provides data on the population of Italian private companies required by law to disclose their financial statements, limited liability companies are better represented in the dataset than other legal entities (e.g., individual entrepreneurs or personal liability companies). Almost the 92% of our estimation sample is represented by limited liability companies.

[25]We test our hypotheses using revenues, value added and EBITDA as outcome variables. The first variable measures annual revenues from sales of goods and services; value added is computed as the difference between revenues and non-labour costs of inputs, while EBITDA measures the firm's operating income before non-operating costs and specific non-cash costs (i.e., depreciation and amortization). All three variables are expressed in logarithmic units.

[26]Depending on data availability.

Finally, we removed the firms participating in a contractual network with legal status to rule out the chance of including them mistakenly in the control group. For the same reason, we dropped the firms that withdrew from an agreement before the end of 2018.

Our final sample comprises 579, 464 firms. The dataset includes 3, 187 firms participating in a contract network[27] that have signed the agreement between 2011 and 2014.

Table 2 shows the frequency distribution of treated and control units by industries as codified according to the Ateco 2007 classification of economic activities[28]. The manufacture of metal products (2-digits code 25) and the provision of technological services (2-digits code 62) appear at the top of the list for the number of treated units. Table 17, appendix A, compares the geographical distribution across the Italian NUTS2 regions.

Table 1: Established network agreements (Net. Agr.) and participants joining a network agreement by year

	Net. Agr. established by year			Participants joining a Net. Agr. by year		
	Without legal status	With legal status	Total	Without legal status	With legal status	Total
2010	25	0	25	136	0	136
2011	218	5	223	1,001	97	1,098
2012	409	23	432	2,118	113	2,231
2013	637	70	707	2,999	614	3,613
2014	417	112	529	2,500	805	3,305
2015	32	12	44	251	65	316
Total	1,738	222	1,960	9,005	1,694	10,699

Note: Statistics on network agreements updated to March 2015 (source: own elaboration on Unioncamere data). The number of network agreements established by year and the number of participants joining a contract by year are displayed distinguishing between network agreements with and without legal status. Figures in columns 4 and 5 include all network participants regardless of their legal nature: not only individual entrepreneurs and companies are taken into account but also diverse partners like non-profit associations or universities, whenever present.

[27] A "soft" network not provided with legal status.

[28] The Ateco 2007 classification of economic activities is the national version of the European nomenclature, the NACE Rev.2. For further information see `https://www.istat.it/en/archivio/17959`

Table 2: Treated and untreated units' distribution by industries

	Treated		Untreated	
	Frequency	Perc.	Frequency	Perc.
25 - Manufacture of fabricated metal products (except machinery and equipment)	305	9.57	28,462	4.94
62 - Computer programming, consultancy and related activities	262	8.22	20,612	3.58
43 - Specialised construction activities	229	7.19	47,233	8.20
28 - Manufacture of machinery and equipment n.e.c.	223	7.00	14,373	2.49
46 - Wholesale trade (except of motor vehicles and motorcycles)	216	6.78	98,635	17.12
70 - Activities of head offices; management consultancy activities	199	6.24	31,787	5.52
41 - Construction of buildings	159	4.99	87,873	15.25
10 - Manufacture of food products	154	4.83	12,634	2.19
71 - Architectural and engineering activities; technical testing and analysis	140	4.39	12,864	2.23
82 - Office administrative, office support and other business support activities	108	3.39	21,370	3.71
27 - Manufacture of electrical equipment	85	2.67	4,987	0.87
26 - Manufacture of computer, electronic and optical products	83	2.60	4,227	0.73
22 - Manufacture of rubber and plastic products	76	2.38	5,970	1.04
15 - Manufacture of leather and related products	73	2.29	5,250	0.91
31 - Manufacture of furniture	66	2.07	5,525	0.96
47 - Retail trade (except of motor vehicles and motorcycles)	64	2.01	74,225	12.88
86 - Human health activities	63	1.98	11,802	2.05
13 - Manufacture of textiles	61	1.91	4,617	0.80
Other industries	621	19.46	83,831	14.55
Total	3,187	100	576,277	100

Note: Pre-matching statistics.

1.4 Empirical strategy

1.4.1 Dynamic treatment effects estimation

To test our hypotheses, we estimate dynamic treatment effects in a setting with variations in treatment timing across units (i.e., units receive the treatment at different times) and multiple time periods. A staggered difference-in-differences (Diff-in-Diff) design was best suited to model our data and perform causal inference (Athey and Imbens, 2021). The policy on network agreements brought novelty as it introduced a new

Table 3: Pre-matching descriptive statistics

		Mean	Std. Dev.	Min.	Max.	Obs.
Revenues[1]		6.117	1.836	0.175	10.836	3,167,328
	T	7.391	1.699	0.228	10.832	25,525
	C	6.107	1.833	0.175	10.836	3,141,803
EBITDA[1]		3.802	1.667	-1.423	8.491	2,798,854
	T	4.960	1.620	-1.398	8.478	23,217
	C	3.792	1.664	-1.423	8.491	2,775,637
Value Added[1]		4.764	1.810	-1.097	9.377	3,025,197
	T	6.184	1.632	-0.916	9.364	24,838
	C	4.753	1.807	-1.097	9.377	3,000,359
Employees[1]		1.693	1.245	0	10.423	2,442,770
	T	2.671	1.380	0	10.423	23,998
	C	1.683	1.240	0	10.229	2,418,772
Group size		10.767	294.441	0	39,512	579,329
	T	10.045	68.311	0	1,496	3,184
	C	10.771	295.210	0	39,512	576,145
Age		15.632	13.665	2	157	575,370
	T	25.044	14.620	6	119	3,187
	C	15.58	13.642	2	157	572,183
Independence		0.118	0.322	0	1	579,464
	T	0.105	0.307	0	1	3,187
	C	0.118	0.322	0	1	576,277
Treatment dummy		0.005	0.074	0	1	579,464

Note: Pre-matching statistics. T stands for treated units while C for control units.

[1] Expressed in natural logarithm. Original financial variables expressed in thousands of Euros.

Industry and regional dummies are omitted.

legal tool to regulate inter-firm strategic cooperation. The legal intervention promoted by the Italian policymaker is not expected to affect firms' competitiveness for the very fact of being in force. Firms must adopt the tool to experience its impact. Enterprises can freely choose whether and when to establish an agreement and are deemed to be treated from the very moment they sign the contract. We aim to capture the dynamic effects stemming from taking part in a formal strategic network regulated through a network agreement.

To perform DiD analyses in a more general setting with panel data and a staggered treatment rollout, researchers typically regress the target variable on a time-varying treatment dummy while controlling for

Table 4: Post-matching descriptive statistics: treated vs controls

		Mean	Std. Dev.	Min.	Max.	Obs.
Revenues[1]	T	7.451	1.644	0.262	10.824	24051
	C	7.344	1.681	0.350	10.834	23868
EBITDA[1]	T	4.979	1.579	-1.398	8.471	21699
	C	4.855	1.658	-1.394	8.468	21244
Value Added[1]	T	6.223	1.576	-0.844	9.364	23267
	C	6.020	1.675	-0.924	9.354	22876
Employees[1]	T	2.578	1.227	0	6.730	21902
	C	2.424	1.281	0	6.498	20948
Group size	T	6.394	43.390	0	1226	2797
	C	6.157	31.311	0	751	2797
Age	T	25.174	13.750	7	101	2797
	C	25.380	13.989	7	121	2797
Independence	T	0.104	0.305	0	1	2797
	C	0.109	0.312	0	1	2797

Note: T stands for treated units while C for control units.

[1] Expressed in natural logarithm. Original financial variables expressed in thousands of Euros.

Industry and regional dummies are omitted.

unit-specific and time-specific fixed effects: in this generalized setup the treatment effect is measured by the so-called *two-way fixed effects DiD estimator* (TWFEDD) (Goodman-Bacon, 2021). However, recently, several studies have raised concerns about the causal interpretation of the TWFEDD estimator, especially when assuming treatment effects heterogeneity (Sun and Abraham, 2020; Goodman-Bacon, 2021; Callaway and Sant'Anna, 2020; De Chaisemartin and d'Haultfoeuille, 2020). To better identify the source of potential issues, Goodman-Bacon (2021) shows that the TWFEDD estimator can be expressed as a weighted average of all 2×2 DiD estimators obtained by comparing each treatment group[29] to one another. Among the 2×2 components of the TWFEDD estimator, some are computed by comparing units treated at different times: earlier-treated units are compared to later-treated units, and the former may act either as the treated or as the control group. The author points out that when early-treated units act as controls (when already treated), DiD estimates could be affected by a bias if the average treatment effect varies over time within groups, even if the common trend assumption[30] is met. This could raise concerns, and it is something a researcher should be aware of when interpreting two-way fixed effects estimates.

To observe the evolution of network agreement impacts over the years, we implement an event study design.

Two-way fixed effects linear regressions could be performed even to draw some dynamic effect estimates. The dynamic specification of the model takes the following form:

$$Y_{i,t} = \alpha_i + \lambda_t + \sum_{\ell=-K}^{-2} \mu_\ell D_{i,t}^{\ell} + \sum_{\ell=0}^{L} \mu_\ell D_{i,t}^{\ell} + \varepsilon_{i,t} \tag{1.1}$$

where $Y_{i,t}$ is the outcome variable, $D_{i,t}^{\ell}$ are relative time indicators, μ_ℓ denote relative time coefficients, α_i and λ_t represent unit and time fixed effects respectively, while $\varepsilon_{i,t}$ is the error term. A set of relative periods is generally excluded from the model to avoid common multi-collinearity issues affecting the "fully dynamic" specification in eq. (1.1). For a panel dataset with N units observed for $T + 1$ periods, the set of excluded periods is denoted with: $g^{excl} = \{-T, \ldots, -K - 1, -1, L + 1, \ldots, T\}$.

Although the event study specification may be appropriate to address the issues highlighted by Goodman-Bacon (2021), Sun and Abraham (2020) argue that even dynamic treatment effects estimates stemming from two-way fixed effects regressions can be biased when assuming effects heterogeneity across treatment cohorts. The authors provide

[29]Each group is identified according to the period when the units received the treatment. The group including never-treated units is typically denoted with ∞.

[30]Specifically the author talks about "variance-weighted common trends", which is a generalization of the common trend assumption in a set up with variation in treatment timing.

a decomposition of the coefficient associated with a generic relative period ℓ (μ_ℓ from eq. (1.1)), showing that it can be expressed as a linear combination of cohort-specific average treatment effects for the treated ($CATT$) from both relative period ℓ and other relative periods $\ell' \neq \ell$. This means that the regression coefficient associated with a relative period indicator ℓ may be contaminated by $CATT$ from periods different than ℓ, which are either included in eq. (1.1) or excluded (thus belonging to g^{excl}). This holds true even under the parallel trend assumption and the so-called "no anticipation" assumption[31]. Each generic $CATT_{e,\ell'}$ that enters the computation of μ_ℓ is weighted by a quantity denoted with $w^{\ell}_{e,\ell'}$ which is found to satisfy some properties[32]. In particular, the weights associated with relative periods $\ell' \neq \ell$ included in the econometric specification sum to zero. Hence, by imposing treatment effects homogeneity across cohorts, in a fully dynamic specification, we could rule out any contamination coming from other relative periods included in (1.1) since the weight $w^{\ell}_{\ell'}$ is zero[33].

However, we cannot plausibly support the hypothesis according to which firms entering a network in different years experience the same path of treatment effects. Inter-firm networks' intrinsic heterogeneity and subsequent regulatory updates are likely to induce heterogeneous responses from units engaged in a contractual agreement at different times.

To overcome the issues affecting two-way fixed effects estimates in event studies, Sun and Abraham (2020) propose a new estimation method robust to treatment effects heterogeneity. They introduce an interaction weighted estimator (IW) derived as a weighted average of cohort-specific

[31]Under the no anticipation assumption, we assume that there is no treatment effect in pre-treatment periods. When it holds true μ_l is a linear combination of post-treatment cohort-specific average treatment effects $CATT_{e,l'}$ for all $l' \geq 0$. All terms $CATT_{e,l<0}$ are assumed to be zero, thus, they drop out from the computation of the relative time coefficient. Nevertheless, if we cannot rule out treatment effects heterogeneity across cohorts, μ_l is still subject to a bias.

[32]The subscript e is used to denote the disjoint cohort comprising units which are first treated at the same time, namely at time e, $\{i : E_i = e\}$. The set of never treated units is denoted with $E_i = \infty$.

[33]In this case we could still have contamination from excluded periods, thus the authors suggest to excluding periods with associated zero treatment effects.

average treatment effects ($CATT_{e,\ell}$) where the weights are given by the sample share of each cohort in relative period ℓ. Formally it is:

$$\widehat{v}_g = \frac{1}{|g|} \sum_{\ell \in g} \sum_{e} \widehat{\delta}_{e,\ell} \widehat{Pr}\{E_i = e | E_i \in [-\ell, T - \ell]\} \tag{1.2}$$

where g is a set of relative periods ℓ, E_i denotes the time when unit i receives the binary absorbing treatment for the first time and e identifies the group (cohort) of units which are first treated at the same time, $\{i : E_i = e\}$. The coefficient $\widehat{\delta}_{e,\ell}$ is given by a linear two-way fixed effects regression where relative time indicators are interacted with cohort indicators (with the exclusion of a control cohort C) and it is a DiD estimator for $CATT_{e,\ell}$. Then, each coefficient $\widehat{\delta}_{e,\ell}$ is weighted by $\widehat{Pr}\{E_i = e | E_i \in [-\ell, T - \ell]\}$, namely the sample share of cohort e at relative time $\ell \in g$. The weights are normalized by the size of g. In a "fully dynamic" specification where g is a singleton, we have simply $|g| = 1$.

To empirically assess network contracts' dynamic causal effects, we rely on Sun and Abraham (2020) estimator in eq. (1.2).

We identify four different cohorts defined by the period when the units were first treated, namely the year when a firm signed an agreement for the first time, plus a cohort denoted with the symbol ∞ to represent never treated units, hence we have $e \in \{2011, 2012, 2013, 2014, \infty\}$. We choose the never treated group to act as the control cohort so we set $C = \{\infty\}$. Then, we exclude relative periods −4 and −1 from the econometric specification.

Controlling for firm-specific fixed effects in the first step of the estimation process (i.e., TWFE regression to get $\delta_{e,\ell}$) allows us to deal with unobservable factors potentially affecting the choice to engage in a network agreement (Cisi et al., 2020).

1.4.2 Selection of the counterfactual group

Under the parallel trend and no anticipation assumptions, $\widehat{\delta}_{e,\ell}$ from eq. (1.2) is a consistent estimator for $CATT_{e,\ell}$ and the IW estimator is consistent for the weighted average of cohort-specific average treatment effects, with the share of treatment cohorts at relative time ℓ acting as weights.

The former assumption implies that the average outcome variable of treated and untreated units would have followed parallel paths in the absence of the treatment. However, since firms are not randomly assigned to the treatment but intentionally choose whether to enter a network, a selection bias is likely to occur. Firms tend to self-select into the treatment (Y. Kim and Vonortas, 2014), and network participants are found to show distinctive observable characteristics compared to enterprises never joining an agreement (Confindustria, 2016; Costa, Luchetti, and Romano, 2017), e.g., they are on average larger and older (Bentivogli, Quintiliani, and Sabbatini, 2013). Thus, we cannot assume that treated and never treated units would have shared the same evolution of the baseline outcome if not treated. To overcome this issue, we select a proper counterfactual group by implementing a *propensity score matching* (PSM). Treated and untreated firms are paired on the basis of their probability of participation $P(X)$, that is the conditional probability of joining a network agreement given a vector of observable covariates (Rosenbaum and Rubin, 1983). This allows us to balance the groups on a set of observable characteristics. Then, we assume that conditional on the participation likelihood, the treatment assignment is independent of firm performance as measured by response variable Y_i (Angrist and Pischke, 2008). Matching techniques have been exploited in combination with difference-in-differences estimation to effectively remove the bias stemming from units' self-selection into the treatment, especially when it is contaminated by time-invariant components (J. J. Heckman, Ichimura, and Todd, 1997; J. Heckman et al., 1998).

To narrow the control group, we made use of a set of covariates that plausibly affect the likelihood of entering a network agreement and are potentially related to the response variables. We estimated $P(X)$ relying on a probit model, then implemented the nearest neighbour matching to pair couples that are the closest in terms of the propensity score. We opted for matching without replacement, in other words, any untreated unit could be paired at most with one treated firm.

Our probit specification includes industry (2-digit ATECO codes) and regional (NUTS1 level) dummies to balance the groups on firms' activities and location.

To estimate $P(X)$, we employed data on firms' ownership and group membership. We controlled for the size of the corporate group each enterprise belongs to, measured by the number of firms involved, then we built a dummy variable to identify companies with a high degree of independence according to the *Bureau van Dijk independence indicator*. The *Independence* variable takes value one if the company is held by known recorded shareholders, none of which with more than 25% of ownership or if the firm falls into the category of units that are "independent by nature". Firms' group membership has been previously found to significantly affect the probability of taking part in a network agreement (Costa, Luchetti, and Romano, 2017; Foresti, Mangolini, and Ferrero, 2014), thus, it is reasonably included in the set of observable matching covariates.

Firm-specific ownership data provided by AIDA are time-invariant, thus, they refer to the end of the period observed. However, we assume companies' ownership structure not to have changed significantly over the time span covered by the data (Riccaboni, X. Wang, and Zhu, 2021). We take it as a reference for the whole period.

We reasonably argue that corporate group size and ownership structure are not significantly affected by participation in formalized network agreements. Contractual networks represent a flexible solution to manage strategic inter-dependencies while keeping autonomy and distinct ownership over key assets (Ménard, 2012). Moreover, the legal framework of network contracts allows participants to choose an increasing degree of formalization up to the creation of a legal entity, thus, firms do not need to establish ownership ties to experience the benefits of a higher integration.

Finally, we included among the explanatory variables firms' age and the lagged value of the revenues as recorded one year before the treatment[34]. The latter variable is commonly used to approximate firms' size, a feature that has been found to condition firms' propensity to join a net-

[34]Firms' revenues act also as a response variable. We rely on the practice of including the pre-treatment lag of the response variable in the estimation of units' likelihood to receive the treatment (Biancalani, Czarnitzki, and Riccaboni, 2021).

work (Bentivogli, Quintiliani, and Sabbatini, 2013).

To match treated and control units, we estimated a cross-sectional probit regression for each treatment cohort. We provide matching diagnostics to compare the matched samples and check if they are balanced on the covariates (see table[35] 6).

Table 5 displays VIF values and correlation coefficients for the explanatory variables employed in the binary outcome model. The statistics do not raise any concerns about potential multicollinearity issues.

Table 5: Correlation matrix

	(1)	(2)	(3)	(4)	VIF
(1) Revenues[1]	1.000				1.11
(2) Group size	0.031*	1.000			1.00
(3) Age	0.301*	0.008*	1.000		1.10
(4) Independence	-0.056*	-0.008*	0.034*	1.000	1.01

Note: Pre-matching statistics. Mean VIF equal to 1.05. Statistics obtained on a total of 3, 166, 298 firm-year observations.

Industry and regional dummies are omitted.

[1] Expressed in natural logarithm.

* $p<0.05$

1.5 Results

As the first step of our empirical approach, we pre-processed the data performing a propensity score matching to build a comparable counterfactual group. Table 6 displays pre and post-matching t-test statistics to assess the extent of balancing achieved on the matched samples[36]. The

[35]Probit estimates and detailed matching statistics and are displayed in tables 18, 19 and 20, appendix A.

[36]Balancing diagnostics in table 6 refer to the *full* sample of treated and matched control units. Causal impacts obtained on the corresponding sample are plotted in figure 1 and displayed in table 21, appendix A. Then, as discussed in the following sections, we estimated dynamic treatment effects on several subsamples of networking units identified based on their size and on the composition of the agreements they signed (please, refer to

Table 6: Pre and post-matching t-test for equality of means on matching covariates

	Unmatched/ Matched	Cohorts			
		2011	2012	2013	2014
Revenues at period -1 (ln)	U	14.59 (0.000)	19.03 (0.000)	18.95 (0.000)	13.49 (0.000)
	M	-0.26 (0.795)	-0.14 (0.890)	0.22 (0.827)	-0.22 (0.826)
Group size	U	-0.24 (0.812)	-0.48 (0.631)	-0.54 (0.593)	-0.1 (0.924)
	M	1.02 (0.307)	-0.28 (0.779)	-0.33 (0.739)	0.47 (0.638)
Age	U	6.06 (0.000)	8.73 (0.000)	3.77 (0.000)	4.29 (0.000)
	M	-0.28 (0.781)	0.02 (0.981)	-0.44 (0.663)	-0.48 (0.635)
Age squared	U	3.95 (0.000)	7.15 (0.000)	2.24 (0.025)	-2.75 (0.006)
	M	-0.01 (0.990)	-0.26 (0.792)	-0.42 (0.673)	0.42 (0.677)
Independence	U	1.12 (0.261)	-1.12 (0.261)	-3.18 (0.001)	-2.75 (0.006)
	M	0.32 (0.749)	-0.55 (0.582)	-1.09 (0.275)	0.42 (0.677)
Industry dummies	U	-1.58 (0.114)	-7.36 (0.000)	-4.37 (0.000)	-3.22 (0.001)
	M	-0.26 (0.793)	-0.27 (0.790)	-0.19 (0.853)	-0.12 (0.903)
Region (NUTS1) dummies	U	-2.67 (0.008)	-2.89 (0.004)	5.31 (0.000)	-1.9 (0.058)
	M	-0.14 (0.893)	-1.58 (0.114)	0.37 (0.711)	-0.81 (0.417)

Note: P-values in parentheses.

diagnostics cover the set of observable characteristics treated and control units have been balanced on, namely revenues (a proxy for firm size), age, ownership structure, economic activity, and location. T-tests outputs suggest that PSM actually mitigated all statistically significant differences in means observed between treated units and unmatched controls.

Tables 3 and 4 show pre and post-matching descriptive statistics on the full sample of treatment cohorts and untreated units. We can observe that the selection procedure brought changes in the means of the main target variables and in the means of matching covariates.

paragraph 1.5.1). To avoid misleading comparisons between the subsamples of networking firms and the control units, we matched every treated subsample to a comparable counterfactual group by running a propensity score matching before every diff-in-diff estimation. We aimed to rule out the existence of systematic differences in observable characteristics between treated and untreated units (Rosenbaum and Rubin, 1983). Matching diagnostics on the subsamples are not displayed due to space constraints. However, they are available upon request.

Once we had a matched control sample, we obtained dynamic treatment effects relying on the Sun and Abraham (2020) heterogeneity robust estimator. For the sake of illustration, figure 11 in appendix A shows the weights[37] stemming from the decomposition of TWFE estimates for relative time coefficients μ_{-2} and μ_{-3}. As previously mentioned, the bias gets critical when affecting pre-treatment coefficients since they are typically used to test for parallel pre-trends. When contamination occurs, checking if $\mu_\ell = 0$ for some leads ℓ may not be a reliable test for common pre-trends. Based on our matched sample, TWFE coefficients μ_{-2} and μ_{-3} are given as a weighted combination of $CATT_{e,\ell}$ with weights estimates as in panel (a) and (b) of figure 11 respectively[38]. In both cases, cohort-specific weights associated with the lags included in the econometric specification are different from zero, raising concerns about possible contamination of TWFE estimates under treatment effects heterogeneity across cohorts. The Sun and Abraham (2020) heterogeneity robust estimator allows us to address this issue.

Figure 1 plots treatment effects estimates obtained on the post-matching final sample of treated and control units: it includes around 2,800 network participants and an equal number of controls[39]. Outputs are available in tabular form in appendix A (table 21). Pre-treatment coefficients for relative periods -2 and -3 are not statistically significant and close to zero, hence we can rule out the presence of non-parallel pre-trends prior to treatment.

We find that participation in contractual networks has a clear positive causal impact on firm revenues. The effect tends to grow as we move away from period 0 (when the unit receives the treatment for the first time) until we reach the third year since treatment assignment. Between the fourth and the sixth year, the effect stabilizes with a slight increase in period 6. Revenues are estimated to be on average 12.1%, 16.6% and 16.8% higher after the first, third and fifth year in a network than they

[37] Weights estimates depicted in figure 11 are obtained on the matched sample.

[38] Due to space constraints we do not report weights estimates underlying other time lags included in the econometric specification. They are available upon request.

[39] Changes in the number of firm-year observations are due to the availability of financial data and missing values.

would have been if firms had never signed an agreement[40].

Similarly, companies' value added and EBITDA are positively affected by participation in network agreements. Firms' value added increase on average by 10.2% after one year of networking and by 15.7% after five years, while the estimated growth in EBITDA with respect to stand-alone controls after the first and fifth year is equal to 7% and 14.9% respectively. This result reveals that inter-firm formalized partnerships, like the ones promoted by the Italian network contracts' framework, do not only allow firms to improve turnover or market share (Leoncini, Vecchiato, and Zamparini, 2020) but may also facilitate rational management of pooled resources leading to cost containment practices followed, in turn, by an increase in intermediate economic margins (Grandori, 1997). Since our findings confirm and reinforce previous evidence on the advantages yielded by formal inter-firm formal ties, hypothesis 1a is supported.

Then, we move the debate forward by providing insights into the temporal evolution of networks' effects and their persistence over time. We observe that, within three or four years from the establishment of the network, causal impacts are increasing in magnitude. The effects on revenues and operating income metrics tend to stabilize between the fourth and fifth year of exposure, with a slight increase in the sixth year. Our findings suggest that formal partnerships actually take time to consolidate and to deliver satisfying and concrete benefits (Rosenfeld, 1996). Hypothesis 1b is, therefore, confirmed. Treatment effects at relative period 7 are generally not statistically significant, though. The lack of statistical significance could be partly due to the limited number of observations available since 2011 cohort members are the only units in our sample that are treated for seven years[41].

As previously mentioned, network participants are required by law to formalize a set of strategic objectives that constitute the pillars of the agreement and shape the activities each partner is committed to. To

[40] The percentage effect is estimated according to the formula $100 \cdot \{\exp(b) - 1\}$, which is used in semilogarithmic equations to interpret the regression coefficient b associated to a dummy variable (Halvorsen, Palmquist, et al., 1980).

[41] Figure 1 displays in parentheses the number of treated units with available data at each relative time period.

provide additional evidence on network agreements' strategic nature, we examined the list of strategic objectives declared by network participants to test whether the explicit statement of specific common goals brings heterogeneity to causal effects. First, we selected a subset of agreements and manually classified them according to the main goals declared by the participants. This activity required a good command of Italian since strategic statements are written entirely in Italian, and an advanced knowledge of business and management technicalities to provide a proper interpretation of networks' strategic intents. The first step of the process allowed us to identify a reliable collection of keywords and sentences to be used to classify the remaining share of agreements employing a text detection algorithm. Finally, we isolated all treated companies participating in networks clearly aimed at increasing turnover by expanding market shares or entering new markets to check if such formalized aims can drive network effects. Figure 2 displays the average treatment effects from participation in "market-oriented" agreements compared to causal effects generated by networks pursuing different goals. In line with our expectations, average causal impacts on firm revenues tend to be higher when firms' efforts are directed to strengthen their market position. This is true in each relative period except at time 0, when, however, the exposure to the treatment is still limited. Network effects on value added and on EBITDA show a different behavior instead. Within three years from treatment assignment, market-oriented agreements generate a lower impact on firms' value added if compared to networks pursuing alternative goals, whereas from the fourth year on, firms joining market-oriented networks benefit from stronger positive effects. Nevertheless, panel b in figure 2 suggests that the gap between the groups is not pronounced. Similarly, we find that market-related objectives do not drive any statistically significant effect on EBITDA until period 2, then companies experience a stronger effect compared to non-market oriented network members.

Hence, the formal definition of a common strategic direction seems to enhance contract agreements' positive impacts, at least concerning the metrics expected to be more responsive to the stated goals, suggesting a long-term-oriented commitment from the participants toward shared objectives. Nevertheless, further checks should be implemented to corroborate such evidence[42].

1.5.1 Network diversity driven by participants' size and spatial concentration

To dig into the contribution of network contracts to firms' economic performance, we moved the analysis further by exploring treatment effects heterogeneity driven by participants' attributes and their interplay.

First, we investigated if firms employing less than ten people one year before signing the agreement can reap more benefits from network participation than firms with ten or more employees[43].

Figure 3 (panels a, c and e) compares dynamic treatment effects obtained on a subsample of micro-enterprises with causal impacts for a set of small/medium-sized/large enterprises exposed to the treatment. While both subgroups experience positive and statistically significant dynamic effects, except for a few non-significant coefficients (see also table 23, appendix A), micro firms can benefit from higher impacts. Causal effects on revenues observed within four years from the network's establishment are aligned for micro and small/medium/large companies and follow a similar dynamic. However, from the fifth year onwards, dynamic impacts for micro-enterprises keep growing while small/medium-sized/large companies show declining effects. After five years in a network agreement, micro firms increase their revenues by 18.6% with respect to stand-alone controls, while small/medium-sized/large enterprises' revenues are 11% higher when treated.

We observe a similar pattern concerning the effects on firms' EBITDA (panel e), while the gap between the groups becomes more visible when treatment effects are estimated on value added (panel c). Participation in

[42]For further details, please, refer to paragraph 1.6.3, *Future avenues of research*.

[43]To partition the sample according to firms' size, we refer to the definition of micro, small and medium-sized enterprises provided by the EU recommendation 2003/361. To simplify, we relied on the staff headcount: we employed the threshold of ten employees to distinguish between micro and small/medium-sized/large enterprises. This choice allowed us to keep our subsamples as balanced as possible in size.

network agreements induces an increase in value added equal to 28.3% for micro-enterprises and 7.3% for larger ones after the fifth year of networking.

These findings provide support to hypothesis 2a, since reveal that smaller firms (micro-enterprises in the specific case) can reap higher benefits from participation in formalized networks, especially regarding their revenue potential and value added.

We moved forward by testing if partners' specific characteristics can drive further heterogeneity in treatment effects experienced by micro firms. To test hypothesis 2b, we investigated whether engaging in a network relationship with larger partners elicits stronger (or weaker) impacts on micro-enterprises' performance. To address this point, we identified the set of micro-enterprises that signed a contract with at least one medium-sized or large partner and the set of micro-enterprises participating in a network where no medium-sized or large firm is involved[44].

