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Collaboration network characteristics and inventors' performance. A multidimensional approach

Ecem Bilge Delicik

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THÈSE DE DOCTORAT

Caractéristiques du réseau de
collaboration et les performances des
inventeurs – Une approche
multidimensionnelle

Ecem Bilge DELICIK

GREDEG

**Présentée en vue de l'obtention du
grade de docteur en Sciences
Économiques d'Université Côte
d'Azur**

Dirigée par : Zakaria BABUTSIDZE,
Professeur, Skema Business School,
Université Côte d'Azur
(GREDEG) and OFCE, Sciences Po
Paris

Co-encadrée par : Ludovic
DIBIAGGIO, Professeur, Skema
Business School, Université Côte
d'Azur (GREDEG)

Soutenue le : 30 Novembre 2022

Devant le jury, composé de :

Lars FREDERIKSEN, Professeur, Aarhus
University

Corinne AUTANT-BERNARD, Professeure, Saint-
Etienne School of Economics (SE²) Muge

OZMAN, Professeure, Institut Mines-Télécom
Business School

Lionel NESTA, Professeur, Université Cote d'Azur
(GREDEG)

Zakaria BABUTSIDZE, Professeur, Skema
Business School, Université Côte d'Azur

(GREDEG) and OFCE, Sciences Po Paris

Ludovic DIBIAGGIO, Professeur, Skema Business
School, Université Côte d'Azur (GREDEG)



THÈSE DE DOCTORAT

Collaboration network characteristics and
inventors' performance – A
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Ecem Bilge DELICIK

GREDEG

**Defense presented for the purpose of
obtaining a PhD in Economics**
of Université Côte d'Azur

Thesis director: Zakaria BABUTSIDZE,
*Professor, Skema Business School,
Université Côte d'Azur (GREDEG) and
OFCE, Sciences Po Paris*

Co-director: Ludovic DIBIAGGIO,
*Professor, Skema Business School,
Université Côte d'Azur (GREDEG)*

Soutenu le : 30 November 2022

In front of the jury, composed of:

Lars FREDERIKSEN, Professor, Director of
Research, Aarhus University

Corinne AUTANT-BERNARD, Professor
Saint-Etienne School of Economics (SE²)

Muge OZMAN, Professor of Management,
Institut Mines-Télécom Business School

Lionel NESTA, Professor, Université Côte
d'Azur (GREDEG)

Zakaria BABUTSIDZE, *Professor, Skema
Business School, Université Côte d'Azur
(GREDEG) and OFCE, Sciences Po Paris*

Ludovic DIBIAGGIO, *Professor, Skema
Business School, Université Côte d'Azur
(GREDEG)*

Titre

Caractéristiques du réseau de collaboration et performances des inventeurs - Une approche multidimensionnelle

Jury :**Président du jury**

Lionel NESTA, Professeur, Université Cote d'Azur (GREDEG)

Directeur de thèse

Zakaria BABUTSIDZE, Professeur, Skema Business School, Université Côte d'Azur (GREDEG) and OFCE, Sciences Po Paris

Co-directeur de thèse

Ludovic DIBIAGGIO, Professeur, Skema Business School, Université Côte d'Azur (GREDEG)

Rapporteurs

Lars FREDERIKSEN, Professeur, Aarhus University

Corinne AUTANT-BERNARD, Professeure, Saint-Etienne School of Economics (SE²)

Examineurs

Muge OZMAN, Professeure, Institut Mines-Télécom Business School

RÉSUMÉ

Cette thèse présente trois essais sur les réseaux de collaboration des inventeurs et leur capacité d'invention. La thèse vise à tester empiriquement l'un des résultats théoriques fondamentaux de l'analyse des réseaux sociaux suggérant que les caractéristiques structurelles des réseaux de collaboration des inventeurs ont un impact sur les capacités d'invention (taux d'inventions, nouveauté et utilisation de leur production). L'une des contributions de ce travail consiste d'isoler les effets de la structure du réseau sur la l'intensité et la diversité des connaissances partagées par les membres du réseau des d'autres effets tels que l'influence des inventeurs après des membres. Les études empiriques des trois essais se concentre sur l'analyse la variation temporelle intra-sujet à partir de données de panel d'inventeurs français extraites de la base de données PATSTAT produite par le bureau européen des brevets.

Le premier essai analyse dans quelle mesure la capacité d'invention individuelle est influencée par les caractéristiques structurelles et relationnelles des réseaux de collaboration. Ce chapitre élabore un cadre théorique qui relie quatre aspects du réseau d'un inventeurs - le nombre de collaborateurs et d'inventeurs indirectement connectés, l'intensité des collaborations et la faiblesse de l'intensité des connexions entre les collaborateurs d'un inventeur (*brokerage*) - à la performance de l'inventeur. Le deuxième essai étudie comment l'accès à des connaissances hétérogènes affecte la relation entre le *brokerage* et la nouveauté de la production des inventeurs. Il fait la distinction entre les avantages structurels apportés par le *brokerage* et les opportunités qui l'accompagnent en termes de connaissances. Il analyse leurs effets sur le niveau de nouveauté des inventions des membres du réseau. Le dernier essai étudie la relation entre le *brokerage* et l'utilisation de la production des inventeurs. L'objectif de ce chapitre est double. D'une part, il vise à identifier l'influence du *brokerage* sur l'utilisation de la production de l'inventeur par les membres localisés du réseau. D'autre part, il étudie l'effet modérateur de la proximité cognitive sur la relation entre le *brokerage* et l'utilisation des inventions du *broker* au sein de la configuration du réseau local.

Les résultats des études longitudinales soulignent qu'il n'y a pas de réponse simple et universelle sur la façon de concevoir le réseau optimal pour les multiples facettes de la performance. La thèse démontre que les collaborateurs indirectement connectés n'exercent aucune influence sur les performances de l'inventeurs et que seuls les collaborateurs proches (c-à-d., ceux situés à une distance à l'inventeur maximale de deux) sont bénéfiques à l'inventeur focal. La structure optimale du réseau de collaborations d'un inventeur est celle dans laquelle l'inventeur est fortement connecté à des ensembles d'inventeurs déconnectés. Cependant, l'étude démontre que l'influence de la structure sur la nouveauté et l'utilisation des idées créées dépendent d'autres caractéristiques des réseaux de collaboration. Pour ce faire, elle distingue les avantages structurels apportés par la structure *brokered* et la représentation qui l'accompagne de l'arbitrage des connaissances et de la proximité cognitive. Les résultats suggèrent que le fait d'être un *broker* centre d'une structure de réseau et d'une clique de connaissances spécialisées est positivement associé à la probabilité de réutilisation des idées des *brokers*. Identifier le mécanisme par la manière dont la structure du réseau de collaboration affecte les performances des inventeurs a des implications importantes. Cela informera les inventeurs sur la façon d'optimiser ou d'adapter leurs réseaux collaboratifs pour répondre aux attentes, ainsi que d'aider les décideurs à concevoir des programmes d'incitation qui maximiseraient la performance organisationnelle.

Mots-clés : Collaborations, réseau *brokered* contre réseau cohésif, perspective de contingence, performance des inventeurs, OEB PATSTAT

ABSTRACT

This dissertation presents three essays on inventors' collaboration networks and their inventive performance. The thesis intends to empirically test the relation between the structural characteristics of inventors' collaboration networks and inventors' performance (i.e., rate of inventions, novelty, and reuse of their output), one of most agreed result in the literature. . In doing so, it provides answers to a fundamental question from the innovation and social network literature and brings a new perspective to empirical analyses of network characteristics by disentangling the intensity and the diversity of shared knowledge and their structure. The empirical tests of the three essays rely on panel data of French inventors extracted from the PATSTAT database provided by the European Patent Office are used to examine the within-subject variation over time.

The first essay analyses the extent to which individual inventive performance is influenced by the structural and relational characteristics of collaboration networks. The chapter elaborates a theoretical framework that relates four aspects of an inventor's network – the number of collaborators and indirectly connected inventors, the strength of collaborations, and brokered network structure (i.e., disconnections between an inventor's collaborators)- to the inventor's output. The second essay investigates how access to heterogeneous knowledge affects the relationship between the brokerage and the novelty of inventors' output. It distinguishes between structural advantages brought by the brokerage and accompanying opportunities in terms of knowledge and scrutinizes their effects on the level of novelty embedded in inventors' output. The last essay investigates the relationship between the brokerage and the reuse of inventors' output. The objective of this chapter is twofold. First, it aims to identify the influence of brokerage on the reuse of the broker's output by localized network members. Second, it investigates the moderating effect of cognitive proximity on the relationship between brokerage and reuse within the local network setup.

Results from the longitudinal studies highlight that there is no simple, universal answer on how to design optimal networks for multiple facets of inventive performance. The thesis demonstrates that indirectly connected collaborators, in general, are found to have no influence on inventors' performance. Only close collaborators (i.e., collaborators located at a maximum of two path length distances from the focal inventor) is positively related to the focal inventor's performance. The analysis shows that the optimal structure of an inventor's collaboration network results from an inventor strongly connected to disconnected sets of collaborators. However, the study further demonstrates the influence of structure on novelty and reuse of generated ideas is contingent upon other features of collaboration networks. To do so, it distinguishes between structural advantages brought by the bridging structure and its accompanying representation of knowledge arbitrage and cognitive proximity. Results suggest that being at the center of a brokered network structure and knowledge specialized clique is positively associated with the diffusion of the inventors' ideas. Pinning down the mechanism explaining how the structure of a collaboration network affects the inventors' performance has important implications. This will inform inventors on how to optimize or adapt their collaborative networks to meet their expectations (i.e., productivity, creativity and influence), as well as help decision-makers design incentive schemes of collaborations that would maximize individual and organizational performance.

Keywords: Collaborations, brokered versus cohesive networks, contingency perspective, inventors' performance, EPO PATSTAT

To my sisters,

The difficult we can do immediately, the impossible takes a little longer.

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“Yasamak bir agac gibi tek ve hur ve bir orman gibi kardescesine”

Nazim HIKMET

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CHAPTER 1

GENERAL INTRODUCTION

PURPOSE AND RESEARCH QUESTIONS

The main objective of this dissertation is to make the contribution of collaboration network characteristics to individuals' innovation performance clearer and the mechanism through which this contribution takes effect. The thesis makes an effort to deconstruct the effects of relational and structural characteristics to evaluate their influence and their contingent value to understand when and where the characteristics are valuable for inventive performance.

In the past decade, the importance of collaborations for inventive performance is well-documented (Burt 2005, 2017; Fleming et al. 2007; Perry-Smith and Mannucci 2017). For instance, a notable study by Singh and Fleming (2010) demonstrates that *“Individuals working alone... are less likely to achieve breakthroughs and more likely to invent particularly poor outcomes”*. Uzzi and his co-authors (2013) further argue that *“Novel combinations of prior work are rare, yet teams are 37.7% more likely than solo authors to insert novel combinations into familiar knowledge domains”*.

However, although the benefits of collaborations make no doubt, the analyses of invention performance have given rise to many discussions on to what extent and how collaborations matter. For instance, collaboration networks may have different –and sometimes opposite- effects on the legitimacy, the social capital of inventors and to what extent their network provide them with a privileged access to different diverse resources. The discussion started as a debate on the properties of the relations with collaborators and their effects on inventive capabilities. More precisely, early work on collaboration networks questioned the benefits of collaboration networks depending on the intensity of the relations between an inventor and his or her co-inventors. For instance, Burt (1992), Coleman (1988), or Granovetter (1973) discussed and demonstrated the structural and relational characteristics of collaboration networks in which inventors increases their combinatorial capabilities and implementation power and has evolved to the recognition that

there is a trade-off between strong versus weak relationships, and, sparse versus dense structures (Burt 2005, 2017; Fleming et al. 2007; Perry-Smith and Mannucci 2017).

In addition, one of the key insights emerging from this stream of research is that the influence of the structure of a collaboration network on different facets of invention performance varies significantly. For instance, the literature demonstrates that being in the center of a sparse network increases the inventor's own creativity while it decreases the usefulness of his or her ideas (Fleming et al. 2007; Perry-Smith and Mannucci 2017). A well-established line of inquiry argues that brokered collaboration networks enhance the focal inventor's creativity (Burt 2004). This is due to the fact that *brokered network structure* occurs when an inventor's collaborators are mutually disconnected, therefore, assumed to increase his or her access to diverse knowledge. The inventor in the center of a brokered network is called as broker who occupies the sole intermediate position between other inventors. Others can interact only through the broker whose position allows an inventor to control knowledge flow within network, therefore, to be aware of novel combinations earlier than other members of the network (Amabile et al. 2019; Burt 2007). On the contrary, because the inventor's collaborators do not know each other brokered networks hinder the emergence of a trusting environment and low intensity of interactions decreases the knowledge diffusion among collaborators. Thus, in a network where mutually disconnected collaborators do not trust and interact with each other, the recognition and acceptance of generated ideas by others will be less likely and more slowly within brokered networks compared to dense networks, termed *cohesive or closed networks*, in which most inventors collaborate and know each other (Fleming et al. 2007; Perry-Smith and Mannucci 2017).

Then, inventors face an obvious problem of choice between generating ideas that are novel or ideas that are useful for future studies. The dilemma appears because an inventor cannot be in both a cohesive in which most inventors are linked and a brokered network in which most inventors are disconnected, at the same time. However, the debates that led to the dilemma built their arguments on very optimistic assumptions that the greatest advantage of network structure is due to the knowledge diversity of disconnected inventors

within brokered networks or the cognitive proximity of connected ones within cohesive networks. Authors routinely assume that each collaboration and mutually disconnected collaborators deliver diverse knowledge and perspective while connected ones establish an environment that is based on mutual trust and easier communication (Burt 2004; Obstfeld 2005; Perry-Smith and Mannucci 2017). However, collaborations could vary widely in terms of knowledge and expertise diversity (McFadyen and Cannella 2017; Singh and Fleming 2010; Sosa 2011; Wang 2016), therefore, communication facilities. In this case, an inventor may appear in a brokered network structure in which mutually disconnected collaborators possess similar knowledge and cognitively proximate or in a closed network where connected collaborators have different expertise and cognitively distant.

The abundance of empirical research has produced intriguing but contradicting findings that leave decision makers (i.e., inventors who build their networks, managers who assign inventors to teams and projects, policy makers who give incentives to boost inventors' collaborations) wondering whether they should create and be part of a highly connected group of inventors or be part of a brokered network in which few inventors bridge a disconnected set of inventors. This question invites us to further clarify the processes and the conditions under which collaboration networks deliver value to inventors.