[44] To define network members' size and classify the agreements depending on the involvement of at least one medium-sized or large participant, we relied again on the number of employees as a dimensional proxy. We assigned the status of "medium-sized/large company" to the units employing an average of at least 50 people in the three years before joining the first agreement. Working on a three-year average allows us to mitigate the presence of missing values in the number of employees for a specific cross-section. However, since the AIDA database covers the population of limited liabilities companies leaving aside alternative legal forms that are not required to disclose the financial statement, we still have a lack of data for a number of network participants. To address this issue and increase the size of the sample, we made the following approximation: the existence of missing observations in the number of employees raises concerns, especially regarding the identification of micro-enterprises joining a network with no medium-sized or large partner involved, since missing values could impede the identification of medium and large companies although they actually joined the network. Since the exclusion of all the agreements where at least one participant exhibits missing observations would lower the sample size, we imposed the threshold of 0.33 as the maximum share of missing values allowed (computed as the number of participants with missing employee data over the total number of network participants) to state that if no medium/large firm is observed among the ones with employee data possibly no medium/large enterprise is involved in the agreement. Results in figure 3 are computed allowing for a maximum of 0.33 network members with missing employee data. To check the robustness of our results, we replicated the analysis imposing a lower threshold equal to 0.1 (a maximum of one over ten missing values allowed). We find that firms engaged with at least one larger enterprise experience higher impacts on revenues. In the third and sixth years of exposure to the treatment, the gap across subgroups shows a slight increase. Similarly, treatment effects on value added are more marked when connecting to larger firms. Concerning operating income (EBITDA), the estimates confirm our main findings. Moreover, network impacts for firms that do not connect with any larger

Figure 3 (panel b, d and f) plots impact estimates on both subsamples. Micro-enterprises that establish a formal relationship with at least one medium-sized/large partner seem to take more advantage of participation in a contractual agreement. The increase in revenues induced by the treatment equals 27.4% after one year and 26% after five years in a formal partnership with larger firms. Connecting with diverse partners causes an increase in value added equal to 28.4% after the first year and 33.8% after the fifth year and an increase in EBITDA equal to 29.4% and 28.4%, respectively. Causal effects follow a similar dynamic over time based on the length of exposure to the treatment in both subgroups (i.e., micro firms with or without a medium-sized/large partner), though we observe a visible gap with stronger effects on revenues, value added and EBITDA for micro firms connected with a larger partner. The gap tends to shrink after the fifth year of exposure when firm value added acts as the target variable, suggesting that even in the absence of a medium/large partner, smaller firms can leverage their complementarities to increase the long-term benefits earned from network agreements. Through network partnerships, small and micro-enterprises can overcome their structural limits and grasp the long-term benefits of efficient governance of pooled production inputs even in the absence of a larger company. However, network impacts on EBITDA show lower statistical significance when firms do not engage in a partnership with larger enterprises (see also table 24, appendix A).

Hence, the benefits experienced by micro-enterprises seem to be driven largely by diversity in terms of participants' size. Hypothesis 2b is therefore supported.

By favoring the activation of spatial externalities and external economies

enterprise are scarcely significant.

As a further check, we repeated the analysis including in the set of firms without any medium-sized or big partner only those belonging to networks where all participants have employee data (no missing values). We observe stronger positive effects on the revenues of firms networking with at least one larger partner. Concerning potential gains on the side of value added and EBITDA, we cannot provide any meaningful comparison since we observe statistically significant pre-treatment coefficients when estimating causal effects elicited by networks not involving medium/large enterprises. We take it as a signal for non-parallel pre-trends.

All the aforementioned results are available upon request.

(Van Oort et al., 2012; Parr, 2002a), partners' spatial proximity is assumed to moderate the impact of formal cooperation agreements on firms' performance. As previously discussed, being located in the same spatial agglomeration could be a source of advantage for network partners. As an example, closeness favors the recurrent exchange of market information and tacit knowledge, allows for an efficient sharing of local infrastructures, and eases the acquisition of inputs from common specialized suppliers (Parr, 2002b; Puga, 2010). On the other hand, firms that rely too much on local connections could suffer from a spatial lock-in and may be unprepared to face market challenges and take new opportunities (Boschma, 2005). Moreover, economic systems may develop at a much broader scale than the local one (Lagendijk, 2002) and fruitful inter-firm connections can extend beyond regional borders since they are not inherently spatial.

To empirically assess whether networks' geographical concentration can benefit its members, we computed for each agreement the percentage of partnering firms located in the same travel-to-work area (TTWA). Then, we partitioned the sample of treated firms based on their participation in a contract network with a degree of spatial concentration in a TTWA falling above or below a given threshold.

We relied on the functional geography of travel-to-work areas to capture the system of informal socio-economic relationships woven within local communities[45]. The Italian National Institute of Statistics (Istat) defines travel-to-work areas as "sub-regional geographical areas where the bulk of the labour force lives and works, and where establishments can find the largest amount of the labour force necessary to occupy the offered jobs[46]" (Franconi, D'alò, and Ichim, 2016). The functional criterion employed to define TTWAs is based on the analysis of workers' commuting patterns, that is, by observing the proportion of commuters crossing TTWA boundaries to reach the workplace[47]. Commuting flows

[45]Please, see also Istat website.

[46]Please refer also to Istat dedicated webpage.

[47]According to the principles outlined by Eurostat (Eurostat, 1992), workers' commuting flows should be traced in order to find boundaries across which relatively few people travel between the workplace and home.

are mapped to group together highly connected local communities and mirror the geographical distribution of labour markets. Each area is designed to internalize commuting flows between work and home (Eurostat, 1992), meaning that most of the zone's employed residents must work locally. Such a territorial partition captures the flow of informal interactions and contacts occurring locally, as workers' commuting flows are a good proxy for informal socio-economic relationships developed within local communities[48]. As previously mentioned, labour mobility is also among the channels through which knowledge, ideas and information flows across firms' boundaries and spreads locally (Eriksson, 2011; Kesidou and Romijn, 2008).

Working on data recorded by the population Census or retrieved from administrative registers, Istat identified around 600 travel-to-work areas across the Italian territory[49].

Panel a, c and e in figure 4 compare dynamic effects experienced by firms joining an agreement with at least 60% of participants in the same TTWA with those experienced by firms involved in a network with less than 60% of participants in the same TTWA. We selected the threshold to obtain two subsets with a similar size: the threshold of 60% allowed us to split in half the sample of treated units.

From panel a, we observe that network impacts on revenues are aligned and follow the same temporal evolution in both subsamples, with firms involved in more concentrated networks experiencing slightly greater benefits in the short term (until period 2). Similarly, positive impacts on EBITDA (panel e) are similar in magnitude in both groups at least until period 5. Then, we find that the gap in treatment effects on value added is not pronounced and increases from period 4 onwards (panel c).

As we compare the firms involved in the most and less concentrated networks we get a different picture, though. We isolated treated units in networks with 80% of members in the same TTWA and the ones in networks with less than 40% of members in the same TTWA: they repre-

[48]Please, see also Istat website.

[49]The mean territorial surface covered by Italian TTWAs is 495 square kilometers, with 90% of TTWA falling below an extension of 880 square kilometers. Please, see also `https://www.istat.it/it/archivio/252261`.

sent the top and bottom 25% of the sample, that is the units participating respectively in the most and less concentrated network agreements.

Graph b in figure 4 shows that the gap in treatment effects on revenues is more marked than in graph a, and we clearly observe that units in highly concentrated agreements can reap greater advantages from formalized inter-firm ties. After one year in a network with more than 80% of members in the same TTWA, firms' revenues are 14.9% higher than those of stand-alone controls, while enterprises in geographically dispersed networks (less than 40% in the same TTWA) experience an increase in revenues by 5.2%. After the third year in a network, firms in dispersed agreements do not experience any significant benefit on revenues.

Networks with more than 80% of participants belonging to the same TTWA yield more benefits on value-added (panel d) and EBITDA (panel f) as well. Dynamic impacts from network agreements with a low proportion of participants in the same TTWA (less than 40%) are scarcely or not statistically significant[50].

These results suggest that as we isolate the networks with the highest and lowest proportion of members in the same TTWA, the advantages of building formal ties with partners in the same spatial agglomeration become more evident[51].

1.6 Conclusions

1.6.1 Discussion

This study provides new insights into the effect that inter-firm cooperation, formalized through the legal tool of network agreements, has on

[50] Please, refer to table 26 in appendix A

[51] For a robustness check, we repeated dynamic impact estimates on two subsamples including units in network agreements with more than 70% and less than 50% of participants in the same TTWA. Results confirm that causal impacts on value added and EBITDA are higher when a greater share of network members are located in the same travel-to-work area. Causal impacts on revenues from networks involving less than 50% of members from the same TTWA are unreliable, though, since the coefficient associated with period -3 is significantly different from zero, suggesting the existence of non-parallel pre-trends, thus, we can't provide any meaningful comparison. Estimates are available upon request.

Italian firms' economic outcomes. It brings novelty as it sheds light on the temporal evolution and persistence of network agreements' impacts in the medium-long term and investigates whether and how heterogeneity in causal effects is elicited by the interplay between network participants' attributes (specifically, size and location). Our focus is on legally secured formal inter-firm partnerships aimed to accomplish a strategic purpose (Massari, Riggio, and Calace, 2015). Indeed, the peculiar feature distinguishing network agreements from alternative aggregation modes is its acknowledged strategic function (Massari, Riggio, and Calace, 2015).

We find that participation in network agreements has a positive and statistically significant effect on participants' revenues, value added and EBITDA. Networking causes, on average, a 12.1% and 16.8% increase in participants' revenues after one year and five years of exposure, respectively. The estimated increase in value added is equal to 10.2% after one year and 15.7% after five years. Concerning EBITDA, firms in a network agreement show an average increase in EBITDA equal to 7% after the first year and 14.9% after the fifth year with respect to standalone controls. Formal ties can provide firms with the assets and capabilities needed to expand their market share or enter new market niches (Coviello and Munro, 1995; Zhou, Wu, and X. Luo, 2007). Moreover, given the opportunity to share risks, pool resources, or undertake stable, long-lasting relationships, firms can benefit from production cost economies and negotiate favorable supply conditions (Jarillo, 1988).

Our rigorous microeconometric approach allows for delivering a causal interpretation of network impacts. On the methodological side, we step forward by coping with the pitfalls of two-way fixed effects Diff-in-Diff regressions in staggered settings (Goodman-Bacon, 2021) while addressing a potential self-selection bias (Angrist and Pischke, 2009). Despite the growing efforts to unveil the contribution of network agreements to firms' performance, only a few empirical works adopt a causal inference approach to the estimation of networks' impacts (Dickson et al., 2021; Burlina, 2020; Costa, Luchetti, and Romano, 2017). Concerning the network agreements phenomenon, a counterfactual method is required to cope with the bias raised by firms' self-selection into the treatment (Confindustria, 2016; Bentivogli, Quintiliani, and Sabbatini, 2013). Moreover, to our knowledge, the extant empirical literature on network agreements does not explicitly address the issues affecting difference-in-differences estimates in settings with a staggered treatment adoption when including several cohorts of networking units in the analysis. Several recent methodological contributions (e.g. Goodman-Bacon, 2021; Callaway and Sant'Anna, 2020) have warned against the potential problems affecting the interpretation of difference-in-differences estimates in settings with multiple time periods and variation in treatment timing across units, especially when treatment effects are expected to be heterogeneous over time (Goodman-Bacon, 2021) and across cohorts (Sun and Abraham, 2020). Relying on the contribution by Sun and Abraham (2020), we cope with the expected heterogeneity of network effects across treatment cohorts, potentially driven by subsequent regulatory updates, other calendar time-varying effects, or the specific characteristics of the firms grouped in each cohort.

Our heterogeneity-robust event study approach not only delivers unbiased estimates in a staggered setting but allows for addressing one major gap in the empirical literature on Italian network agreements. Indeed, despite the growing interest in the Italian networking policy, we still have a paucity of evidence on the evolution and persistence over time of network agreements' benefits (Costa, Luchetti, and Romano, 2017).

We observe that, on average, dynamic treatment impacts keep growing in magnitude until the third year of exposure to the treatment. The value created by the agreements stabilizes between the fourth and fifth year of cooperation, with a further increase after six years of exposure. Dynamic treatment effects show that the positive impact networks have on firm performance takes several years to grow and stabilize, supporting the hypothesis that networking initiatives usually take time to reach fruition and create value (Rosenfeld, 1996). Network outcomes can mature following the speed at which learning occurs and knowledge is absorbed (Latham and Le Bas, 2006). In the post-formation phase of the alliance, coordination costs typically curb the relationship (Gulati and H. Singh, 1998; Gulati, Wohlgezogen, and Zhelyazkov, 2012), then, as network members explore how to combine their complementary resources and invest in coordination routines, the network starts delivering increasing value (Zollo, Reuer, and H. Singh, 2002). However, if partners' resources converge too much as the result of incremental adjustments and joint investments, the growth in network outcomes may slow down (Dyer, H. Singh, and Hesterly, 2018). This can explain why dynamic impacts from network agreements tend to stabilize in the medium-long term, despite still being present. Our results, indeed, unveil network impacts' persistence in the medium-long term. Networks significantly improve firms' performance until the sixth year in a formal strategic agreement. Then, potentially due to the limited number of firms observed for seven years into the treatment, estimates lose statistical significance.

To better dig into the implications of formal strategic inter-firm networks and test whether the value creation potential of the alliance depends on relation-specific features, we explored how the interplay between partners' attributes shapes the identity of the relationship and drives heterogeneous effects.

Starting from the estimation of average treatment effects on micro-enterprises, we reinforced previous evidence on the gains smaller firms can reap from formal networking (e.g., Watson, 2007; Costa, Luchetti, and Romano, 2017; Aiello et al., 2023). We observed that firms with fewer than ten employees[52] derive higher advantages from network participation than larger enterprises, especially after the fifth year of accession. After the fifth year, indeed, the growth in revenues caused by participation in formal networks is equal to 18.6% for micro firms, while small/medium-sized/large companies' revenues grow by 11%.

Smaller firms are typically curbed by limited resources (Kelliher and Reinl, 2009). Financial, technological and expertise constraints can hinder micro firms' competitiveness, and the shortage of information and capabilities can prevent them from exploiting future opportunities on national and international markets (A. Bonaccorsi, 1993; D. North, Smallbone, and Vickers, 2001). In contexts and industries where the scale and scope of operations are critical to succeed, smaller firms suffer from the

[52]The number of employees is measured one year before the treatment assignment.

competition of larger enterprises (Gomes-Casseres, 1997). Besides, resource constraints can prevent them from affording the costs and risks of in-house technology development (Tether, 2002; Freel and Harrison, 2006). When the liabilities of a small size become too heavy, smaller enterprises can rely on network ties to improve their revenue potential and better manage production inputs without increasing their size or losing flexibility. Recurrent and legally secured relationships can facilitate the acquisition of valuable resources (Stuart, 2000), external knowledge (Inkpen and Tsang, 2005), information on market and industry trends (O'donnell, 2014) and allow mitigating the risks of innovation (Teng, 2007; Tether, 2002). By relying on a network structure, smaller firms can improve and secure their market position. When required by the nature of competition, micro-enterprises may establish formal agreements to increase their scale and scope without losing flexibility (Gomes-Casseres, 1997). Cooperation on input activities, including research or technological development, can enable cost economies that smaller firms could not achieve internally (Oughton and Whittam, 1997). Thus, the benefit they experience with respect to stand-alone smaller firms[53] is greater. Most importantly, we find that partners' characteristics affect the agreement's value-creation potential, inducing heterogeneity in network impacts. Given their intrinsic relational nature, the value inter-firm networks deliver originates from the establishment of idiosyncratic relationships (Dyer and H. Singh, 1998). However, although networks' composition is deemed to be at the core of their potential benefits, we still lack evidence on the degree of heterogeneity in causal impacts elicited by the interplay of members' attributes. In particular, little attention has been devoted to unveiling the implications of partners' size diversity (Cantele and Vernizzi, 2015). Micro-enterprises engaging with at least one medium-sized or large company experience a more pronounced impact than micro-enterprises with no such partner. Connecting to diverse partners causes an estimated increase in revenues equal to 27.4% after one year and 26% after five years. The estimated increase in value added is equal to 28.4% and 33.8% after the first and fifth years, respectively. Mi-

[53] Viz. non-treated firms.

cro firms establishing ties with at least one medium-size/large partner increase their EBITDA by 29.4% after one year and 28.4% after five years.

This result is consistent with previous findings (Stuart, 2000) highlighting the inherent potential of formal ties to well-endowed larger companies. Micro-enterprises connecting with at least one larger partner reap stronger benefits from formal cooperation since the early years of networking. Indeed, the gap in treatment effects between the sub-groups of micro-enterprises connecting, respectively, with larger firms or similar companies is pronounced even before the third year of cooperation, especially concerning revenues and EBITDA. Although in the post-formation phase of the agreement treatment effects experienced on average by micro-enterprises are slightly greater than the benefits obtained by larger firms[54], connections to larger companies seem to boost network returns so that the gap in treatment effects becomes more prominent[55].

From the very start of the alliance, smaller firms can take advantage of partners' consolidated market position (Mitchell and K. Singh, 1996), superior assets and reputation (Parida, Westerberg, et al., 2010), indeed. Smaller firms engaging in a partnership with larger ones can reach world markets quickly or experience production cost economies without the need for expensive investments that yield delayed returns (Doz, 1987). Especially in high-technology fields, mutually enriching partnerships can be activated with smaller firms providing specialized competencies in exchange for larger firms' market and financial support (Narula, 2004).

Lower diversity in partners' sizes still contributes to increasing micro-enterprises revenues and value added compared to stand-alone counterparts. Still, such a network configuration takes more time to deliver substantial benefits. Plausibly, the process of knowledge accumulation (Cohen and Levinthal, 1990), the incremental improvement of capabilities, and the successive investments in relation-specific assets (Dyer and H. Singh, 1998) take longer to yield concrete returns when firms' initial resource endowments are poorer.

[54] Please, refer to figure 3 and table 23.
[55] Figure 3 and table 24.

Formal networks' value creation potential is assumed to be affected by the spatial distribution of their members as well. If geography still matters in shaping firms' activities and competitiveness (Morgan, 2004), partners' proximity is claimed to moderate the outcomes of formal co-operation agreements through the activation of spatial spillovers and external economies (Van Oort et al., 2012). New evidence was needed to integrate previous studies on the relationship between network agreements' geographical dispersion and networking firms' performance (Cisi et al., 2020; Rubino and Vitolla, 2018). While the majority of the empirical studies assessing the effects of networks' geographical dispersion rely on administrative units (NUTS2 or NUTS3 areas) to assess partners' proximity (Rubino, Vitolla, and Garzoni, 2019; Rubino and Vitolla, 2018; Cisi et al., 2020; Cantele and Vernizzi, 2015), we employed a territorial partition defined on a functional basis to infer heterogeneity in treatment effects induced by partners' co-location.

When partitioning the sample of networking firms according to the threshold of 60% of partners in the same TTWA, we observe a similar dynamic in treatment effects across subgroups over time. We may assume that the positive implications of co-location, among which the activation of spatial spillovers and external economies (Audretsch and Feldman, 1996), are somehow counterbalanced by the benefits of inter-regional links that open up the chance of acquiring novel and diversified knowledge (Boschma, 2005).

However, as we isolate the agreements with the highest and lowest percentage of partners in the same TTWA, the advantages of formalizing ties mostly within a highly-connected spatial agglomeration become more evident. Networks with more than 80% of members from the same TTWA favor an increase in revenues equal to 14.9% after one year in the agreement and by 17.5% after five years. The estimated increase in value added is equal to 10.6% after the first year and 13.9% after the fifth year. The EBITDA of firms in a highly concentrated agreement shows a statistically significant improvement from period two onward compared to non-networking units.

Our findings suggest that formal inter-firm agreements could be even more favorable when a very high percentage of network members belong to the same tightly connected socio-economic community identified by travel-to-work areas. TTWAs group together highly connected territorial units where socio-economic interactions are expected to be frequent and intense (Franconi, D'alò, and Ichim, 2016). The higher the share of network agreements' members in the same TTWA, the stronger the informal mechanisms reinforcing the legally secured cooperation. Networking firms may benefit from the exchange of ideas and information through recurrent face-to-face interactions eased by geographical proximity (Cardamone, 2017). Network partners can absorb and exchange knowledge conveyed by labour flows (Eriksson, 2011). The formal cooperation between proximate firms is expected to be backed and reinforced by shared values (Rinaldi and Cavicchi, 2016), a common background (Huggins, 2000), and trust (Milanesi, Guercini, and Tunisini, 2020) which typically tie the members of a regional community together. TTWA's territorial extension[56] is such that co-located partners can experience external cost economies in the acquisition and management of resources, e.g., by sharing infrastructures, facilities, and plants (Parr, 2002b).

Moreover, proximity eases the convergence towards efficient coordination routines (Gulati, Wohlgezogen, and Zhelyazkov, 2012; Dyer, B. C. Powell, et al., 2007) mitigating coordination costs. Direct communication channels among nearby firms (Enright, 1995) and faster discovery of co-located partners' attributes allow for anticipating tasks' coordination requirements (Reuer, Zollo, and H. Singh, 2002) and create more value even right after the establishment of the agreement.

To sum up, our work reveals that the benefits delivered by inter-firm partnerships formalized through network agreements take time to grow and stabilize. The advantages reaped by network members persist over time (at least until the sixth year of cooperation) and change in magnitude depending on how firms' attributes combine to shape the identity of the relationship.

[56] Italian TTWAs' mean territorial extension is 495 square kilometers.

1.6.2 Policy and managerial implications

From a policy perspective, our research confirms that the Italian network agreement policy promotes the establishment of long-term oriented strategic ties. We found, indeed, that strategic cooperation formalized through network agreements yields benefits that are persistent in the medium-long term. Given the expected complexity of inter-firm strategic coordination and the implied learning processes, we observed that participation in network agreements takes time to create value. Causal impacts grow and reach stability not before the third year of cooperation. On these premises, the policymaker should provide adequate communication to let potential entrants mature the right expectations on network agreements' value creation potential.

Then, we argue that the policy is correctly addressed to smaller firms. As smaller enterprises struggle to keep up with globalized markets because of resource constraints, the establishment of long-lasting ties becomes crucial since it provides access to complementary resources, facilitates the improvement of firms' market position, and gives the chance to share costs and risks (Parida, Westerberg, et al., 2010). Thus, we observe that smaller firms (i.e. micro firms) can reap more benefits from network ties, especially when engaging with larger, consolidated partners.

The industrial policy promoted by the Italian Government is modeled on the characteristics of the Italian production system, renowned for the massive presence of micro, small and medium-sized firms, which stand out for their contribution to Italian GDP and employment (Ministero dello Sviluppo Economico, 2016). However, given the prominent role played by micro-enterprises and SMEs in European economies (European Commission, Executive Agency for Small and Medium-sized Enterprises, Murphy, et al., 2021) and the growing commitment shown by European policymakers to favoring the ecosystem of Micro-SMEs, we believe that the Italian intervention could be cited as an example of "best practice" to be followed by international leaders when undertaking initiatives for Micro-SMEs. This work sheds new light on the advantages brought by formal networking policies, underscoring the role of firm-specific and network-specific characteristics in delivering economic benefits. Even if dealing with an industrial policy developed at the national level, our research addresses an international audience as well, given the ever-growing interest by other governments in networking policies supporting Micro-SMEs. Our evidence calls for tailored interventions accounting for partners' heterogeneity and geographical location.

From a managerial perspective, these results provide further support to networking initiatives as a means to overcome competitive and structural limitations. Going beyond the conception of inter-firm networks as hybrid organizational solutions driven by efficiency-related arguments, we adopt a strategy-oriented perspective to claim the effective role of formal networks in strengthening firms' long-term competitiveness. The acquisition of focal resources and superior performance may thus be achieved through the adoption of a relational approach and the renewal of the enterprise's organizational structure. Resource accessibility enabled by inter-firm connections and openness become pillars on which the competitive advantage may be grounded. Long-term competitive success can be reached by rethinking the position of the firm in the business environment and in the social network.

When the firm engages in network relationships to strengthen its competitive stance, partners' selection acquires strategic relevance. Managers should carefully assess the gains and threats of connecting to diverse partners. Our findings suggest that smaller firms could benefit from larger enterprises' consolidated market position, complementary resources, capabilities and good reputation. However, they should be able to manage the costs and pitfalls of diversity. The definition of network members' rights and duties secured by an enforceable framework protects against aggressive value-capture tactics by prominent partners.

Similarly, partners' geographical location is another critical factor that managers must not neglect when planning to establish long-term oriented formal connections.

1.6.3 Future avenues of research

Our study has several limitations which pave the way for future research on the topic of network agreements. First, due to the recent introduction of the Italian policy on network agreements, the time span covered by the data is still limited. Despite the sustained growth of participating firms after the introduction of the policy (Confindustria, 2016), the phenomenon is still at an early stage. We collected secondary data on around three thousand limited-liability firms in a network agreement, however, the econometric approach we relied on would potentially allow for handling many more observations. Moreover, we were forced to limit our analysis to a narrow selection of treatment cohorts. As we aimed at capturing the effects of legally-secured strategic interactions, we couldn't restrict the analysis to the short-term (e.g., one or two years after receiving the treatment) (Foresti, Mangolini, and Ferrero, 2014) as we would not have been able to grasp the economic implications of lasting strategic ties. Therefore, to be able to observe treated units for at least four years after entering an agreement, only firms signing a network agreement between 2011 and 2014 have been empirically studied. As new data are released and more firms embrace this legally-recognized organizational solution, we have the opportunity to extend the analysis to further treatment cohorts (i.e., units entering an agreement in 2015 and thereafter) and work on a broader longitudinal dataset.

Then, a wider diffusion of the legal tool and its constant observation over the years would allow for keeping track of participating firms' performance while in the agreement and after leaving it. Indeed, future studies could be devoted to examining the post-treatment effect of participation in network agreements to test whether the benefits stemming from such a peculiar kind of formalized partnership persist after the dissolution of formal network ties.

The empirical examination of the geographical dimension of network-shaped interactions could go further by studying whether strong and lasting ties enabled by network agreements can counterbalance the pitfalls of being geographically isolated. Firms' degree of geographical isolation could be measured by relying on the identification of inner areas[57] provided by Istat[58] or by computing appropriate metrics already exploited in empirical studies on agglomerations (e.g. L. Wang, Helms, and Li, 2020).

As previously mentioned, further evidence should be provided to test whether the explicit statement of shared goals can elicit heterogeneous outcomes. First, the classification of network agreements according to their primary strategic purposes needs further attention. Simple manual identification of a set of keywords must be replaced by the employment of a proper classification approach based on Natural Language Processing (NLP) techniques. NLP would allow for processing effectively thousands of entries delivering a precise and broader collection of the major objectives pursued by network agreements. Then, several cross-group comparisons must be performed to assess whether setting specific goals elicits heterogeneous impacts on participants' performance. The analysis can't be confined to market-oriented initiatives only. Subsamples of networking units will be isolated and compared according to the main purpose of the agreement (e.g., efficiency improvement, internationalization, cost containment).

Besides, there is room for further investigation of the heterogeneous effects driven by networks' composition. Network diversity can be analyzed by looking at its industrial composition. A network agreement may bring together firms operating at different stages of the supply chain, or it can tie companies conducting business on the same market (Bentivogli, Quintiliani, and Sabbatini, 2013; Cardoni, 2012). Hence, an agreement could be more or less homogeneous in terms of the industries in which the partners operate. Previous empirical works have explored

[57]Inner areas are identified as areas remotely connected to the major urban centers and their associated infrastructure, thus characterized by depopulation and degradation. Istat (the Italian National Institute of Statistics) classifies Italian municipalities based on their distance from *Service Centers*, defined as municipalities that offer a wide range of essential services like healthcare, education, and transport. Areas that are more than 20 minutes far from *Service Centers* are mapped as inner areas. For further information on the Italian locations qualified as inner areas, please see `https://www.istat.it/it/archivio/273176`.

[58]Italian National Institute of Statistics.

the association between network agreements' sectoral diversity and networking firms' performance (e.g. Burlina, 2020; Cisi et al., 2020; Cantele and Vernizzi, 2015; Rubino and Vitolla, 2018). Most studies, however, performed the analysis on the subsample of treated units only. Such an approach does not allow for capturing heterogeneity in treatment effects driven by networks' composition. As a future line of research, we propose to extend our empirical approach to compare treatment effects computed on subsamples of firms in a network agreement identified according to the different degrees of sectoral diversity. The aim is to unveil whether and how dynamic treatment effects change as we modify the degree of industry diversification of a network agreement.

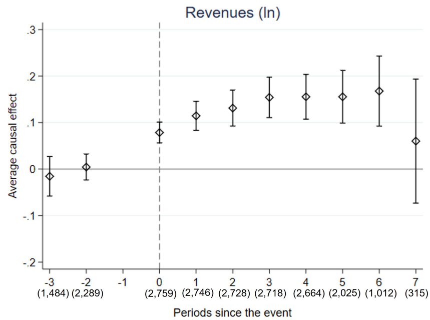
Similarly, future studies could be devoted to exploring heterogeneity in treatment effects driven by networks' size. While the empirical literature on network agreements highlights the significant relationship between the size of an agreement and the performance of its members (e.g. Burlina, 2020; Cisi et al., 2020; Rubino, Vitolla, and Garzoni, 2019), we still lack evidence on whether the number of firms involved in an agreement triggers heterogeneity in treatment effects.

Finally, we measured network agreements' causal impacts on a narrow selection of performance metrics, namely, revenues, value added and EBITDA. Future works could extend the set of response variables to study the implications of signing a network contract on firms' innovative capacity[59] and labour productivity[60].

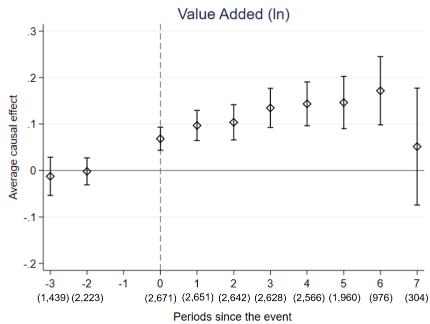
[59]The actual realization of innovative outcomes could be measured by looking at the number of registered patents attributed to the firm (Acs, Anselin, and Varga, 2002).

[60]In empirical firm-level studies, labour productivity is typically measured as value added per employee (e.g. Damiani, Pompei, and Ricci, 2018; Neckebrouck, Schulze, and Zellweger, 2018) or sales per employee (e.g. Iverson and Zatzick, 2011).

(a)



(b)



(c)

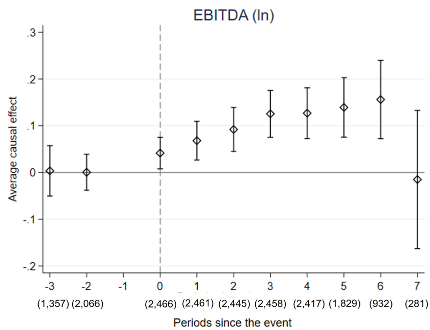


Figure 1: Dynamic treatment effects on the full sample.

The graphs plot average dynamic effects estimates and confidence intervals. Treatment effect estimates are obtained controlling for firm-specific and calendar year fixed effects on 47913 (panel a), 46108 (panel b) and 42891 (panel c) firm-year observations respectively. In parentheses is the number of treated units with available data at each relative period.

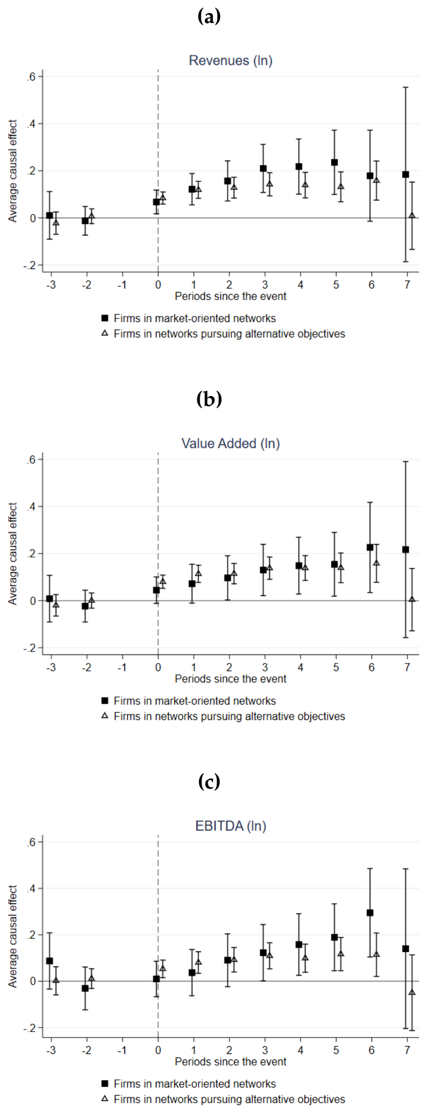


Figure 2: Dynamic treatment effects driven by network objectives.

The graph compares average causal effects estimated on different subsamples identified by the strategic goals set by network members. Treatment effects estimates are obtained by controlling for firm-specific and calendar-year fixed effects. Results for the subgroup of firms in market-oriented networks are obtained on 8219 (panel a), 7917 (panel b) and 7380 (panel c) firm-year observations. Results for the group of firms in networks pursuing alternative objectives are estimated on 39593 (panel a), 38182 (panel b) and 35573 (panel c) firm-year observations.

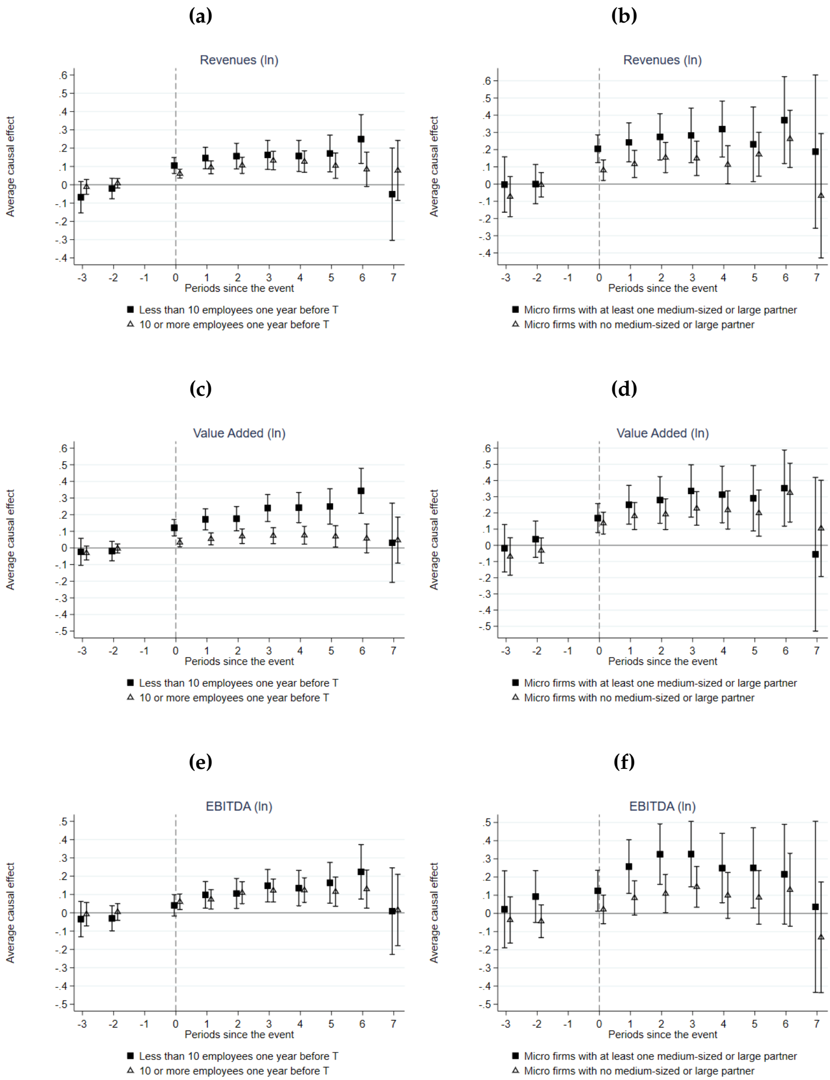


Figure 3: Dynamic treatment effects by participants' size and partners' size.

The graphs compare average causal effects estimated on different subsamples identified by network participants' size and participation in networks involving at least one medium-sized or large partner. Treatment effects estimates are obtained by controlling for firm-specific and calendar-year fixed effects. Results are obtained on 20048 (panel a), 19163 (panel c), 17749 (panel e) firm-year observations for the group including firms with less than ten employees one year before signing an agreement while treatment effects on firms with ten or more employees are estimated on 26077 (panel a), 25057 (panel c) and 23575 (panel e) firm-year observations. Dynamic effects for the group of micro firms signing an agreement with at least one medium-sized or large partners are obtained on 4872 (panel b), 4654 (panel d) and 4285 (panel f) firm-year observations while impact on micro firms with no medium-sized or large partner are obtained on 11572 (panel b), 11052 (panel d) and 10208 (panel f) firm-year observations.

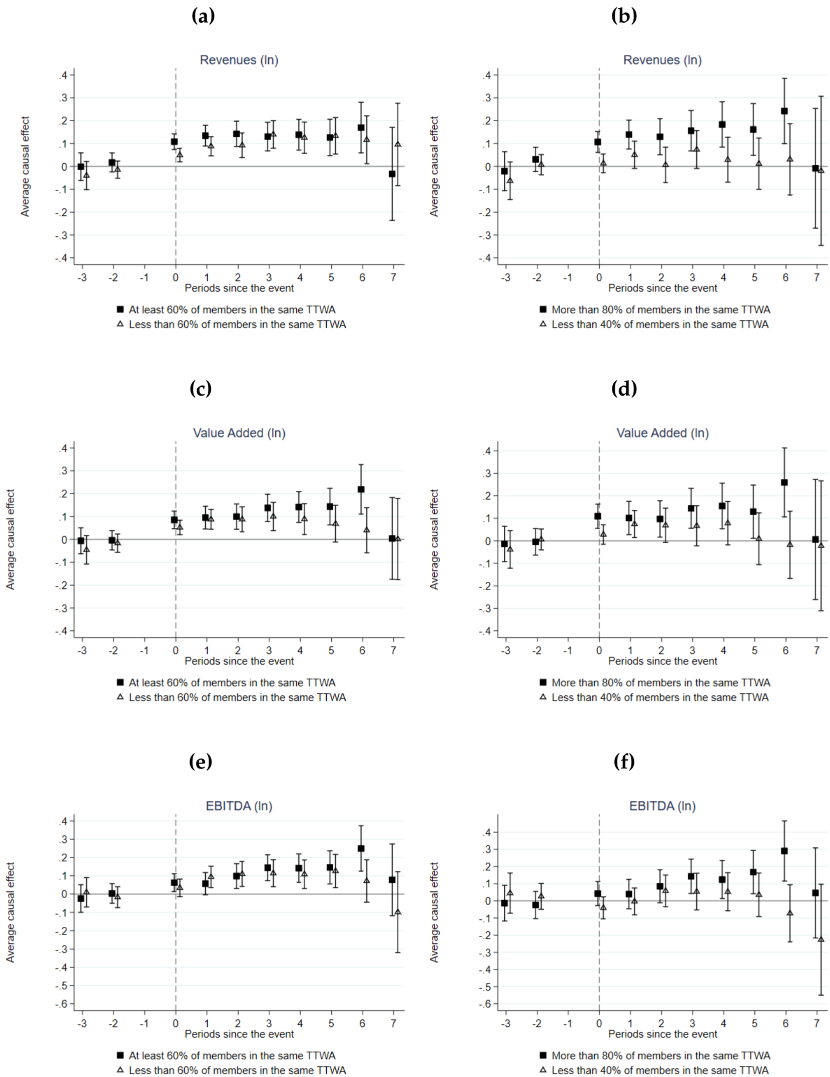


Figure 4: Dynamic treatment effects based on network members' location.

Graphs compare average causal effects estimated on different subsamples identified by network participants' spatial concentration in one travel-to-work area. Treatment effects estimates are obtained by controlling for firm-specific and calendar-year fixed effects. Results for the subgroup of firms in network agreements with at least 60% of members in the same TTWA are obtained on 24720 (panel a), 23773 (panel c) and 22291 (panel e) firm-year observations while results for firms in networks with less than 60% of participants from the same TTWA are estimated on 22474 (panel a), 21707 (panel c) and 20139 (panel e) firm-year observations. Treatment effects from networks with more than 80% of participants in the same TTWA are obtained on 12173 (panel b), 11687 (panel d) and 10919 (panel f) firm-year observations while estimates for the subsample of firms in networks with less than 40% of members in the same TTWA are obtained on 11123 (panel b), 10748 (panel d) and 9909 (panel f) firm-year observations.

Chapter 2

Are Family Firms Good Neighbours? A Spatial Analysis of Italian Technology-Intensive Firms

The content of this chapter was published in the Journal of Small Business and Enterprise Development as Amato, Pieroni, et al. (2021). Variations have been implemented based on referees' comments.

2.1 Introduction

Is distance dead? This question has animated the debate among regional scholars and geographers about the enduring importance of geographical proximity in shaping the spatial distribution of economic activity and the competitiveness of firms, localities and regions (Morgan, 2004; Lychagin et al., 2016). In particular, it was argued that with the spread of information and communication technologies (ICT) and the advent of the digital economy, there would be a resulting decline in the importance of locations in favor of a "flat" world (Nijkamp, 2017). Nevertheless, extensive empirical research on agglomerations and business clusters has provided evidence undermining the death of distance thesis, arguing instead that geography still matters (Bathelt, Malmberg, and Maskell, 2004; Morgan, 2004; Porter, 2000). Indeed, spatial proximity to economic agents conditions firms' activities and entrepreneurial behaviors (Crowley and Jordan, 2022).

Productivity is a long-established measure of firm's performance used in the investigation of the locational advantages offered by spatial proximity (Fazio and Maltese, 2015; Van Oort et al., 2012; He, Y. Chen, and Schramm, 2018). Firm's co-location was found to generate positive externalities[1] from one economic agent to another because of reciprocal synergies among them (Eriksson, 2011). At the foundation of productivity spillovers lies the transmission of tacit knowledge and information, through face-to-face and informal interactions eased by geographical proximity, the labour mobility and the increased local competition among firms sharing the same social and economic *milieu* (Porter, 2000; Cardamone, 2017; Du and Vanino, 2021). Spatial spillovers are regarded as being geographically bounded and subject to a distance-decay effect, in the sense that their positive effect vanishes as the distance between firms increases (Audretsch and Feldman, 2004; Mariotti et al., 2015; Owoo and Naudé, 2017; M. Andersson, Klaesson, and Larsson, 2016).

While aggregated or density measures at territorial level have been mostly used to capture externalities (Fazio and Maltese, 2015; Amara and Thabet, 2019; Van der Panne, 2004), there is a growing interest in modeling productivity spillovers across firms through spatial econometric techniques (Anselin and Bera, 1998; Elhorst, 2014; Anselin, Florax, and Rey, 2013; He, Y. Chen, and Schramm, 2018). By exploiting geographic coordinates to define the structure of firms' vicinity (i.e., geographic proximity), current evidence suggests a "neighbour effect" is usually in place, with firm's productivity that is strongly affected by the level of efficiency of nearby firms (Martínez-Victoria, Maté-Sánchez-Val, and Lansink, 2019; Owoo and Naudé, 2017). Spatial externalities

[1] Externalities (known also as agglomerations economies) consist of geographically-bounded resources or locational factors that reside outside firms but which are drawn on – directly or indirectly – by those firms hence leading to increasing return to scale (e.g., productivity) and higher innovativeness as compared to firms located elsewhere (Parr, 2002b).

indeed operate at a finer geographical scale than the one identified by commonly employed territorial units, e.g., administrative areas like regions, provinces, or municipalities (M. Andersson, Larsson, and Wernberg, 2019; M. Andersson, Klaesson, and Larsson, 2016).

Some business characteristics are found to play a different role in eliciting productivity spillovers. For instance, R&D efforts (Cardamone, 2017; Lychagin et al., 2016) and the international scope (Wei and Liu, 2006) of geographically close firms are sources of productivity spillovers. Indeed, the beneficial effects of firm R&D activities are not confined within the organizational boundaries but instead "spill-over" into the immediate surrounding to the advantage of co-located firms (Audretsch and Feldman, 2004). Geographical concentration eases the exchange of knowledge and information, frequent face-to-face interactions, the exploitation of technological and scientific knowledge developed by R&D centers, thus reducing the costs and mitigating the risks associated with innovation (Breschi and Lissoni, 2001b). Then, as innovation is notably a pivotal driver of productivity (Syverson, 2011), firms' efficiency is indirectly stimulated by proximate firms' innovation efforts through the activation of the typical knowledge transmission channels like labour mobility and informal interactions (Cardamone, 2017). Additionally, the presence of foreign MNCs - through input-output linkages and imitative behavior - was found to lead to efficiency benefits for nearby firms (Blomström and Kokko, 1998; Eriksson, 2011).

Given this, a firm-specific characteristic that so far has been neglected in the debate on agglomeration economies, is represented by the family status of the firm as stemming from the involvement of a family in ownership and managerial positions (Westhead and Howorth, 2007). That is pretty surprising given the ubiquity of this kind of firm across territorial settings (Zellweger, 2017), sectors of activity (F. W. Andersson et al., 2018) and size (Carney et al., 2017). As the academic debate has focused traditionally on the way the interrelationship between family and business domains shapes the family firm's choices and outcomes in a unique way (Yu et al., 2012), the explicit recognition of family businesses has been steadily growing in the investigation of firms across space (Stough et al., 2015; Berlemann and Jahn, 2016; Basco, Stough, and Suwala, 2021). Family firms are regarded as being intrinsically spatial, that is, more responsive to the geographic distance and spatial unevenness in the availability of resources and business opportunities than their non-family counterparts (Amato, Backman, and Peltonen, 2021). At the same time, they are inherently territorial, with business operations taking place mainly at the local level with the family and the business sharing the same relational space (Kalantaridis and Bika, 2006). However, nothing is known about the ability of family firms to leverage spatial proximity for the benefit of neighbouring firms. Some aspects of family firms such as the strong entrepreneurial orientation (Cruz and Nordqvist, 2012), embeddedness in the local setting (Block and Spiegel, 2013) and proactiveness (De Massis, Chirico, et al., 2014) contrast sharply with others, such as family inertia (Chirico and Nordqvist, 2010), lower labour mobility (Bassanini et al., 2013) and a reluctance to share knowledge and information with others (Gomez-Mejia et al., 2011) with the result to either foster or hamper productive spillovers. Hence, we pose the following research question: *is proximity to family firms beneficial for nearby firms?*

Then, as firms' innovation efforts represent an acknowledged source of spatially bounded knowledge spillovers, acting like a stimulus for proximate firms' productivity (Cardamone, 2017; Medda and Piga, 2014), we wonder whether innovation in family firms may enhance or mitigate the indirect impact they exert on the efficiency level of nearby enterprises.

To investigate the family firms-productivity spillovers link, we rely on the population of medium-high and high-tech firms located in Italy for the year 2018. Italy represents an interesting setting for the purpose of our study for three main reasons. First, for the steady decline of Italy's productivity since the middle of the 1990's, especially as compared with the other main euro zone countries (Calligaris et al., 2016). Second, because of the prominence of family-owned and managed firms as backbone of the national entrepreneurial fabric (AIDAF, 2021), especially in manufacturing (Cucculelli and Storai, 2015). And, finally, because spatial proximity of technology-intensive firms companies is a prerequisite for the leakage - both unintentional and voluntary - of useful knowledge and information (i.e., technological spillovers) and, therefore, source of locational advantages in terms of higher levels of productivity and innovativeness (Medda and Piga, 2014). That contributes to explaining the dynamism and competitiveness at international level of Italian medium-high and high-tech firms (IntesaSanPaolo, 2019).

To address our research question, we take into account distance between firms by adopting spatial econometric models. The findings reveal the existence of spatial dependence, with the productivity of a firm related to the productivity of neighbouring firms, hence confirming that a neighbour effect is in place in the context of technology-intensive Italian firms. Nevertheless, some firm-specific characteristics explain the advantages or disadvantages arising from co-location. In particular, closeness to patenting companies is found to be a source of productive spillovers and, therefore, beneficial to nearby firms. Conversely, our findings show that spatial proximity to family firms can cause negative externalities adversely affecting the productivity of neighbouring firms. However, and this is our last finding, the negative externalities vanish when family firms are also innovators. The results appear to hold true for different cut-offs of the inverse-distance matrix and specification of the response variable.

Our study makes several contributions. First, it contributes to the growing efforts aiming at combining family business and regional studies to the mutual benefit of both research areas (Stough et al., 2015; Basco, Stough, and Suwala, 2021). Specifically, for family business studies, the inclusion of the spatial dimension provides new insights into the family business phenomenon beyond internal dynamics. As for regional studies, our findings point to the need to take into account the family status of the firm - as the primary source of heterogeneity - in the investigation of the spatial dimension of economic activity and the advantages brought by agglomeration. Second, our study has policy implications. As spatial proximity matters, our findings encourage cluster development initiatives as a way to foster - via productivity spillovers - the competitiveness of co-located firms and, indirectly, that of localities and regions (Van Oort et al., 2012). Besides, this work suggests that any public policy initiative that attempts to foster, via spatial spillovers, the competitiveness of both firms and localities cannot neglect the role played by family firms (Basco and Bartkevičiūtė, 2016). As intrinsically ubiquitous and locally embedded, innovative family firms appear uniquely positioned to lubricate the mechanisms through which productivity spillovers take place (Amato, Ricotta, and Basco, 2022). Hence, the policy implications of our study are twofold. First, policy should support the innovative efforts of family firms as a way to offset the productivity gap vis-à-vis non-family firms. Second, local development policies should guide location choices encouraging the spatial clustering of firms nearby innovative family firms in a way to trigger mutually beneficial exchanges and activate positive externalities.

The rest of this article is structured as follows. The next section gives an overview of the productive spillovers literature and develops the hypotheses. The third section describes the data, descriptive statistics, and the econometric study design. The fourth section explains the main results. The fifth and final section discusses the main conclusions.

2.2 Theoretical background and hypotheses

2.2.1 The productivity in the Italian industry: basic facts

Since the middle of '90s, Italy has been experiencing an inexorable decline in productivity which is arguably at the root of the long-lasting stagnation of the "Belpaese", especially in comparison with the most important Eurozone countries, France and Germany. In particular, three main shocks – which Italian firms were not able to cope with – changed the competitive environment profoundly. First, the advent of globalization and the the rise of new low-cost competitors. Second, the loss of lever of currency devaluation, as adjustment mechanism. And, finally, the ICT revolution from which only large-scale firms benefited (Calligaris et al., 2016). As regards the specific causes of this decline, the empirical evidence points the finger at the model of specialization of Italian manufacturing system characterized by traditional sectors with a low level of technology (Faini and Sapir, 2005), the increase of the share of temporary (and mostly inexperienced) staff following the Italian labour market reform in 1997 (Daveri and Parisi, 2015), the inefficiency of the public sector (R. Giordano et al., 2015) and the mismatch between the demand and supply of labour (Montanari, Pinelli, and Torre, 2015).

Firm size distribution together with ownership and managerial characteristics were put forward as being the structural causes of Italian stagnation: the smaller size of Italian firms than the European average and the predominance of family-owned and managed firms, respectively (Calligaris et al., 2016; Bugamelli, Cannari, et al., 2012). Specifically, firm distribution in manufacturing is highly concentrated in the small and medium-sized class accounting for almost the 96% of enterprises in the country (OECD, 2020). The majority of these were family firms whose owners were found to select managers more for loyalty and primogeniture than for their capabilities, hence resulting in a talents misallocation (Lippi and Schivardi, 2014). That, alongside a lower propensity to innovate and internationalise (Bugamelli, Lotti, et al., 2018; Bugamelli, Cannari, et al., 2012) and the tendency towards the selection of less-risky investment projects (Cucculelli, Mannarino, et al., 2014), resulted into a lower productivity levels for family firms. However, existing empirical evidence is somewhat inconclusive as regards whether family firms are more (McConaughy et al., 1998; Martikainen, Nikkinen, and Vähämaa, 2009) or less (Barth, Gulbrandsen, and Schønea, 2005; Chrisman, Devaraj, and Patel, 2017) efficient than non-family firms.

2.2.2 Productivity spillovers led by innovators

Since the pioneering studies of Marshall, 1890, agglomeration literature has emphasized the importance of the firm's co-location as a source of increasing returns and positive externalities. From this perspective, an early interest focused on testing the agglomeration economies as stemming from the spatial proximity of firms belonging to the same industry (i.e., "Marshall-Arrow-Romer" externalities) (Van Oort et al., 2012; Fazio and Maltese, 2015) or the economic diversity which is mainly related to the urban size or local variety (”Jacobinian” externalities) (Parr, 2002b; Van der Panne, 2004). In line with this, aggregated measures at predefined spatial levels (e.g., regions, provinces and local labour systems), were employed to capture externalities (Fazio and Maltese, 2015) on the assumption that geographic concentration promoted useful knowledge spillovers relevant for firms' performance (Van Oort et al., 2012).

At the core of agglomeration economies lies the free-of-charge flow of knowledge and information which is exchanged - both informally and intentionally – among physically proximate firms (Audretsch and Feldman, 2004; Grieser et al., 2022). Close proximity to knowledge sources enables spatially constrained externalities occurring locally (Rammer, Kinne, and Blind, 2020). Given its non-rivalry and non-excludable nature (Breschi and Lissoni, 2001a)[2], knowledge created may not remain confined within the organizational boundaries but rather spill-over into the immediate surroundings to the advantage of the productivity of co-located firms (Harris et al., 2019). Specifically, local labour mobility and informal interactions in the *milieu* with specialized suppliers, customers and competitors are the channels through which knowledge spillovers occur (Kesidou and Romijn, 2008). While face-to-face contacts with competitors facilitate the exchange of information about novelties and innovation and market opportunities (Breschi and Lissoni, 2001a), competitive pressure prompts the adoption of best practices and technology of other efficient companies, hence stimulating the productivity of nearby firms (Cardamone, 2017; Du and Vanino, 2021).

Since knowledge spillovers stem from technology's incomplete excludability, a firm's productivity level depends not only on the innovation activity carried out internally (Parisi, Schiantarelli, and Sembenelli, 2006; Hall, Lotti, and Mairesse, 2009) but also on the innovative efforts of spatially proximate firms belonging to the same industry as well as to related ones (Medda and Piga, 2014). The interplay between knowledge

[2]Knowledge that spillovers are a (pure) public good that can be exploited by more than a few users simultaneously (non-rivalry) and which is freely available to those looking to it (non-excludability)(Breschi and Lissoni, 2001a).

collaborations and spillovers with external parties contributes to fostering firms' productivity and innovation (Audretsch and Belitski, 2023). Indeed, innovation by one firm – by means of learning and interaction – may be adopted by adjacent firms, enhancing their productivity levels in turn (Wei and Liu, 2006). In other words, geographical proximity enables the capitalization of complementaries across firms' research activities (Lychagin et al., 2016) resulting in spatially-bounded locational advantages (Eriksson, 2011). For instance, Cardamone (2017) shows how spatial proximity determines an indirect effect of innovative efforts on firms' productivity. Put differently, the innovative activity of a given firm influences not only that firm's productivity but, through spillover effects, also that of nearby firms.

Based on the aforementioned evidence, we infer that closeness to innovative enterprises can lead to positive externalities. Hence, we posit the following hypothesis:

> Hypothesis 1: *geographical proximity to innovative firms positively affects the productivity level of nearby firms*.

2.2.3 Productive spillovers led by family firms

The effectiveness of productive spillovers is closely related to the type of adjacent firms and based on ownership and managerial characteristics (Blomström and Kokko, 1998). Among these, the family firm status arising from the presence of a family in the dominant coalition of the firm (Basco, 2013). Aside from the internal dynamics, the owning family may uniquely affect – either positively or negatively – the channels through which productivity spillovers occur (i.e., informal interactions, labour mobility and local competition) and, therefore, the advantages of co-location (Van der Panne, 2004; Audretsch and Feldman, 2004).

Given that the knowledge flowing freely across the locality is mainly tacit - that is highly contextual and difficult to codify – face-to-face interactions and personal relationships are critical for its transmission (Breschi and Lissoni, 2001a; Kesidou and Romijn, 2008). As spatial proximity facilitates informal interactions (Boschma, 2005), embedded ties enhance the exchange of valuable knowledge among economic actors for their mutual benefit (Uzzi, 1997). Family firms are found strongly embedded in localized network of relationships inside which knowledge flows (Kalantaridis and Bika, 2006). "Anchorage" to the local *milieu* is deemed to facilitate not only the access to sticky knowledge and novel information (Amato, Backman, and Peltonen, 2021), but also its dissemination throughout the locality to the benefit of nearby firms (Block and Spiegel, 2013). Given their long-term orientation, family firms may be prone to building long-lasting relationships with external partners (Feranita, Kotlar, and De Massis, 2017), thereby easing the transfer of such knowledge and information (Sirmon and Hitt, 2003). However, at the same time, the intentional leaks may collide with the inter-generational aspirations of family firms, as precious knowledge and information that may be guarded jealously inside the family boundaries (De Massis, Frattini, Kotlar, et al., 2016). Moreover, the family's desire to retain the direct control of the firm's operations (Gómez-Mejía et al., 2007), can hinder external cooperation, hence impeding the exchange of valuable knowledge and information for firm performance.

Inter-firm mobility of workers and managers represents an additional channel for productive spillovers (Blomström and Kokko, 1998) with the result to "enhance the accumulation of local knowledge and to increase the performance of plants" (Eriksson, 2011, p. 132). Labour mobility is common for highly-skilled and educated workers in R&D intensive firms, such as those typically belonging to medium-high and high-tech industries (Fosfuri and Rønde, 2004). However, the lower turnover of both non-family employees and managers that usually characterizes family firms (Bassanini et al., 2013; González et al., 2015) may impede the build-up of such localized knowledge and, hence, dampen productive spillovers.

Finally, the intense local competition associated with co-location, is deemed to force indigenous firms to use the existing technology and resources more effectively (Blomström and Kokko, 1998; Martínez-Victoria, Maté-Sánchez-Val, and Lansink, 2019). While the resulting environmental dynamism can spur the entrepreneurial orientation of all firms (Lumpkin and Dess, 2001), family firms – due to their desire for long term survival, along with their agility in decision-making and involvement in its implementation - may profit more from such a local competitive pressure (Casillas, Moreno, and Barbero, 2010) and indirectly, by the learning and imitation effect, also co-located firms (Mariotti et al., 2015). Nevertheless, the paternalistic culture of family firms may prevail over entrepreneurial orientation leading to a state of "family inertia" which, in turn, influences negatively resource-recombination processes (Chirico and Nordqvist, 2010).

Based on the competing above-mentioned arguments, location close to family firms can alternatively be cause of either positive or negative spatial externalities. Hence, two opposite hypotheses are posed:

> Hypothesis 2a: *geographical proximity to family firms affects positively the productivity level of nearby firms*.

> Hypothesis 2b: *geographical proximity to family firms affects negatively the productivity level of nearby firms*.

The involvement of a given family in ownership and managerial positions is deemed to have an impact on innovation strategies and technology advances as well (De Massis, Frattini, and Lichtenthaler, 2013; Kotlar et al., 2013), thus affecting the firm's own productivity and - by means of spillovers - also that of nearby firms especially in technology-intensive environments (Medda and Piga, 2014). The family's tight control over the firm, wealth concentration, and the importance attached to non-financial goals, lead family firms to avoid highly-risky projects and investments in disruptive innovations which could maximize short-term returns but threaten family's socio-emotional endowment (Alberti and Pizzurno, 2013; Nieto, Santamaria, and Fernandez, 2015). Family owned and managed firms are generally expected to pursue incremental and less radical innovations. Family involvement in the business has been generally associated with lower levels of R&D investments, while, concerning innovation outputs as the number of filed patents and product innovations, the findings are mixed (De Massis, Frattini, and Lichtenthaler, 2013). The tendency to adopt a more conservative stance could prevent the firm from becoming a potential source of positive spillovers driven by innovation in technology-intensive environments. Such an approach may exacerbate the distance in terms of knowledge, skills and competencies between firms, thereby hindering interactive learning processes (Boschma, 2005). However, despite the fact that family involvement in the business is associated with lower R&D efforts (Kotlar et al., 2013), family firms display a higher conversion rate of innovation input into output (e.g., patents, product launches) than non-family firms (Duran et al., 2016). Family owners' sensitivity towards long-term goals - including non-financial ones - a cautious management and conservation of resources and their reluctance to loosen their control on business operations may lead to higher efficiency levels in managing R&D activities (H.-L. Chen and Hsu, 2009). Hence, given that R&D investments and innovation outputs are typically associated to productivity gains (Hall, Lotti, and Mairesse, 2009), family firms pursuing innovation may become a source of spatial externalities, thus influencing the advantages of co-location.

As spatial proximity promotes the spontaneous exchange of knowledge and information among nearby firms (Kesidou and Romijn, 2008), innovative family firms may strongly influence collective learning, the dynamic and cumulative buildup of knowledge and diffusion processes, occurring through repeated social interactions in the local area (Capello and Faggian, 2005). Given that such interaction is greatly impacted by the degree of trust existing among co-located firms (Bathelt, Malmberg, and Maskell, 2004), the reciprocal and trust-based relationships among family members are likely to be replicated outside the organizational boundaries (Arregle et al., 2007), moulding and strenghtening the bond between innovating firms and their neighbours (Bird and Wennberg, 2014). By sharing the same space of relationships, the owing family and the firm ease the exchange of knowledge and information in the locality (Kalantaridis and Bika, 2006). Hence, the local embeddedness of family firms is deemed to heighten the advantage of spatial proximity to innovator for nearby firms. For instance, Amato, Ricotta, and Basco (2022) find that the spatial concentration of innovative family enterprises, by fostering knowledge spillovers, is positively associated with the innovative performance of co-located firms.

In the same way as non-family firms, family firms engaging in innovations may contribute to local productive spillovers via labour mobility (Kesidou and Romijn, 2008). The relevance of highly skilled workers as a factor driving firm-level innovation and, therefore, overall firm performance (Hall, Lotti, and Mairesse, 2009), may increase the family firm's turnover (González et al., 2015). A higher labour turnover may assist family firms in building and constantly nurturing a stock of human capital crucial to keep up with changing technology trends (McGuirk, Lenihan, and Hart, 2015), primarily when firms work on the frontiers of knowledge (Fosfuri and Rønde, 2004). The various skills learned while working for an innovative family firm may spillover as the employees move to nearby firms (Blomström and Kokko, 1998), or set up their own businesses (Kesidou and Romijn, 2008). Since the process of inter-firm mobility is chiefly local, social ties of former employees are deemed to increase social cohesion among plants (Breschi and Lissoni, 2001a), therefore enhancing the accumulation of local knowledge and the performance of spatially proximate firms (Eriksson, 2011).