Chapters of the thesis follows the studies emphasizing the importance of relative (Ahuja 2000; Perry-Smith and Mannucci 2017; McFadyen et al. 2009) and contingent (Burt 2021; Carnabuci and Diószegi 2015; Fleming et al. 2007; Tsai 2009) value of collaboration network characteristics. The *contingent value* argument helps us to understand under which circumstances the characteristics are valuable for inventive performance. More importantly, the thesis questions the assumption about structure – content couples such as *brokered networks – diversity of collaborators' knowledge* or *closed networks – cognitive proximity of collaborators* and sets three main goals. First, it develops a theoretical framework to provide an understanding of the extent to which individual inventive performance is influenced by the structural and relational characteristics of collaboration networks. Second, it elaborates the framework by making a

distinction between network structure and its content related to network members' attributes (i.e., unique knowledge they provide to the focal inventor and their cognitive proximity). The elaborated framework simultaneously assesses the network structure and the content as sources of inventive performance and let us to understand the influence of pure structural and relational characteristics on inventors' performance. Moreover, it demonstrates the extent to which content and structure of a network moderates each other's influence. The model allows for an in-depth analysis of the advantages and disadvantages of each feature. Third, it theorizes about the specific mechanisms and strategies through which each feature delivers value to different facets of inventive performance (i.e., rate of invention, novelty of output, and reuse of output).

The dissertation consists of three essays that address the influence of collaboration network characteristics analyzing the influence of brokered network structure from different theoretical angles. In the first essay, I raise the question of how inventive performance is influenced by the structural and relational characteristics of collaboration networks. It argues that individual inventive performance is influenced by three main features of collaboration networks: network size (i.e., the number of collaborators and the number of indirectly connected inventors), the strength of collaborations, and brokered network structure (i.e., disconnectedness between a focal inventor's collaborators). Building on the recent literature it argues that each source presents complementary opportunities and at the same time requires different strategies to exploit those opportunities. The second essay analyzes the propensity of an inventor within a brokered network to produce novel invention. Making a distinction between the structure (i.e., the disconnectedness of the collaborators) and knowledge heterogeneity provided by the focal inventors' collaborators allows us to evaluate exclusively the benefits of the only network structure. The third essay, also makes a distinction between structure–content couples (Ter Wal et al. 2016; Guan et al. 2017; Rodan and Galunic 2004) and it takes contingency approach (Burt 2021; Carnabuci and Diószegi 2015; Tsai 2009) by making a distinction between cognitive proximity of network members to be confident about the sole influence of brokered network structure. As a contribution to recent literature, the study shows that the influence of the structure

changes depending on the focused sphere of influence, the structure of the network does not guarantee a given content of it and even further they change each other's influence on the inventor's performance.

My dissertation makes three main theoretical contribution to the literature discussing the characteristics of collaboration networks --depending on its structure, the nature of the links between co-inventors or similarity of collaborators' attributes-- and their effects on an inventor's performance. First, it suggests that the added and relative value of collaborations on the inventor's performance depend on the collaborators' social distance to the focal inventor and on their integration within the network. From a methodological standpoint, the framework makes more focused predictions on the relative value of the outcomes of French inventors depending on the characteristics of their collaboration network. Second, it argues that neither relational characteristics (i.e., number or strength of collaborations) nor attributes of collaborators (i.e., their cognitive proximity and the uniqueness of their knowledge) is guaranteed by a specific structure (i.e., brokered, or cohesive network structure). From a theoretical standpoint the frameworks allow for an in-depth analysis of the similarities and differences in the value, and opportunities inherent in collaboration networks' characteristics. Third, it theorizes about the two critical features of collaboration networks – structure and content (i.e., knowledge heterogeneity and cognitive proximity) –, their value, the strategies to exploit their value, and their utility for the concerned facet of inventive performance (i.e., rate of inventions, novelty, and reuse of inventor's output). They together, further justify the need for adopting the framework in future analyses.

DETERMINANTS OF INVENTIVE PERFORMANCE: A NETWORK PERSPECTIVE

Prior research focusing on individual inventive performance provides alternative perspectives. A well-established tenet among invention and strategy researchers is that inventors' ability to use novel technologies or recombine existing technologies, are key drivers of their inventive performance (Galunic and Rodan 1998; Hargadon and Sutton 1997; Henderson and Clark 1990; Sosa 2011; Yayavaram and Ahuja 2008). In addition to the inventors' creativity and combinatory skills which are critical for the idea generation phase, others pay attention to the more advanced phases of invention journey and emphasize the importance of idea implementation and approve the acceptance of the ideas and their reuse by others as key drivers of inventive performance (Baer 2012; Fleming et al. 2007; Hargadon and Sutton 1997; Obstfeld 2005; Rodan and Galunic 2004; Tortoriello and Krackhardt 2010; Uzzi and Spiro 2005). Naturally, the sources they focus on and the managerial implications they provide are contradictory to each other. However, almost all studies make an assumption about a perfect association between network structure and content (based on the attributes of collaborators).

Creativity and idea elaboration

Collaboration networks and its characteristics serve as an indication of combinatorial capabilities which increases with the exposure to diverse resources. To start with, creativity during the idea generation phase is highly associated with brokered network structure and weak¹ ties because inventors within loosely integrated, namely weak, collaborations and brokered collaboration networks are assumed to connect with non-redundant collaborators (Burt 2004; Granovetter 1973; Hargadon and Sutton 1997). Disconnectedness

¹ Strength of a tie can be defined in many ways. The chapters of the thesis assign the strength of the ties -- strength of the collaborations-- considering the frequency of co-inventor relationships and the team size. This is explained in detail in the next chapter.

within networks and weakly connected collaborators indicate that inventors provide diverse knowledge, different perspectives, and resources to the focal inventor (Burt 1992, 2004). Moreover, the focal inventors within brokered networks keep a position through which the knowledge between disconnected collaborators can flow and be transferred. They have a greater capacity to monitor and control a content rich information flow for their own benefit (Burt 1991; Obstfeld 2005; Padgett and Ansell 1993). As a result, collaboration network brokers are assumed to be more likely to be exposed to heterogeneous knowledge elements, and further, be aware of novel combinations earlier than others (Burt 2004).

In addition, collaboration networks serve as an indication of trust and willingness to share within the network. Scholars stress the importance of strong relationships and cohesive social structure in which most inventors are to each other (Burt 2005, 2017; Coleman 1988; Fleming et al. 2007; Perry-Smith and Mannucci 2017; Reagans and McEvily 2003; Rowley et al. 2000). Strong relations and cohesive structure of the networks characterize the formation of cooperative norms, a convergence in vision and common language among collaborators, therefore, facilitating the knowledge exchange in both explicit and tacit forms. The appearance of high-quality knowledge exchange and trust fosters the benefits of knowledge spillover and the commitment of inventors to their collaborations. As a result, inventors within highly integrated relations and collaboration networks are assumed to benefit from constructive feedback, shared norms, and vision to improve and elaborate their ideas.

Idea implementation and its reuse

In addition to the generation and improvement of an idea, collaboration networks foster the implementation of an idea, its diffusion, and its reuse by other actors.

Scholars focusing on the latest phases of the invention journey started a conversation resulting in a debate on brokered versus cohesive networks as a source of inventive performance. On the one hand, collaboration networks act as a source of social capital which is derived from control over knowledge flow, therefore,

increased awareness and combinatory capabilities (Burt 2004). Focal inventors within brokered networks occupy sole intermediate positions among others and, therefore, hold the advantage of keeping or sharing knowledge with others as they want (Obstfeld 2005). Knowledge arbitrage advantages are assumed to appear for brokers because they know of a knowledge difference between multiple pools of inventors and exploit this by bringing the knowledge from one pool to another. The arbitrage and political maneuverability lead to their dominance within their ego network and increase their legitimacy. As a result, the central inventors within brokered networks can convince others that their ideas are valuable and move their ideas further increase by using available sources as they want.

On the other hand, a brokered network structure will result in an inefficient knowledge diffusion within the network which hinders the detection and the adoption of the broker's ideas by others, whereas in cohesive networks, high level of interactions among collaborators act as a facilitator for faster knowledge transfer through many direct connections and, therefore, increases the diffusion of a generated idea (Coleman 1988; Fleming et al. 2007; Tortoriello et al. 2015; Tortoriello et al. 2012). In addition, high intensity of interactions is assumed to allow for a convergence in the used language and smoothen the communication between collaborators within cohesive networks. As a result, the likelihood of being understood and the reuse of an idea by others increases within closed networks.

In addition to the structural characteristics, maintaining strong versus weak relationships is associated with the latest phases of the invention journey. The strength of the ties indicates higher social and cognitive proximities which facilitate the communication with collaborators and acceptance by them. Being involved in strong collaborations becomes crucial under certain conditions in which novel ideas are on the table. This is due to the fact that complex ideas either consist of unusual set of technologies or unusual combinations of known technologies. Under such circumstances, understanding and accepting an idea require a high quality of knowledge exchange and sharing.

The differences in how scholars define the sources of the inventive performance vary significantly by the differences in which facet of inventors' output and the assumption they build on. Consequently, scholars investigating the influence of collaboration networks provide contradictory implications and suggestions. The three essays of my dissertation are motivated by the observation of the alternative drivers of inventive performance through collaborations and by the confusion raised from conventional assumptions that guarantee proximities among collaborators. I start by questioning the generalizability of empirical studies for French inventors and investigated the relative importance of relational and structural characteristics. Then, I continue by focusing on the most effective characteristic of the collaboration networks on inventors' performance and further analyzed its validity for different facets of inventive performance. In the last two essays, I was motivated to dig into the micro mechanisms to better understand the contingent value of structure.

RESEARCH METHODOLOGY AND DATA

Research methodology

In order to address research questions, I follow the literature that already merges the social network analysis and innovation studies, especially those analyzing collaborations among individuals. In many studies of the literature, social network analysis has been applied as a methodological approach to portray the value of collaboration network characteristics to the inventive performance. The same methodology is implemented in the following chapters to compute inventors' performance and explanatory variables.

To gauge the advantages to which a particular inventor is provided through interaction with his or her contacts, it is not enough to evaluate his or her dyadic relations with each contact; the similarity of one collaborator's attributes to another in the network, their redundant benefits, and connections to each other must be taken into account. For instance, assume that inventor X has three collaborators (K, L, and M) each of whom has similar technical expertise, yet their specialty is completely different from X's expertise area. In this case, while the dyadic approach reflects potential knowledge benefits from collaborations, social network analysis allows us to evaluate the set of collaborations' benefits by considering all members of the ego network. Throughout the following chapters of the thesis, the terms co-invention networks, collaboration networks, innovation networks, are used interchangeable to on behalf of ego networks of French inventors.

Ego networks are ego-centered networks consisting of a focal actor, termed ego, a set of collaborators who are directly tied to the ego, and inventors who are indirectly connected to the ego. In the following chapters of the thesis, the actors of the ego networks are inventors who are located in France. Co-patenting relationships are used to construct the links within focal inventors' collaboration networks. The chapters of the thesis focus on ego network analysis, but the exact definition of an ego-network varies across literature. Some works consider it as a focal inventor and a set of immediate collaborators (Cannella and McFadyen

2016), while others include all actors that the focal inventor can reach through intermediary collaborations (Ahuja 2000). Because the thesis aims to understand the influence of several characteristics of collaboration networks, it starts the analyses with no boundaries based on the distance between inventors and ego². As a result, among the networks constructed, there are even ego networks containing more than one million inventors. One of the biggest challenges of the thesis has been the incredible size of collaboration networks. The constructions of the ego networks and the calculations of characteristics took more than 6 months and that require very high computational power.

Data

The analyses and the findings rely on panel data sets, which are constructed from the European Patent Office worldwide patent statistical database – EPO PATSTAT – for the purposes of the dissertation. According to the World Intellectual Property Organization, the top 5 Intellectual Property offices account for more than 85% of all patent filings in the world in 2020 and EPO is one of them.

Despite its imperfections caused by actors who may avoid sharing their inventive activities and may limit their patent submissions for their best inventions, patents are the best quantitative measure to observe an inventor's performance and their collaborations (Fleming and Sorenson 2004) . The increased availability of structured EPO PATSTAT database benefits empirical research on the economics and management of innovation. The database provides bibliographic patent data for over 100 patent offices, reaching back to the nineteenth century. This database is important to the scientific world because it offers raw data that is gathered transparently; therefore, it promises to increase the quality of empirical research in many fields.

² For instance, if there are indirectly connected inventors who are connected to the focal inventor with 20 path lengths – with 19 intermediary inventors--, they are also included in the beginning.

However, it is not easy to navigate such database³, and its complexity makes it less attractive and more challenging for users.

To validate the generalizability of the results as much as possible, I chose not to apply any limitation by focusing on a specific technology or sector. Patents from 1990 to 2010 is used to construct variables, while the time frame of the regression analysis is limited to patents that applied to the European Patent Office between the years 1995 and 2010. This is necessary to have sufficient time left for collaboration network period prior to the performance year. The set of focal inventors contains only inventors who are located in France. However, the data used to construct networks also contains inventors located outside France for the purpose of not missing collaborative links that cross French borders. Therefore, the study involved cleaning and manipulating a very large database with more than 70 million patents and more than 1 million French inventors. To do so, I needed to learn and use a general-purpose programming language, Python, to aggregate network, inventor, and team level variables. Once the ultimate observation dataset is finalized, I used a powerful statistical software, Stata, for the purposes of all statistical analysis (i.e., descriptive and regression analysis).

³ The database is composed of a number of tables that adhere to a relational database schema. It includes more than 20 tables and 6 of them are used to construct all variables included in the analyses. A key of each separated table is frequently the identifier of patent applications and used to link tables with each other. The core table (*tls201_appln*) of the chosen 6 tables provides descriptive information such as identity of patent applications and the application year. Two of the tables (*tls212_citation* and *tls211_pat_publn*) provide information about citation traffic within patents. The input within another table (*tls_209_appln_ipc*) allows identification of patents by technology. The last 2 tables (*tls207_pers_appln* and *tls206_person*) provide information about the identification of applicants, let us to identify whether a given identification number of an applicant represents an inventor or an institution, and the inventors' residency country.

OVERVIEW OF THE THREE ESSAYS

Collaboration networks and the quantity of inventors' output

The first essay of my dissertation is interested in the influence of *the structural and relational characteristics of collaboration networks on inventive performance of an individual*. I argue that there are three distinct sources of collaboration benefits that have different predictive values for individual achievements: network size (i.e., number of collaborators and indirectly connected inventors), the strength of collaborations and non-redundancy of the collaborators (i.e., disconnections between a focal inventor's collaborators). Building on current and past research on social networks and ego-centric collaborative networking I argue that each source presents unique, non-equipollent opportunities and at the same time requires different strategies to derive those opportunities.

My first argument is that the sources differ in the utility that might be derived from them including through directly and indirectly connected collaborators. Weak relationships allow for the potential relational advantages through the quantity of total gathered resources, information, and knowledge as well as the widest choice of interaction collaborators (Granovetter 1973, 1983; Ibarra and Andrews 1993; Umphress, et al., 2003) while brokered network structure in which the focal inventor is spanning several structural holes⁴ provides opportunities for earlier exposure to a wide range of views, knowledge, and perspectives as well as opportunities to come up with and implement good ideas (Amabile et al. 2019; Aral and Van Alstyne 2011; Burt 1991, 1992, 2004, 2005; Carnabuci and Diószegi 2015). Strong relationships appear between collaborators who are willing to devote their time, attention, and effort to support each other, sharing the risks and higher quality of information transfer and tacit knowledge (Coleman 1988; Gulati 1995; Inkpen

⁴ Structural holes are the gaps in information flows between the focal inventor's collaborators because they are not connected to each other. A network with many structural holes termed as a brokered network.

and Tsang 2005; Larson 1992; Reagans and McEvily 2003; Rowley et al. 2000) while closed network structure in which a focal inventor's collaborators are connected to each other provides a trusting environment and norms of cooperation that facilitates the information flow, knowledge sharing and rapid feedback from collaborators in case it is needed (Baer 2012; Coleman 1998; Fleming et al.2007; Perry-Smith and Mannucci 2017; Walker et al. 1997). My second argument the substantive benefits of collaborators will vary depending on their distance to the focal inventor, and whether the collaborator has direct connections. In addition to the social distances between collaborators and the focal inventor, the substantive benefits will be limited to an extent by the similarities between the types and amounts of resources provided by collaborators. Based on those arguments I first, identify the structural and relational characteristics of collaboration networks contributing to the focal inventor's performance. Second, I compare the relative contribution of collaboration network features to provide suggestions on designing effective and efficient networks to increase individual performance. I use European Patent Office worldwide patent statistical database – EPO PATSTAT –to construct collaborative networks and all variables. A longitudinal dataset with more than 200 000 inventor-year observations from 1995 to 2010 is generated from the EPO PATSTAT database. A panel data–negative binomial estimator is preferred because of the inflation and overdispersion that the explanatory variable exhibits (quantity of inventors' output).

Overall, results of the study shows that even within the same network, collaborators differ significantly in the magnitude and nature of benefits (i.e., resource and tacit knowledge sharing, and information spillover) they provide to the focal inventor depending on their social distance. In fact, the results of the statistical analysis demonstrate that collaborators other than socially very close ones (i.e., the ones located at a maximum of two path length distances) do not provide any benefit to the focal inventor. I find that; non-redundancy and strength of relationships are more important than enlarging the frontiers of the networks by increasing the number of indirectly connected collaborators, even further, ones. Moreover, being part of

brokered networks in which otherwise disconnected collaborators are strongly tied to the focal inventor allows for the best performing focal actor.

Collaboration networks and novelty of inventors' output: the interplay between knowledge heterogeneity and brokerage

Building on the second chapter's conclusion I dig into the structural characteristics (i.e., being the focal inventor within brokered networks) of collaboration networks as it is the most effective contributor to increasing the focal inventor's performance. The lead question in the second essay of my dissertation is *how heterogeneous knowledge accessible through the collaborators influences the relationship between being a broker and the novelty of the focal inventor's output*. Joining the research on the contingent value of brokered networks, I look at the structure and content-related factors of collaboration networks to predict the value of each focal inventor's ego network source to better performance and theorize about the strategies inventors and their managers should pursue in order to increase individuals' creativity and the novelty of their ideas. Inspired by the controversial conclusions on which structure (i.e., brokered versus constraint networks) is better for inventive performance, I question the assumption made by the great majority of prior literature of a direct association between network structure and the nature of accessible knowledge within the network. More specifically, I question the conventional assumption that suggests a direct association between being a broker and collaborating with inventors possessing unique knowledge. To do so, the study suggests a way to make a distinction between the structural characteristic of an ego network (i.e., brokered structure) and the content of an ego network (i.e., knowledge heterogeneity provided only by collaborators).

My first argument is that brokered networks serve as sources of knowledge arbitrage and increase the focal inventor's creativity. Brokered networks in which focal inventors collaborate with otherwise disconnected actors are associated with working with diverse knowledge, perspective, and resources providers (Brass and Burkhardt 1993; Burt 1992, 2004; Hargadon and Sutton 1997; Lee 2010; Zaheer and Soda 2009) that

serve as sources of combinatory skills (Fleming et al. 2007; Perry-Smith and Mannucci 2017). Because focal inventors have control over the information flow within the brokered network, they can be aware of and exploit the knowledge available within their ego networks, therefore, increasing the novelty of their output. In certain circumstances, being a broker (i.e., being the focal inventor of a brokered network) allows the inventor to be more legitimate which helps him or her to implement his or her novel ideas easier than inventors within constraint networks in which all inventors tied to each other (Burt 2017; Rodan and Galunic 2004). Yet, knowledge arbitrage advantages of a broker can happen if disconnected inventors do not possess each other's knowledge. Building on the contingent value of brokerage, my second argument is that brokered networks act as a source of costs. These costs simply can be coordination and communication costs among disconnected sets of inventors and maintenance costs of the non-redundant ties. Moreover, novel ideas are hard to be understood and to be supported by others as they contain high uncertainty and are more complex combinations. However, sparse networks do not provide a trusting environment, therefore, decrease the willingness to share risks, resources, and knowledge between collaborators (Obstfeld 2005; Uzzi and Spiro 2005). As a result, if the focal inventor of a brokered network cannot use the positioning as a source of knowledge arbitrage, being a broker can become detrimental to his or her creativity.

In this study, I use the same database – EPO PATSTAT – to construct collaborative networks, to measure the available knowledge heterogeneity⁵ within the networks, and the novelty of inventors' output. A longitudinal dataset with more than 80 000 inventor-year observations from 1995 to 2010 is aggregated

⁵ EPO PATSTAT database has approximately 650 4-digit subclasses to categorize used technologies for the inventions. I used 4-digit technological classes which are narrow enough to observe the heterogeneous expertise holders and knowledge heterogeneity provided by collaborators and to observe novel combinations of technologies.

from the EPO PATSTAT database as the study focus on inventors who have at least one patent in the given performance year. As in the second chapter, a panel data–negative binomial estimator is preferred because of the inflation and overdispersion which explanatory (i.e., the novelty of inventors’ output) variable exhibits.

Overall, the results indicate that being a broker does not guarantee access to heterogeneous resources. Structural brokerage and having access to diverse knowledge through collaborators moderate each other’s influence on the novelty of inventors’ output. Last, the fact that an inventor enjoys being a broker is contingent upon the existence of knowledge heterogeneity within his or her ego network. Otherwise, besides the lack of knowledge arbitrage advantages, being a broker becomes detrimental to his or her own creativity because the communication, coordination costs, and lack of trust among inventors outweigh.

Collaboration networks and the reuse of inventors’ output: the interplay between cognitive proximity and brokerage

In the final essay, I seek to find an answer to the question of how cognitive proximity among local network members (including the focal inventor) does⁶ affect the relationship between reuse of the focal inventor’s ideas and being a broker. The study is again attached to the contingent value of being a broker and contribute to the ongoing debate on the brokered versus constraint networks. In the previous chapters, I show that being a broker does not guarantee collaborators providing unique knowledge and there are brokers who do not take the advantage of their collaboration networks to increase the novelty of their output. There are multiple facets of inventive performance: quantity, novelty, and usefulness of output. An inventor can enjoy

⁶ Local network is the very close network of the focal inventor. Its members include the focal inventor’s direct collaborators and their direct collaborators. In other words, all inventors with a maximum of two social distances to the focal inventor.

his position depending on the incentives and benefit from the collaboration networks to increase one specific facet of inventive performance (i.e., the reuse of the inventor's ideas). Thus, after investigating the first two facets of inventive performance in the first two chapters, in the third chapter I concentrate on the third aspect of inventive performance and dig in to understand the association between brokerage and the reuse of inventors' ideas.

The chapter first makes an argument that the effects of brokered networks may vary significantly for different spheres of influence. To do so, I make a distinction between a complete collaborative network (i.e., simply all active inventors appear in the EPO PATSTAT database), and its sub-section to which the focal inventor belongs. Sub networks are termed as local networks and are constrained by maximum of two collaborative links (i.e., the focal inventor, the ones who directly collaborated with the focal inventor and their collaborators). Brokered networks increases the focal inventor's creativity and implementation capabilities with strategic advantages attached to knowledge arbitrage capabilities and legitimate positioning (Burt 2007; Perry-Smith and Mannucci 2017; Rodan and Galunic 2004). However, they are claimed to decrease the usefulness of generated ideas by others (Guimerà et al. 2005; Obstfeld 2005; Perry-Smith and Mannucci 2017; Uzzi and Spiro 2005). This is due to the fact that brokered networks prevent the emergence of trust and common language, hinder the acceptance of generated ideas, and slow down their diffusion (Fleming et al. 2007; Tortoriello and Krackhardt 2010; Uzzi 1997). I argue that the mentioned disadvantages will disappear within the local network in which collaborators are part of the same team and most of the collaborators are directly tied to each other, thus, they are less likely to perform opportunistic behaviors. The social proximity among local network members facilitates knowledge exchange and enables them to interact with each other easily. My second argument is that the focal inventor of a brokered network can take even more advantages of his or her position in case the collaborators are cognitively proximate to each other. The proximity helps inventors to communicate with a minimum effort and appreciate the ideas generated by the broker even if they do not have an efficient information flow within the network. To do

so, I question the assumption of brokered networks consist cognitive distant set of inventors that appears in most of the previous studies and make a distinction between the cognitive proximity of the local network members and the network structure (i.e., the level of brokerage).

In this essay, I use the same longitudinal dataset used in third chapter, with more than 80 000 inventor-year observations. Again, a panel data–negative binomial estimator is preferred because of the inflation and overdispersion which explanatory (i.e., the future of inventors’ output by local network members) variable exhibits.

Overall, I find that the advantages of being the focal inventor within a brokered versus constraint network are contingent upon the cognitive proximity of local network members. The study contributes to the ongoing debate on cohesive versus brokerage by showing that the detrimental effect of brokered networks can be overcome through social and cognitive proximity of collaborators. Even further the focal inventor of a brokered network conditionally enjoys more than an inventor within constraint network to increase the reuse of his or her ideas. However, constraint networks become advantageous for unique technological expertise holders because the high intensity of interactions helps them to overcome consequences of working with cognitively distant collaborators. Although both closed and brokered networks seem to be beneficial for usefulness of inventors’ ideas, being a broker where a high level of cognitive proximity exist is the most fruitful environment to increase the reuse of inventor’s ideas within his or her local network.

CHAPTER 2⁷

⁷ This chapter is based on a joint work with my supervisors, Ludovic Dibiaggio and Zakaria Babutsidze.

COLLABORATION NETWORKS AND QUANTITY OF INVENTORS' OUTPUT

ABSTRACT

The study analyses the extent to which an individual's inventive performance is influenced by the structural and relational characteristics of her collaboration network. The chapter develops a framework that theorizes the relationship between structural characteristics –the number of collaborators, the number of inventors indirectly connected to the focal inventor and brokerage, termed brokered network, - and relational characteristics –the strength of relations– to the focal inventor's output. Results from the longitudinal study highlight the positive association between collaborators as well as spanning structural holes -direct collaborations with otherwise isolated collaborators- to increase the quantity of inventors' inventions. Yet, the overall network of indirect connections is found to have no influence. Only most proximate indirect connections (i.e., collaborators located at a maximum of two path length distances) contribute to the focal inventor's performance. The findings on the strength of relationships and structural holes further reinforce the basic conclusion that the quality of collaborative relationships and the complementarity (i.e., non-redundancy) of the collaborators is more important than the number of the collaborators. Thus, the analysis of the optimal structure of an inventor's collaboration network confirms the advantage of an inventor strongly connected to disconnected sets of inventors.

INTRODUCTION

Several studies have indicated that the network of collaborations of an inventor influences her inventive behavior and performance (Burt 1991, 2000, 2004, 2017; Obstfeld 2005; Coleman 1988; Granovetter 1973; Perry-Smith 2006; Fleming et al.2007; Quintane and Carnabuci 2016). There is a strong research tradition in management supporting the idea that brokered collaboration network structure provide greater information advantages and social capital (Burt 1991, 2000, 2004, 2017). Collaboration networks provide access to resources, facilitate knowledge sharing and contribute to inventors' social capital by building trust and increasing legitimacy in the network. However, despite the growing consensus that collaboration networks matter, the specific influences of different features of a network structure on the inventors' performance remain unclear for two reasons. First, the generalizability of much published research on the structure of collaboration networks is problematic. The conclusions are rather controversial, and there is no general agreement about the influence of structural collaboration network characteristics on inventors' performance. Second, the research to date has tended to focus on one network feature such as cohesive network structure or attribute such as experience of collaborators at once rather than observing their relative impact or interplay with each other.

Debates have arisen over the structural (i.e., topological structure of networks) and relational (i.e., number and strength of the ties within those networks) dimensions that can appropriately be regarded as advantageous. According to one view, dense networks with many connections linking the members of a network facilitate learning by interactions (i.e., one inventor taps into another's knowledge and experience by communication). Collaboration network structures are seen as beneficial to the extent that networks are *closed*⁸ (Coleman 1988; Fleming et al.2007; Walker et al. 1997). The rate of return from being within closed

⁸ A closed network structure occurs in case many members of the network are interconnected.

networks is similar to studies focusing on the benefits of strong relationships. Strength of ties also are found to facilitate higher quality information transfer and tacit knowledge between connected inventors (Gulati 1995; Inkpen and Tsang 2005; Larson 1992; Reagans and McEvily 2003; Rowley et al. 2000). Both closed networks and collaboration networks formed by strong ties are argued as indications of shared understanding, trust and collaborative integration that foster knowledge sharing and learning by interactions. Yet, they do not guarantee the availability of diverse resources.