An innovative family firm is also likely to raise the level of local competition, hence forcing nearby firms to manage their resources more effectively to survive (Blomström and Kokko, 1998). Specifically, local firms may improve their productivity by copying the same technologies, production, and marketing techniques that nearby innovating family firms employ (Mariotti et al., 2015). However, non-financial motives are also likely to spur also the imitation of both locally-based competing and non-competing firms, where "pride and the desire to look good in the local community motivate firms to attempt to outdo each other"(Porter, 2000, p. 23). The imitation effect is likely to be even more intense when the prestige and reputation of innovating family firms are associated with their long-term success and market recognition both within and outside the local *milieu* (De Massis, Frattini, Kotlar, et al., 2016). Hence, by copying family firms, nearby enterprises may improve the internal resource orchestration efficiency to enhance their competitiveness and, indirectly, that of the local economy through spatial externalities on firm performance (Van Oort et al., 2012).

Based on the above-mentioned theoretical arguments, we infer that closeness to innovative family firms is source of productive spillovers. Therefore, the following hyphotesis is formulated:

> Hypothesis 3: *geographical proximity to family firms pursuing innovation affects positively the productivity level of nearby firms.*

2.3 Methodology

2.3.1 Data

The empirical analysis has been carried out using secondary data obtained from three main sources. First, financial data and information on firms' ownership and management composition are drawn from Aida - Bureau Van Dijk (BvD) dataset[3]. Second, patent information is obtained from Orbis Intellectual Property[4]. Finally, information about foreign sales is drawn from a unique database coming from the Italian National Institute of Statistics (Istat)[5].

For the purpose of our study, we focused on active medium-high and high-technology firms located in Italy for the year 2018. To select companies according to the level of technological intensity, we relied

[3] Aida - BvD is a comprehensive dataset that collects information about the population of limited liability companies located in Italy. A wide set of economic and financial variables - with up to ten years of history - such as revenues, costs, number of employees, tangible and intangible assets, legal status, sector of activity and location are provided.

[4] Orbis Intellectual Property links global patent data to companies and corporate groups. Specifically, 115 million patents are linked to information on about 300 million companies so that an extensive patent portfolio for a given company is provided. In order to match the information contained in Aida-BvD and that contained in Orbis Intellectual Property, the BvD ID number - which uniquely identifies each company - has been used.

[5] Information about firms' exports stems from the so-called Intrastat System. It consists of a set of procedures – based on firms' declarations – that ensure the fulfillment of two key functions. First, the fiscal control of intra-community trade in goods and services carried out by national operators with the rest of the European community, and second, statistics on the exchange of goods carried out by national operators with the rest of the European community. We matched the information contained in both Aida-BvD and Orbis Intellectual Property with those provided by Istat by means of VAT number, which uniquely identifies companies.

on the Eurostat classification based on NACE Rev. 2 at 2-digit level[6]. Specifically, based on the level of their technology intensity (R&D expenditures/value added), Eurostat groups manufacturing activities into: i) medium-high technology, which consists of the following industries: *Manufacture of chemicals and chemical products*(20), *Manufacture of electrical equipment*(27), *Manufacture of machinery and equipment n.e.c.*(28), *Manufacture of motor vehicles, trailers and semi-trailers*(29) and, finally, *Manufacture of other transport equipment*(30); and, ii) high-technology, consisting of the following industries: *Manufacture of basic pharmaceutical products and pharmaceutical preparations*(21) and *Manufacture of computer, electronic and optical products*(26).

Our sample is comprised uniquely of active medium-high and high-tech firms with at least 10 employees. We excluded micro-enterprises, whose innovation strategies are mainly based on incremental (or adaptive) innovations and engaging in lower R&D efforts and patent activity vis-à-vis larger firms showing a greater propensity to internally generate technological knowledge embodied in patents (Evangelista, Iammarino, et al., 2001; Faherty and Stephens, 2015)[7]. The initial sample consists

[6]NACE represents the European standard classification of productive economic activities. In 2002, a major revision of NACE was launched with the regulation establishing NACE Rev. 2 adopted in December 2006. It includes provisions for the implementation of NACE Rev. 2 and the coordinated transition from NACE Rev. 1.1 to NACE Rev. 2 in various statistical domains. NACE Rev. 2 is to be used, in general, for statistics referring to economic activities performed from 1 January 2008 onwards. For more information please refer to: https://ec.europa.eu/eurostat/web/nace-rev2.

[7]In Italy a model of incremental innovation prevails, characterized by a large amount of "Innovators without research", that is firms who claim to have introduced product and process innovations without R&D investments. These firms, mostly micro and small enterprises, have a significantly lower ability to patent and register industrial designs, trademarks and copyright (Bugamelli, Cannari, et al., 2012). Their peculiar innovation strategies are such that standard innovation input and output measures are likely to underestimate or not mirror their innovation efforts properly. A well-known weakness of R&D and patent information is that it does not depict more "downstream" forms of innovation, such as the incremental improvements of products and process innovations, as well as the adoption of technologies embodied in new equipment, that are not protected through patents (Evangelista, Iammarino, et al., 2001). That is particularly true for micro-enterprises that engage mostly in such adaptive innovations as compared to large enterprises. There is a tangible risk that the metric we employ in our study to identify innovative firms (please, refer to paragraph 2.3.2) is not able to capture the output of the peculiar innovation strategies pursued by micro-enterprises. Micro-enterprises actually differ significantly from small, medium-sized and large firms as regards their propensity to apply for a patent. Table 33

of 25,182 companies. After removing micro-enterprises (11,092 observations), duplicates of information on latitude and longitude coordinates (2 observations), and missing data (1,375 observations), we obtained a final sample of 12,713 firms.

Tables 27 and 28 in the Appendix show the sample distribution by industry and size, respectively. Table 27 indicates that the sampled firms are mainly concentrated in medium-tech industry (11,093 out of total companies). Table 28 shows that small firms account for the majority (9,423) followed by medium (2,743) and large companies (547).

2.3.2 Variables

Dependent variable

Our dependent variable is labour productivity (*Productivity*) which has been widely used in the investigation of the effects of spatial externalities on firm performance (Fazio and Maltese, 2015; Raspe and Oort, 2011). It is measured as the natural logarithm of a firm's value added per employee (Van Oort et al., 2012). Value added is obtained as the difference between the firm's revenues and the cost of intermediate goods and ser-

provides empirical support for such a statement. It displays probit estimates obtained regressing the *Innovator* dummy (please, refer to paragraph 2.3.2 for its definition) on a set of firm-level explanatory variables. We control alternatively for a categorical variable named *Size category* (specifications 1 and 3), built according to the definition of micro, small and medium-sized enterprises provided by the EU recommendation 2003/361, and a binary variable named *Micro* (specification 2 and 4) which takes value 1 if the firm employs less than 10 people. As the firms' innovation efforts can take time to yield results, we repeated the estimates by using the one-year lead of the dependent variable in specifications 3 and 4 in order to model the temporal gap. We observe that with respect to micro-enterprises, all the categories of small, medium-sized, and large enterprises are associated with a larger probability of applying for a patent. Consistently, specifications in columns 2 and 4 show that micro-enterprises are innovators with a lower probability. Table 31 displays the estimation sample composition by size. The third column shows the share of enterprises that applied for a patent by size category. Only 1.2% of micro-enterprises submitted an application. As a further check, we run several t-tests (please, see table 32), confirming that the percentage of micro-enterprises applying for a patent is significantly lower than the share of small, medium-sized, and large enterprises submitting at least one application.

Such findings may be due to the limits ascribed to patent information in capturing incremental innovations or to the pitfalls of a smaller size. Indeed, micro-enterprises suffer from major limitations due to financial pressure, a negative management style, and poor material and ICT infrastructure, which represent major barriers to innovation (Evangelista, Perani, et al., 1997).

vices needed in the production process. Hence, value added includes salaries, amortizations, interests, taxes and profits. Firms' value added (*Value Added*) has been used as an alternative dependent variable for a robustness check (Owoo and Naudé, 2017).

Explanatory variables

Since R&D expenditures represents a partial measure of firm innovation (Hall, Lotti, and Mairesse, 2009), we adopt an "output approach" by considering the outcome of the innovation process in lieu of the input. Specifically, we chose patent application to approximate a firm's innovative potential. That is because, regardless of whether the patent is eventually granted or not, the application for this intellectual property right entails a significant element of innovation (Cabrer-Borras and Serrano-Domingo, 2007). For each firm we have information on the number of published utility patent applications carried out in a given year. On that basis, we create a dichotomous variable *Innovator*, coded '1' if the i-th firm has applied for a patent, and '0' otherwise.

To identify the family status of the firm, we rely on the demographic approach which considers the involvement of a family in both ownership and managerial positions as sufficient condition to capture the influence of the family in the business (Basco, 2013). Specifically, we count on the Global Ultimate Owner (GUO)[8] indicator provided by Aida-BvD and we consider a firm as family-owned and managed if two conditions are met: i) the i-th firm reports a GUO with "one or more named individuals or families" (Cucculelli and Storai, 2015; Cucculelli and Peruzzi, 2020); and, ii) the GUO is also manager. The latter condition occurs whenever the GUO serves in positions at the highest level of the company management, as sole administrator, CEO, managing partner, legal representative

[8] A global ultimate owner is the individual or entity at the top of the corporate ownership structure, that is the shareholder with the highest direct or total percentage of ownership and, as such, able to exert a control over the company. Aida-BvD identifies the following types of GUO: Bank, Financial company, Insurance company, Industrial company, Mutual and pension fund, Foundation & Research Institute, Public authorities, States, Governments, Individuals or families, Employees–managers–directors, Self-ownership, Private equity, Public, Unnamed private shareholders, Other unnamed shareholders aggregated.

or chairman[9]. Therefore, we create a dummy variable (*Family firm*) coded '1' if the i-th firm is family-owned and managed, and '0' otherwise. The interaction term *Innovator×Family firm* is introduced to test whether the effect on productivity associated to the firm's family status differs across groups, conditional on their being innovators or not. Specifically, we want to investigate whether and to what extent spatial proximity to an innovative family firm is beneficial for neighbouring firms.

Control variables

We control for a set of firm characteristics potentially affecting the level of labour productivity. First, we control for the size of the firm expressed as the natural logarithm of total number of employees (*Size*). As exporting firms are found to be more productive than non-exporters (Fryges and Wagner, 2008), we control for firms' international scope (*Exporter*). In so doing, we create a dummy variable coded '1' if the firm sells abroad and '0' otherwise. We control for the age of the firm (*Age*) expressed as the number of years since its foundation. To account for the intangible capital as a key component of the knowledge of the firm and driver of labour productivity (Marrocu, Paci, and Pontis, 2012), we control for the value of intangible fixed assets per employee (*Intangibles*)[10]. To account for the firm's financial structure, we control for the ratio between equity and total liabilities (*Leverage*). As workers' skill intensity is deemed to affect firm productivity (Cardamone, 2017), the cost of labour per employee

[9]However, contrary to Cucculelli and Storai (2015) and Cucculelli and Peruzzi (2020) who rely solely on the GUO, we also consider the overlap between ownership and management as prerequisite to qualify a given business as a family firm.

[10]The intangible fixed assets are those that by definition lack materiality. Their evaluation and budget is regulated by the OIC (Italian accounting standards) n° 24 issued by the "Organismo Italiano di Contabilità". Intangible fixed assets are shown in section BI of the assets side of the balance sheet and are comprised of the following items: BI1) start-up costs; BI2) R&D and advertising expenditures; BI3) costs incurred for either the acquisition or development and license of patents; BI4) concessions, licenses and trademarks; BI5) goodwill; BI6) assets under constructions and payments on accounts; and, BI7) others. For more information, please refer to: https://www.fondazioneoic.eu/wp-content/uploads/downloads/2015/01/OIC-24-Immobilizzazioni-immateriali.pdf.

is considered in the estimates (*LC ratio*)[11]. Foreign ownership, by introducing new knowledge and best technical and managerial practices into the firm (Blomström and Kokko, 1998), may affect a firm's productivity level positively. Hence, we include a dichotomous variable (*Foreign*) coded '1' if the firm is held by a foreign owner, and '0' otherwise. To account for the efficiency gains due to the membership to a business group (Cardamone, 2017), we include a dummy variable (*Group*) coded '1' if the firm is part of a business group, and '0' otherwise. We control also the firm's affiliation to the so-called "contratto di rete". This consists of a legal instrument through which participants realize aggregations and mutual cooperation, whilst maintaining their autonomy and legal identity. Hence, we include a dummy variable (*Network agreement*) coded '1' if the firm signed the above-mentioned contract, and '0' otherwise[12]. To control for whether firms' labour productivity is affected by unobserved heterogeneity across industries and regions, we include six dummy variables corresponding to the different medium-high and high-tech NACE codes (*Industry*) and five dummy variables corresponding to the first-level Italian NUTS regions (*Region*)[13], respectively. Table 7 summarizes the variables employed in the study.

[11]The rationale behind the inclusion of labour cost ratio per employee as proxy of quality labour is that skill intensity should be correlated with higher wages (Cardamone, 2017).

[12]Introduced in the Italian legal system with the Law no. 33 of 9 April 2009, the "contratto di rete" can be stipulated by entrepreneurs regardless their respective nature (that is individual businesses, companies and public entrepreneurs, also non-commercial) as a type of collaboration the aim of which is to realize shared projects and objectives, increase the innovative capacity and competitiveness. We retrieved the information on the contracts on the Italian Chamber of Commerce and matched it by means of firms' VAT number. For more information, please refer to: `http://contrattidirete.registroimprese.it/reti/`.

[13]NUTS stands for "Nomenclature of Territorial Units for Statistics". It consists of the geocode standard adopted by Eurostat for referencing the territorial division of EU member countries for statistical purposes. With regard to Italy, the three NUTS levels are the following: NUTS 1, consisting of 5 Groups of regions; NUTS 2, which is made up of 20 Regions; and, finally, NUTS 3, consisting of 107 Provinces. Below the NUTS level, two Local Administrative Units (LAU) are identified: LAU 1, which corresponds to NUTS 3 level and LAU 2 consisting of 8094 Municipalities (*Comuni*).

Table 7: Variable description

Variable	Description
Dependent variable	
Productivity	Value added per employee taken in logarithm
Value added†	Value added in absolute value taken in logarithm
Independent variables	
Innovator	Dummy variable coded "1", if the firm i has filed a patent, "0" otherwise
Family firms	Dummy variable coded "1", if the firm i is family-owned and managed, "0" otherwise
Control variables	
Size	Number of total employees taken in logarithm
Intangibles	Intangibles fixed assets per employee
Network agreement	Dummy variable coded "1", if the firm i is part of a network, "0" otherwise
Age	Number of years since its establishment
Exporter	Dummy variable coded "1", if the firm i sells abroad, "0" otherwise
Leverage	Shareholder equity on total liabilities
LC ratio	Labour cost per employee
Group	Dummy variable coded "1" if firm i is part of a business group, "0" otherwise
Foreign	Dummy variable coded "1" if firm i is held by a foreign owner, "0" otherwise
Industry	Dummy variables according to the level of technological intensity based on NACE Rev. 2 codes
Regions	Dummy variables according the NUTS 1 level classification

Note(s):† Robustness check

2.3.3 Econometric specification

To test our hypotheses, we consider the following cross-sectional model:

$$\text{Productivity}_i = \alpha_0 + \beta_1 \text{Innovator}_{i,t-1} + \beta_2 \text{Family firm}_i + \mathrm{c}^T_{i,t-1}\delta + \phi_s + \omega_r + \varepsilon_i \tag{2.1}$$

where α_0 is the constant term; β_1 and β_2 measure the effect of our variables of interest on the dependent variable; $c_{i,t-1}$ is a vector collecting a set of control variables that captures firms' heterogeneity and δ is the coefficient vector; ϕ_s and ω_r denote the industry-specific and region-specific fixed effects respectively and ε_i indicates the error term. It is worth noting that endogeneity issues may arise due to simultaneity between *Productivity* and *Innovator*. Indeed, while innovation is positively related to a firms' efficiency, the opposite is true with only the most productive firms capable of filing a patent. To lessen this issue, which may lead to biased estimates, we rely on the one-year lagged patent application information, in our case 2017. Always to ease simultaneity bias, we lag the financial control variables by one period.[14]

In a second specification of our model, we extend equation (2.1) by including the interaction term *Innovator×Family firm*, since we are interested in disentangling the effect of family firm status on productivity conditional on their being innovators or not. Specifically, the model is stated as follows:

$$\begin{aligned}\text{Productivity}_i = \alpha_0 + \beta_1 \text{Innovator}_{i,t-1} + \beta_2 \text{Family firm}_i + \\ + \beta_3 (\text{Innovator}_{i,t-1} \times \text{Family firm}_i) + \mathrm{c}_{i,t-1}^{T} \delta + \phi_s + \omega_r + \varepsilon_i\end{aligned} \tag{2.2}$$

where β_3 conveys the effect of the interaction term on the dependent variable.

In order to investigate the role of spillovers enabled by geographical proximity, a spatial econometric approach is taken into account (Anselin and Bera, 1998; Elhorst, 2014). By modeling disaggregated geo-coded firm-level data through spatial econometric techniques, we can capture the spatial externalities occurring at a fine geographical scale (M. Andersson, Klaesson, and Larsson, 2016; M. Andersson, Larsson, and Wernberg, 2019; Rammer, Kinne, and Blind, 2020).

Specifically, given that the outcome for a firm in location l may be influenced by those of nearby firms, we include the a spatial lag of the response variable of equation (1), thus estimating a spatial autoregressive (SAR) or spatial lag model such as the following:

$$\mathbf{y} = \rho \mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{2.3}$$

where $\mathbf{y}$ denotes the n-vector of the dependent variable, which is the log of labour productivity in this case; $\mathbf{X}$ is an $n \times k$ matrix which collects all explanatory variables in equation (2.2), including industry-specific and region-specific dummies; $\boldsymbol{\beta}$ is the parameter vector associated to the exogenous regressors (plus a constant term) and $\boldsymbol{\varepsilon}$ is the n-vector representing idiosyncratic errors. $\mathbf{W}$ is the $n \times n$ spatial weight matrix based on the

[14]Specifically, *Size*, *Intangibles*, *Leverage*, *Export*, *LC ratio* and *Network agreement* refer to 2017.

distance between each firm-pair and parameter ρ is referred to as the spatial autoregressive coefficient. The computation of **W** is based on a distance matrix. Information on the firm's latitude and longitude coordinates is employed to compute **W**. Specifically, for any firm in the dataset, Aida-BvD provides information on the firm's headquarter. We compute a row-normalized inverse-distance matrix where distance is based on the Haversine distance measure (Cardamone, 2017).

In models including spatial lags of the dependent variable, such as SAR models, a change to an explanatory variable in a specific spatial unit can potentially affect all the other units' dependent variables. Hence, unlike non-spatial models, the interpretation of the coefficient estimates is not straightforward and could be misleading. In such a setting, the direct and indirect (or spatial spillover) effects are derived by computing partial derivatives (LeSage and Pace, 2009). The direct effect measures the impact that a change in the i-th observation of the r-th regressor, that is X_{ir}, has on y_i, while the indirect effect reflects the impact of X_{jr} on y_i. To elaborate on this, the SAR model of equation (2.3) can be written as follows:

$$(\mathbf{I} - \rho\mathbf{W})\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{2.4}$$

that is:

$$\mathbf{y} = \sum_{r=1}^{k} \mathbf{S}_r(\boldsymbol{W})\mathbf{X}_r + (\mathbf{I} - \rho\mathbf{W})^{-1}\boldsymbol{\varepsilon} \tag{2.5}$$

where $\mathbf{S}_r(\boldsymbol{W}) = (\mathbf{I} - \rho\mathbf{W})^{-1}\mathbf{I}\beta_r$. In models including endogenous interaction effects the derivatives of y_i with respect to X_{ir} and X_{jr} are given respectively by:

$$\frac{\partial y_i}{\partial X_{ir}} = \mathbf{S}_r(\boldsymbol{W})_{ii} \tag{2.6}$$

and

$$\frac{\partial y_i}{\partial X_{jr}} = \mathbf{S}_r(\boldsymbol{W})_{ij} \tag{2.7}$$

where element ii of matrix $\mathbf{S}_r(\boldsymbol{W})$ from (2.6) measures the impact on y_i arising from a change in the i-th observation of variable r (direct effect) while equation (2.7) shows the effect on y_i from changes in observation j of variable r (indirect or spillover effect). We depart from the independent data model since we assume the cross derivative $\partial y_i / \partial X_{jr}$ to be potentially different from zero and units' i own derivative $\partial y_i / \partial X_{ir}$ usually to deviate from β_r. The sum of (2.6) and (2.7) corresponds to the total effect (LeSage and Pace, 2009).

Since typically direct and indirect effects vary from one observation to another, we need a summary measure to find the direct and spillover effects. The direct effect could be then summarized by computing the average of the diagonal elements in $\mathbf{S}_r(\boldsymbol{W})$, obtaining the so-called *average direct impact*. If we instead take the average of the row sums or of the column sums in matrix $\mathbf{S}_r(\boldsymbol{W})$ we get the *average total impact to an observation* and the *average total impact from an observation* respectively[15]: the two are numerically equivalent. Finally, by definition, the *average indirect impact* is obtained as the difference between the average total impact and the average direct impact.

Another form of spatial dependence occurs when dependence works through the error process, that is the errors from different firms may display spatial covariance. More specifically, a shock in the error μ of a firm at a location l, could be transmitted to other physically close firms. In this case, the spatial error model (SEM) is generally viewed as combination of standard regression model with a spatial autoregressive model in the error term μ (Elhorst, 2014). Hence, equation (1) would be expressed as follows:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\mu} \tag{2.8}$$

with:

$$\boldsymbol{\mu} = \lambda \mathbf{W} \mu + \varepsilon$$

where λ is the autoregressive parameter and ε is a random error term.

[15]The sum over all the elements in the i-th row yields the total impact on y_i resulting from a unit change in all n observations of the r-th regressor, while the sum across the j-th column measures the impact on the response variable of all units stemming from a unit change in regressor r-th element j (LeSage and Pace, 2009).

In order to select the specification which better describes our data, models (2.3) and (2.8) have been compared with the Spatial Durbin model (SDM), which embodies spatial lags of both the dependent and independent variables and is generally assumed as the starting point for the choice of spatial specification (Cardamone, 2017; Elhorst, 2014). This approach relies on the particular features of the SDM. By involving both endogenous and exogenous interaction effects, the model rules out the bias stemming from the exclusion of the spatial dependence in the dependent and explanatory variables when they are actually present. The SDM produces unbiased estimates even when the true data generating process is a SAR, a SAC[16] or a SEM (with a loss of efficiency in the last case), providing also a correct inference on the dispersion of coefficient estimates under a SAR or SEM data generating process (LeSage and Pace, 2009). For its properties, the SDM is a good starting point in the selection of the most appropriate model specification (Elhorst, 2010).

All spatial models introduced in this work have been estimated by maximum likelihood (MLE). Since we assume the error terms are not identically distributed conditional on the value of the covariates, we computed heteroskedasticity-consistent standard errors (or robust standard errors).

2.4 Results

2.4.1 Descriptive statistics and univariate results

Table 8 shows the descriptive statistics. While 10% of firms filed a patent[17], family firms account for nearly 34% of the businesses considered in our study. On average, firms are nearly 26 years old and 80% of them sell abroad. More than 70% of firms are part of a group and nearly 14% are held by a foreign owner.
An examination of the mean comparison tests and their related *t* stats in

[16]The term SAC refers to the spatial autoregressive model with autoregressive errors, a specification including both spatial lag and spatial error dependence.

[17]The number of patent applications ranges from 0 to 496 with mean of 1 and standard deviation of 9.794.

Table 32 indicates that family firms are, on average, less productive, innovative, smaller and less export-oriented than non-family counterparts. Additionally, being part of a business group represents an organizational solution for the totality of Italian technology-intensive family firms.

Figure 5 displays the firms' distribution across Italian regions. As expected, the figure mirrors the Italy's territorial unevenness, with technology-intensive manufacturing firms mostly concentrated in the central-northern part of the country. Instead, figure 6 shows the territorial density in terms of regional share of family firms. The figure gives a more uniform pattern of their spatial distribution in the Italian context [18]

In Table 10 we report the correlation matrix. While the association between family firm status and productivity is negative and statistically significant, being innovator is positively associated with firm's efficiency. Likewise, firm's size, intangibles assets and export propensity are strongly correlated with labour productivity. Inspection of the variance inflation factors (VIFs) displayed in the same table, reveals that multicollinearity is not a concern in our data. Indeed, all VIF coefficients are below the tolerance threshold of 10 (Bird and Wennberg, 2014).

2.4.2 Regression results

We first estimate equation (2.1) and (2.2) by Ordinary Least Squares (OLS)[19]. As shown in Model (1) of Table 11, the coefficient of *Innovator* is positive and statistically significant at 1% level (β=0.106; p<0.01) which suggests

[18]Tables A3 and A4 in the Appendix provide the information displayed in Figure 1 and Figure 2 in tabular form, respectively.

[19]In order to check the robustness of our results to the possible presence of multi-plant enterprises in our sample, we ran OLS estimates on a subsample of enterprises identified according to the number of branches reporting to the firm and the location of their operational headquarters. The term branch refers to a company's secondary location reporting directly to the headquarters, which is not legally separated from the parent corporation. When the sample is restricted to enterprises with no branches (no secondary location) or one branch but legal and operational headquarters in the same municipality, the results in table 11 are confirmed. We ran the same check by estimating the spatial autoregressive models (SAR) in equations 2.1 and 2.2. Consistently with our main findings, we still observed that innovation in family firms narrows the average performance gap with non-family businesses, and mitigates the negative externalities experienced by nearby enterprises. Estimates from the robustness checks are available upon request.

Table 8: Descriptive statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Productivity^{L}	*12,713*	4.170	0.521	-1.744	7.540
Innovator	*12,713*	0.099	0.299	0	1
Family firms	*12,713*	0.343	0.474	0	1
Innovator×Family firm	*12,713*	0.025	0.157	0	1
Size^{L}	*12,713*	3.382	1.026	0	10.404
Intangibles	*12,713*	12.278	113.496	0	9.951.339
Leverage^{W}	*12,713*	0.992	1.374	0.002	8.267
LC ratio	*12,713*	45.674	49.392	0.040	5096.25
Exporter	*12,713*	0.801	0.399	0	1
Age	*12,713*	25.769	16.165	1	125
Network agreement	*12,713*	0.035	0.186	0	1
Group	*12,713*	0.709	0.453	0	1
Foreign	*12,713*	0.136	0.342	0	1

Note(s): ^{L}Expressed in natural logarithm. ^{W}Winsor at 1 and 99% tail.

that innovative firms have higher level of labour productivity than non-innovative ones. Conversely, family firms show lower levels of efficiency. Indeed, all things being equal, the coefficient of *Family firm* is negatively associated with labour productivity (β=-0.091; p<0.01). This result is consistent with previous studies showing the lower productivity of family firms with respect to non-family counterparts (Barth, Gulbrandsen, and Schønea, 2005; Chrisman, Devaraj, and Patel, 2017). Additionally, this finding provides further support with regard to the 'productivity gap' of family firms in the Italian context (Bugamelli, Lotti, et al., 2018). By looking at the control variables, firm size, intangibles fixed assets per employee together with exporting are positively associated with labour productivity. Membership of a business group and being held by a foreign company is related to a higher level of efficiency.

Model (2) includes the two-way interaction term *Innovator×Family firm*, which allows us to observe inter-group differences in the effect of innovation and family status of the firm on productivity. The coefficient of the interaction term is positive and highly significant at 1% level (β=0.102; p<0.01). The impact of innovation on productivity

Table 9: Test of means

Variable	Non-family firms	Family-firms	Test for difference of means	
			Difference of means	t-statistics
Productivity^{L}	4.213	4.086	0.127	13.158***
Innovator	0.113	0.073	0.040	7.149***
Size^{L}	3.503	3.151	0.352	18.622***
Intangibles	14.624	7.793	6.830	3.223***
Leverage^{W}	1.043	0.895	0.148	5.769***
Exporter	0.819	0.767	0.051	6.842***
Age	26.627	24.129	2.498	8.297***
LC ratio	47.126	42.900	4.227	4.585***
Network agreement	0.036	0.034	0.002	0.6
Group	0.558	0.999	-0.441	-58.723***
Foreign	0.197	0.020	0.177	28.484***
Observations	*8,346*	*4,367*		

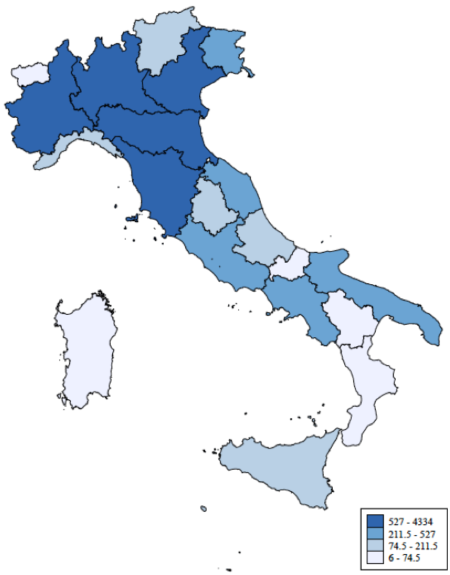
Note(s): ^{L}Expressed in natural logarithm. ^{W}Winsor at 1 and 99% tail. Level of statistical significance * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

is found to be stronger for family firms than for non-family counterparts. Indeed, while innovative family firms have a substantial premium in log productivity equal to[20] 0.181 with respect to non-innovative family firms, non-family firm's gain in log productivity amounts to 0.079 when innovating. More importantly, the productivity gap between family and non-family firms vanishes when both businesses are innovators. Estimates from model specification (2) show that family firm status does not have a detrimental effect if family firms are also innovators. Indeed, the gap in log productivity between innovating family firms and non-family counterparts is positive and equal to 0.001[21]. For a more straightforward interpretation of this result, we plot the interaction term in Figure 7 which shows that the productivity differential between family and non-family firms is particularly wide when the two types of firms are not innovators (left-side of the figure). However, the discrepancy is cancelled out

[20] We derive the controlled difference in the logarithm of the dependent variable between innovative family firms and non-innovative family firms as (β_1+β_3), which is equal to 0.181.

[21] We derive the controlled difference in the logarithm of the dependent variable between innovative family firms and innovative non-family firms as (β_2+β_3) amounting to 0.001. Conversely, the difference in log productivity associated with family firm status when firms are not innovative is expressed by β_2 which is negative and amounts to -0.101.

Figure 5: Medium-high and High-tech firms across regions



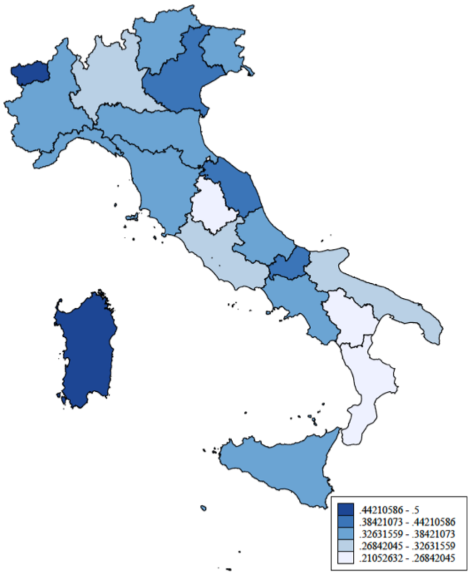
Note(s): Absolute value, 2018

when both family and non-family firms are innovators (right-side of the figure).