According to alternate views, however, structural advantages derive from weak ties (Granovetter 1973) and spanning structural holes (Burt 1991, 1992, 2004, 2017, 2021). First, researchers suggest that weak collaborations serve as a source of richer contents that differs from that the focal inventor already knows. This is due to the fact that weak ties tend to connect nonredundant collaborators who belongs to different groups of inventors (Granovetter 1973, 1983; Ibarra and Andrews 1993). Second, brokered networks where focal inventors spanned by several structural holes creates similar opportunities for focal inventors. Being in contact with otherwise disconnected collaborators helps the focal inventor access diverse knowledge and have control over knowledge flows within her ego network (Burt 1991, 1992). By tapping information from these collaborators (Aral and Van Alstyne 2011; Burt 2004; Carnabuci and Diószegi 2015), inventors spanning several structural holes are more likely to come across different pieces of technological knowledge and combine them in an unexpected way, which are critical for providing novel approaches and creative solutions (Amabile et al. 2019; Burt 2005). Both open networks and collaboration networks formed by weak ties are argued to facilitate access to diverse resources that is available in the network. Yet, these structural and relational characteristics do not guarantee the willingness of collaborators to share their possessed knowledge.

In addition, prior literature has led to the important insight that enlarging the frontiers of the networks with a large number of indirectly connected collaborators may be an effective way for actors to enjoy the benefits of collaborations without paying the maintenance costs of relationships (Burt 1992). Although such strategy

seems to be a cost-free --and therefore an attractive-- way of taking the advantages of collaborative linkages, it is for sure that the value of network size will be associated with the equipollency of the benefits provided by collaborators and indirectly connected inventors. The substitutability of the collaborators and indirectly connected inventors will be limited to an extent by the similarities between the types and amounts of the benefits provided by them.

From a social network perspective, the contradictory structural requirements of having access to diverse resources and being able to take advantage of available resources provide completely different normative implications. Further, there are studies demonstrating that co-existence of unexpected characteristics is possible. For instance, according to a stream of research building on Granovetter's argument (1973), tie strength and density are generally strongly correlated and mutually reinforcing. However, a notable study focusing on almost 200 researcher's performance and knowledge creation demonstrates that the optimal network structure can be a combination of strong direct ties and sparse connections among collaborators (McFadyen et al. 2009). According to their conclusion, this combination provides the best of the worlds for access to resource diversity coupled with an efficient access to tacit knowledge and shared experiences. My study aims to clarify and identify the features of collaboration networks contributing to performance of inventors who are located in France. In addition, by examining the relative contribution of structural characteristics the study intends to provide a perspective for designing effective and efficient networks to increase the inventor's output. Examining the relationship between collaborative networks and invention output can provide both a clarification of the role of different elements of network features (i.e., relational, and structural dimensions) in the invention process and an empirical indicator of the effectiveness of knowledge flows through such networks.

The chapter is structured as follows. Section 2 provides an overview of the literature analyzing structural collaborative network characteristics as key determinants of inventor's performance, showing the attention to available knowledge diversity, and knowledge sharing. The contrary arguments associated with structural

and relational network characteristics is emphasized in this section. Building on this, I outline the advantages and disadvantages of inventor's structural and relational network characteristics, and I develop hypotheses regarding the way they can contribute to an inventor's output. Section 3 describes the empirical setting, data sample and discusses the empirical methodology. Section 4 presents the results, and Section 5 concludes.

COLLABORATION NETWORKS AND INVENTORS' OUTPUT

Although research on individuals' performance has traditionally been the province of psychologists (Ford 1996), sociologists have recently joined the discussion. They agree on the importance of collaboration networks' structure for inventors' performance. Yet, despite a growing number of empirical studies (e.g., Ahuja 2000; Burt 1992; Fleming et al. 2007; Obstfeld 2005; Reagans and McEvily 2008), the generalizability of the conclusions and relative importance of each dimension are far from being settled.

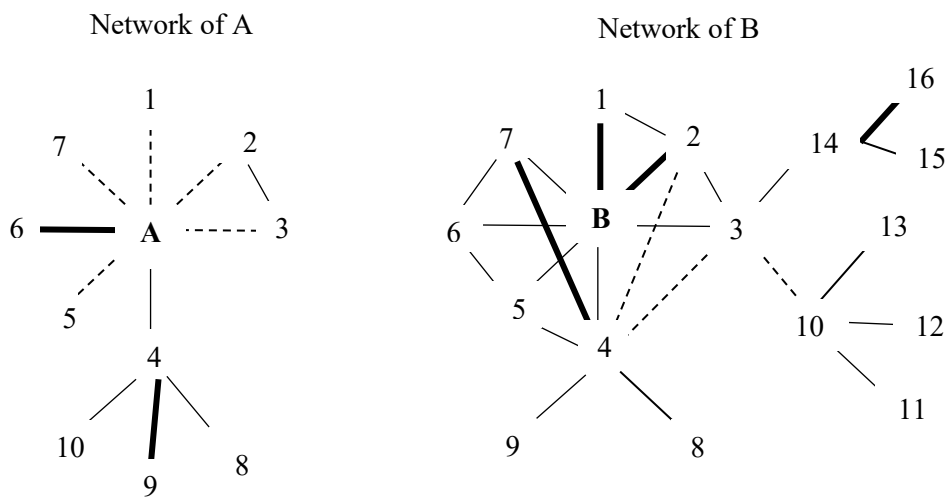
Extant social network analysis literature identifies the antecedents and analyzes the consequences of network features and builds a ground to understand information flows, opportunities through collaborations, advantages and constraint of resources embedded within the collaborative networks (Ahuja 2000; Borgatti and Halgin 2011; Burt 1995; Cannella and McFadyen 2016). According to network theory actors can benefit from the relational and structural characteristics of their collaboration networks. Studies emphasize that the characteristics of collaboration networks is associated with the diversity of resources available to inventors, interactive learning, constructive feedback, and trust, therefore, inventive performance (Burt 2005; Fleming et al. 2007; Perry-Smith and Mannucci 2017; Nooteboom 2000).

The study considers four characteristics of an inventor's collaboration network are supposed to contributed to the benefits mentioned above. These characteristics are 1) the number of collaborators, 2) the number of indirectly connected inventors (inventors who can be reach in the focal inventor's ego network through his or her collaborators or their collaborators), 3) the strength of each couple of inventor's collaborative relationships, and 4) the degree to which an inventor's collaborators are linked to each other within the focal inventor's ego network (i.e., spanning structural holes, termed brokerage). Figure 1 shows these four dimensions in the ego networks of two illustrative inventors: A and B. The links between inventors appear in case they co-invent. Inventor A has 7 collaborators (from 1 to 7) and 3 indirectly connected inventors (8, 9, 10) that can be reached at two-step through his or her direct collaborator numbered as 4. Some of these

connections are stronger than others. The thickness of the lines increases with the strength of the relationships between inventors. For instance, dashed lines are assigned to be the weakest ties within illustrated networks. The study assigns the thickness of the links by how frequently two inventors work together and the links are weakened by the team size of the two inventors. Further, A's collaborators are mostly disconnected to each other, creating an open network with many structural holes that are the gaps between A's collaborators (1 through 7). In comparison, inventor B has same number of collaborators, yet more (from 8 to 16) indirectly connected inventors. In B's network, the average strength of ties, on average, is greater than A's collaborations. Last, his or her collaborators are mostly linked to each other, creating a cohesive network with almost no structural holes.

Each of these four dimensions, influence the focal inventor's performance. An inventor's collaborators provide knowledge and resource-sharing opportunities. Indirectly connected inventors can provide knowledge spillover benefits while they do not entail resource-sharing benefits. The strength of ties between couples of inventors indicates shared understanding, high quality of information and tacit knowledge transfer between collaborators (Gulati 1995; Inkpen and Tsang 2005; Larson 1992; Reagans and McEvily

Figure 1. An illustration of structural characteristics in two hypothetical networks



2003; Rowley et al. 2000). Finally, spanning several structural holes among collaborators affects both access to diverse resources and resource-sharing opportunities (Burt 1992, 1995, 2004).

Number of directly and indirectly connected collaborators

The first relational dimension I consider is the number of collaborators that a focal inventor has during the given network period.

The number of an inventor's collaborators can contribute to his or her inventive output by providing essential benefits: resource and knowledge sharing, complementarity (non-redundant resources), and scale (Ahuja 2000; Gonzalez-Brambila et al. 2013; Nagapie and Ghoshal 1998). First, relying on a network of collaborators provide access to critical resources –such as technological knowledge-- for invention. Inventive performance often demands the simultaneous use of different sets of skills, perspectives, and experiences in the invention process (Perry-Smith and Mannucci 2017; Sosa 2011; Burt 2004). However, developing new skills, learning new knowledge, and acquiring know-how for rapidly changing technologies are difficult and costly for an inventor (Mitchell and Singh 1996; Sorenson et al. 2006). Collaborating with co-inventors enables her to (freely) access knowledge and contribution of all co-inventors in her network. Therefore, being part of a collaborative network provides her with the opportunity to receive a greater amount of resource compared to a being a lone inventor (Singh and Fleming 2010). Collaborating with other inventors facilitates bringing together complementary skills from different inventors. Furthermore, benefiting from free knowledge, as a member of a collaborative network, she can enjoy others' specialization. Second, there are size effects of collaborative networks. collaborating for a project will provide more fruitful investments. For instance, in an R&D collaborative project of three co-inventors, if each inventor devotes an amount of time t and an amount of attention a to the project, then the total effort dedicated to the project is $3t$ and $3a$ s. Therefore, this view emphasizes positive effects of collaborative networks exclusively: collaborations increase the probability of successful outcomes because they increase

combinatorial capabilities by increasing the amount of knowledge available, increase invested time to the project by sharing the work load and provide more rigorous selection of ideas by including all collaborators' contribution (Singh and Fleming 2010).

An alternative view suggests negative network size effects and argue that, after a certain threshold, adding collaborators is detrimental to inventive performance. i Indeed, maintaining direct ties requires attention and therefore increasing the number of collaborators is costly. (Belkhouja et al. 2021). However, most of these studies focus on researchers' knowledge creation processes and productivity in academia where researchers have the rights to select their collaborators and chose as many collaborators as they want. By contrast, in the context of industrial innovation, an inventor is generally part of a team that is created by a manager. Because the institutions focus on increasing the efficiency of their inventors, the number of collaborators is not expected to increase in an uncontrolled manner. As a result, the first hypothesis I put forward is:

Hypothesis 1: Inventors with a larger number of collaborators will have greater output.

The second relational dimension I consider is the number of indirectly connected collaborators that a focal inventor has during the given network period.

The wealth of resources accessible through one's direct connections is subject to resources provided by their own collaborators (Ahuja 2000; Gulati and Gargiulo 1999; Zaheer and Bell 2005). An ego network that includes directly and indirectly connected inventors creates a channel of communication between the focal inventor and many other actors. A focal inventor's direct collaborations bring information, knowledge, and a different skill sets from their own collaborators (Gulati and Gargiulo 1999).

Having access to external resources provide focal inventors with strategic advantages in two forms (Leonard-Barton 1984). First, inventors have limited cognitive capacities, to invest in all technologies and

pursue many projects. Thus, they can benefit from co-inventors' knowledge and increase their performance. Second, any information gathered through collaborators is an output of information processing that collaborators invested in. It is the return of the learning investment in a piece of specific information or technology. Therefore, the focal inventor can more efficiently decide which direction to go and increase his or her performance by benefiting others' experiences and attempts that both succeed and failed. As a result, the second hypothesis⁹ I put forward is:

Hypothesis 2: Inventors with a larger number of indirectly connected inventors will have greater output.

The degree to which collaborators benefit the focal inventor, however, is likely to be contingent on the number of his or her existing indirectly connected inventors. Inventors with few indirectly connected inventors can have more chances to enjoy greater benefits from their collaborators than the ones with many indirectly connected inventors. A focal inventor's collaborators are required to dedicate their attention and time to their collaborators other than the focal inventor. For instance, inventor B in Figure 1 collaborates with inventor 4. However, the collaborator (4) cannot dedicate all his or her attention and time to inventor B because he or she collaborates also with inventors 2, 3, 5, 7, 8, 9. On the contrary, inventor A collaborates with inventor 1 who does not share his or her attention and time with others. Therefore, an inventor with

⁹ In this case, it is certain that the benefits of indirect ties need to be considered to explain subsequent inventive performance of focal inventors. However, treating all indirect ties equally is not the best way to analyze their effects on inventors' output. First, because the knowledge diffusion performance depend on the distance between co-inventors, the shortest path length will vary the benefits of ties (Sorenson, Rivkin, and Fleming 2006). Second, the distance being equal, the potential knowledge to be shared through collaborations will change the benefits of ties depending on the possessed knowledge by collaborated inventors (G. Ahuja 2000). Therefore, I construct alternative measurements including distance and information of collaborators for testing the hypothesis put forward.

many indirectly connected collaborators can limitedly interact and benefit from their collaborators. Considering an inventor's limited time and attention to allocate to his or her collaborators (Belkhouja et al. 2021; Cohen and Levinthal 1990), although the benefits of collaborators and indirectly connected inventors are hypothesized to be positively associated with inventive performance, I expect that they negatively moderate each other's benefits. As a result, the third hypothesis I put forward is:

***Hypothesis 3:** The positive association between collaborators and an inventor's output will be negatively moderated by the number of the indirectly connected inventors: the greater the number of indirectly connected inventors, the smaller the benefit from collaborators.*

Strength of collaborations

The third relational dimension is the strength of collaborations. It is a quite important characteristic of an inventor's collaboration network because maintaining collaborators does not guarantee that the possessed knowledge will be shared within the network. Strength indicates that inventors communicate with each other frequently and reflects "how well" an inventor knows his or her collaborators. The average strength of relationships affects the level of integration of co-inventors and the level of commitment of collaborators. Inventors hold strong collaborative relationships in case they frequently work together, therefore, they have similar objectives, same incentives and opportunity to share information (Boorman 1975; Granovetter 1973, 1983; Krackhardt 1992).