A preliminary step in the spatial econometric empirical analysis, is the detection of spatial autocorrelation. To this end, we perform the Moran's I test which examines whether a given phenomenon is spatially clustered or not (Elhorst, 2014; LeSage and Pace, 2009). The null hypothesis is that errors are *i.i.d.*. The highly significant positive value of the statistic (181.45; $p < 0.01$), leads us to reject the null hypothesis suggesting the existence of a spatial autocorrelation in productivity across Italian technology-intensive manufacturing firms. Hence, a positive association exists between observations that are physically close to each other with the most efficient firms that tend to cluster together[22]. This pattern is

[22] After fitting a linear regression including the dependent variable only (productivity),

Figure 6: Family firm regional density



Note(s): Percentage, 2018

deemed to lie at the core of regional science and geography, as expressed in the Tobler (Tobler, 1970, p. 236)'s first law of geography according to which "everything is related to everything else, but near things are more related than distant things". Therefore, the presence of spatial autocorrelation justifies the adoption of spatial econometric models.

In Table 12, we report SAR and SEM estimation results. Following previous studies (Elhorst, 2014; Cardamone, 2017), we perform the likelihood ratio (LR) tests to compare the above-mentioned models with the SDM. Test results are reported at the bottom of Table 12 and reveal that the null hypothesis in favour of the SAR model cannot be rejected. Conversely, we reject the hypothesis that the SEM describes the data better

we carry out the Moran's I test with the following command on Stata: *estat moran, errorlag(W)* where W refers to the row-standardized inverse distance matrix.

Table 10: Correlation matrix

	VIF	Productivity	Innovator	Family firm	Size	Intangibles	Leverage
Productivity	-	1					
Innovator	1.17	0.182*	1				
Family firm	1.60	-0.116*	-0.063*	1			
Size	1.55	0.287*	0.353*	-0.163*	1		
Intangibles	1.03	0.113*	0.073*	-0.029*	0.051*	1	
Leverage	1.06	0.273*	0.034*	-0.051*	0.076*	0.056*	1
LC ratio	1.04	0.208*	0.085*	-0.041*	0.096*	0.054*	0.0435*
Exporter	1.20	0.289*	0.140*	-0.061*	0.279*	0.018*	0.043*
Age	1.21	0.205*	0.066*	-0.073*	0.268*	-0.019*	0.206*
Network agreement	1.02	0.0139	0.047*	-0.005	0.066*	-0.0006	-0.026*
Group	1.62	0.135*	0.122*	0.462*	0.230*	0.041*	-0.0009
Foreign	1.32	0.214*	0.115*	-0.245*	0.335*	0.075*	0.059*

	VIF	LC ratio	Export	Age	Network agreement	Group	Foreign
LC ratio	-	1					
Exporter	-	0.0804*	1				
Age	-	0.089*	0.209*	1			
Network agreement	-	0.0049	0.012	0.0088	1		
Group	-	0.065*	0.081*	-0.024*	0.0303*	1	
Foreign	-	0.112*	0.113*	0.031*	-0.014	0.204*	1

Note(s): Number of observations: *12,713*. Mean VIF=2.85. Level of statistical significance * $p < 0.05$

than the SDM (both p-values associated to the test statistics fall below 0.10). Relying on these results, we focus our attention on the SAR as the main model to carry out our econometric analysis. Notwithstanding this, we display SEM estimation results for comparison purposes.

With regard to the SAR model, the ρ autoregressive coefficient is statistically significant which implies a spatial dependence in labour productivity across firms. Hence, the level of a firm's productivity is affected by the productivity of geographically proximate firms. Parameter estimates from the spatial autoregressive model (SAR) are substantially aligned with those obtained through OLS with the main differences that, when the spatial dependence between observations is accounted for, the coefficient of *LC ratio* turns out to be positive and statistically significant at 1% percent level (β=0.001; p<0.01).

By modeling endogenous interaction effects, the SAR allows to compute average indirect impacts to test the existence of spatial spillovers stemming from neighbouring firms[23]. Table 13 reports the average direct, indirect and total impact of the explanatory variables of interest pertaining to Model(1) and Model(2) of Table 12, respectively. By looking at the indirect effects of Model (1) two main results stand out. First, all things being equal, spatial proximity to innovators is a source of positive spillovers. Indeed, the indirect effect of *Innovator* is positive and statistically significant at 1% level (0.0078;$p < 0.01$). Hence, Hypothesis 1 is supported. Second, family firms are cause of negative externalities, with geographical propinquity to family firms that appears to be detrimental for the productivity of nearby firms. In this case, in fact, the indirect effect of *Family firm* is negative and highly significant (−0.0067;$p < 0.01$). This finding provides support for Hypothesis 2b. Conversely, when disentangling the indirect effect by including an interaction term in the econometric specification, we observe that geographical proximity to family firms which are also innovators, gives a different picture. Indeed, the indirect effect associated to the interaction term *Innovator*×*Family firm* is positive and statistically significant (0.0075; $p < 0.01$) which provides evidence that geographical closeness to family firms which are also innovators eases the locational disadvantages resulting from proximity to non-innovating family firms. Therefore, Hypothesis 3 is supported.

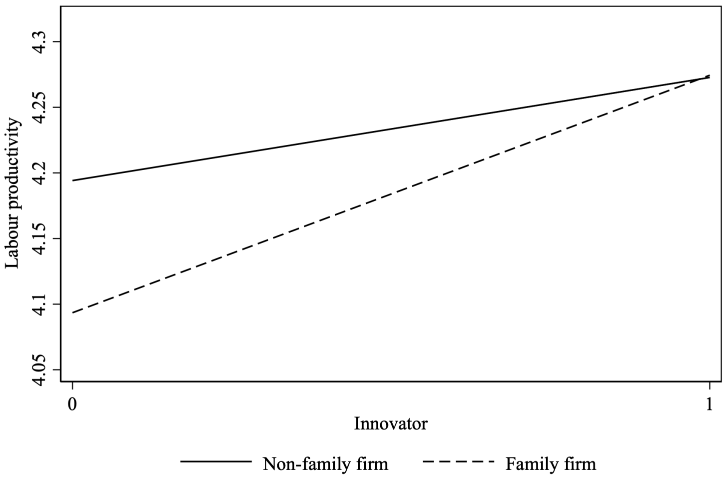
To corroborate our results, we performed a robustness check whose findings are displayed in Table 3.3.4. First, we employed the value added as an alternative dependent variable (Model 1 and 2)[24]. Previous empirical studies tackling nearby firms' spatial dependence (Owoo and Naudé, 2017) and family firms' productivity (Barbera and Moores, 2013) used value added to measure firms' output and capture their performance. The employment of metrics to gauge firms' output per worker (e.g., value added per employee) together with proxies of output in absolute terms (value added) provides a comprehensive picture of firms' performance. Second, we computed an inverse distance SWM by setting a distance

[23] After *spregress*, the post-estimation command *estat impact* allows to estimate spillover effects on Stata. In particular, the statistical package gives back the direct, indirect and total impacts.

[24] As the coefficient of *Size* in Model 1 and 2 is particularly high, we can rule out any multicollinearity issue. Indeed, the VIF of *Size* and the mean VIF are 1.51 and 1.23 respectively.

cut-off. In so doing, we considered neighbours only those firms within a distance of 50 km (Model 3 and 4). Finally, we further raised the cut-off to 100 km (Model 5 and 6). In all cases we estimated a SAR models to compute average impacts which are shown in Table 15. Concerning productivity, regression coefficients and average impacts estimates are consistent with those from the main analysis, confirming our results. Findings from models (1) and (2), employing the value added as the outcome variable, consistently point out that being innovators narrows the average performance gap between family and non-family businesses, thereby mitigating locational disadvantages.

Figure 7: Two-way interaction



2.5 Conclusion

2.5.1 Discussion

The aim of this paper is to investigate the existence of productivity spillovers in the context of technology-intensive manufacturing firms. To this end,

Table 11: OLS results

	(1)	(2)
	OLS	
	Productivity	
Innovator	0.106***	0.079***
	(0.017)	(0.019)
Family firm	-0.091***	-0.101***
	(0.010)	(0.010)
Innovator×Family firm		0.102***
		(0.026)
Size	0.050***	0.050***
	(0.009)	(0.009)
Intangible	0.000**	0.000**
	(0.000)	(0.000)
Leverage	0.083***	0.083***
	(0.005)	(0.005)
Exporter	0.207***	0.207***
	(0.011)	(0.011)
Age	0.002***	0.001***
	(0.000)	(0.000)
LC ratio	0.001	0.001
	(0.001)	(0.001)
Network agreement	0.035*	0.035*
	(0.018)	(0.018)
Group	0.110***	0.113***
	(0.011)	(0.011)
Foreign	0.089***	0.090***
	(0.022)	(0.022)
Constant	3.729***	3.731***
	(0.046)	(0.046)
Observations	*12,713*	*12,713*
R^2	0.282	0.282
Industry-specific FE	Yes	Yes
Region-specific FE	Yes	Yes

Note(s): Clustered robust standard errors in parentheses.
*$p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

spatial econometric techniques have been employed to estimate the role of spatial proximity in explaining firms' productivity besides internal-specific characteristics. In spite of the fact that a large body of literature has shown the locational advantages arising from the spatial concentration of economic activity, the family status of the firm has been traditionally omitted from the discourse on agglomeration economies.

Our study reveals that spatial proximity matters, with the level of firm productivity being heavily dependent upon the productivity of geographically close firms. The existence of such a spatial dependence

Table 12: SAR and SEM results

	(1)	(2)	(3)	(4)
	SAR		SEM	
	Productivity	Productivity	Productivity	Productivity
Innovator	0.105*** (0.014)	0.078*** (0.016)	0.105*** (0.014)	0.078*** (0.016)
Family firm	-0.090*** (0.010)	-0.100*** (0.011)	-0.092*** (0.010)	-0.101*** (0.011)
Innovator × Family firm		0.102*** (0.030)		0.101*** (0.030)
Size	0.049*** (0.005)	0.049*** (0.005)	0.049*** (0.005)	0.049*** (0.005)
Intangibles	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Leverage	0.082*** (0.003)	0.082*** (0.003)	0.082*** (0.003)	0.082*** (0.003)
Exporter	0.207*** (0.011)	0.207*** (0.011)	0.208*** (0.011)	0.207*** (0.011)
Age	0.002*** (0.000)	0.001*** (0.000)	0.002*** (0.000)	0.002*** (0.000)
LC ratio	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Network agreement	0.036* (0.021)	0.036* (0.021)	0.036* (0.021)	0.036* (0.021)
Group	0.109*** (0.011)	0.113*** (0.011)	0.111*** (0.011)	0.114*** (0.011)
Foreign	0.087*** (0.013)	0.088*** (0.013)	0.089*** (0.013)	0.090*** (0.013)
Constant	3.431*** (0.050)	3.434*** (0.050)	3.727*** (0.021)	3.729*** (0.021)
ρ	0.070*** (0.011)	0.070*** (0.011)		
λ			0.071*** (0.012)	0.070*** (0.012)
Log pseudolikelihood	-7648.936	-7643.189	-7651.795	-7646.140
Wald Chi-Square	5053.00	5068.87	4861.82	4877.89
Observations	*12,713*	*12,713*	*12,713*	*12,713*
Pseudo R^2	0.282	0.282	0.281	0.282
Industry-specific FE	Yes	Yes	Yes	Yes
Region-specific FE	Yes	Yes	Yes	Yes
LR test - SAR versus SDM	26.55	26.40		
p-value	0.186	0.235		
LR test - SEM versus SDM			32.27	32.30
p-value			0.055	0.072

Note(s): Robust standard errors in parentheses. Parameters ρ and λ denote the spatial autoregressive coefficient and the spatial autocorrelation coefficient respectively. Maximum likelihood estimates.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

among Italian technology-intensive manufacturing firms is shown by the autoregressive coefficient ρ. However, particular characteristics of neighbouring firms are found to generate either positive or negative externalities (or spillovers effects). Specifically, three main results emerge. First, proximity to innovators is found to be beneficial for the productivity of neighbouring firms. This is consistent with previous empirical evidence on productivity spillovers stemming from innovation efforts (Cardamone, 2017). Hence, besides the in-house innovation, also that developed by other companies affects the efficiency of nearby firms positively. The knowledge and information generated internally do not remain confined within the organization's boundaries but rather spread

Table 13: Average impacts from SAR specifications

	Model (1)		
	Direct	Indirect	Total
Innovator	0.1055*** (7.47)	0.0078*** (4.7)	0.1134*** (7.45)
Family firm	-0.0904*** (-8.68)	-0.0067*** (-5.05)	-0.0971*** (-8.65)
	Model (2)		
	Direct	Indirect	Total
Innovator	0.0782*** (4.81)	0.0058*** (3.79)	0.0840*** (4.80)
Family firm	-0.1004*** (-9.28)	-0.0074*** (-5.15)	-0.1078*** (-9.24)
Innovator×Family firm	0.1017*** (3.39)	0.0075*** (2.97)	0.1093*** (3.39)

Note(s): Level of statistical significance * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
z-values in parentheses.

outwards to the advantage of nearby firms. Spatial proximity facilitates the process of information sharing and knowledge diffusion across companies in this respect.

The second finding is related to the family status of the firm. Family firms are found less productive than their non-family counterparts. This result is in line with previous studies carried out in Italy (Cucculelli, Mannarino, et al., 2014; Bugamelli, Lotti, et al., 2018). Without claiming to be exhaustive, family firms' lower productivity could, at least to some extent, be interpreted in light of their peculiar attitude toward innovation, especially in technology-intensive sectors (De Massis, Frattini, and Lichtenthaler, 2013). Family members' reluctance toward involvement in risky projects, seen as a potential threat to the family's socioemotional wealth, their fear of losing control and their conservative attitude may discourage investments in innovation, leading to a state of "inertia". This, in turn, can have a detrimental effect on the firm's own productivity, thereby hampering the generation of productive spillovers. As shown by average indirect impacts estimates, when the geographical distance is accounted for, spatial proximity to family firms is generally detrimental for nearby firms. In particular, the spillover effect is found to be negative, hence revealing the existence of negative externalities stemming from geographical proximity to family firms. However,

Table 14: Robustness check

	(1)	(2)	(3)	(4)	(5)	(6)
	SAR Value added		SAR Productivity (50 km)		SAR Productivity (100 km)	
Innovator	0.157*** (0.015)	0.128*** (0.017)	0.105*** (0.014)	0.078*** (0.016)	0.105*** (0.014)	0.078*** (0.016)
Family firm	-0.106*** (0.011)	-0.116*** (0.012)	-0.090*** (0.010)	-0.100*** (0.011)	-0.090*** (0.010)	-0.100*** (0.011)
Innovator×Family firm		0.110*** (0.032)		0.102*** (0.030)		0.101*** (0.030)
Size	0.996*** (0.005)	0.996*** (0.005)	0.049*** (0.005)	0.049*** (0.005)	0.049*** (0.005)	0.049*** (0.005)
Intangibles	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Leverage	0.079*** (0.003)	0.079*** (0.003)	0.082*** (0.003)	0.082*** (0.003)	0.082*** (0.003)	0.082*** (0.003)
Exporter	0.195*** (0.011)	0.194*** (0.011)	0.207*** (0.011)	0.206*** (0.011)	0.207*** (0.011)	0.206*** (0.011)
Age	0.001* (0.000)	0.001* (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.002*** (0.000)	0.001*** (0.000)
LC ratio	0.002*** (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Network agreement	0.048** (0.023)	0.048** (0.023)	0.036* (0.021)	0.035* (0.021)	0.036* (0.021)	0.035* (0.021)
Group	0.131*** (0.012)	0.134*** (0.012)	0.109*** (0.011)	0.113*** (0.011)	0.109*** (0.011)	0.113*** (0.011)
Foreign	0.095*** (0.014)	0.096*** (0.014)	0.087*** (0.013)	0.088*** (0.013)	0.087*** (0.013)	0.088*** (0.013)
Constant	3.670*** (0.049)	3.673*** (0.049)	3.407*** (0.049)	3.410*** (0.049)	3.409*** (0.050)	3.411*** (0.050)
ρ	0.033*** (0.006)	0.033*** (0.006)	0.076*** (0.011)	0.076*** (0.011)	0.076*** (0.011)	0.075*** (0.011)
Moran's I test	256.72***		267.97***		261.67***	
Log pseudolikelihood	-8447.596	-8441.640	-7644.124	-7638.378	-7645.027	-7639.287
Wald Chi-Square	77543.130	77627.042	5068.738	5084.653	5065.334	5081.202
Observations	*12,713*	*12,713*	*12,713*	*12,713*	*12,713*	*12,713*
Pseudo R^2	0.859	0.859	0.282	0.283	0.282	0.283
Industry-specific FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-specific FE	Yes	Yes	Yes	Yes	Yes	Yes

Note(s): Robust standard errors in parentheses. The ρ symbol denotes the spatial autoregressive coefficient. Maximum likelihood estimates.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

if we disentangle the indirect effects of family firm status on the basis of whether or not the firm is an innovator, we find that when firms pursue innovation, the negative indirect impact associated to family firms is counterbalanced and is wiped out. Thus, our third finding is that, since innovative family firms are as efficient as their innovative non-family counterparts, being located close to family firms which are also innovators is no longer a source of locational disadvantages for nearby firms.

Family firms' long-term orientation, careful management of resources, tight control over business operations fosters an efficient conversion of innovation inputs into outputs (Duran et al., 2016) stimulating the firm's own productivity. The average direct impacts from model specification (2) of Table 11 show that productivity gains stemming from innovation are stronger for family firms than for non-family firms. It follows that innovative family firms may contribute to the creation of a vibrant and beneficial to firm performance in the local setting where productivity spillovers - stemming from multiple mechanisms such as informal interactions, inter-firm labour mobility and local competition - influence the productivity levels of firms closeby. Because of the anchorage to their home-territory (i.e., local embeddedness) (Amato, Backman, and Peltonen, 2021) and trust-based and reciprocal relationships with local partners (Arregle et al., 2007), innovative family firms can become good neighbours (Amato, Ricotta, and Basco, 2022) or just contribute - by spurring inter-firm mobility and local competitive pressure - to the creation of a dynamic and fertile *milieu* (Block and Spiegel, 2013; Berlemann and Jahn, 2016).

To sum up, while our findings show that the family firms may generally have a detrimental indirect effect on neighbouring firm' productivity, we observe the locational disadvantages vanish when nearby family firms are also innovators.

2.5.2 Contributions and policy implications

This study makes several theoretical and policy contributions. First, it contributes to the literature on agglomeration economies and productivity spillovers (Audretsch and Feldman, 2004; Lychagin et al., 2016). As aggregated measures at a predefined spatial levels have been traditionally employed to detect the advantages of geographical proximity (Van Oort et al., 2012; Fazio and Maltese, 2015), quite recently productivity spillovers between firms have been explicitly considered through spatial econometric models aimed at capturing the spatial dependence and interaction of firms (Cardamone, 2017; Martínez-Victoria, Maté-Sánchez-Val, and Lansink, 2019). From this perspective, our study identifies the family status of the firm as an additional source of heterogeneity in the investigation of externalities and the spatial dimension of the firm's economic activity.

Second, our paper contributes to the growing efforts to bring together family business and regional studies (Basco, Stough, and Suwala, 2021; Berlemann and Jahn, 2016). While the internal dynamics – as stemming from the interplay between family and business domains – have represented the main area of interest, the investigation of family firms in connection with the location where they dwell is still in its infancy. Our study sheds new light on the distinctive role of family firms in influencing the spatial advantages of co-location, that can become either a source of positive or negative externalities depending on whether or not they are innovators.

From a policy perspective, our study reveals that spatial proximity still matters. Specifically, the belief that co-location – by supporting firms' learning and the development of advantageous linkages – enhances the productivity of indigenous firms is further supported by our findings. And as such, cluster policies and initiatives aimed at strengthening and rejuvenate the competitiveness of regions and localities should look at the spatial proximity as a crucial ingredient (Porter, 2000) bearing in mind, however, that "clustering and agglomeration are about more than spatial proximity per se...and cluster policies will need to to do much more than just increasing co-location if they are to boost local, and national, productivity" (Harris et al., 2019, p. 482). Also, the wide discrepancy in terms of productivity levels across family and non-family firms calls for renewed attention from policy makers, towards the former in particular (Basco and Bartkevičiūtė, 2016; Basco, Stough, and Suwala, 2021). Our findings suggest innovation can be a key to eliminating, or at least mitigating, the productivity gap between family firms and their non-family counterparts, especially in technology-intensive industries. Innovation is found to be a source of benefits not only for family firms themselves, but also for neighbouring firms. Hence, public interventions designed to achieve higher level of professionalization and innovativeness may result in improved efficiency of family firms which in turn may stimulate the development of a more dynamic and beneficial local *milieu*. Public policies may take the form, not only of public R&D subsidies to further innovation, but also interventions aimed at promoting the technological transfer and the public-private cooperation (Bugamelli, Cannari, et al., 2012).

Finally, from the managerial perspective, our results may provide useful suggestions with regard to the location choices of new (e.g., startups) or existing companies. In particular, businesses would benefit considerably from geographical proximity to innovative family and non-family firms.

2.5.3 Future avenues of research

Our research has several limitations which could pave the way for future research. First, since our paper relies on cross-section data, future studies should employ a spatial econometric approach on a longitudinal setting. Second, our research encompasses only high-tech and medium-high tech manufacturing firms. Hence, a natural extension of this study would be to include knowledge-intensive business services (KIBS) in the investigation of productivity spillovers (Kesidou and Romijn, 2008). Third, micro firms with fewer than 10 employees may be fruitfully considered because, especially for micro-enterprises, spatial externalities may play a pivotal role in overcoming the constraints associated with the limited size (Yi and C. Wang, 2012). Fourth, the alleged endogeneity of the *Innovator* dummy in the productivity equation needs further attention. Future developments of our work should be devoted to formally tackling the issue. Among the strategies developed to study how innovation affects productivity, the empirical literature proposed the estimation of a system of equations modeling three relationships (Crépon, Duguet, and Mairessec, 1998). The first relates the firm's R&D investments to their determinants; the second links innovation outputs to R&D efforts and the third estimates productivity based on innovation outputs. An alternative solution to estimating dummy endogenous variable models lies in the implementation of a generated instrumental variable approach in two steps (Wooldridge, 2002). Fifth, we did not measure the different channels through which productivity spillovers occur (Blomström and Kokko, 1998; Bathelt, Malmberg, and Maskell, 2004). Therefore, future studies should uncover the different mechanisms - knowledge spillovers enabled by informal interactions, labour mobility and local competition - on which family firms, to a considerable extent, rely and that distinguish them from non-family counterparts. Sixth, Industry 4.0 technologies are causing profound changes in manufacturing industry, affecting the competitiveness of enterprises, local production systems (e.g., Marshallian

Industrial Districts, business clusters) and regions. Hence, future studies should explore the role played by spatial proximity in the adoption of such technologies related to the fourth industrial revolution involving firms in a particular area, family and non-family. Seventh, given the greater concerns of family firms for the well-being of their local community where are located (Berrone et al., 2010), it would be worth investigating the role of family firms in the diffusion of environmentally friendly technologies in pollution-intensive industries. Family firms' community of care together with spatial proximity may promote the adoption of green innovations across contiguous firms. Finally, our theoretical arguments and empirical exercise are based on the premise that geographical proximity would favour the transmission of tacit knowledge and the exploitation of complementaries for nearby firms. However, the gradual recognition of the space as relational – which is not only physical but also comprised of a set of territorialized social relationships (Capello and Faggian, 2005; Dicken and Malmberg, 2001) – calls for the adequate recognition of non-spatial dimensions of proximity (e.g., social, cognitive and institutional) (Boschma, 2005) potentially affecting the ability of family firms to alter the process of information and knowledge dissemination occurring in space (Bird and Wennberg, 2014; Amato, Ricotta, and Basco, 2022). Hence, future studies are needed to investigate the interplay of proximity dimensions, types of businesses (e.g., family and non-family firms) and spatial externalities. Qualitative studies, such as in-depth investigations of firms in their real-life context, may be extremely valuable in this respect.

Table 15: Robustness check: average impacts (all)

	Direct impacts	**Indirect impacts**	**Total impacts**
		Value Added Model (1)	
Innovator	0.1573*** (10.47)	0.0053*** (4.89)	0.1626*** (10.45)
Family firm	-0.1057*** (-9.53)	-0.0035*** (-4.84)	-0.1092*** (-9.53)
		Value Added Model (2)	
Innovator	0.1277*** (7.39)	0.0042*** (4.42)	0.1320*** (7.38)
Family firm	-0.1165*** (-10.12)	-0.0039*** (-4.90)	-0.1204*** (-10.11)
Innovator×Family firm	0.1102*** (3.45)	0.0037*** (2.93)	0.1139*** (3.45)
		50 km cut-off Model (3)	
Innovator	0.1056*** (7.48)	0.0085*** (5.01)	0.1141*** (7.45)
Family firm	-0.0901*** (-8.65)	-0.0072*** (-5.36)	-0.0973*** (-8.63)
		50 km cut-off Model (4)	
Innovator	0.0783*** (4.82)	0.0063*** (3.92)	0.0845*** (4.81)
Family firm	-0.1001*** (-9.25)	-0.0080*** (-5.49)	-0.1081*** (-9.22)
Innovator×Family firm	0.1017*** (3.39)	0.0082*** (3.03)	0.1098*** (3.39)
		100 km cut-off Model (5)	
Innovator	0.1056*** (7.48)	0.0084*** (4.96)	0.1140*** (7.45)
Family firm	-0.0902*** (-8.67)	-0.0072*** (-5.30)	-0.0974*** (-8.64)
		100 km cut-off Model (6)	
Innovator	0.0783*** (4.82)	0.0062*** (3.90)	0.0845*** (4.81)
Family firm	-0.1002*** (-9.27)	-0.0080*** (-5.43)	-0.1082*** (-9.23)
Innovator×Family firm	0.1016*** (3.39)	0.0081*** (3.02)	0.1098*** (3.39)

Note(s): Average impacts estimates refer to SAR specifications displayed in table 3.3.4.

Level of statistical significance * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

z-values in parentheses.

Chapter 3

COVID-19 vaccination and unemployment risk: lessons from the Italian crisis

The content of this chapter was published in Scientific Reports as Pieroni, Facchini, and Riccaboni (2021b). Variations have been implemented based on referees' comments. Previous versions of the study can be retrieved as Pieroni, Facchini, and Riccaboni (2021a) and Pieroni, Facchini, and Riccaboni (2021c).

3.1 Introduction

The beginning of the vaccination campaign in response to the COVID-19 pandemic is considered the first fundamental step in recovering from the damages of the spread of coronavirus (SARS-CoV-2) worldwide. The epidemic has triggered a combined health and socio-economic crisis, with severe consequences: in 2020, the world economy shrank by 4.3% (Chetty et al., 2020; World Bank, 2021). On the supply side, social distancing measures issued by national governments placed workers under stay-at-home orders, shut down 'non-essential' activities, and challenged supply chains. On the demand side, the pandemic has reduced consumer spending, virtually wiping out demand in entire economic sectors such as hospitality, tourism, and travel sectors.

Vaccine strategic distribution plans generally follow the WHO guidelines (WHO, 2004) and, in line with the scientific literature (Medlock and Galvani, 2009; Sah et al., 2018; Scala et al., 2020), EU countries set rules to prioritizing population according to multiple risk criteria related to age, work, and health vulnerability. Guidelines usually do not consider the low-risk healthy population composing a large part of the working force, putting a consistent share of the population on the same ground in the staging of the vaccination rollout.

Here we propose a criterion for administering COVID-19 vaccines in the most advanced stage of vaccination campaigns. As a driving principle, we propose the return-to-work facilitation for the beneficiaries of wage guarantee schemes and workers facing a high unemployment risk, with the expected benefit of a more efficient allocation of public funds and a reduction of future job losses. We also provide evidence on the effectiveness of mobility restrictions for the Italian case implementing an instrumental variable (IV) framework. From the public health point of view, our findings show that a one-percent drop in mobility implies a 0.6 percent drop in excess deaths in the following month. On the other hand, a 1% drop in human mobility corresponds to a 10% increase in the Wage Guarantee Fund (WGF) in the next month. We exploited weather shocks as a source of exogenous variation in human mobility patterns to provide consistent estimates and overcome endogeneity issues. This approach is consistent with the econometric strategy followed in several empirical studies (Aral and Nicolaides, 2017; Miguel, Satyanath, and E. Sergenti, 2004; Bohlken and E. J. Sergenti, 2010) that exploited a naturally occurring source of variation, like the one observed in weather patterns, to infer causal relationships between variables in an IV setting.

The criterion of prioritizing workers at high unemployment risk is also compared to an alternative one based on the working population. The comparison shows that prioritizing workers based on unemployment risk exposure benefits people at a higher risk of marginalization in urban areas.

Our work contributes to the ongoing scientific debate on the epidemiological and socio-economic impact of contagion containment policies (Glaeser, Gorback, and Redding, 2020; Krenz and Strulik, 2021; Borri et al., 2021) proxied by shocks in mobility flows. We provide evidence on the effectiveness of mobility restrictions both from the public health point of view and the socio-economic one. Relying on the hypothesis that people's movements favor the spread of the disease (Birge, Candogan, and Feng, 2022; Fajgelbaum et al., 2021; Bisin and Moro, 2022; Cintia et al., 2020), a stream of empirical studies explored the relationship between mobility shocks following the adoption of social distancing measures and the propagation of the pandemic (Krenz and Strulik, 2021; Glaeser, Gorback, and Redding, 2020), with particular attention to its most severe consequences (Borsati, Nocera, and Percoco, 2022; Borri et al., 2021; Yoo and Managi, 2020). Going beyond the public health sphere, we examine and discuss the socio-economic implications of lockdown policies on private sector economic activities and workers' unemployment risk (G. Bonaccorsi et al., 2020; Fana et al., 2020; Béland, Brodeur, and Wright, 2020) relating mobility shocks to the employment of furlough schemes. Then, we move the discussion forward by proposing a criterion for administering COVID-19 vaccines in the most advanced stage of vaccination campaigns (Medlock and Galvani, 2009; Sah et al., 2018) in a context with a limited endowment of vaccine doses. We recommend a criterion where the main aim of reducing morbidity and mortality comes together with a socio-economic rationale, as the one of reducing unemployment risk. With a few exceptions (Çakmaklı et al., 2021), socio-economic criteria and workers' vulnerability are almost neglected in the discussion concerning the delivery of vaccine doses. We trigger the discussion by integrating the socio-economic perspective in the debate (Czaller, Tóth, and Lengyel, 2021; Czaller, Tóth, and Lengyel, 2022).

From July 2021 on, a new EU Regulation (The EU Digital COVID Certificate Regulation) allows European citizens to obtain a COVID-19 Certificate, which in principle should facilitate free movements across EU member states. Following the guidelines, some European countries are introducing the COVID-19 Certificate not just for traveling purposes but also as a requirement to enter indoor public spaces, attend events or get access to restaurants. The enforcement of the new measures has started a debate on extending the COVID-19 Certificate as a requirement to come back safely to the workplace. In this vein, Italy has already made the Certificate compulsory for school and university personnel. As non vaccinated workers in more professional categories and countries could be potentially impacted by similar restrictions in the near future, the need to account for people's employment status and unemployment risk in delivering vaccine doses gets even more relevant.