Literature has demonstrated some of the key benefits of the strength of ties such as trust and high quality of knowledge and information exchange (Nonaka 1994; Perry-Smith and Mannucci 2015; Phelps et al. 2012; Sosa 2011). Strong linkages foster knowledge transfer and communication effectiveness. First, the emerging trust through the strength of the ties reduces the likelihood of opportunistic behaviors such as misusing shared knowledge. Consequently, trust increases the propensity of co-inventors to share knowledge (Gulati 1995; Inkpen and Tsang 2005; Larson 1992; McEvily et al. 2021; Reagans and McEvily

2003; Rowley et al. 2000). Second, maintaining strong relationships with collaborators makes interactions easier and more effective and facilitates the invention processes. Maintaining strong relationships means that collaborators have already established some norms, learn how to communicate, and develop a common language. Finally, prior experience reduces the cost of searching new collaborators for new projects (Gulati 1995; Inkpen and Tsang 2005; Larson 1992; Rowley et al. 2000).

In addition, the literature on learning and creativity highlights the importance of strengthening collaborative relationships for two reasons. First, trust and willingness to share knowledge generate learning by interactions (Nooteboom 2000; Perry-Smith and Mannucci 2017). Second, even if collaborators do not learn from one another, they still are likely to benefit from others' expertise through feedback. A focal inventor who hold strong direct collaborations can enjoy constructive and rapid feedback from their collaborators to move their projects further (Perry-Smith and Mannucci 2015, 2017; Phelps et al. 2012).

The same applies for indirectly connected inventors. Even further, from the focal inventors' perspective it became more crucial to be part of a network in which strong relationships are hold among inventors (excluding the focal inventor). Strength of collaborations will increase the knowledge spillover benefits through collaborators by paying no costs of maintenance. Therefore, the fourth hypothesis I put forward is:

***Hypothesis 4:** Inventors who hold stronger relationships (both direct and indirect) will have greater output.*

The level of non-redundancy of collaborators

In addition to the relational dimensions of the collaboration networks, literature suggests that a third dimension of an inventor's ego network is also likely to be important for inventive performance: brokerage (i.e., high level of structural holes around the focal inventor). Structural holes are the gaps in information flows between the focal inventor's collaborators because they are not connected to each other. For instance, inventor A in figure 1 has many structural holes among his or her collaborators (no connections between 1,

3, 5, 6, 7). For ego networks, this dimension indicates the extent to which a given focal inventor's collaborators belong to different groups of inventors. to each other (Borgatti 1997; Burt 1992; Ahuja 2000). Networks with many structural holes are termed as brokered or sparse networks and put the focal inventors in a gatekeeper role. Literature on the effects of brokered and dense networks is mixed.

On the one hand, researchers demonstrate the benefits of ego networks with few structural holes and emphasize that resource-sharing benefits within an information-rich network arise from actors' trust in one another and from their willingness to combine skills and share knowledge (Coleman 1988; Fleming et al. 2007; Obstfeld 2005; Uzzi and Spiro 2005). According to these studies' conclusion, ego networks that are rich in structural holes prevents the emergence of a trusting environment. Consequently, they hinder the commitment of actors, increase the tendency for opportunistic behaviors, and hold inventors back to share their unique knowledge. However, most of these studies are not at the individual level and focus on firms that have similar objectives (Dyer and Nobeoka 2000; Gulati and Singh 1998; Uzzi 1997; Walker et al. 1997). On the other hand, inventors embedded in loosely connected networks will have knowledge brokerage opportunities. According to Burt's structural hole theory, collaborations are redundant to the degree that they lead to the same inventors. The theory indicates that inventors on either side of the structural holes bring different flows of information (Burt 1992, Hargadon and Sutton 1997). The notion of structural holes has been assumed to be a valid indication of the extent to which an inventor's position in the network confers the greatest access to novel information and good ideas (Burt 1992, 2004). Minimizing redundancy or maximizing the level of structural holes is an important aspect of an efficient and information-rich network construction (Burt 1992).

In addition to knowledge benefits, the focal inventor spanning several structural holes keeps a very strategic position within their ego networks. The focal inventor enjoys the position by having control over the information flow because he or she reserves the right to let the information flows from one side of the network to the other side(Quintane and Carnabuci 2016). As a result, an inventor spanning many structural

holes is assumed to be exposed to diverse knowledge, to have a higher awareness of available resources in his or her surroundings by having a superiority over the control of information flow.

To reflect how these perspectives relate to inventors, one can consider how inventions are generated and how acquired knowledge is shared among inventors. In the context of industrial innovation, there are within firm connections and teams working on projects focusing on a specific new technology, a set of technologies to create novel combinations or their applications in other contexts. They may have internal collaborations and external ones with other economic actors in their ecosystem. In the end, their aim is either to increase the absorptive capacity of their institutions, to protect and to codify their ideas by patenting. In general, they do expect to have intellectual property rights to generate profits based on it. Although, for industrial innovation, knowledge sharing seems to be less frequent to protect institutional secrecy and more complex (Gilsing et al. 2008), these arguments are less relevant for inventors for two reasons. First, inventors are part of the same project and team, therefore, they have the same goals and incentives. Even if the projects include multiple firms, the interorganizational relationships through inventors can emerge only after their mutual agreements that, again, emphasize joining forces to overcome a technological challenge. Second, unlike a notable study demonstrating that spanning structural holes feed the opportunistic behaviors of competitor firms (Ahuja 2000), at individual level studies relational dimension (i.e., strength of relationships) is more valid as an indication of trust among collaborating inventors compared to spanning structural holes (McFadyen et al. 2009; Perry-Smith and Mannucci 2015). As a result, although trust and cooperation norms contribute to inventive performance, it is hypothesized that structural holes in ego-networks of individual inventors are positively associated with inventive performance. Then, the last hypothesis I put forward is:

***Hypothesis 5:** Inventors that are embedded in networks richer in structural holes are associated with greater output.*

METHODOLOGY

Setting and data

To test my hypotheses and to answer – if and to what extent collaboration networks influence inventors’ performance – an empirical study of French inventors is conducted. A single inventor embedded in a collaborative network for a given performance year is focused. The unit of analysis is an inventor-year pair. To construct independent variables, collaborative networks containing focal inventors and the set of collaborators to whom the focal inventor is directly and indirectly tied are defined. In this chapter, ego networks do not have any boundaries based on a given number of maximum path length of indirectly connected inventors.

The model and measurements

Dependent variable

I measured Patents it , as the number of patent applications, for inventor i in performance year t . The majority of patent applications are examined and ruled upon within the upcoming years of application. I used the original application date to assign a patent to the particular year in which it was originally applied for. For instance, a patent applied for in 2004 but granted in 2007 is considered a 2004 patent. This procedure permitted consistency in the treatment of all patents and controlled for differences in delays that may occur in granting patents after the application is filed. Dependent variables used in this and in the following chapters are always measured based on the patents produced with a one-year lag to the network period. For instance, if the networks are created by using the patents applied between years $t-5$ and $t-1$, the number of inventor’s patents in year t is measured. Thus, the patent count for 2005 is regressed against the 2004-2000 period values of other covariates.

Independent variables

Number of collaborators is measured by an inventor's degree centrality in the network. This variable represents the number of directly collaborators of an inventor.

Number of indirectly connected collaborators are measured with four alternative ways¹⁰. The first one is the simple count of focal inventors' collaborators' collaborators. Their social distance to the focal inventor is 2-path length. This variable is named as *indirect 1st*. The second version of indirectly connected inventors is the simple count of collaborators who does not have a direct connection to the focal inventor but is reachable through any number of steps. This variable does not apply a limitation to the number of steps to access the focal inventor and is named as *indirect connections - count*.

However, this simple count of indirectly connected inventors does not consider the weakening or decay in the relationship strength between the inventors who are connected by increasingly longer path distances. For instance, it counts that both inventors with two social distances and inventors (i.e., the ones connected with 1 intermediary inventor in between) with 5 social distances (i.e., the ones connected with 4 intermediary inventors in between) to the focal inventor have the same influence within the focal inventor's collaborative network. Yet, larger social distance connecting inventors is likely to decrease the benefits of collaborators compare to closer ones. For this reason, third alternative measure of indirectly connected inventors captures distance effect on benefits of collaborations. This variable is named as *indirect connections - distance weighted* and measured as in the previous studies relying on Burt's (1991) frequency decay measure (Ahuja 2000). I first determine the distance weight of path lengths by using their distance to the focal inventor. I weighted the indirect connections count with their distance strength and summed all

¹⁰ A hypothetical ego network is illustrated to provide an example of the construction of four alternative number of indirectly connected collaborators. Please see Appendix 1.A.

distance weighted connections to measure this variable. The argument for weighting is that in terms of distance strength, the longer distance means the weaker path distances, and the shorter ones mean the collaborators with stronger distance weights. Also, the strength of path distance should vary with the collaboration structure in which it occurs. Therefore, decay in the distance weighted relationship strength is related to the number of other inventors accessible at any social distance (Burt 1991).

The variable is constructed as

$$ind. collab. - distance weighted = \sum_{i=2}^{\max(i)} \left(1 - \frac{n_i}{N}\right) c_i,$$

where i is the level of path length, N is the network size (including the focal inventor), n_i is the number of connections up to i^{th} level of path length (excluding the focal inventor) and c_i is the number of connections at i^{th} level of path length.

The fourth indirect tie variable is called as *indirect connections - distance and information weighted*. In collaboration networks, some inventors create more than others and hence can be the source of more information. Therefore, collaborating with inventors who produce more lead to increase inventor's output more than others. Even if the shortest path lengths to the focal inventor are same for two collaborators, their benefits may change depending on their own productivity. The third indirectly connected inventors' measurement accounts for a lowered probability of knowledge spillover benefits across larger social distances. Therefore, the number of patents applied by the collaborator is included to the equation used to construct *indirect connections - distance weighted* variable. To do so, I first capture the productivity of co-inventors by total patent count between years t-5 and t-1¹¹. Then, I took the multiplication of the patent

¹¹ Patents in this period are used to create networks and inventive performance is measured based on patents in year t.

count and the distance weighted tie strength as Burt's (1991) frequency decay measure (Ahuja 2000). The variable is constructed as

$$Ind. Collab. - Distance \& Information Weighted = \sum_{i=2}^{\max(i)} \left(1 - \frac{n_i}{N}\right) pc_i,$$

where i is the level of path length, N is the ego network size (including the focal inventor), n_i is the number of connections up to i^{th} level of path length (excluding the focal inventor), and pc_i is the total patent count of i^{th} level of path length connections.

Once indirect and direct variables are generated, four alternatives of the interaction variables based on four versions of indirectly connected inventors are constructed to observe the moderating effect of indirectly connected inventors on collaborators.

Strength of collaborative ties is measured by assigning weights to each dyadic collaborative relations relying on Newman's (2001) network weighting measurement¹². The measurement of the weights takes into account the frequency of co-patenting behavior, as well as the size of each patent's co-inventing team. First, the tie strength between inventor x and inventor y is computed as

$$ts_{xy} = \sum_p \frac{1}{n_p - 1},$$

where p is the set of patents that inventors x and y collaborated on during the reference period and n_p is the number of inventors for each patent p . Second, I sum the tie strengths derived from each of the patents

¹² A hypothetical network is illustrated to provide an example of weighted ties. See Appendix 1.A.

written by a couple of inventors. Based on these weighted ties, the three strength variables included in my analysis are calculated.

Notice that any network contains several disjoint sets of relationships. Because the study observes the collaborations in three main groups (i.e., direct, indirect 1st, and indirect connections) I construct the strength of collaborative for the three main sets of collaborations. First set collects all dyadic connections that involve the focal inventor. Averaging over strengths of these ties gives us the variable *average strength of direct ties*. The second set of ties includes the collaborations between focal inventor’s collaborators and two-step collaborators (i.e., collaborators’ collaborators). The second variable is the average tie strength of these ties and named as *average strength of 1st order indirect ties*. The last set of connections includes all ties between indirectly connected inventors in the focal inventor’s network. Averaging over strengths of these ties results into the *average strength of indirect ties*.

To construct the *brokerage*¹³, I used the ratio of non-redundant collaborators to total collaborators for the focal inventor (Burt 1991). The measurement relies on constraint measurement and the level of the structural holes available in the focal inventor’s network (Borgatti 1997; Burt 1992; Ahuja 2000). The brokerage measure is a constrained version of betweenness centrality. The measure counts paths between nodes assigned to different sets of inventors, gives a rise to gatekeeper role while a traditional betweenness centrality measure counts shortest paths between all nodes. Following the literature, brokerage is constructed as

$$B_{i,t} = \frac{\sum_v (1 - \sum_w p_{iw} m_{vw})}{c_{i,t}},$$

¹³ The same measurement is used also for the following chapters.

where v runs through all collaborators of inventor i , p_{iw} is the proportion of focal inventor i 's connections invested in the relations with contact w , and m_{vw} denotes the marginal strength of a tie between collaborators v and w , and $C_{i,t}$ is the total number of contacts for inventor i in the network period attached to the performance year t . Not to increase the complexity of the measurement and to remain interpretable, I assume equal tie strengths.

Control variables

To obtain meaningful results, several characteristics are included in the empirical model. The control variables are organized on two levels. The first set relates to individual-level characteristics of the focal inventor such as experience, previous performance and so on. Second set includes team-level variables to control for the team composition for focal inventor's patenting activities.

To control for the team composition within focal inventor's patent portfolio two indicators are used. The first one is the *single firm*. It is the percentage of the focal inventor's patents in which all inventors come from the same company during the period of five years preceding performance year. Second, *single country* is the ratio of the focal inventor's patents in which his or her collaborators are located in the same country for five years preceding the performance year, to his or her all patents. The last variable of this set is the *technology diversity*. Demonstrations have been made for the association between knowledge diversity and actors' innovation performance (Cohen and Levinthal 1990; Galunic and Rodan 1998; Rodan and Galunic 2004; Sorenson et al. 2006; Sosa 2011b). Although the chapter does not make any prediction on its effect, the influence of diverse technology access is controlled because it increases the inventor's combinatory

skills (Sosa 2011). A simple count of unique technological classes¹⁴ appear in the focal inventor's and collaborators' patents during the network period is used to construct the variable.

The inventor-level set includes three variables: *experience*, *first inventor*, *previous patent count*. The variable *experience* counts the number of years between performance year and the first year the focal inventor appears in EPO database. The measure of *first inventor* is the share of the patents that the focal inventor was listed first, during the period of five years preceding performance year. I also control the previous performance of focal inventors by including the number of patents they have applied for over the last 10 years preceding the performance year, namely *previous patent count*.