3.2 Methods

3.2.1 Data availability statement

Regarding Facebook human mobility, all data are provided under an academic license agreement with Facebook through its "Data for Good" program. Facebook releases data upon request to nonprofit organizations and academics. Concerning the socio-economic variables and the mobility matrix that we have used to validate the pre-lockdown Facebook mobility data, they are all publicly available through the Italian Statistical Office ISTAT (`http://dati.istat.it/`), except for the WGF allowed hours, that are available through INPS, the National Social Insurance Agency (`https://www.inps.it/OpenData/`).

3.2.2 Human mobility data

We analyzed mobility between and within NUTS-3 regions (corresponding to the Italian provinces) based on "Disease Prevention Maps" provided by Facebook through its "Data for Good" program (Maas et al., 2019). These maps consist of anonymous and aggregated information of Facebook users collected starting from their mobile phones with GPS enabled. Data do not directly indicate numbers of individuals traveling but are constructed by Facebook with proprietary methods (including mechanisms to ensure privacy protection) to provide an index that correlates with the actual movement of people. We collected data relative to movements between and within Italian NUTS-3 regions from February 23 to October 1st 2021. Mobility contraction has been estimated by using the Facebook "Movement Range" data, providing, for each NUTS-3 region, an estimate of the average daily contraction of mobility with respect to the pre-lockdown period. The metric captures the change in the average distance covered by people who habitually travel within a NUTS-3 region. It is a global measure as it accounts for human mobility flows originating both from inside and outside each Italian province. In other words, *Mobility range* is the average change in the mean radius covered by those who habitually commute within the NUTS-3 region regardless of whether they come from inside or outside the province. It is expressed in percentage points and aggregated by months to be consistent with the temporal resolution of our longitudinal dataset. Data are not publicly available; Facebook provided them under an academic license agreement. The reader is referred to section 4 of the supplementary information for a comparison and robustness check between Disease Prevention Maps data and the mobility census data provided by ISTAT.

3.2.3 Excess mortality data

Following (Buonanno, Galletta, and Puca, 2020), we considered the excess mortality data as representative of the epidemic spreading. Such an assumption is needed to overcome the potential issues related to the endogeneity of testing policies (showing different criteria, especially during the first wave of the epidemics), hospital capacity, and difference in death classification at the local level. Excess mortality data are available through the website of the National Statistical Office (ISTAT). For each municipality, data report the daily number of deaths for the years 2015-2020. Excess mortality has been computed by aggregating data at NUTS-3 level (Italian provinces) and comparing the number of deaths with the 2015-2019 average: it expresses the difference between the number of deaths recorded in 2020 and the average number of deaths that occurred in the previous five years. The temporal aggregation has been set at the weekly level.

3.2.4 Furlough schemes

Furlough schemes are measured as the number of Wage Guarantee Funds allowed hours to proxy the impact of national policies and imposed shutdowns on private sector economic activities. Data on WGF allowed hours are available at the National Social Insurance Institute (INPS). Monthly allowed hours are aggregated at NUTS-3 region level (Italian provinces) and cover both the economic sectors (ATECO) and the type of worker furloughed (worker or employee).

3.2.5 Rainfall

Daily weather data covering year 2020 have been collected from the weather forecast website ilmeteo.it. Relying on these data, we computed the share of consecutive rainy days recorded in a month over 2020 at Italian provinces (NUTS 3 level).

3.2.6 Betweenness centrality

Betweenness centrality (Newman, 2010) has been estimated on the directed and weighted network computed from the Facebook data accounting for the mobility between NUTS-3 regions (namely: mobility between administrative regions). A sample picture of the mobility network is provided in section 6 of the supplementary material (figure S5).

3.2.7 The instrumental variable model

Empirical estimates concerning the effect of mobility patterns on the COVID-19 death toll and wage integration schemes are likely to be affected by endogeneity issues, potentially in the form of reverse causality or omitted variable bias (Glaeser, Gorback, and Redding, 2020; Krenz and Strulik, 2021; Borri et al., 2021). To disentangle endogeneity and provide consistent estimates, we leveraged the exogenous variation in weather patters across geographies and over time as a source of exogenous shocks to human mobility. The employment of weather data in econometric models is widely observed in the empirical literature (Bohlken and E. J. Sergenti, 2010; Miguel, Satyanath, and E. Sergenti, 2004; Sandholt Jensen and Skrede Gleditsch, 2009; Sarsons, 2015; Muscillo, Pin, and Razzolini, 2021; Aral and Nicolaides, 2017): given their exogenous nature, weather metrics have been exploited in IV frameworks to infer causal relationships between explanatory and outcome variables.

To perform our analysis, we computed the share of consecutive rainy days (at least two in a row) recorded in a month to be used as an instrument. The choice to exclude "isolated" rainy days from the count is meant to leave out transient phenomena, which potentially have no or just a little impact on human mobility. This actually improves the relevance of the instrument.

In order *Rainfall* to be a valid instrument, specific conditions must be satisfied: the metric has to be exogenous (i.e., uncorrelated with the error term) and must be correlated with the endogenous regressor, namely mobility range. Concerning the first requirement (the exogeneity condition), we argue that *Rainfall*, a naturally occurring phenomenon, is not related to the unobservable factors affecting the dependent variables (wage guarantee fund hours and excess deaths). Relying on the exclusion restriction assumption, we state that an induced change in mobility must be the main channel through which weather conditions (*Rainfall* specifically) may affect the use of furlough schemes and the number of excess deaths. We reasonably accept the latter hypothesis by assuming weather conditions to have a very negligible impact on the economic trends of a developed country like Italy (which in turn could lead to a higher request for furlough schemes) as well as a negligible effect on the number of excess deaths which are primarily due to the pandemic. Additionally, we formally ran a test to rule out concerns due to *Rainfall* potential weakness when estimating the first-stage regression. First stage statistics confirm the relevance of our instrumental variable (see sub-section "Endogeneity and IVs relevance test" below and Appendix C.1, section C.1.3 - Regression tables).

The first stage and main equations for the IV model are given by

$$\begin{aligned} Mob.Range_{i(t-1)} &= \pi IV_{i(t-1)} + \gamma Lockdown_t + pv_i + \eta_{it} \\ ln(y)_{it} &= \beta Mob.Range_{i(t-1)} + \delta Lockdown_t + pv_i + \varepsilon_{it} \end{aligned} \quad (3.1)$$

where pv_i denotes NUTS 3 region-specific fixed effects, which allow controlling for time-invariant unobserved characteristics of Italian provinces. The unit-specific fixed effects absorb all the unobserved variation across Italian provinces (NUTS-3 regions)[1]. Both stages include the *Lockdown* dummy which takes value 1 in the months of March, April and May to control for potential time-related effects due to the enforcement of the first countrywide lockdown. In the main equation, the logarithm of the dependent variable is regressed on a month-lagged value of the explanatory variable *Mobility Range*: usually, a delay of about one month occurs between the time in which a firm requires the wage supplementation schemes and the time it is officially authorized and recorded (INPS and Banca d'Italia, 2020). Similarly, changes in the mobility induced by restriction measures are followed with some delay by a decrease of COVID-19 deaths (Leung et al., 2020). To be in line with the instrumented variable the IV has been lagged by one month.

We perform a GMM estimation of the coefficients of the model. Concerning the interpretation of parameter β, a unitary increase in mobility implies a $(\beta * 100)\%$ variation in the dependent variable (since 'Mobility range' is not expressed in percentage points, a unitary change in mobility means actually a 100% change).

[1]Our estimation strategy controls for time-invariant sources of heterogeneity across NUTS-3 regions. Since our dataset comprises monthly observations and covers a period between six and eight months, unit-specific fixed effects should also account for the economic and demographic heterogeneity usually captured by yearly or infra-annual indicators made available by the official National Statistics providers (e.g., Istat - Italian National Institute of Statistics - and the MEF - The Ministry of Economy and Finance- for the Italian case).

3.3 Results

3.3.1 Effects of lockdown

Right after the pandemic outbreak in Italy (Lopreite et al., 2021), the Italian government has extended by decree (Decree Law n. 18/2020 issued on March 17) the extant wage guarantee schemes against the pandemic crisis to strengthen employment protection. The National Social Insurance Agency (INPS) and Bank of Italy (INPS and Banca d'Italia, 2020) reported that from March to April 2020 around 50% of employers in the private sector had been allowed to use wage compensation schemes according to the new rules in force.

The growth of wage supporting schemes by the employers observed from March can be partially explained in light of an additional labour market measure issued in March, the firing freeze, i.e., a temporary suspension of firings, that dropped sharply as compared to their average level in 2017-2019 (Casarico and Lattanzio, 2022).

Figure 8 shows the temporal evolution of the main variables of interest in our empirical analysis. On the right-hand side, Figure 8 shows the monthly average Wage Guarantee Fund (in terms of accumulated hours), while the panel on the left depicts the weekly average number of excess deaths and the weekly average drop in mobility over a time window spanning from January to October 2020. By the end of February, mobility drops significantly (up to 60%) while the number of excess deaths almost simultaneously shows a sharp increase. From the end of March on, we observe a rapid decrease in excess deaths following strict confinement measures. The same does not happen to the Wage Guarantee Fund: in the post-lockdown period, the average allowed Wage Guarantee Fund keeps values three orders of magnitude greater than in previous months. National public policies have had a remarkable impact on labour market flows. According to recent estimates, if measures like the extension of wage supplementation schemes together with firings freeze and financial supports for firms had never been issued, there would have been 600 thousand more firings in 2020 because of the pandemic crisis (Viviano, 2020).

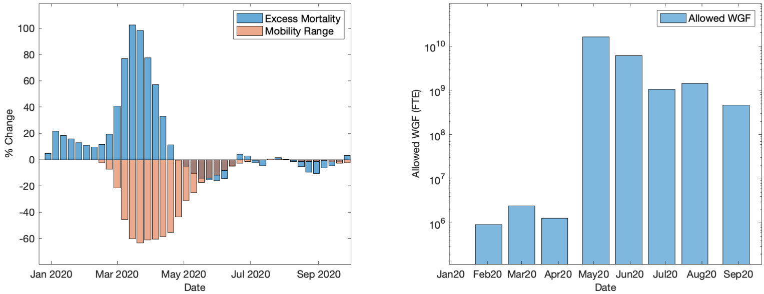


Figure 8: Wage Guarantee Fund, excess deaths and mobility range over time

The subplot on the left displays the average number of excess deaths per week and weekly average mobility changes. The subplot on the right shows the trend over time of the monthly average amount of allowed working hours covered by the Wage Guarantee Fund. The two-week moving average is reported for excess deaths and mobility range.

3.3.2 Impact of restrictions on mortality and unemployment risk

Mobility restrictions have been enforced in many counties to curtail the diffusion of COVID-19 and reduce excess deaths. However, the diffusion of COVID-19 cases has also induced people to reduce non-essential movements spontaneously.

Table 16 displays the main results from the instrumental variable model (3.1). Columns (1) and (2) show coefficient estimates obtained by regressing the logarithm of excess deaths on a one month lagged change in mobility. Results have been estimated on the longitudinal dataset comprising monthly observations from March 2020 to October 2020 on 107 Italian provinces (NUTS 3 regions). Model specification in column (1) controls for time-related effects with the *Lockdown* dummy variable, which takes value 1 in those months when the first national lockdown was in force in Italy: March, April and May.

We find a positive and statistically significant relationship between a change in mobility and excess deaths, which holds true when we control

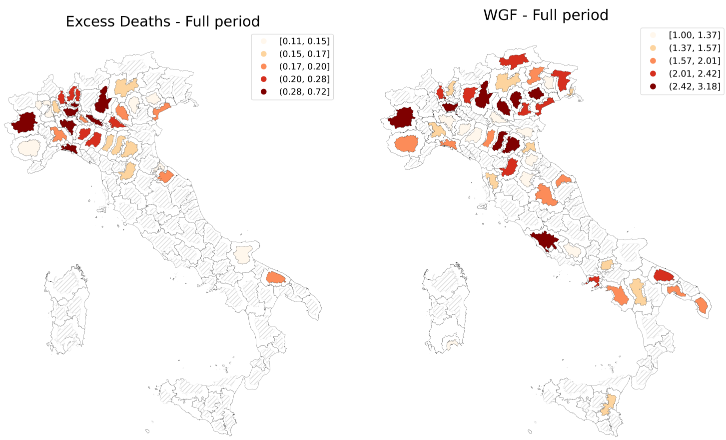


Figure 9: Graphical representation of the NUTS 3 region-specific fixed effects estimated through model (3.1)

The color intensity of NUTS-3 regions (Italian provinces) is proportional to the associated fixed-effect coefficient: darker colors denote higher coefficients. Each region in the plot is rescaled according to the average change in mobility occurred between March and April 2020. The map on the left displays NUTS 3 specific fixed-effects estimates obtained when regressing the logarithm of excess deaths on mobility range (table 16, column 1); the right-hand picture shows fixed-effects estimates when the Wage Guarantee Fund is the dependent variable (table 16, column 5).

for time trends related to the enforcement of the countrywide lockdown. Column (1) shows that excess deaths decrease by around 0.6 percent at time t if mobility drops by one percent in the previous month. In the first stage regression rainfall has an expected negative and statistically significant effect on mobility (see Appendix C, section C.1.3 - Regression tables).

Concerning the consequences of reducing mobility flows on employment risk, in the analysis of the Wage Guarantee Fund we use the same instrumental variable model in (3.1), exploiting the monthly share of consecutive rainy days as an exogenous instrument. First stage results confirm the negative effect of rainfall on mobility (see Appendix C, section

C.1.3 - Regression tables). Model specifications in columns (5) and (6) have been estimated on the period going from March to August 2020, according to the wage guarantee fund data availability.

Results in column (5) show a negative and significant effect of mobility on the dependent variable: a 1% percent drop in mobility at time $(t-1)$ corresponds to a 10.1% increase in the allowed Wage Guarantee Fund in the following month. This implies that the enforcement of national policies effectively curtailed the contagion, discouraged mobility flows and fostered the use of wage compensation schemes provided by law (Decree Law No. 18/2020 of 17 March 2020) to support workers. The magnitude of the effect captures the exceptional drop in mobility flows and the massive ensuing employment of furlough schemes recorded upon the outbreak of the pandemic and in the following months. With the enforcement of the strictest restrictions from March on, mobility flows in Italy decreased remarkably by 50% or more (Cintia et al., 2020; Pepe et al., 2020). Mobility limitations imposed by the national lockdown were unprecedented in their breadth and societal burden. Almost contextually, with the extension of wage guarantee schemes and the enforcement of employment protection measures (Casarico and Lattanzio, 2022), almost 40% of the private-sector workers were furloughed in the months of March and April (INPS and Banca d'Italia, 2020). As previously discussed, even after the gradual lift of the lockdown restrictions, the employment of wage compensation schemes was way higher than in the pre-pandemic and lockdown period as a reaction to the pandemic disruption. Such a temporal dynamic contributes to heightening the magnitude of the effect despite the gradual resumption of mobility flows recorded in the post-lockdown period.

As a robustness check, all model specifications have been estimated instrumenting for mobility with the NUTS 3 region's betweenness centrality in the mobility network, and with the share of labour force employed in "essential" industries (columns (3)-(4) and (7)-(8)). Regression outputs confirm our findings (see methods and section 3 of SI).

A comprehensive view of the impact of restrictions is observed in Figure 9, which provides a graphical representation of NUTS 3 region-specific fixed effects estimates obtained from the main equation of the instrumental variable model (table 16, columns (1) and (5)). The intensity of the color filling each territorial unit on the map is proportional to the associated fixed-effect coefficient: darker colors express higher coefficients. NUTS 3 regions whose coefficients are not statistically significant are in grey. The borders of the regions have been re-scaled according to the average mobility contraction experienced during the lockdown period.

Considering the excess mortality, the left panel of figure 9, highlights the NUTS 3 regions explaining a higher increase in the dependent variable in the whole period (once controlling by mobility and lockdown-related time trends). The most affected regions are located in the northern part of Italy. This also reflects the uneven spread of the disease across Italian regions (Ascani, Faggian, and Montresor, 2020) observed during the first epidemic wave.

The map appears to be less polarized when considering the Wage Guarantee Fund (figure 9, right-hand side). Even if the observable pattern is different, we still observe that higher coefficients are concentrated in the north of the country and in the main urban areas located in central and southern Italy.

3.3.3 Endogeneity and IVs relevance tests

We tested the endogeneity of the main explanatory variable mobility range, running a C test of endogeneity: the value of the test statistic lets us reject the null hypothesis that the regressor is exogenous. This is true for every model specification in table 16 (all p-values fall below 0.013).

About the relevance of the instruments, first stage F-statistics suggest that IVs are strong: when instrumenting by rainfall, F-statistics range from 23.69, model specification (6), to 82.04, model specification (1). When we instrument by NUTS 3 regions betweenness and share of essential residents F-statistics range from 292.32, model specification (3), to 498.91, model specification (4).

Table 16: Instrumental variable regression results for excess death and WGF

	ln Excess Deaths$_{it}$				ln Wage Guarantee Fund FTE$_{it}$			
	MAIN REG.		ROBUSTNESS CHECK		MAIN REG.		ROBUSTNESS CHECK	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	IV	IV	IV	IV	IV	IV	IV	IV
Mobility range$_{i(t-1)}$	0.667***	0.954***	0.491***	0.047*	-10.133***	-12.452***	-5.218***	-3.109***
	(0.160)	(0.300)	(0.061)	(0.028)	(0.864)	(2.142)	(0.242)	(0.174)
Lockdown	0.359***		0.300***		-2.829***		-1.564***	
	(0.058)		(0.032)		(0.257)		(0.126)	
Observations	846	846	855	855	611	611	618	618
Root MSE	0.212	0.327	0.204	0.225	1.350	2.546	0.981	1.243
Instrumental variable(s)	Rainfall	Rainfall	Share essent. Betweenness	Share essent. Betweenness	Rainfall	Rainfall	Share essent. Betweenness	Share essent. Betweenness

Columns from (1) to (4) and from (5) to (8) display IV regression estimates for excess deaths and the Wage Guarantee Fund respectively. Robust standard errors are reported in parentheses. All models control for NUTS 3 region-specific fixed effects. Specifications in columns (1), (3), (5) and (7) control for time trends with the Lockdown dummy, which takes value 1 when the first countrywide lockdown was in force (March, April, May).
Estimates in columns (1)-(2) and (5)-(6) are obtained instrumenting for mobility range by the share of consecutive rainy days recorded in a month. As a robustness check, model specifications in columns (3)-(4) and (7)-(8) employ both the time-varying share of essential residents and NUTS 3 regions' betweenness centrality as excluded instruments for mobility range. All IVs have been lagged by one month to be in line with the endogenous regressor. First stage and reduced form results are reported in Appendix C.1 (see section C.1.3).
For comparative purposes, section C.1.3 in Appendix C.1 displays fixed-effects estimates obtained without employing any instrumental variable, still controlling for NUTS 3 region-specific and time-specific fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.3.4 Robustness check

To corroborate our results, we performed a robustness check instrumenting for mobility by the time-varying share of essential residents (the share of labour force employed in economic sectors designated as essential according to the provisions of Prime Ministerial Decrees) and by the time-varying betweenness centrality of NUTS-3 regions. Following Glaeser, Gorback, and Redding (2020) and Krenz and Strulik (2021), we rely on the assumption that the centrality of a province in the mobility network and the share of people employed in essential industries have an impact on excess deaths just through mobility flows. A similar argument applies to wage guarantee schemes.

Concerning the impact of a contraction in mobility on furlough schemes, we still observe a negative and statistically significant relationship between mobility range and wage guarantee fund allowed hours, consolidating our previous results (table 16, column (7)-(8)). Once again, regression outputs are robust to the inclusion of the lockdown dummy. Estimates from the first stage show that more central NUTS 3 regions and regions with a lower fraction of essential working residents have experienced a higher drop in mobility (see SI, section 3 - Regression tables). About the effectiveness of mobility restrictions in curtailing the contagion, coefficients in columns (3) and (4), table 16, confirm that a contraction in mobility implies a drop in the number of excess deaths in the following month.

Finally, as a further check, model specifications (1)-(2)-(5)-(6) have been estimated employing an alternative measure for rainfall share, which computes the actual number of rainy days in a month, including isolated ones. We observe just a marginal change in coefficient estimates but lower first-stage F-statistics; thus, the choice of including just consecutive rainy days in the metric actually improved IV relevance. The interested reader can find the results of a fixed effect panel model without IVs and all the results for alternative model specifications in Appendix C.1.

3.4 Discussion

3.4.1 Implications for the vaccination campaign

Our empirical analysis suggests prioritizing the areas where the effect of mobility restriction had a higher impact on the unemployment risk. Mobility has a causal effect on mortality and the number of infected people. To mitigate the health impact of the epidemics is essential to reduce the health risk of those essential workers that contribute to increasing mobility at the regional level. Therefore, essential workers and workers not eligible for remote working should be prioritized since they increase mobility, thus inducing higher excess mortality.

When considering the other categories, we find that under the public health point of view, they are composed of substantially equivalent persons. The priority, in this case, should be driven by socio-economic considerations, and to this aim and we suggest putting in a higher priority those workers having a higher unemployment probability or a higher risk of losing their job, increasing the likelihood to return to work. We propose to put in higher priority the areas where the observed increase

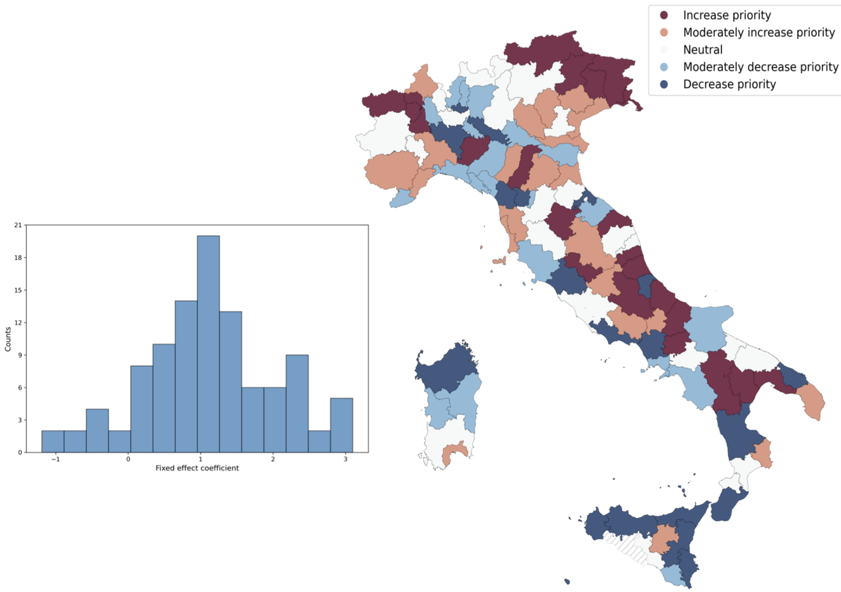


Figure 10: Left panel: Histogram of the Fixed effect values for WGF in the different Italian provinces (NUTS-3 regions); Right panel: Adjusted prioritization policy according to the ranking difference between WGF fixed effects and number of workers.

in allowed WGF is stronger.

Referring to figure 9, on the right panel, we observe that the increase in the number of WGF allowed hours is not uniform, showing a consistent variability among Italian NUTS 3 regions. Colour intensity reflects the intensity of the fixed effects coefficients as from the IV model (table 16, column (5)). Leveraging on this effect, we propose to rank the regions according to the intensity of their fixed effects, where higher values lead to those most in need for wages supplementation schemes.

Such criterion should be more effective from the socio-economic point of view, and to show it, we compare the proposed allocation with a benchmark based on working population (WP). Each province i is ranked according to the two criteria explained above, and we indicate with R_i^{WP} and R_i^{WGF} the position of the region i in the Working Population and

Wage Guarantee Fund criteria. To highlight possible inequalities, we compare the criteria by subtracting WP to WGF rankings:

$$\Delta_i^{WGF} = R_i^{WGF} - R_i^{WP} \tag{3.2}$$

where Δ_i^{WGF} is the difference in the ranking positions between WGF and the working force ranking. The distribution of Δ is reported in figure 10. The intensity of the color is proportional to Δ_i^{WGF}. Areas in light colors between blue and red tones are similar according to both criteria ($\Delta \sim \pm 10$); they are therefore equivalent under both criteria. Provinces in blue and dark blue shades correspond to NUTS 3 regions having $\Delta_i^{WGF} < 0$; then they would be disadvantaged in the case of WP criterion. On the other hand, provinces in red and dark red shades ($\Delta > 0$), would be disadvantaged by distribution criteria based on public expenditure (WGF).

3.5 Conclusions

We analyse the impact of human mobility on excess mortality and the use of furlough schemes in Italy. The impact of lockdown is both found in low-income areas (as in G. Bonaccorsi et al. (2020)) and also appears significant in the productive regions of northern/center Italy and in and urban areas of southern Italy. This is explained by the fact that the lockdown has had a greater impact on people in the low income bracket in urban areas, who became vulnerable and at greater risk of marginalisation. To mitigate the unemployment risk we assume that safe return-to-work will be possible for vaccinated workers, reactivating mobility and restoring full production capacity. This is because the negative health consequences of human mobility will be neutralized. To this aim, we propose a vaccine prioritization policy of the health and active share of the population in two stages. First, access to vaccination should be guaranteed to essential workers and the ones not eligible for remote working. Then, return-to-work should be facilitated for the beneficiaries of wage guarantee schemes and workers facing higher unemployment risks. This will be beneficial both in terms of a reallocation and more efficient use of public funds and in terms of reduction of potential job losses. It is important to highlight that our recommendations refer to the phase of the vaccination campaign when vulnerable categories according to the national strategic plan have already been vaccinated and immunized against the virus.

The proposed strategy puts in advantage those workers employed in the areas in which wage integration measures have been used more, allowing them to come back sooner to a safe workplace (not taking into account potential market labour flows -especially firings- which could occur when public policies issued to increase employment protection will cease), triggering a gradual economic recovery. The expected benefit of this policy can be interpreted mostly in terms of a gradual resumption of most economic activities and in terms of potential alternative allocations of public funds. We recall that, according to the European Commission (European Commission, 2021), the Italian government has committed around 19 billion euros to cover wage supplementation schemes. Under the public health point of view, results show the existence of a positive and significant association between 'one month lagged' mobility changes and the excess deaths recorded: a one percent drop in mobility (w.r.t. the baseline) explains a 0.6 percent drop in the number of excess deaths in the following month.

Our results are relevant for an international audience as well since similar employment protection measures have been issued by European governments as a response to the pandemic. Short-time furlough schemes meant to support the firms affected by the crisis have been introduced or extended in Europe (European Commission, 2021). European Union member states are allowed to ask for European funds in order to cover such employment protection measures: financial support in the form of loans granted on favorable terms is provided under the SURE instrument (temporary Support to mitigate Unemployment Risks in an Emergency).

With regards to the short availability of the vaccines and their optimal distribution, the results presented are particularly relevant in middle and low-income countries, where the share of people fully vaccinated against COVID-19 is significantly lower with respect to high-income countries, with percentages ranging between 1 and 30% (Mathieu, Ritchie, and H., 2021).

Given the heterogeneous impact of the pandemic on local employment (Cerqua and Letta, 2020) and across sectors (Dueñas et al., 2021), this criterion could be extended to address even those workers who lost their job because of the pandemic crisis: immunity against COVID-19 could facilitate applying for and starting a new job in more safely. However, as already mentioned, the prospected scenario does not take into account the labour market dynamics (especially firings) occurring when employment protection policies are lifted[2] (Casarico and Lattanzio, 2022). The integration of the demand side in the analysis may support providing a comprehensive assessment of our proposal. Hence, future research should be devoted to assessing how the interplay between the supply and demand of labour for sectors or occupational categories in the next post-pandemic future could affect vaccinated workers' allocation on the market and mitigate their exposure to unemployment risk.

As our work focuses on the Italian case, future extensions can contribute to understanding how mobility patterns may influence employment risk and vaccination campaigns in other countries and across different sectors of the economy.

Finally, our proposal to prioritize essential workers, those not eligible for remote working and workers facing a high unemployment risk, could be further refined. The policy can be defined based on workers' occupation and employment sector (Czaller, Tóth, and Lengyel, 2021; Czaller, Tóth, and Lengyel, 2022) while looking at the sanitary and socio-economic implications of each proposed scenario. In this respect, the establishment of a priority ranking across occupations can be supported by the systematic assessment of the occupational risk of infections by economic sectors provided by INAIL[3] and adopted by the National Scien-

[2]The last provisions regarding the temporary suspension of individual and collective dismissals are included in the Decree-Law n.41/2021 ("Sostegni"), Decree-Law n.73/2021 ("Sostegni bis") and in the Italian Budget Law for 2022.

[3]Acronym for the National Institute for Insurance against Accidents at Work. For further information, please, visit INAIL website.

tific Committee set up by the Italian government against the crisis[4] (Iavicoli et al., 2020; Marinaccio et al., 2020). Each economic sector, identified according to the Ateco national classification, is ranked based on the associated infection risk. The risk accounts for the degree of physical proximity to others required by the tasks performed, for the probability of being in contact with infected people (e.g., health sector) and for the social aggregation connected to the job. The ranking could be integrated with information on the possibility of performing the tasks remotely (Barbieri, Basso, and Scicchitano, 2022) to assess better whether prolonged stay-at-home orders exacerbate the unemployment risk by type of occupation. Each proposal should be completed by a cost-benefit analysis. The cost of implementing a vaccination policy ranking workers by occupations and sectors has a fiscal, economic and social nature. By definition, allocation programs come at a cost in terms of public expenditure. Public funds should be correctly allocated in an attempt to curb infections while ensuring the continuity of economic activities. Then, the socio-economic consequences of the different vaccine supply scenarios must be carefully examined. Workers' priority ranking should be defined to minimize productivity losses incurred when people performing high-skilled tasks are required to work from home. At the same time, the policy should be designed to mitigate workers' unemployment risk, especially for those who must work on-site or are employed in the economic sectors which have been most severely hit by the pandemic crisis.

[4]The Committee was set up to provide action-oriented policy advice on the COVID-19 emergency.

General Conclusion

This doctoral dissertation is a collection of essays that address debated topics in management, industrial policy and regional studies. It also contributes to the emerging debate on the socio-economic implications of the COVID-19 pandemic, discussing vaccine delivery criteria for the most advanced stage of the vaccination campaign. Specifically, Chapter 3 is devoted to exploring the consequences of government responses to the spread of the novel SARS-CoV-2 virus. Based on that, we discuss our proposal for allocating vaccines across low-risk healthy groups.

All studies focus on the Italian case, as it provides an ideal scenario to study networking policies, localized productivity spillovers and the socio-economic consequences of government responses to the pandemic crisis. Despite being restricted to the Italian case, our results may appeal to an international audience as well, given the growing interest in network and cluster policies[5] shown by national governments and given the enforcement of comparable mobility restrictions and employment protection measures worldwide to cope with the pandemic emergency (OECD, 2022).

This section discusses the main contributions stemming from each Chapter and suggests possible paths for future research.

Chapter 1 provides evidence of the positive impact participation in formal networks has on firms' revenues, value added and EBITDA. The study reinforces previous findings on the benefits ascribed to formalized

[5]For further information, please refer to `https://ec.europa.eu/growth/smes/sme-strategy/sme-performance-review_en#sba-fact-sheets`.

cooperation. It moves the discussion further by shedding light on the temporal evolution and persistence of network agreements' effects over time. We find, indeed, that strategic cooperation formalized through network agreements yields benefits that are persistent in the medium-long term[6] and take time to grow and reach their peak. Then, we claim that the specific combination of partners' profiles is a pivotal driver of networks' value creation potential. As expected, our work confirms that micro firms can reap higher benefits from network participation than larger companies (i.e., the subsample of small, medium-sized, and large firms), especially when tied to a medium-sized or large partner. Compared to stand-alone smaller firms often struggling with the limited availability of resources, micro-enterprises embracing networking practices can access complementary assets, share input costs, integrate skills, consolidate their market position, or enter new markets (Parida, Westerberg, et al., 2010). When tied to larger companies, micro-enterprises can exploit the partners' consolidated market position, superior assets, and reputation. Besides, connecting to heterogeneous firms offers the chance to exchange diverse knowledge and non-redundant information on market trends with mutual advantages, especially in dynamic high-technology fields. Nevertheless, firms must be capable of absorbing the knowledge and stimuli they constantly receive for learning to occur (Boschma, 2005). As diversity and dependence asymmetries between partners can encourage the prominent part to strengthen its domain, the legal definition of network members' rights and duties protects against hostile value appropriation tactics.

The Italian policymaker introduced the legal framework to favor market-induced network formation and stimulate the spontaneous adoption of a promising and growing managerial practice (Arrigo and Tassani, 2016). The evidence discussed in Chapter 1 supports the thesis that inter-firm cooperation secured by enforceable mechanisms effectively delivers lasting advantages. The Italian intervention can be cited as an example

[6]Due to the recent introduction of the policy, we observe a maximum of seven years after the start of the treatment. However, given the limited number of units in our panel getting treated for seven years, estimates for period 7 must be taken carefully. For further details, please refer to Chapter 1, section 1.3 and 1.5.

of "best practice" among the initiatives implemented to transpose the "Small Business Act" principles into concrete actions.

This study contributes to a stream of research dealing with the empirical assessment of policy interventions and government-supported programmes developed to encourage the formation of inter-firm networks for the benefit of smaller enterprises. Unlike most empirical studies addressing the topic, our work exploits recent methodological enhancements in estimating treatment effects in settings with staggered treatment adoption (Athey and Imbens, 2021). We followed the estimation strategy proposed by Sun and Abraham (2020), which allows computing networks' contribution to firms' performance over time and delivers heterogeneity[7] robust estimates, overcoming the issues affecting two-way fixed effects estimates in staggered settings. To address the bias arising from firms' self-selection into the treatment, we implemented a propensity score matching balancing the counterfactual group on a set of observable covariates. Our rigorous approach allowed us to deliver a causal interpretation of formal network impacts, providing evidence of their evolution over time.

Networks are not necessarily territorial phenomena, meaning they can easily overcome regional boundaries connecting firms located in different geographical areas (Boschma, 2005). The policy itself has been designed to promote the exploitation of opportunities both on a local and global scale, as there is no explicit requirement regarding members' location[8] (Massari, Riggio, and Calace, 2015). Notwithstanding, we observe that firms take more advantage of network ties when most of their partners belong to the same travel-to-work area with respect to those belonging to geographically dispersed networks. This suggests that the partnerships formalized through a contract can be even more favorable when firms can exploit the advantages of spatial proximity (e.g., agglomeration economies, knowledge spillovers) and when they share a common cultural and social background.

[7]Heterogeneity across treatment cohorts.

[8]For further information, please see also `https://contrattidirete.registroimprese.it/reti/`.

The implications of enterprises' geographical proximity are better explored in Chapter 2. The chapter unveils the relevance of spatial proximity and localized connections in affecting firms' productivity levels, adding evidence against the "death of distance" thesis (Nijkamp, 2017).

Our results reveal the existence of spatial dependence among nearby firms' productivity levels. We drew from spatial econometrics to model the dependence among firms' productivity. By estimating a spatial autoregressive model (SAR), we could test the existence of spatial spillovers (or indirect effects) stemming from proximate firms' specific features. Consistently with a body of literature providing evidence of productivity spillovers generated by R&D activities (e.g. Cardamone, 2017), we find that proximity to firms pursuing innovation is a source of positive externalities.

We move further by exploring whether being located close to family firms can yield indirect efficiency gains. Family firms are widely diffused over the Italian territory and play a prominent role in the national entrepreneurial fabric (AIDAF, 2021; Cucculelli and Storai, 2015). They are long-term oriented enduring realities that typically establish strong historical, cultural and social connections with the local community (Amato, Backman, and Peltonen, 2021). Family firms' embeddedness in regional contexts can condition the processes regulating regional growth and development (Basco, 2015), although there is still a lack of evidence of the role of family businesses in generating productivity externalities.

Our findings show that closeness to family firms is a source of negative productivity externalities. However, we observe that when family firms are also innovators, the detrimental indirect effect is counterbalanced and is wiped out.

The research presented in Chapter 2 contributes to the extant scientific debate by exploring family firms in spatial settings and creating a bridge between family business and regional studies.

Despite the growing diffusion of information and communication technologies (ICT) claimed to have a distance-destroying capacity (Morgan, 2004), we find that geographical proximity still affects economic activities since it activates localized processes (e.g., spillovers through labour mobility, informal interactions) which stimulate nearby firms' productivity. This evidence has practical implications as it enriches the debate on the design of adequate policies for regional development. Policymakers should consider the importance of firms' co-location when promoting cluster policies to strengthen regions' competitiveness. Besides, our research confirms that innovation carried out by local players activates positive productivity spillovers and contributes to the creation of a fertile *milieu* where knowledge spills out of firms' boundaries either intentionally or unintentionally. This is why public interventions designed to encourage firms' innovativeness are highly recommended.

The socio-economic consequences of public measures against a sudden and unprecedented shock are examined in Chapter 3. Specifically, the Chapter contributes to a novel research line by analyzing how changes in mobility streams following government restrictions and behavioral adjustments impacted the number of excess deaths and employee furloughs recorded in Italy after the pandemic breakout. We observe that mobility constraints effectively prevent the worst consequences of the contagion, as a mobility contraction of 1% corresponds to a mortality reduction of 0.6%. On the other hand, mobility drops increase the number of Wage Guarantee Fund allowed hours, which signals a higher unemployment risk caused by the severe difficulties experienced by Italian enterprises.

To overcome the endogeneity issues likely to affect the relationship between our main explanatory variable, namely *mobility range*, and both dependent variables[9] (i.e., excess deaths and Wage Guarantee Fund FTE), we implemented an instrumental variable model. We exploited the exogenous variation in weather patterns across Italian NUTS3 regions as a naturally occurring source of variation in human mobility. Empirical scholars have already exploited rainfall patterns in instrumental variable settings (e.g. Miguel, Satyanath, and E. Sergenti, 2004; Aral and Nicolaides, 2017). We proposed a similar approach to investigate a novel phenomenon, as we used the exogenous change in weather patterns to esti-

[9]For further information, please refer to the methods section 3.2.7 and C.1.1, appendix C.

mate the effect of mobility flows on the death toll and the use of furlough schemes in a pandemic context. Our empirical approach allowed us to give a causal interpretation of regression estimates and provide early evidence of the consequences of policy responses to the pandemic shock.

As soon as we obtained our IV results, governments released COVID-19 vaccine distribution plans setting the rules to identify priority groups. This allowed us to discuss a potential strategy for administering vaccine doses in the most advanced stage of the vaccination campaign[10] based on socio-economic criteria. We stressed the nexus between mobility contractions, excess mortality, and employee furlough to suggest prioritizing beneficiaries of wage guarantee schemes. The rationale behind the proposal lies in promoting return-to-work policies. If vaccinated, workers facing a high unemployment risk can return to a safe workplace sooner as the most severe consequences of the disease would be neutralized. The expected benefit was a gradual recovery of economic activities with the progressive lift of the most strict mobility restrictions and a more efficient allocation of public funds.

Hence, the work reproduced in Chapter 3 brings novelty in that it provides early insights into the health and socio-economic consequences of mobility perturbations in a pandemic context and suggests a criterion for delivering vaccine doses in the advanced stage of the vaccination campaign. On the methodological side, it applies a peculiar IV strategy in a novel context.

Avenues for future research

Each contribution included in this thesis leaves room for several future research paths.

One of the limitations affecting the empirical examination of the Italian network agreements policy lies in its recent introduction. The cohort of treated units is still narrow and the time span covered by the data is limited. Indeed, only a few enterprises are observed for seven years into the treatment[11]. As more firms embrace this legally-recognized organi-

[10]When the healthy active population is left to be vaccinated.

[11]Please, refer to Chapter 1 section 1.3 and 1.5 for more details on the time span covered

zational solution and new data are released, we have the chance to infer networks' causal impacts by working on a much broader longitudinal dataset. A wider diffusion of contract networks and their constant observation over time would allow for keeping track of the units entering new agreements and leaving existing ones. A possible extension of the study could examine the post-treatment effect of network participation, to test whether the benefits of the partnership persist or cease after the dissolution of formal network ties. By adding new insights into the long-term consequences of networking and their persistence over time, we can enrich the debate on the strategic implications of inter-firm formal cooperation. Future research should raise policymakers', scholars' and managers' awareness that firms' competitiveness and innovativeness can be founded on the renewal of the enterprise's organizational structure by keeping the organization open to nurture fruitful and durable collaborations.

Concerning the exploration of firms' spatial dependence and productivity spillovers, future studies should extend the analysis to the firms active in knowledge-intensive business services (KIBS) to add more evidence of the benefits of local knowledge spillovers. Then, as the findings in Chapter 1 stress the importance of cooperative ties for enhancing the performance of micro-enterprises, future research could be devoted to testing whether the exploitation of local, informal connections with co-located enterprises favors micro firms' productivity development.

The contribution of geographical proximity to economic outcomes and firms' efficiency could be studied in relation to other dimensions of proximity (e.g., cultural, organizational proximity), as the interplay between them could provide alternative explanations for the development of regional economies (Boschma, 2005).

As already discussed, the scientific and institutional debate on the competitiveness of the entrepreneurial system should not overlook the systemic nature of the firm. Since embedded in a net of social ties (Granovetter, 1985), enterprises are typically connected to the territorial surroundings, which contribute to shaping their characteristics and identity

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by the data and statistical significance of estimates referring to relative time 7.

(Dicken and Malmberg, 2001). Further efforts should be devoted to understanding how external contingencies affect firms' performance.

The context where firms are rooted and carry out their core activities provides a lens to better interpret firms' behavior and outcomes (Johns, 2001). The external context is a source of situational opportunities and constraints that affect organizational dynamics and create the conditions that may favor or hamper firms' competitiveness (Johns, 2006). By altering the functional relationship between variables, the context can influence the extent to which firms' efforts lead to success (Syverson, 2011). This is why studying the environment where economic activities take place helps to address many controversial topics in management studies as the one concerning family firms' productivity. Productivity represents a long-debated and unsolved issue in family business research. Indeed, existing empirical evidence is somewhat inconclusive regarding whether family firms are more (e.g. Martikainen, Nikkinen, and Vähämaa, 2009) or less (e.g. Neckebrouck, Schulze, and Zellweger, 2018) productive than non-family firms. Despite the efforts to reconcile the emergence of competing findings, the investigation of family firms' productivity has been mainly "place-less". By incorporating the context into the research, we can unveil whether and under which conditions family firms can leverage their specificities to take advantage of the current contingencies and reach superior performance. Specifically, to integrate the contextual dimension into the research, the context can be meaningfully identified with local institutions. Institutions provide the structure which regulates most of the social and economic interactions (D. C. North, 1990). Differences in institutional settings across countries or regions explain the differential performance of economies and affect firms' productivity by altering the set of rules that shape business activities (e.g. Ganau and Rodrıguez-Pose, 2019). As institutions act as a primary source of constraints, their configuration can provide the key to interpreting the controversial consequences of family ownership on firms' efficiency. For this reason, the contextualization of family firms research can add new elements for a better understanding of why consistent entrepreneurial behaviors can generate conflicting or inconsistent outcomes (Johns, 2006).

Our current research moves in this direction and is devoted to empirically assessing how the efficiency gap between family and non-family firms evolves depending on the quality of local institutions.

On the methodological side, quantitative methods could be integrated with qualitative ones to better gauge the complex socio-economic mechanisms that link the firm to the territorial surroundings and encourage the formation of strategic ties. Collecting qualitative data through in-depth interviews could unveil the inner mechanisms driving decision-making processes, support the development of solid theoretical frameworks and guide the interpretation of ambiguous results (Grigoropoulou and Small, 2022).

Finally, the empirical investigation of the socio-economic consequences following an unprecedented disruption of mobility flows paves the way for promising future research paths as well.

The granularity of human mobility data released by Facebook through its "Data for Good" program[12] allows for computing the change in mobility flows occurring in a narrow area around a point in space. This makes it possible to merge human mobility data and firm-level financial data based on the lat-long coordinates of firms' geographical locations. The setup of a unique dataset is the preliminary step to studying the effect of changes in mobility that occurred after the COVID-19 pandemic outbreak on firms' performance, measured by financial metrics such as revenues or productivity. The research would provide further insights into the impact of restrictive measures and mobility adjustments on the private sector. As we observe changes in human mobility occurring nearby firms' headquarters, we could ascribe part of the variation to workers' mobility, as the enforcement of social distancing measures and stay-at-home orders has encouraged remote working solutions (telework) whenever possible.

By merging firm-level and granular mobility data, we can observe firms' sensitivity to unexpected mobility shocks and point out which industries are less exposed to the risk of worsening their performance if in-place activities are restricted.

[12] For further information, please refer to section 3.2.2, appendix C.

Given the nature of the data, the empirical approach should be adequate to address the endogeneity bias, which is likely to affect the relationship between mobility changes and firms' revenues.

In addition, future research should be devoted to understanding the consequences of the pandemic response on firms' productivity.

Appendix A

Appendix to Chapter 1

A.1 Supplementary information

Table 17: Treated and untreated units' distribution by regions

	Treated		Untreated	
	Frequency	Perc.	Frequency	Perc.
Lombardia	772	24.22	120,679	20.94
Emilia-Romagna	490	15.37	47,394	8.22
Toscana	277	8.69	38,782	6.73
Lazio	258	8.1	69,740	12.10
Veneto	246	7.72	52,773	9.16
Abruzzo	212	6.65	11,820	2.05
Campania	136	4.27	54,279	9.42
Piemonte	126	3.95	31,800	5.52
Puglia	126	3.95	32,894	5.71
Marche	123	3.86	16,917	2.94
Friuli-Venezia Giulia	92	2.89	9,622	1.67
Umbria	89	2.79	7,762	1.35
Calabria	45	1.41	11,453	1.99
Sicilia	44	1.38	32,259	5.60
Liguria	39	1.22	10,532	1.83
Basilicata	38	1.19	4,260	0.74
Sardegna	38	1.19	10,646	1.85
Trentino-Alto Adige	28	0.88	9,426	1.64
Molise	7	0.22	2,392	0.42
Valle d'Aosta/Vallée	1	0.03	843	0.15
Total	3,187	100	576,273	100

Note: Pre-matching statistics.

Table 18: Probit model on treatment status: full sample estimates

	(1) Cohort 2011	(2) Cohort 2012	(3) Cohort 2013	(4) Cohort 2014
Revenues one year before T (ln)	0.170***	0.149***	0.150***	0.134***
	(0.013)	(0.009)	(0.008)	(0.009)
Group size	-0.001**	-0.001	-0.001***	-0.000
	(0.000)	(0.001)	(0.000)	(0.000)
Age	0.010**	0.000	-0.002	-0.002
	(0.005)	(0.003)	(0.002)	(0.002)
Age squared	-0.000**	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Independence	0.067	-0.025	-0.095***	-0.106**
	(0.050)	(0.039)	(0.037)	(0.046)
Constant	-4.749***	-3.643***	-3.808***	-3.565***
	(0.297)	(0.107)	(0.102)	(0.101)
Observations	258,843	280,197	298,223	318,583
Pseudo R^2	0.126	0.087	0.083	0.066
Industry dummies	Yes	Yes	Yes	Yes
Region (NUTS1) dummies	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

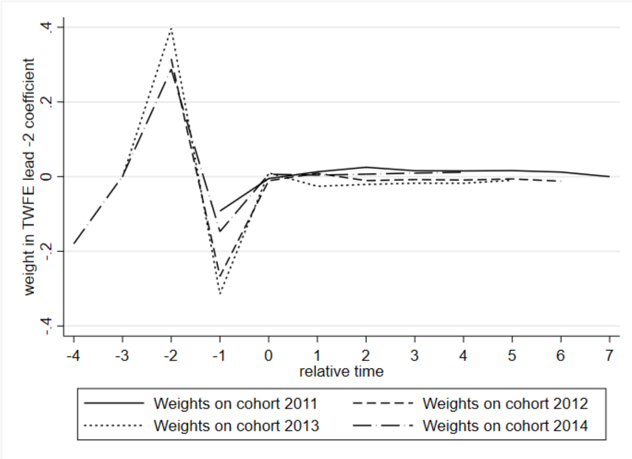
Table 19: Matching statistics for cohorts 2011 and 2012

	Unmatched/ Matched	Mean		t-test	
		Treated	Controls	t	p-value
First treated in 2011					
Revenues in 2010 (ln)	U	7.712	6.338	14.59	0.000
	M	7.712	7.742	-0.26	0.795
Group size	U	6.871	10.698	-0.24	0.812
	M	6.871	5.026	1.02	0.307
Age	U	28.154	23.976	6.06	0.000
	M	28.154	28.411	-0.28	0.781
Age squared	U	948.850	740.940	3.95	0.000
	M	948.850	949.590	-0.01	0.990
Independence	U	0.151	0.131	1.12	0.261
	M	0.151	0.143	0.32	0.749
Industry dummies	U	27.474	28.420	-1.58	0.114
	M	27.474	27.734	-0.26	0.793
Region (NUTS1) dummies	U	2.943	3.140	-2.67	0.008
	M	2.943	2.957	-0.14	0.893
First treated in 2012					
Revenues in 2011 (ln)	U	7.540	6.320	19.03	0.000
	M	7.540	7.552	-0.14	0.890
Group size	U	5.315	10.344	-0.48	0.631
	M	5.315	5.854	-0.28	0.779
Age	U	27.174	23.087	8.73	0.000
	M	27.174	27.156	0.02	0.981
Age squared	U	950.260	700.920	7.15	0.000
	M	950.260	966.530	-0.26	0.792
Independence	U	0.114	0.128	-1.12	0.261
	M	0.114	0.124	-0.55	0.582
Industry dummies	U	25.442	28.424	-7.36	0.000
	M	25.442	25.611	-0.27	0.790
Region (NUTS1) dummies	U	2.997	3.142	-2.89	0.004
	M	2.997	3.104	-1.58	0.114

Table 20: Matching statistics for cohorts 2013 and 2014

	Unmatched/ Matched	Mean		t-test	
		Treated	Controls	t	p-value
First treated in 2013					
Revenues in 2012 (ln)	U	7.265	6.222	18.95	0.000
	M	7.265	7.249	0.22	0.827
Group size	U	5.441	10.366	-0.54	0.593
	M	5.441	5.871	-0.33	0.739
Age	U	23.720	22.204	3.77	0.000
	M	23.720	23.966	-0.44	0.663
Age squared	U	728.080	662.820	2.24	0.025
	M	728.080	744.560	-0.42	0.673
Independence	U	0.092	0.124	-3.18	0.001
	M	0.092	0.106	-1.09	0.275
Industry dummies	U	27.002	28.514	-4.37	0.000
	M	27.002	27.106	-0.19	0.853
Region (NUTS1) dummies	U	3.372	3.145	5.31	0.000
	M	3.372	3.350	0.37	0.711
First treated in 2014					
Revenus in 2013 (ln)	U	7.114	6.139	13.49	0.000
	M	7.114	7.135	-0.22	0.826
Group size	U	9.077	10.209	-0.1	0.924
	M	9.077	7.651	0.47	0.638
Age	U	23.492	21.229	4.29	0.000
	M	23.492	23.881	-0.48	0.635
Age squared	U	755.050	622.970	3.55	0.000
	M	755.050	783.230	-0.46	0.644
Independence	U	0.084	0.119	-2.75	0.006
	M	0.084	0.077	0.42	0.677
Industry dummies	U	27.186	28.635	-3.22	0.001
	M	27.186	27.281	-0.12	0.903
Region (NUTS1) dummies	U	3.039	3.145	-1.9	0.058
	M	3.039	3.108	-0.81	0.417

(a) Weights $w_{e,\ell}^{-2}$ for lead -2 (μ_{-2})



(b) Weights $w_{e,\ell}^{-3}$ for lead -3 (μ_{-3})

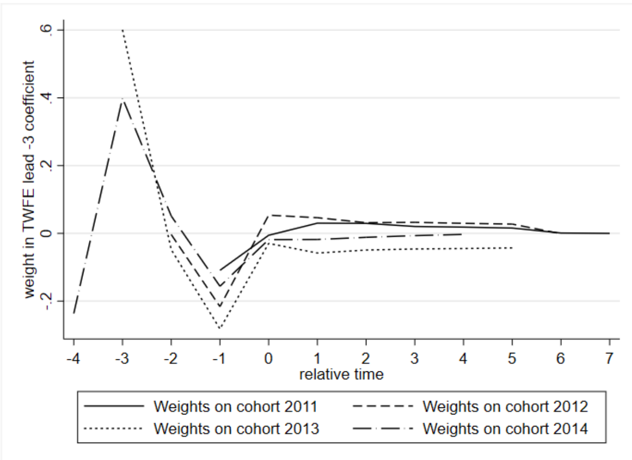


Figure 11: Weights in two-way fixed effects relative time coefficients. The figure plots weight estimates for TWFE coefficients μ_{-2} and μ_{-3} in a fully dynamic specification excluding relative times -1 and -4. Coefficients μ_{-2} and μ_{-3} are supposed to test the existence of pre-trends and are given as a weighted combination of cohort specific effects $CATT_{e,\ell}$.

Table 21: Event Study Analysis: full sample

	(1) Revenues (ln)	(2) Value Added (ln)	(3) EBITDA (ln)
-3 y before T	-0.016	-0.013	0.003
	(0.022)	(0.021)	(0.028)
-2 y before T	0.004	-0.002	0.000
	(0.014)	(0.015)	(0.020)
0 y in T	0.079***	0.068***	0.041**
	(0.011)	(0.013)	(0.017)
1 y in T	0.114***	0.097***	0.068***
	(0.016)	(0.017)	(0.021)
2 y in T	0.131***	0.104***	0.092***
	(0.020)	(0.019)	(0.024)
3 y in T	0.154***	0.135***	0.125***
	(0.022)	(0.022)	(0.026)
4 y in T	0.155***	0.143***	0.127***
	(0.025)	(0.024)	(0.028)
5 y in T	0.155***	0.146***	0.139***
	(0.029)	(0.029)	(0.032)
6 y in T	0.168***	0.172***	0.156***
	(0.038)	(0.037)	(0.043)
7 y in T	0.060	0.051	-0.015
	(0.068)	(0.064)	(0.075)
Observations	47913	46108	42891
R^2	0.895	0.896	0.843
Root MSE	0.573	0.559	0.688
Firm-specific FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Note: Robust standard errors clustered by firm ID in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 22: Event Study Analysis: dynamic effects by network objectives

	Networks aimed at increasing market shares and entering new markets			Networks declaring other objectives		
	(1) Revenues (ln)	(2) Value Added (ln)	(3) EBITDA (ln)	(4) Revenues (ln)	(5) Value Added (ln)	(6) EBITDA (ln)
-3 y before T	0.011	0.008	0.087	-0.022	-0.020	0.002
	(0.052)	(0.051)	(0.062)	(0.024)	(0.023)	(0.031)
-2 y before T	-0.012	-0.023	-0.031	0.007	-0.000	0.011
	(0.031)	(0.034)	(0.047)	(0.016)	(0.016)	(0.022)
0 y in T	0.068***	0.044	0.010	0.084***	0.080***	0.053***
	(0.026)	(0.029)	(0.039)	(0.013)	(0.014)	(0.019)
1 y in T	0.122***	0.072*	0.037	0.119***	0.114***	0.080***
	(0.034)	(0.042)	(0.051)	(0.018)	(0.019)	(0.024)
2 y in T	0.157***	0.097**	0.090	0.128***	0.115***	0.092***
	(0.043)	(0.048)	(0.058)	(0.022)	(0.022)	(0.027)
3 y in T	0.210***	0.130**	0.123**	0.143***	0.138***	0.109***
	(0.052)	(0.056)	(0.062)	(0.025)	(0.024)	(0.029)
4 y in T	0.218***	0.149**	0.158**	0.139***	0.138***	0.099***
	(0.060)	(0.061)	(0.068)	(0.028)	(0.027)	(0.031)
5 y in T	0.236***	0.154**	0.189**	0.132***	0.139***	0.117***
	(0.070)	(0.069)	(0.074)	(0.032)	(0.032)	(0.036)
6 y in T	0.179*	0.226**	0.295***	0.158***	0.158***	0.114**
	(0.098)	(0.098)	(0.097)	(0.042)	(0.041)	(0.048)
7 y in T	0.184	0.217	0.140	0.009	0.004	-0.050
	(0.189)	(0.191)	(0.176)	(0.073)	(0.068)	(0.083)
Observations	8219	7917	7380	39593	38182	35573
R^2	0.896	0.893	0.847	0.891	0.891	0.838
Root MSE	0.574	0.572	0.676	0.583	0.569	0.692
Firm-specific FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors clustered by firm ID in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Event Study Analysis: dynamic effects by firm size

	Less than ten employees one year before treatment: micro firms			Ten or more employees one year before treatment: small, medium-sized and large firms		
	(1) Revenues (ln)	(2) Value Added (ln)	(3) EBITDA (ln)	(4) Revenues (ln)	(5) Value Added (ln)	(6) EBITDA (ln)
-3 y before T	-0.068	-0.023	-0.034	-0.012	-0.031	-0.008
	(0.044)	(0.041)	(0.049)	(0.021)	(0.021)	(0.033)
-2 y before T	-0.021	-0.019	-0.030	0.008	-0.003	0.005
	(0.029)	(0.030)	(0.035)	(0.013)	(0.014)	(0.023)
0 y in T	0.105^{***}	0.121^{***}	0.041	0.060^{***}	0.033^{**}	0.060^{***}
	(0.022)	(0.025)	(0.030)	(0.012)	(0.013)	(0.022)
1 y in T	0.146^{***}	0.172^{***}	0.098^{***}	0.095^{***}	0.055^{***}	0.074^{***}
	(0.030)	(0.032)	(0.037)	(0.018)	(0.018)	(0.027)
2 y in T	0.156^{***}	0.176^{***}	0.105^{**}	0.106^{***}	0.070^{***}	0.110^{***}
	(0.036)	(0.037)	(0.042)	(0.023)	(0.022)	(0.031)
3 y in T	0.163^{***}	0.240^{***}	0.148^{***}	0.132^{***}	0.074^{***}	0.122^{***}
	(0.040)	(0.041)	(0.045)	(0.026)	(0.025)	(0.032)
4 y in T	0.157^{***}	0.242^{***}	0.135^{***}	0.127^{***}	0.076^{***}	0.124^{***}
	(0.043)	(0.046)	(0.049)	(0.030)	(0.027)	(0.034)
5 y in T	0.171^{***}	0.249^{***}	0.164^{***}	0.104^{***}	0.070^{**}	0.115^{***}
	(0.051)	(0.054)	(0.057)	(0.035)	(0.033)	(0.041)
6 y in T	0.250^{***}	0.343^{***}	0.224^{***}	0.084^{*}	0.057	0.129^{**}
	(0.068)	(0.069)	(0.076)	(0.048)	(0.044)	(0.053)
7 y in T	-0.052	0.031	0.009	0.078	0.047	0.015
	(0.129)	(0.122)	(0.121)	(0.084)	(0.071)	(0.099)
Observations	20048	19163	17749	26077	25057	23575
R^2	0.851	0.838	0.780	0.858	0.860	0.805
Root MSE	0.661	0.686	0.766	0.512	0.482	0.642
Firm-specific FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors clustered by firm ID in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 24: Event Study Analysis: network diversity based on partners' size

	Micro firms with at least one medium-sized or large partner			Micro firms with no medium-sized or large partner		
	(1) Revenues (ln)	(2) Value Added (ln)	(3) EBITDA (ln)	(4) Revenues (ln)	(5) Value Added (ln)	(6) EBITDA (ln)
-3 y before T	-0.003	-0.018	0.023	-0.073	-0.069	-0.036
	(0.082)	(0.075)	(0.108)	(0.059)	(0.059)	(0.065)
-2 y before T	-0.000	0.038	0.093	-0.004	-0.032	-0.043
	(0.058)	(0.057)	(0.073)	(0.036)	(0.040)	(0.046)
0 y in T	0.205***	0.168***	0.124**	0.080***	0.137***	0.022
	(0.041)	(0.046)	(0.057)	(0.030)	(0.034)	(0.040)
1 y in T	0.242***	0.250***	0.258***	0.117***	0.181***	0.085*
	(0.058)	(0.061)	(0.075)	(0.040)	(0.043)	(0.048)
2 y in T	0.274***	0.280***	0.326***	0.154***	0.192***	0.109**
	(0.069)	(0.073)	(0.085)	(0.045)	(0.048)	(0.054)
3 y in T	0.283***	0.336***	0.326***	0.149***	0.228***	0.146**
	(0.081)	(0.082)	(0.092)	(0.051)	(0.053)	(0.057)
4 y in T	0.319***	0.313***	0.249**	0.112**	0.218***	0.099
	(0.083)	(0.089)	(0.098)	(0.056)	(0.060)	(0.065)
5 y in T	0.231**	0.291***	0.250**	0.173***	0.199***	0.088
	(0.111)	(0.103)	(0.113)	(0.065)	(0.073)	(0.075)
6 y in T	0.371***	0.353***	0.215	0.262***	0.325***	0.130
	(0.129)	(0.120)	(0.140)	(0.085)	(0.093)	(0.102)
7 y in T	0.189	-0.055	0.036	-0.068	0.104	-0.132
	(0.227)	(0.242)	(0.240)	(0.184)	(0.152)	(0.155)
Observations	4872	4654	4285	11572	11052	10208
R^2	0.862	0.840	0.790	0.849	0.839	0.781
Root MSE	0.655	0.664	0.745	0.644	0.675	0.763
Firm-specific FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors clustered by firm ID in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 25: Event Study Analysis: geographical concentration in a travel to work area