Econometric issues and estimation

A panel dataset where I observe patenting behavior of inventors over an extended period is structured. The descriptive analysis shows that the dependent variable takes only integer values and has an overdispersed and an inflated distribution. Considering the specific features of the variable itself and its distribution, it is preferred to use a panel data specific Negative Binomial estimator. The estimator lets us control for overdispersion—where the variance is quite greater than the mean—and inflation which the data exhibits. Therefore, the selected estimator provides efficient, consistent, and unbiased coefficients. Despite the high number of observations, the difference between the coefficients of a random effect modal and a fixed-effect modal is double-checked by using a likelihood ratio test. As expected, the test pointed to the use of a random effect modal.

¹⁴ European Patent Office (EPO) separates the technologies in classes and subclasses. To construct this variable, I used the 4-digit technological classes assigned to the related patents by EPO.

Although the chapter investigates several characteristics of a focal inventor's collaboration network, the inclusion of the inventors who did not work with two or more collaborators would be misleading for the analysis. This is because inventors who did not work with at least two collaborators cannot become brokers (i.e., inventors spanning structural holes) within their network. Therefore, following previous studies (Ahuja 2000, Fleming et al. 2007), I use only cases where the focal inventor has at least two collaborators. 32 092 unique inventors and 227,679 inventor-year combinations are used to obtain random-effects Negative Binomial estimates (with added year fixed-effects and technology residuals¹⁵) of empirical models. Tables 4 and 5¹⁶ respectively provide descriptive statistics and pairwise correlations of main variables across all retained observations. These statistics indicate some multicollinearity between some of the structural characteristics such as the number of direct and the number of indirect 1st connections. This is an expected correlation considering the relationship between the number of direct and indirect ties, as acquiring an indirect connection is only possible through direct connections. The same applies to high positive correlation between the number of indirectly connected inventors and technology diversity

¹⁵ Despite the potential bias deriving from ignored technological fixed effects, I couldn't manage to include fixed effects of the technologies in the models as they are. This is due to the fact that the addition of almost 650 4-digit technologies created computational problems (i.e., conformability and non-achieved convergence errors) that appeared in the software used for regression analyses (Stata MP-17). As a solution, a base model that includes only technology fixed effects is simply run to create a new variable with the residuals that came out from the model. The variable then is included in the main models as a representation of technology fixed effects. This lets us prevent any bias that may occur in the results without technology-fixed effects. The residuals could not be calculated for 4-digit and 3-digit versions because of the same errors. Therefore, the models include the 2-digit technology residuals that provide convergence. This choice is done to strengthen our statistical model.

¹⁶ Please see Appendix 1.B

considering the literature demonstrating that remote collaborators can generate knowledge spillover benefits for the focal inventor (Ahuja 2000; Gulati and Gargiulo 1999; Zaheer and Bell 2005).

RESULTS and DISCUSSION

I estimate four distinct models¹⁷. The set of models begins with Model 1, which highlights the influence of collaborators on the focal inventor's performance. To do so, it includes the number of collaborators and the strength of the relationship with them, as well as control variables, technology residuals, and year-fixed effects. In the next stage, Model 2 appends a stand-alone number of indirectly connected collaborators and the strength of the indirect ties for four alternative measures of indirectly connected inventors. Model 2a, 2b, 2c, and 2d include respectively indirect 1st connections, indirect connections – count, indirect connections – distance weighted, and indirect connections – distance & information weighted. Model 3a, 3b, 3c, and 3d are constructed to examine the moderating role of indirectly connected inventors (four measures) on the relationship between collaborators and the focal inventor's performance. Here I add the interaction term between the number of collaborators and indirectly connected inventors, to set up from Model 3s. Finally, Model 4a, 4b, 4c, and 4d add the brokerage variable to complete the specification. The extended models allow us to evaluate the hypotheses put forward in section 2. I use the complete specification (models 4a to 4d) to discuss the results.

¹⁷ Considering studies demonstrating the non-linear relationship between the diversity of collaborators and inventors' productivity (Belkhouja et al. 2021; Nooteboom et al. 2007; Reagans and McEvily 2003) I also conducted supplementary analyses to evaluate the robustness of the results. To do so, I simply include the square of the number of collaborators. Although the inclusion of the squared variables results in the significance of all variables, the interpretation of the results provided strong support for the reported results. This is due to the fact that almost all observations were located on the left side (i.e., less than 0.1 percent of them were located on the right side) of the turning point of the inverted U-shaped relationships between the number of collaborators and inventors' performance. As a result, I preferred to run linear models for the ease of the interaction variables' interpretation.

To start with, Table 1¹⁸ report the regression coefficient estimated for variable of interests across all models explaining the focal inventor's performance in terms of the number of patent applications. The results support the predictions for hypotheses 1, 4, and 5 while hypotheses 2 and 3 are not supported.

On the one hand, the coefficient of collaborators is positive and significant, supporting hypothesis 1, which predicts a positive relation between collaborators and inventors' output. The result of the study both verifies and qualifies the prescription to use collaborators as an efficient and effective way of maximizing network benefits. In an inventor linkage network, an inventor's collaborators serve for resource-sharing and information spillover benefits and contribute positively and significantly to his or her inventive output.

On the other hand, regarding the hypothesis 2, predicting a positive relationship between indirectly connected collaborators and inventors' output, the indirectly connected inventor's coefficient (for all measurements except indirect 1st connections) is negative and significant, not supporting the hypothesis for three alternative measurements. However, the number indirect 1st connections are positive and significant, supporting hypothesis 2's prediction of positive relationship between indirectly connected inventors and inventors' output. Thus, the benefits of indirectly connected collaborators have appeared only up to two-step collaborators. The results provide support for the basic premise that network effectiveness can be enhanced through collaborators or their collaborators (Burt, 1992).

¹⁸ For full regression outputs please see Table 6, Table 7, and Table 8 in Appendix 1.C.

Table 1. Results from panel negative binomial estimation: quantity of inventor's output

VARIABLES	<i>inventor's performance - quantity of inventor's output</i>				
	1	2a	2b	2c	2d
number of collaborators	0.00889*** (0.000598)	0.00964*** (0.000656)	0.00927*** (0.000599)	0.00905*** (0.000598)	0.00912*** (0.000598)
indirect 1 st connections		-0.000200*** (7.65e-05)			
indirect connections – count			-6.39e-07*** (1.00e-07)		
ind. collab. – distance weighted				-3.45e-06*** (4.10e-07)	
ind. collab. - distance & information weighted					-3.18e-07*** (4.48e-08)
avg. strength of direct ties	0.0515*** (0.00362)	0.0423*** (0.00369)	0.0441*** (0.00367)	0.0443*** (0.00367)	0.0442*** (0.00367)
avg. strength of 1 st order indirect ties		0.0519*** (0.00350)			
avg. strength of indirect ties			0.0616*** (0.00411)	0.0609*** (0.00412)	0.0617*** (0.00411)
direct collab. # indirect 1 st collab.					
direct collab. # indirect collab.					
direct collab. # ind. collab. dist. weight.					
direct collab. # ind. collab. dist. & inf. weight.					
brokerage					
observations	227,679	227,679	227,679	227,679	227,679
number of inventors	32,092	32,092	32,092	32,092	32,092

Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table 1 - continued

VARIABLES	<i>inventor's performance - quantity of inventor's output</i>			
	3a	3b	3c	3d
number of collaborators	0.0110*** (0.000683)	0.00968*** (0.000626)	0.00924*** (0.000621)	0.00930*** (0.000625)
indirect 1st connections	0.000295*** (8.29e-05)			
indirect connections – count		-4.57e-07*** (1.31e-07)		
ind. collab. - distance weighted			-3.05e-06*** (5.45e-07)	
ind. collab. - distance & information weighted				-2.84e-07*** (5.80e-08)
avg. strength of direct ties	0.0437*** (0.00369)	0.0444*** (0.00367)	0.0444*** (0.00368)	0.0443*** (0.00368)
avg. strength of 1 st order indirect ties	0.0511*** (0.00351)			
avg. strength of indirect ties		0.0615*** (0.00411)	0.0609*** (0.00412)	0.0616*** (0.00411)
direct collab. # indirect 1 st collab.	-1.27e-05*** (1.88e-06)			
direct collab. # indirect collab.		-4.99e-09** (2.39e-09)		
direct collab. # ind. collab. dist. weight.			-1.03e-08 (9.50e-09)	
direct collab. # ind. collab. dist. & inf. weight.				-9.53e-10 (1.04e-09)
brokerage				
observations	227,679	227,679	227,679	227,679
number of inventors	32,092	32,092	32,092	32,092

Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table 1 - continued

VARIABLES	<i>inventor's performance - quantity of inventor's output</i>			
	4a	4b	4c	4d
number of collaborators	0.00791*** (0.000724)	0.00694*** (0.000672)	0.00661*** (0.000663)	0.00659*** (0.000669)
indirect 1 st connections	0.000321*** (8.05e-05)			
indirect connections – count		-4.19e-07*** (1.30e-07)		
ind. collab. - distance weighted			-2.92e-06*** (5.38e-07)	
ind. collab. - distance & information weighted				-2.71e-07*** (5.75e-08)
avg. strength of direct ties	0.0369*** (0.00377)	0.0378*** (0.00376)	0.0379*** (0.00376)	0.0377*** (0.00376)
avg. strength of 1 st order indirect ties	0.0524*** (0.00351)			
avg. strength of indirect ties		0.0622*** (0.00411)	0.0616*** (0.00412)	0.0623*** (0.00411)
direct collab. # indirect 1 st collab.	-1.07e-05*** (1.83e-06)			
direct collab. # indirect collab.		-2.48e-09 (2.36e-09)		
direct collab. # ind. collab. dist. weight.			-2.07e-09 (9.19e-09)	
direct collab. # ind. collab. dist. & inf. weight.				1.20e-10 (1.02e-09)
brokerage	0.272*** (0.0202)	0.269*** (0.0202)	0.268*** (0.0201)	0.270*** (0.0202)
observations	227,679	227,679	227,679	227,679
number of inventors	32,092	32,092	32,092	32,092

Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

An aspect of the results of the second hypothesis is worth probing further. Although the mentioned three alternative indirectly connected inventors' measurements seem to be negatively correlated with the inventors' output, providing some quantitative indication of their effect could help in interpreting the real-life validity of the coefficients. To better investigate the indirect collaborator's negative effect, I examine the impact of an increase in each alternative measurement on the predictive margins of patenting output of the focal inventor. Even an increase of the number of indirectly connected inventors (for all three alternative measurements) from zero to the maximum observed number of indirectly connected inventors, it does not cause even one patent application reduction. Therefore, I can claim that the negative coefficients of the indirectly connected inventors are significantly different from zero. Yet the magnitude of the effect is not large enough to generate an overall negative effect on the focal inventor's output.

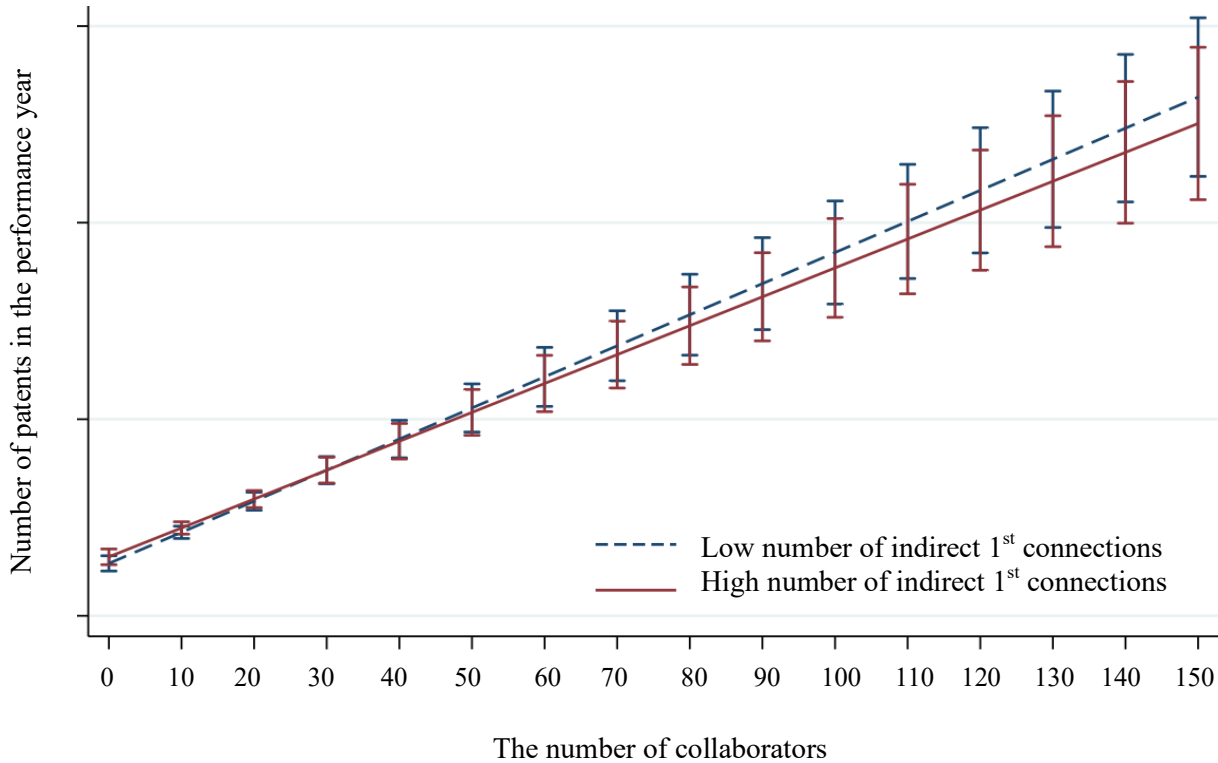
Similar to the results of the second hypothesis, also hypothesis 3, predicting a negative impact of the interaction between directly and indirectly connected collaborators on inventors' output is partially supported. While a negative interaction appears for the indirect 1st connections, the significance of the interaction variables disappears for the other alternative three indirectly connected inventors' measurements. Thus, The results suggest that caution is required while building larger networks, especially with two-step collaborators even if they provide knowledge benefits. However, the insignificance of other alternative indirect measures indicates that the negative interaction of two-step collaborators is worth probing further. To do so, I estimated the predictive margins of inventors' output and illustrate them in Figure 2¹⁹. The figure considers the standard errors and allows us to better observe the moderation of

¹⁹ Low and high number of indirect 1st connections are defined as the level at respectively 10th and 90th percentiles of indirect 1st connections distribution. Confidence interval corresponds to 95% confidence level.

indirect 1st connections on the relationship between collaborators and inventors' performance. According to Figure 2, I do not observe a significant difference between inventors who have a low or a high number of indirect 1st connections. Therefore, I can claim that the third hypothesis is not supported at all.

The coefficient of strength of the ties is positive and significant, supporting hypothesis 4, which predicts a positive influence of strong collaborations on inventors' performance. The results on the strength of ties qualify the prescription to maintain collaborations with the ones who previously have worked with. In an inventor linkage network, the strength of the collaboration relationships serves as a mechanism for shared understanding, trust, reciprocity and the transfer of high-quality information and tacit knowledge (Gulati 1995; Inkpen and Tsang 2005; Larson 1992; Reagans and McEvily 2003; Rowley et al. 2000), therefore, contributes positively and significantly to the focal inventor's output.

Figure 2. Predictive margins: inventor's performance



To compare the relative influence of the number of collaborators and the strength of ties, I can examine the impact of a one-standard-deviation increase in each on the patenting output of an inventor. First, a one-standard-deviation increase in the number of collaborators increases the patenting rate by 5 percent ($0.0079 \times 6.88 - 0.000011 \times 6.88 \times 22.32$) while a one-standard-deviation increase in the average strength of direct ties increases the patenting rate by 2.9 percent (0.037×0.78). Second, a one-standard-deviation increase in the average strength of 1st order indirect ties and the number of indirect 1st connections increase the patenting rate 5 percent (0.0524×0.957) and 1.2 percent ($0.000321 \times 50.63 - 0.000011 \times 7.25 \times 50.63$) respectively. Thus, the coefficient on the collaborators and strength of their ties suggests that both of them do contribute to innovation output; however, the magnitude of the average strength of direct ties' contribution is smaller than the number of collaborators. This result provides a support for the previous view on the strength of weak ties argument, although strength of relationships is positively associated with inventors' output. On the contrary, the contribution of average strength of the indirect 1st order ties is bigger

than the number of indirect 1st connections. Given that unlike direct ties, indirect ones entail no maintenance costs for the focal inventor, the knowledge spillover benefits through strong indirect collaborations are extremely welcome.

Finally, hypothesis 5 predicted a positive effect of being in the center of sparse networks on inventors' output. The results indicate, in support of Burt's position, that being embedded in networks richer in structural holes is associated with increased inventive output. The findings on being in the center of a brokered network reinforce the fundamental conclusion that the benefits of diversity (such as information, experience, perspective) that is provided by having many structural holes in an inventor's network outweigh the disadvantages of not developing and improving collaboration routines provided by a group of cohesively interconnected inventors. The positive association between brokerage and inventors' output is also explained by the lack of trust and the reluctance to share knowledge between collaborators. These are not the main features of inventors' networks in which collaborators are generally members of the same team. Most importantly, considering the estimated coefficients, being a broker by spanning many structural holes is the most important structural characteristics to increase the focal inventor's performance. This result points to the criticality of the positioning in the network and of the necessity to share non-redundant knowledge among the collaborators rather than focusing on the quantity of the collaborations.

Several coefficients of control variables are also significant (all models). Technology diversity of the network members is positive and significant, supporting the argument that combinatory capability issues are likely to be important in the context of the inventors' collaborations (Carnabuci and Operti 2013; Sosa 2011). Being a focal inventor within an ego network where all collaborators are located in the same country favors the focal inventors' output, supporting the argument that short distances and geographical proximity facilitate the exchange of explicit and also tacit knowledge (Boschma 2005).

Being part of a single firm is positively associated with patenting frequency in this research. Prior research on the impact of institutional proximity on innovative activity has been mixed, with studies showing both a positive and a negative impact of institutional proximity on inventive performance (Balland et al. 2015; Boschma 2005). Two broad arguments relate institutional proximity to inventive output. It can encourage inventive performance by providing stable conditions for interactive learning, common language, shared habits, and a law system securing ownership and intellectual property rights. Institutional proximity can also imply institutional lock-in and rigidity which leaves no room for the successful implementation of new ideas. The results of this research support the first interpretation suggesting that collaborations among members of a single firm is positively associated with the focal inventor's patent.

Among other control variables, being in the first order in the inventors' name list and having a higher previous performance are positively associated with increased output of the focal inventors while experience is negatively associated. This indicates that there may be significant individual-level unobserved effects of the career life cycle in the data that are captured by the experience variable. I assume that the inventors who have higher experience may be the ones who have higher responsibilities and are ranked above the others according to status or authority within their organizations. Having more experience may require attention and time distribution among different projects that may or may not be about patenting.

CONCLUSION

This study examines the influence of several aspects of an inventor's ego network – number of collaborators, strength of collaborations and non-redundancy of the collaborators – on the individuals' inventive performance. The results suggest that the four dimensions of a network structure play different roles in the invention process. First, collaborators serve as sources of diverse resources and information, indirectly connected collaborators at the two-step distance to the focal inventor serve primarily as sources of knowledge spillover benefits. Yet, the collaborators with more than two path lengths are not found to significantly affect the focal inventor's performance. Second, the strength of the collaborative relationships serves as the collaborative integration and high quality of information and tacit knowledge. Third, I predicted, but do not find any support that collaborators' influence are moderated by the number of focal inventors' indirectly connected collaborators. Last, spanning many structural holes within the ego network serve as a source of non-redundant resources and combinatorial capabilities.

This study is motivated by two theoretical puzzles and their implications for inventors in their collaboration networks. First, I seek to evaluate whether building networks with large numbers of indirectly connected collaborators is an effective way for inventors to enjoy the benefits of network size without cost of maintaining the relationships with collaborators (Burt 1992). Second, I seek to understand the degree to which brokered networks and the strength of ties are appropriately regarded as the optimal (Granovetter 1973; Coleman 1998; Burt 1992). The arguments and conclusions of the study shed some light on both issues.

The study highlights the fact that even within the same network, directly and indirectly connected collaborators differ significantly in the nature of benefits that they provide to the focal inventor. Although I did not directly control for the content of the collaborations, I argued that direct ties provide resource-sharing and knowledge spillover benefits while indirect ones provide only the latter. Beyond the differences

between direct and indirectly connected inventors, I observe a notable decay on the benefits of indirectly connected collaborators' benefits. Clearly, under these circumstances, there is a limited degree of substitution between collaborators at different social distances to the focal inventor. Another aspect of the study, the findings on the strength of relationships and structural holes further reinforce the basic conclusion that the quality of collaborations and complementarity (i.e., non-redundancy) of the collaborators is more important than the quantity of the collaborators. The results of the statistical analysis further illuminate that *only* close collaborators (i.e., the ones located at a maximum of two path length distances) are of benefit to the focal inventor's performance.

The study makes contributions to my understanding of the social network theory and practice by exploring the interplay between an individual's collaborative network structure and their inventive performance. It provides a suggestion for an optimum network structure to increase the focal inventor's performance. Considering all the results, the most fruitful environment of a focal inventor is in which he or she hold strong relationships with non-redundant collaborators. Collaborating with inventors who work with different set of inventors is the most important feature of the network to raise the productivity of the collaborative networks. In addition, the benefits of the focal inventor gains increase in case the in-contact members hold strong relationships with actors who are disconnected to the focal one. The strength of their relationships helps to receive more information and tacit knowledge from others, therefore, raise in the collaborators' potential value to the focal inventor.

My propositions also suggest a number of possible empirical and theory-based avenues for future research. First, considering the highlighted effectiveness of the close collaborators, it would not be wrong to point to the importance of teams the focal inventor is part of. The way an institution creates the teams and set of teams could create a significant change in the inventors', even further, unit and institutional level performances. Building on this perspective, different levels of analysis would be helpful to better explore the mechanism between collaboration networks and inventive performance.

Another fruitful line of research would be to focus on theoretical mechanisms in such studies and to develop more detailed description of inventive performance rather than quantity of inventions. It would make sense to anticipate that different network profiles might be associated with multiple facets of inventive performance (such as novelty and success of inventions). For instance, on the one hand, non-sparse networks might result in efficiency and effectiveness when inventors need risk-taking, supportive feedback, and peer-review processes to increase the novelty of the inventions. On the other hand, spanning many structural holes might promote the efficiency in selecting impactful ideas by increasing the focal inventor's chances of being aware of the valuable and most promising ideas.

My final point concerns the optimistic assumption on the positive association between spanning structural holes and access to non-redundant collaborators and resources. Although the role of network structure has led to the identification as network attributes such as trust, diverse information, legitimacy, and controlling power, researchers have been unable to agree on the form of collaboration network structures that constitute the mentioned benefits. For instance, Coleman (1988) have presented that densely interconnected collaboration networks as ideal to increase the trusting environment, therefore, the inventive performance. On the contrary, others have followed Burt's (1992) structural hole theory and emphasized the advantages of brokered networks in which the focal inventor is exposed to heterogeneous resources to increase the inventive performance. For the inventors seeking to improve social capital to increase their own performance, these non-aligned propositions suggest a confusing set of choices.

At one level, the conclusion of the study adds further complexity to this problem by highlighting the importance of a combination brokered but strongly connected collaborations. The conclusion of the study and ongoing debate on brokered versus cohesive networks encourage future studies on making a distinction between the structural compositions and attributes of the collaborations. This is due to the fact that being in the center of very sparse network may not guarantee a set of content rich collaborations or lack of trust. These assumptions might be acting as obstacles to understand the real mechanism behind the relationship

between network structure and inventive performance. In addition to the main mechanism, it would open new avenues to test the micro-mechanisms in the relationship between collaboration network structure and inventive performance.

To conclude, it is important to make a distinction between the content of the collaborations and the network structure for two reasons. First, this will allow us to examine the association between structure and content with no bias. Second, it will create opportunities to test the interplay between these two characteristics of the inventors' networks and further provide other opportunities for future managerial implications. This conclusion provides a great motivation for the second and third chapters of the thesis.

CHAPTER 3²⁰

²⁰ This chapter is based on a joint work with my supervisors, Ludovic Dibiaggio and Zakaria Babutsidze.

COLLABORATION NETWORKS AND NOVELTY OF INVENTORS' OUTPUT: THE INTERPLAY BETWEEN KNOWLEDGE HETEROGENEITY AND BROKERAGE

ABSTRACT

This chapter investigates how access to heterogeneous knowledge affects the relationship between brokerage and novelty of inventor's output. I distinguish between structural advantages brought by brokerage and those brought by diversity of knowledge coming from the collaboration network and scrutinize their effects on the level of novelty embedded in inventor's output. I use panel data of French inventors and examine the within-subject variation over time. Results suggest that the influence of being a broker on the novelty of an inventor's output is moderated by the level of knowledge heterogeneity accessed through disconnected collaborators. Results highlight that on the one hand, being exposed to heterogeneous knowledge compensates the costs of brokerage. On the other hand, being a broker significantly complements exposure to heterogeneous knowledge. At the same time, I observe that higher levels of brokerage create a negative effect on the novelty of an inventor's output despite its strategic advantages. Negative effects might be there also for low levels of brokerage, but those outweigh the advantages only for the high levels of brokerage. On the contrary, being a broker becomes more advantageous within the non-redundant content collaboration networks. The study contributes to the social network literature and develops a deeper understanding of the brokerage's influence on inventor's creativity.

INTRODUCTION

As it is highlighted in the previous chapter, the capacity of an inventor to produce novel ideas depends on his or her ability to access and combine pre-existing knowledge elements (Clement et al. 2018; Fleming 2001; Fleming et al. 2007; Gonzalez-Brambila et al. 2013; Uzzi and Spiro 2005; Van Rijnssoever and Hessels 2011). Novel ideas form through collaborations and interactions among multiple inventors who contribute to the creative processes (Perry-Smith 2006; Perry-Smith and Mannucci 2017). Consequently, the literature focusing on inventive performance and the previous chapter relate inventors' creativity to their collaboration network characteristics (Burt 2004; Lee et al. 2015; Singh 2005; Singh and Fleming 2010; Wang 2016).

More precisely, existing scholarship points toward the importance of inventor's position within his or her collaboration network. Authors highlight the advantage of being a broker (Brass and Burkhardt 1993; Burt 1991, 1995; Coleman 1988; Ibarra and Andrews 1993). In this setting, a broker is an individual who occupies a specific location in a collaborative network bridging disconnected collaborating groups of inventors. Usually, close-knit collaborative sub-networks are assumed to belong to the same discipline. Therefore, bridging multiple disconnected clicks is interpreted as access to heterogeneous knowledge and such position is associated with the boost in inventive capability (Burt 2004; Fleming et al. 2007; Paruchuri 2009).

Beyond the capacity to access heterogeneous knowledge, being a broker also provides strategic advantages resulting from the position in the collaboration network. First, because his or her collaboration network is composed of relatively non-redundant contacts (compared to others), an inventor in a brokering position is more likely to gain a reputation. Being known by different groups of inventors he or she can increase the visibility and the legitimacy of his or her ideas to promote his or her novel ideas further (Burt 1991, 2004; 2017; Paruchuri and Awate 2017; Quintane and Carnabuci 2016). Second, as a broker, the inventor has

greater capacity to monitor and control information flows than others and therefore has more influence on the conception and the development of projects carried out in the network (Nerkar and Paruchuri 2005; Shah et al. 2018).

However, a brokering position also generates significant coordination costs. A broker needs to devote significant attention to every disconnected collaborator. But because she has limited time and attention to dedicate to his or her co-authors, she is likely to incur additional costs in terms of continuously adapting to different working cultures and methods when collaborating with multiple groups of inventors (Burt 2017; McFadyen and Cannella 2017; Sorenson et al. 2006). Furthermore, having access to diverse pieces of knowledge may not bring effective sourcing of this knowledge. The ability to access the heterogeneous knowledge elements needs to be complemented by collaborators' willingness to share their acquired knowledge. In addition, combining different, and sometimes distant, pieces of knowledge also requires a willingness of collaborators to share the risk as it is less likely to be accomplished (Mueller et al. 2011). Therefore, novelty requires high trust -both for high knowledge-sharing and high risk-sharing capacity with collaborators, which is hard to cultivate within sparse networks (Perry-Smith and Mannucci 2017).

The great majority of prior literature assumes a direct association between network structure and access to diverse knowledge. In fact, brokerage is routinely used as a measure of access to heterogeneous pieces of knowledge (Burt 2017; Fleming et al. 2007). A notable exception is Rodan and Galunic (2004) who argue for separating structural measure of brokerage from knowledge heterogeneity, a well-known feature of network content (Moody 2004; Sammarra and Biggiero 2008). It is not hard to conceive disconnected sets of collaborators possessing similar knowledge content. It is also plausible that significant levels of knowledge heterogeneity remain in a fully connected network. Therefore, holding a high level of brokerage for an inventor does not automatically guarantee an increase in knowledge diversity.