	At least 60% of members in the same TTWA			Less than 60% of members in the same TTWA		
	(1) Revenues (ln)	(2) Value Added (ln)	(3) EBITDA (ln)	(4) Revenues (ln)	(5) Value Added (ln)	(6) EBITDA (ln)
-3 y before T	-0.001	-0.006	-0.024	-0.040	-0.046	0.010
	(0.031)	(0.029)	(0.038)	(0.031)	(0.032)	(0.041)
-2 y before T	0.017	-0.004	0.003	-0.014	-0.016	-0.017
	(0.021)	(0.021)	(0.027)	(0.019)	(0.020)	(0.029)
0 y in T	0.108***	0.085***	0.062**	0.049***	0.052***	0.034
	(0.017)	(0.020)	(0.025)	(0.015)	(0.016)	(0.025)
1 y in T	0.134***	0.095***	0.057*	0.088***	0.088***	0.094***
	(0.023)	(0.025)	(0.031)	(0.021)	(0.022)	(0.030)
2 y in T	0.142***	0.100***	0.099***	0.092***	0.088***	0.110***
	(0.028)	(0.028)	(0.034)	(0.027)	(0.028)	(0.035)
3 y in T	0.130***	0.138***	0.144***	0.140***	0.100***	0.114***
	(0.032)	(0.030)	(0.036)	(0.031)	(0.032)	(0.038)
4 y in T	0.138***	0.142***	0.142***	0.125***	0.089**	0.108***
	(0.034)	(0.034)	(0.040)	(0.035)	(0.035)	(0.040)
5 y in T	0.126***	0.143***	0.146***	0.134***	0.069*	0.126***
	(0.041)	(0.041)	(0.046)	(0.041)	(0.041)	(0.046)
6 y in T	0.170***	0.219***	0.249***	0.116**	0.040	0.072
	(0.057)	(0.055)	(0.063)	(0.053)	(0.050)	(0.059)
7 y in T	-0.033	0.004	0.078	0.096	0.001	-0.099
	(0.104)	(0.091)	(0.100)	(0.092)	(0.091)	(0.113)
Observations	24720	23773	22291	22474	21707	20139
R^2	0.889	0.888	0.834	0.899	0.899	0.840
Root MSE	0.585	0.572	0.699	0.562	0.545	0.683
Firm-specific FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors clustered by firm ID in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 26: Event Study Analysis: geographical concentration in a travel to work area

	More than 80% of members in the same TTWA			Less than 40% of members in the same TTWA		
	(1) Revenues (ln)	(2) Value Added (ln)	(3) EBITDA (ln)	(4) Revenues (ln)	(5) Value Added (ln)	(6) EBITDA (ln)
-3 y before T	-0.021	-0.014	-0.013	-0.063	-0.038	0.045
	(0.044)	(0.040)	(0.053)	(0.042)	(0.043)	(0.060)
-2 y before T	0.031	-0.005	-0.024	0.007	0.006	0.026
	(0.027)	(0.030)	(0.040)	(0.023)	(0.024)	(0.038)
0 y in T	0.107***	0.109***	0.042	0.013	0.028	-0.041
	(0.023)	(0.027)	(0.036)	(0.021)	(0.022)	(0.033)
1 y in T	0.139***	0.101***	0.040	0.051*	0.074**	-0.003
	(0.032)	(0.038)	(0.044)	(0.031)	(0.031)	(0.040)
2 y in T	0.130***	0.097**	0.085*	0.007	0.069*	0.058
	(0.040)	(0.041)	(0.049)	(0.040)	(0.039)	(0.047)
3 y in T	0.156***	0.144***	0.143***	0.074*	0.067	0.054
	(0.045)	(0.045)	(0.051)	(0.042)	(0.046)	(0.055)
4 y in T	0.183***	0.155***	0.124**	0.029	0.078	0.053
	(0.051)	(0.052)	(0.057)	(0.050)	(0.049)	(0.057)
5 y in T	0.161***	0.130**	0.167***	0.012	0.009	0.036
	(0.058)	(0.060)	(0.064)	(0.057)	(0.059)	(0.065)
6 y in T	0.242***	0.259***	0.291***	0.031	-0.018	-0.073
	(0.073)	(0.078)	(0.089)	(0.080)	(0.076)	(0.085)
7 y in T	-0.008	0.006	0.046	-0.019	-0.022	-0.226
	(0.134)	(0.136)	(0.134)	(0.166)	(0.147)	(0.165)
Observations	12173	11687	10919	11123	10748	9909
R^2	0.893	0.887	0.839	0.904	0.900	0.852
Root MSE	0.584	0.579	0.688	0.550	0.544	0.669
Firm-specific FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors clustered by firm ID in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix B

Appendix to Chapter 2

B.1 Supplementary tables

Table 27: Sample distribution by industry

NACE Rev. 2 codes – 2 digit level	Freq.	Percent	Cum.
20 - Chemicals	1,482	11.66	11.66
21 - Pharmaceutical	289	2.27	13.93
26 - Computer, electronic and optical products	1,331	10.47	24.40
27 - Electric equipment	1,921	15.11	39.51
28 - Machinery and equipment n.e.c.	6,307	49.61	89.12
29 - Motor vehicles, trailers and semi-trailers	774	6.09	95.21
30 - Other transport equipment	609	4.79	100.00
Total	*12,713*	100.00	

Table 28: Sample distribution by size

Size category	Freq.	Percent	Cum.
Small	9,423	74.12	74.12
Medium	2,743	21.58	95.70
Large	547	4.30	100.00
Total	*12,713*	100.00	

Table 29: Sample distribution by region

Region	Freq.	Percent	Cum.
Abruzzo	174	1.37	1.37
Basilicata	30	0.24	1.60
Calabria	35	0.28	1.88
Campania	387	3.04	4.92
Emilia-Romagna	1,854	14.58	19.51
Friuli-Venezia Giulia	318	2.50	22.01
Lazio	395	3.11	25.12
Liguria	189	1.49	26.60
Lombardia	4,334	34.09	60.69
Marche	368	2.89	63.59
Molise	12	0.09	63.68
Piemonte	1,302	10.24	73.92
Puglia	234	1.84	75.76
Sardegna	27	0.21	75.98
Sicilia	162	1.27	77.25
Toscana	659	5.18	82.44
Trentino-Alto Adige	164	1.29	83.73
Umbria	114	0.90	84.62
Valle d'Aosta	6	0.05	84.67
Veneto	1,949	15.33	100.00
Total	*12,713*	100.00	

Table 30: Family firm regional density

Region	mean
Abruzzo	0.354
Basilicata	0.290
Calabria	0.257
Campania	0.367
Emilia-Romagna	0.337
Friuli-Venezia Giulia	0.377
Lazio	0.297
Liguria	0.347
Lombardia	0.317
Marche	0.427
Molise	0.417
Piemonte	0.333
Puglia	0.329
Sardegna	0.444
Sicilia	0.371
Toscana	0.364
Trentino-Alto Adige	0.353
Umbria	0.215
Valle d'Aosta	0.5
Veneto	0.391
Total	*0.343*

Table 31: Sample composition by size and innovation propensity

Size category	Freq.	Share of innovators by size
Micro	10,345	0.012
Small	9,622	0.036
Medium	2,785	0.162
Large	555	0.459
Total	23,307	0.050

Note: descriptive statistics computed on the probit estimation sample (table 33). Firms are identified as innovators if they have applied for at least one patent.

Table 32: T-test on innovation propensity

	T-test
Micro vs All	-24.14 (0.000)
Micro vs Small	-10.99 (0.000)
Micro vs Medium	-35.86 (0.000)
Micro vs Large	-66.31 (0.000)

Note: P-values in parentheses. T-statistics computed on the probit estimation sample (table 33).

The tests compare the share of micro-enterprises identified as innovators with the same metric computed for small, medium-sized, and large enterprises, respectively. The t-test in the first row compares the share of innovative micro-enterprises with the average percentage of innovators in the sample of small, medium-sized, and large firms.

Table 33: Probit regression: patent propensity

	(1) Innovator$_t$	(2) Innovator$_t$	(3) Innovator$_{t+1}$	(4) Innovator$_{t+1}$
Size category				
Small	0.423***		0.417***	
	(0.034)		(0.056)	
Medium	1.172***		1.205***	
	(0.045)		(0.070)	
Large	2.044***		2.105***	
	(0.073)		(0.086)	
Micro dummy		-0.657***		-0.695***
		(0.033)		(0.053)
Family firm	-0.170***	-0.347***	-0.200***	-0.380***
	(0.037)	(0.033)	(0.038)	(0.033)
Age	-0.000	0.005***	-0.002*	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Intangible	0.000**	0.000**	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	0.012	0.011	0.029**	0.026**
	(0.011)	(0.009)	(0.012)	(0.010)
Network agreement	0.306***	0.434***	0.269***	0.431***
	(0.071)	(0.070)	(0.079)	(0.081)
Group	0.271***	0.544***	0.320***	0.620***
	(0.048)	(0.047)	(0.051)	(0.050)
Foreign	-0.085*	0.195***	-0.081**	0.213***
	(0.048)	(0.044)	(0.040)	(0.032)
Constant	-2.664***	-2.260***	-2.959***	-2.542***
	(0.068)	(0.076)	(0.096)	(0.094)
Observations	23307	23307	23307	23307
Pseudo R^2	0.212	0.133	0.244	0.149
Log pseudolikelihood	-3663.151	-4029.612	-2691.479	-3028.139
Industry-specific FE	Yes	Yes	Yes	Yes
Region-specific FE	Yes	Yes	Yes	Yes

Clustered standard errors in parentheses.

Micro is the baseline category for the *Size category* variable.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix C

Appendix to Chapter 3

C.1 Supplementary Information

The content of this section has been published as Supplementary Information for Pieroni, Facchini, and Riccaboni (2021b). Partial reproduction of this content, with variations, can also be retrieved in Pieroni, Facchini, and Riccaboni (2021a).

C.1.1 The instrumental variable approach

To provide insights into the impact of mobility contraction on furlough schemes and excess deaths, we implemented an instrumental variable model accounting for Italian NUTS 3 regions' unobserved heterogeneity.

As already pointed out in previous scientific works, mobility is likely to be endogenous with variables strictly related to the spread of the disease, such as the number of COVID-19 cases or excess deaths (Glaeser, Gorback, and Redding, 2020; Krenz and Strulik, 2021; Borri et al., 2021). A potential reversed causality issue may affect the estimates since mobility flows are adjusted when people observe an increase (or decrease) in the spread of COVID-19.

A similar argument applies to the relationship between mobility and the amount of the Wage Guarantee Fund. Reduced mobility can explain an increase in the Wage Guarantee Fund since the enforcement of containment measures meant to discourage mobility and limit social interactions could foster the use of wage guarantee schemes to reduce physical proximity in the workplace. However, temporary suspension of working activities could itself explain a further drop in commuting flows. This could be the most intuitive way to interpret the relationship between mobility and furlough schemes but is not the only one, as mobility could impact the Wage Guarantee Fund even through different channels. If fewer people move because of containment rules or fear of contagion, we may observe a decline in demand for goods and services by final consumers. In turn, employers may opt for a temporary reduction of working time and ask for wage compensation schemes to cope with a contraction in demand even as a potential effect of consumer substitution patterns (Goolsbee and Syverson, 2021).

Our empirical approach leverages the exogenous variation in weather patterns over time and across geographies to overcome endogeneity concerns. We instrumented for mobility by the share of consecutive rainy days recorded in a month over 2020 at Italian NUTS 3 level, namely *Rainfall share*. We built the metric excluding from the count "isolated" rainy days not belonging to a series comprising at least two consecutive rainy days.

Rainfall shocks have been widely used as instruments in econometric settings affected by endogeneity, as in several scientific works investigating the relationship between economic shocks and conflicts (Miguel, Satyanath, and E. Sergenti, 2004; Sarsons, 2015; Sandholt Jensen and Skrede Gleditsch, 2009; Bohlken and E. J. Sergenti, 2010), where income growth is instrumented by the exogenous variation in rainfall. A connection between weather shocks and income can be observed and theoretically justified for those countries whose economy depends mainly on rain-fed agriculture. However, the availability of developed irrigation infrastructures together with new agriculture technologies and a more relevant contribution of the industrial sector to the national (and regional) economy, make income growth less sensitive to weather shocks. In the specific case of Italy, we assume weather conditions to have a very negligible impact on economic activities, therefore we claim that the effect of rainfall on furlough schemes does not go through a potential shock on economic activities but through an induced variability in human mobility. Similarly, we assume human mobility patterns to be the only channel through which weather shocks can potentially have an impact on the number of excess deaths recorded during the pandemic.

To corroborate our findings, we performed a robustness check exploiting two alternative instruments for mobility.

The choice of the first instrument is inspired by Glaeser, Gorback, and Redding (2020). Looking at the provisions of Prime Ministerial Decrees issued between March and May[1] we computed the time-varying share of essential residents (*Share Essentials*) in each NUTS 3 region, that is, the share of labour force which was allowed to move during the first national lockdown since employed in economic sectors designated as essential by the Italian government. The share of authorized employees has been multiplied by the 2019 employment rate of Italian provinces[2] to proxy the share of essential workers of NUTS 3 regions.

As a second instrumental variable (IV), we computed the time-varying betweenness centrality (Newman, 2010) of Italian NUTS 3 regions in the mobility network built on Facebook data movement between administrative regions. A low value of the betweenness centrality is a proxy of Italian NUTS 3 regions' remoteness (Krenz and Strulik, 2021). Mobility range measures the average reduction of mobility within an administrative region, in contrast, the betweenness centrality looks at the whole network, in a global perspective, providing a ranking of Italian NUTS 3 areas based on their importance of bridging different regional mobility systems. Based on this, we assume this quantity to be less or even not susceptible to changes in the number of fatalities or the number of Wage Guarantee Fund allowed hours at a local scale (i.e. changes referring to the single NUTS 3 region).

Following the argument in Glaeser, Gorback, and Redding (2020) and Krenz and Strulik (2021), we assume that the centrality of a territorial

[1] Our references are Dpcm March 11, Dpcm March 22, Dpcm April 1, Dpcm April 10, Dpcm April 26 and Dpcm May 17, 2020.

[2] Source of employment data is ISTAT (Italian National Institute of Statistics) Labour Force Survey.

unit in the mobility network and the share of people employed in essential industries have an impact on excess deaths just through mobility flows. A similar argument applies for the Wage Guarantee Funds allowed hours.

We estimated three specifications of the model, as displayed in the following section (table 36 for excess deaths and 38 for the Wage Guarantee Fund): the first one employs only the betweenness centrality as an IV, the second one includes just *Share Essentials*, the third model uses both variables as excluded instruments.

C.1.2 Variables used

Table 34: Data description

	Mean	Std. Dev.	Min.	Max.	Obs.
W.G.F. FTE	14676.54	30937.9	0	355018.5	856
Excess deaths	48.884	264.510	-478.2	5181.4	1070
Mobility Range	-0.185	0.199	-0.688	0.155	1177
Rainfall share	0.197	0.158	0	0.774	1274
Betweenness	0.030	0.065	0	0.581	855
Share Essentials	60.459	13.131	23.746	79.2	1284

Descriptive statistics for the main variables included in the econometric model. The Wage Guaranetee Fund (W.G.F.) is expressed in full time equivalent (FTE) units.

C.1.3 Regression tables

In this section, we provide further details on regression outputs and statistics.

Table 35 reports IV estimates obtained regressing the Wage Guarantee Fund (in FTE units) and excess deaths on mobility range. Model specifications in columns (1) and (2) control for time trends including the lockdown dummy variable. As a further check, estimates have been repeated controlling for time-related effects with a set of dummy variables defined for each month. The alternative specification yields a positive and statistically significant coefficient for mobility when excess deaths is the dependent variable, while, concerning the Wage Guarantee Fund, mobility's coefficient loses statistical significance, potentially because of the short time horizon covered by wage guarantee fund data. Results from this check are available upon request.

More details about robustness checks outputs are displayed in tables from 36 to 39.

Table 35: Wage Guarantee Fund and Excess Deaths: first stage and reduced form regressions

	ln Wage Guarantee Fund FTE$_{it}$			ln Excess Deaths$_{it}$		
	(1) Main	(1.f) First Stage	(1.r) Reduced Form	(2) Main	(2.f) First Stage	(2.r) Reduced Form
Mobility range$_{i(t-1)}$	-10.133***			0.667***		
	(0.864)			(0.160)		
Lockdown	-2.829***	-0.268***	-0.114	0.359***	-0.304***	0.155***
	(0.257)	(0.016)	(0.111)	(0.058)	(0.014)	(0.017)
Rainfall share$_{i(t-1)}$		-0.487***	4.931***		-0.436***	-0.291***
		(0.061)	(0.456)		(0.048)	(0.070)
Observations	611	611	611	846	846	846
Number Ids	104	104	104	107	107	107
Root MSE	1.350	0.200	1.405	0.212	0.177	0.208
First Stage F-Stat.	62.87			82.04		
NUTS3 regions FE	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses.

Columns from (1) to (1.r) and from (2) to (2.r) display IV regression estimates for the Wage Guarantee Fund and excess deaths respectively, when controlling for time-related effects with the Lockdown dummy variable. Results are obtained instrumenting for mobility range by the share of consecutive rainy days recorded in a month over 2020 at NUTS 3 level. The models control for NUTS 3 region-specific fixed effects.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 36: Robustness check: excess deaths regression results

	ln Excess Deaths$_{it}$			
	(1)	(2)	(3)	(4)
	FE	IV	IV	IV
Mobility range$_{i(t-1)}$	0.321***	0.733***	0.492***	0.491***
	(0.042)	(0.201)	(0.060)	(0.061)
Lockdown	0.252***	0.374***	0.303***	0.300***
	(0.038)	(0.067)	(0.032)	(0.032)
Constant	6.231***			
	(0.007)			
Observations	856	855	856	855
Number Ids	107	107	107	107
Individual FE	Yes	Yes	Yes	Yes
Overall R^2	0.137			
Root MSE	0.188	0.215	0.204	0.204
First Stage F-Stat.		53.64	565.13	292.32
Hansen J stat.				1.550
Instrumental variable(s)		Betweenness	Share essentials	Share essentials Betweenness

Robust standard errors in parentheses.

Regression estimates are obtained on the panel comprising monthly observations from March 2020 to October 2020 on a cross-section of 107 Italian NUTS 3 regions. Model specification in column (2), employs the betweenness centrality as an instrument for mobility; specification in column (3) employs share essentials and column (4) shows results obtained using both time-varying IVs. For comparative purposes, column (1) displays fixed-effects estimates obtained assuming mobility to be exogenous.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 37: Robustness check: excess deaths first stage and reduced form regressions

[A] First Stage

	(2) Mobility range$_{i(t-1)}$	(3) Mobility range$_{i(t-1)}$	(4) Mobility range$_{i(t-1)}$
Betweenness$_{i(t-1)}$	-1.376***		-0.409***
	(0.188)		(0.150)
Lockdown	-0.286***	-0.102***	-0.102***
	(0.015)	(0.012)	(0.012)
Share essentials$_{i(t-1)}$		0.017***	0.017***
		(0.001)	(0.001)
Observations	855	856	855
Number Ids	107	107	107
Root MSE	0.180	0.120	0.119
Individual FE	Yes	Yes	Yes

[B] Reduced form

	(2) ln Excess Deaths$_{it}$	(3) ln Excess Deaths$_{it}$	(4) ln Excess Deaths$_{it}$
Betweenness$_{i(t-1)}$	-1.008***		-0.547**
	(0.283)		(0.265)
Lockdown	0.164***	0.253***	0.252***
	(0.018)	(0.025)	(0.025)
Share essentials$_{i(t-1)}$		0.009***	0.008***
		(0.001)	(0.001)
Observations	855	856	855
Number Ids	107	107	107
Root MSE	0.208	0.198	0.197
Individual FE	Yes	Yes	Yes

Robust standard errors in parentheses.

First stage and reduced form results refer to model specifications displayed in columns (2), (3) and (4) of table 36.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 38: Robustness check: Wage Guarantee Fund regression results

	ln Wage Guarantee Fund FTE$_{it}$			
	(1) FE	(2) IV	(3) IV	(4) IV
Mobility range$_{i(t-1)}$	-5.680***	-3.254***	-5.304***	-5.218***
	(0.192)	(0.748)	(0.242)	(0.242)
Lockdown	-1.673***	-1.051***	-1.576***	-1.564***
	(0.093)	(0.234)	(0.125)	(0.126)
Constant	8.273***			
	(0.019)			
Observations	619	618	619	618
Number Ids	104	104	104	104
Individual FE	Yes	Yes	Yes	Yes
Overall R^2	0.438			
Root MSE	0.890	1.099	0.978	0.981
First Stage F-Stat.		49.29	599.79	305.92
Hansen J stat.				9.961
Instrumental variable(s)		Betweenness	Share essentials	Share essentials Betweenness

Robust standard errors in parentheses.

Regression estimates are obtained on the full period covered by WGF data, spanning from March 2020 to August 2020. Model specification in column (2), employs the betweenness centrality as an instrument for mobility; specification in column (3) employs share essentials and column (4) shows results obtained using both time-varying IVs. For comparative purposes, column (1) displays fixed-effects estimates obtained assuming mobility to be exogenous.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 39: Robustness check: Wage Guarantee Fund first stage and reduced form regressions

[A] First Stage

	(2) Mobility range$_{i(t-1)}$	(3) Mobility range$_{i(t-1)}$	(4) Mobility range$_{i(t-1)}$
Betweenness$_{i(t-1)}$	-1.426***		-0.329**
	(0.203)		(0.159)
Lockdown	-0.249***	-0.068***	-0.069***
	(0.017)	(0.013)	(0.013)
Share essentials$_{i(t-1)}$		0.017***	0.017***
		(0.001)	(0.001)
Observations	618	619	618
Number Ids	104	104	104
Root MSE	0.203	0.130	0.130
Individual FE	Yes	Yes	Yes

[B] Reduced form

	(2) ln WGF FTE$_{it}$	(3) ln WGF FTE$_{it}$	(4) ln WGF FTE$_{it}$
Betweenness$_{i(t-1)}$	4.641***		-1.336
	(1.395)		(1.412)
Lockdown	-0.239*	-1.217***	-1.223***
	(0.126)	(0.149)	(0.149)
Share essentials$_{i(t-1)}$		-0.092***	-0.093***
		(0.007)	(0.007)
Observations	618	619	618
Number Ids	104	104	104
Root MSE	1.528	1.269	1.269
Individual FE	Yes	Yes	Yes

Robust standard errors in parentheses.

First stage and reduced form results refer to model specifications displayed in columns (2), (3) and (4) of table 38.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.1.4 Facebook and census data

In this section, we test how Facebook data represent a reliable approximation of the population commuting for work and study, i.e. excluding those that do not habitually move within the provinces and between the provinces. Our idea is to test this reliability by looking at the data provided by the Italian statistical office in 2011, i.e the last census data collection in Italy.

Both data are presented in the form of a origin-destination (OD) matrix, where the links express the number of commuters who travel between and within provinces. In the case of ISTAT data, people move for study or work, in all time slots, and data are averaged over a period of one year. On the other hand, Facebook data account for the people moving daily, sampled at 8 hours intervals. In order to compare data, we averaged over the whole available period the Facebook data obtaining an averaged origin-destination matrix. Our hypothesis is that the temporal averaging leads to a origin destination matrix accounting for the habitual commuting of students and workers.

Figure 12 shows the plot of the weight of the links accounted in both OD matrices. From a linear fit we find that Facebook data and ISTAT data are on average 1 to 7.5 ratio, confirming the data provided by G. Bonaccorsi et al., 2020. As a further test, we considered only the Facebook traffic recorded during the daytime (8AM-4PM), comparing it to the corresponding period of ISTAT data. Results are depicted in Figure 13, where the agreement of the two datasets is conserved. According to these results we could consider, although sampling a smaller part of the population, Facebook movement data reliable to characterize of the mobility of regular commuters.

Figure 12: Scatter plot of the commuting flows of ISTAT and Facebook mobility data.

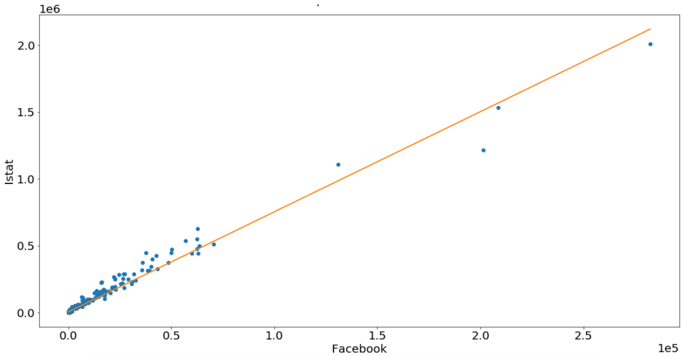
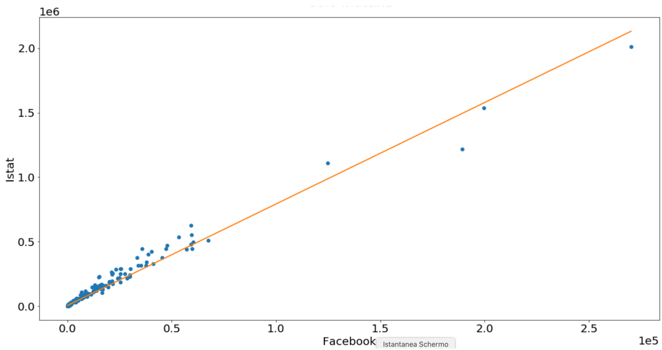


Figure 13: Focus on daytime (8AM-4PM): Scatter plot of the commuting flows of ISTAT and Facebook mobility data. Fit 7.49, $R^2 = 0.97$



C.1.5 Maps and plots

Figure 14: Monthly Wage Guarantee Fund allowed hours: January to April

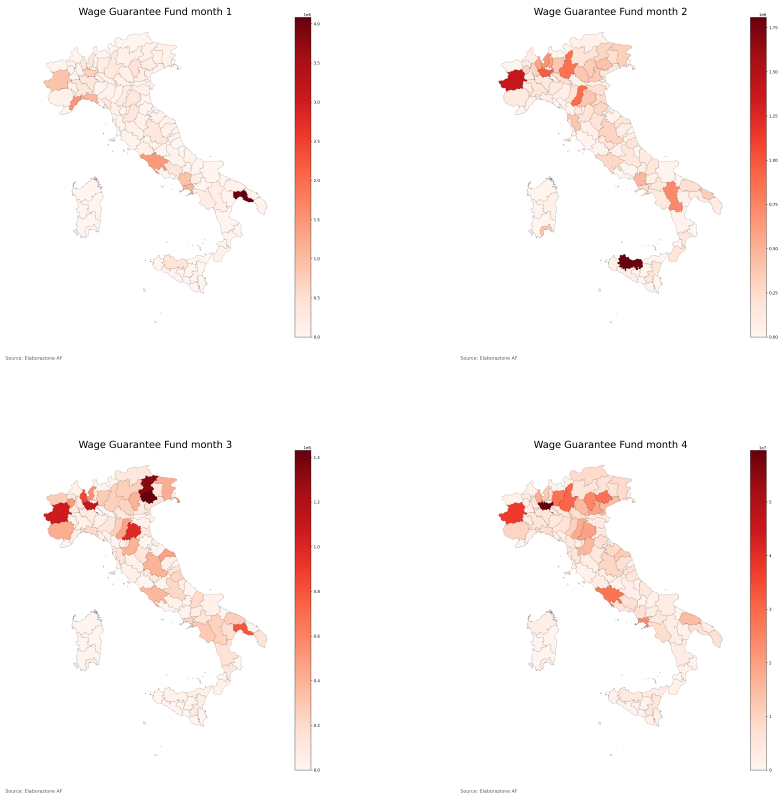
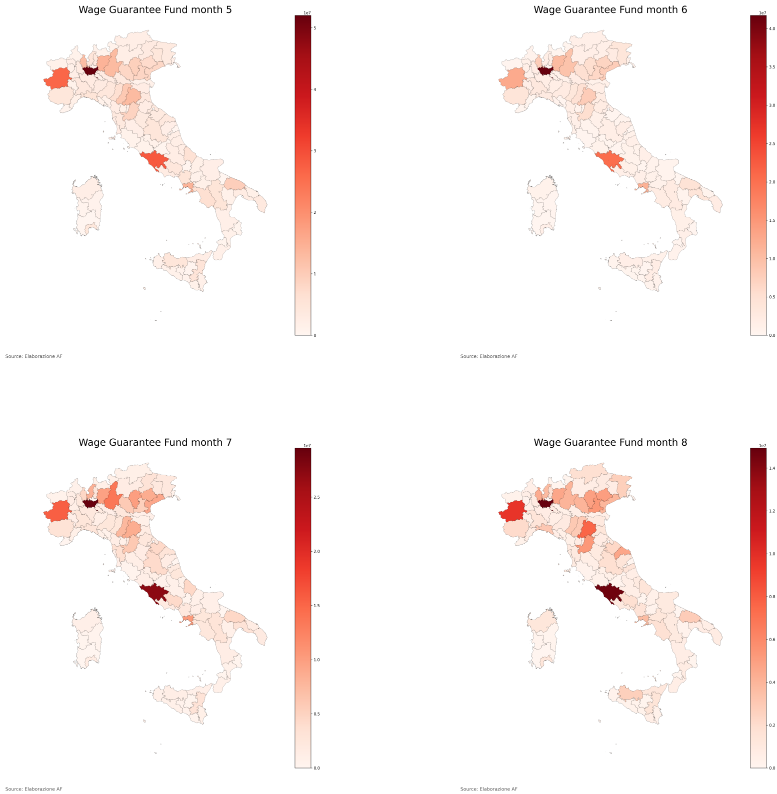


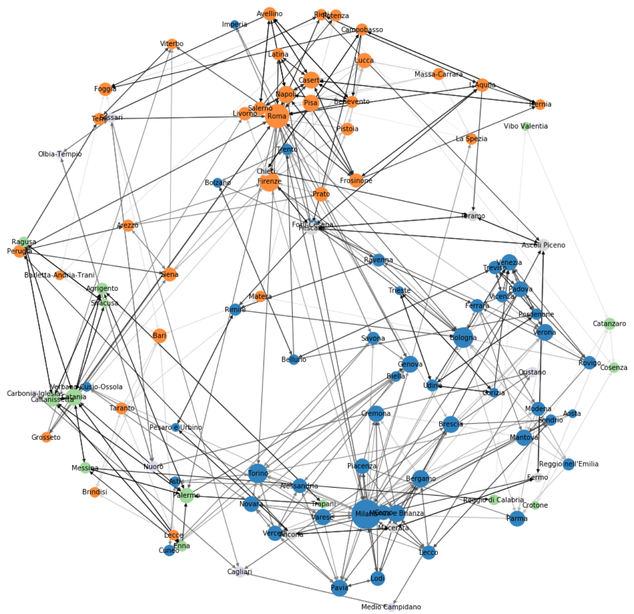
Figure 15: Monthly Wage Guarantee Fund allowed hours: May to August



C.1.6 Network of the NUTS-3 level origin-destination matrix

The origin-destination matrix has been estimated starting from the data provided by the Facebook data-for-good repository. The resulting oriented and weighted network is depicted in figure 16. Node color indicates the community of each node, node size is proportional to betweenness centrality and the intensity of the edge accounts for the intensity of the people flow between two NUTS-3 regions.

Figure 16: Directed and weighted network of the origin-destination matrix of NUTS-3 region. Average of the pre-pandemic period (Jan-Feb 2020).



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