This chapter aims at identifying knowledge heterogeneity conditions under which brokerage affects inventive performance in terms of novel combinations they created. As argued above, a brokering position provides structural advantages as well as disadvantages beyond those associated with knowledge arbitrage. On the one hand, being in a position that bridges disconnected groups of inventors would allow an inventor to control information flow and participate in projects which are likely to develop more novel ideas. On the other hand, being a part of close-knit collaborative click would allow for the emergence of more trusting, and risk-sharing environment, which is also crucial for developing novel ideas (Burt 2017; 2021). This highlights the fact that the novelty of inventor's output could have distinct relationships with the multiple components of brokerage. A careful analysis of the mechanism requires the examination of the multiple components of brokerage by creating a distinction between its knowledge exploitation benefits and structural consequences. In this study, I analyze the moderating role of knowledge heterogeneity on the relation between being a broker and the novelty of French inventors' output.

The chapter is structured as follows. Section 2 provides an overview of the literature analyzing collaborative networks of inventors, showing the attention dedicated knowledge, and emphasizes the distinction between network structure (i.e., the level of brokerage) and network content (i.e., the level of knowledge heterogeneity) as key determinants of inventor's creativity. Building on this distinction, I outline the advantages and disadvantages of inventor's network characteristics, and I develop hypotheses regarding the way they contribute to the novelty of an inventor's output. Section 3 describes the empirical setting, data sample and discusses the empirical methodology. Section 4 presents the results, and Section 5 concludes.

BROKERAGE and the NOVELTY of INVENTOR'S OUTPUT

Collaborations embed the inventor in a collaborative network. The structure of interactions in this network can generate advantages and costs that are not exclusively related to the level of knowledge heterogeneity the inventor can access (Hottenrott and Lopes-Bento 2016; Singh and Fleming 2010). The literature recognizes that the structure of the inventor's collaborative network provides them with a strategic position and may contribute to increase his or her capacity to develop and implement novel ideas (Burt 2004; Fleming et al. 2007; Obstfeld 2005; Perry-Smith 2006).

Prior research has essentially focused on brokerage as the main structural feature of an ego-network (Lee 2010; Quintane and Carnabuci 2016). An inventor assumes the role of a broker when she connects disjoint collaborative communities. Brokerage is found to boost inventor's performance for multiple reasons (Burt 2017; Fleming et al. 2007; Rodan and Galunic 2004; Tortoriello et al. 2015).

Brokerage as a source of knowledge arbitrage

Following the recombinant search view, invention relies on the recombination of pre-existing knowledge elements (Fleming, 2001; Fleming and Sorenson 2001, 2004). Hence, an inventor's creativity relies on his or her capacity to access different knowledge elements (Sosa 2011) as this increases the potential of identifying promising new (re)combinations (McFadyen and Cannella 2017).

An inventor can access heterogeneous knowledge in two ways. The inventor can accumulate such knowledge through his or her own previous experience, or she can access different knowledge elements through his or her collaborators (Conti et al. 2014; Gonzalez-Brambila et al. 2013; Taylor and Greve 2006). Literature has demonstrated that interactions with disconnected collaborators are assumed to be an indicator of the access to more heterogeneous knowledge, diverse fields of expertise and varied points of view (Brass and Burkhardt 1993; Burt 1991; Hargadon and Sutton 1997; Zaheer and Soda 2009). Moreover, a broker is

in the position to control information flows in their surroundings and has the capacity to exploit available knowledge to their own benefit (Burt 2004; Lee 2010). In certain settings, brokerage can also provide higher legitimacy and prestige which could help the inventor to further promote his or her ideas (Burt 2017; Rodan and Galunic 2004).

Brokerage as a source of costs

In addition to knowledge arbitrage advantages of brokerage, such a key position could also be associated with distinct costs and may negatively influence the novelty generation. First, a brokering position generates significant coordination costs because a broker needs to devote significant attention to maintain the connections among disconnected collaborators. Moreover, a broker is expected to act like a translator between collaborators from different working cultures and adapt to different methods when collaborating with inventors from multiple clicks (Burt 2017; Cannella and McFadyen 2016; Sorenson et al. 2006). Second, the lack of interactions among the inventor's collaborators prevents the emergence of a shared culture and of a trusting environment. As a result, the lack of willingness of some contributors to freely share their knowledge could hinder the broker's inventive capacity (Coleman 1988; Perry-Smith and Mannucci 2017; Reagans and McEvily 2003; Uzzi and Spiro 2005). Then, the first thing to suspect is whether a broker is exposed to heterogeneous knowledge.

Importantly, the large majority of previous research makes no distinction between structural position of a broker and his or her access to more heterogeneous knowledge. However, it is worth noticing that while brokerage is a structural characteristic, knowledge heterogeneity is a feature of the intellectual content residing within inventor's ego-network. The important contribution by Rodan and Galunic (2004), albeit in a different setting, has convincingly demonstrated that a brokering position does not guarantee the heterogeneity of knowledge available to the individual. Although their study focuses on the managerial performances, this highlights the importance of using alternate measure of knowledge heterogeneity in

order to investigate the role of purely structural influence of brokerage. This disentanglement will allow for better understanding of determinants of inventor's performance in terms of the novelty of his or her output.

Hypotheses

In the following sections, I put forward three hypotheses that are later tested using extensive dataset collecting information on all French inventors. Based on the literature reviewed in the previous sections, if novelty emerges from the assemblage of new combinations, then I expect that higher levels of brokerage will improve inventor's capacity to create novel combinations. Brokers maintain an advantage as they are strategically positioned to be aware of new and previously uncombined ideas earlier than others (Burt 2004; Fleming et al. 2007). In contrast, positioning within densely connected networks whose members collaborate with one another will expose an inventor to higher rate of recycling of ideas. Moreover, closed collaboration networks increase the possibility of a shared vision and groupthink that may lead to fewer novel ideas (Thomas-Hunt et al. 2003). If a broker is more likely to receive non-redundant knowledge that enhances the inventor's creativity, the inventor who brokers connections between his or her collaborators should create more novel ideas. Consequently, the first hypothesis I put forward is:

***Hypothesis 1:** An inventor is more likely to create novel combinations if he or she brokers relations between otherwise disconnected collaborators.*

I expect that the exposure to knowledge heterogeneity through non-redundant collaborators lets brokers take advantage at best of their core positioning within their ego networks. This happens for multiple reasons. First, an inventor in brokering position by definition, is like the core member of a sparse collaboration network. Therefore, a broker has greater capacity to monitor and control information flows than other inventors. When keeping the gatekeeper position within a sparse network is combined with a high level of knowledge heterogeneity within the same network increases the chances of being aware of new combinations. Finally, a brokerage position is associated with a certain prestige, which gives the inventor

greater visibility and recognition by his or her pairs. As a result, his or her inventions are more likely to be accepted and implemented than those of non-brokers. Consequently, the second hypothesis I put forward is:

***Hypothesis 2:** If an inventor's connections bring heterogeneous knowledge to the collaboration network, being a broker is positively associated with the novelty of his or her combinations.*

When it comes to networks that are homogenous in knowledge, the picture is different. It is important to notice that the information arbitrage depends on the availability of heterogeneous knowledge. Therefore, the benefits of being a broker within a sparse network is mainly associated with increased combinatory capabilities attached to the non-redundancy of his or her collaborators. Moreover, coordination costs are required to hold the brokerage position and remain collaborations among the disconnected sets of inventors. Hence, all the benefits provided his or her by a brokerage position described above will not hold when the low level of knowledge heterogeneity of the ego-network is considered.

In addition, the loosely connected structure of broker's collaborative network may significantly reduce his or her capacity to participate in novel projects (Perry-Smith and Mannucci 2017). Disconnectedness among a broker's collaborators and the associated low level of interactions reduces the likelihood of a common language and a shared vision (Fleming et al. 2007). Lower intensity of interactions also prevents the emergence of trusting environment and reduces the propensity to engage in risky projects (Burt 2017). Therefore, a broker has no motivation to jump through hoops to be part of novel patents.

Conversely, I expect that the likelihood to engage in novel and risky projects is associated with the level of density – closure – of a collaborative network. An inventor in highly connected networks has higher chances to have constructive feedback from their colleagues to improve their ideas. Densely connected collaboration networks decrease the likelihood of poor outcomes thanks to within-team peer review and filtering (Singh and Fleming 2010). An inventor within closely connected network have trust, a common language and

shared vision within his or her network will share risks with his or her collaborators (Obstfeld 2005; Uzzi and Spiro 2005). Hence, for a given level of risk, inventors within a closed network enjoy a high likelihood of coming up with more complex ideas even if they need to incorporate technologies out of their expertise.

As a result, if a broker's collaboration network exhibit low levels of knowledge heterogeneity, and thus low opportunities to exploit its position, I expect low level of novelty of his or her inventions. In other words, I expect that an inventor is more likely to create novel combinations within a cohesive – knowledge redundant collaborative network. Consequently, the last hypothesis I put forward is:

***Hypothesis 3:** If an inventor's connections bring homogenous knowledge to the collaboration network, being a broker is negatively associated with the novelty of his or her combinations.*

METHODOLOGY

Setting and data

To test my hypotheses about the role of brokerage on the novelty of inventor's output an empirical study of French inventors is conducted. I focus on a single inventor embedded in a collaborative network for a performance year. The unit of analysis is again, an inventor-year pair. In order to construct variables, ego networks are defined as collaborative networks containing focal inventor's collaborators and their collaborator's collaborators. These sub-networks are referred to as ego-networks of a focal inventor.

The model and measures

Dependent variable

Novelty of inventor's output

According to previous studies, patents with new combinations reflects the extent to which an invention is novel (Arts and Fleming 2018; Fleming et al. 2007; Verhoeven et al. 2016). Consistent with the existing literature, the study uses the number of new subclass pairs within each of a focal inventor's patents as a measure of *novelty of inventor's output*. I first identified the first appearance of a previously uncombined pair of subclasses in each patent. To do so, each pairwise combination of subclasses is compared with all pairwise combinations of last five years' patents in EPO database. I then summed this indicator measure for all patents of the focal inventor during the performance year. I prefer to assign the combinations as novel by comparing them to the last 5-years' prior-art as to strength my statistical model²¹.

²¹ As robustness check, I assigned the combinations as new, compared to last 10 years' patents and compared to all previous patents in EPO database. I have also used *novel patent count* measure as a

The EPO database has approximately 650 subclasses defined over time. 640 out of these 650 subclasses have already been seen in the database before 1995 that is the left limit of analyzed performance years. Therefore, although I take new combinations as a measure of novelty, I also check the patents with a single new technology despite they are not a combination. My descriptive analysis showed that more than 50 million patents are available in the EPO database from 1995 to 2010. 32 patents out of them have included new technological subclass and only 3 of them had 1 technological subclass. In the end, I am confident about the performance of my measurement which relies on the number of new combinations.

Independent variables

In this study, the independent variables are network-based variables. I have two independent variables. The first one is knowledge heterogeneity of the ego-network with two alternative measures of it. The second one is brokerage as the structural measure of the ego-network.

Brokerage

Previous studies in invention literature use the density of ego-network as an indicator of the level of brokerage (Fleming et al. 2007; Podolny and Stuart 1995; Rodan and Galunic 2004). However, I argue that such a simplistic measure does not sufficiently highlight the structural characteristics of brokerage. Brokers are inventors at the cross-roads of knowledge streams and this needs to be reflected in the measurement. In order to take this important feature into account I borrow the measure from the structural hole literature

robustness check by assigning the patents who at least have one new combination as novel. Alternative measurement and alternative windows provide no qualitative changes in results. I prefer abstaining from relying on alternative measures considering statistical convergence performance of the model.

(Ahuja 2000; Borgatti 1997; Burt 1995). Following these authors, I define the measure of brokerage as it is used in the previous chapter (see pg. 54).

Knowledge heterogeneity

The second explanatory variable is *knowledge heterogeneity*. This variable captures the level of knowledge heterogeneity the focal inventor has access to within his or her ego-network. I used two alternative measures to capture the variable.

Naturally, collaborators of an inventor—that is his or her co-authors—are more important than remote collaborators. The immediate neighborhood of collaborators is commonly defined as a set of inventors from whom the focal inventor can source knowledge, and is referred to as his or her ego-network (Borgatti 1997; Burt 1995). As the independent variable wants to capture the knowledge benefits, ego-network includes the focal inventor, their immediate collaborators, and their collaborators' collaborators²².

The first version of the variable is a simple one to capture the knowledge diversity of the focal inventor's ego-network. This measure considers all patents produced by ego-network members including the focal inventor during the network period (i.e., the last five years preceding the performing year). In order to quantify this variable, I used the one's complement of the Herfindahl-Hirschman Index²³. The index of network i is computed as

$$hhi_i = \sum_t s_{it}^2 ,$$

²² This is inspired and supported by the second chapter's results.

²³ For more details on Herfindahl-Hirschman Index, see Appendix 2.A.

where s is technology field t 's share in the patents produced by the network members. To create the share of technology j , I use 4-digit technological classes of each patent.

Imagine an ego network where 5 patents are produced uses only one 4-digit technology. Then the illustrated network is fully concentrated on one technological field. Then the *knowledge heterogeneity* $_{hhi}$ will be equal to $0 = 1 - (5/5)^2$. An alternative example is an ego network with, again, 5 patents but use Technology 1 (Tec1) and Technology 2 (Tec2), respectively in 5 and 3 of these 5 patents. In this case, the *knowledge heterogeneity* $_{hhi}$ of the illustrated ego network would be $0.47 = 1 - ((5/8)^2 + (3/8)^2)$. In the second illustrated network, there are more dominated technologies, and it puts the focal inventor in a more knowledge-diverse environment.

Although this is a valid diversity measurement, the variable captures the heterogeneity provided by *collaborators* imperfectly. This is due to the fact that the first measure provides the heterogeneity level of the ego network's knowledge portfolio. It considers all patents produced by an ego network and does not distinguish the focal inventor's and collaborators' knowledge. Therefore, I can only claim that lesser concentration means more heterogenous knowledge available within the ego network. However, I cannot claim that knowledge heterogeneity comes through collaborations. As the brokerage is associated with having collaborators who hold different expertise, I went for an alternative yet more specific measure.

The alternative measure of the variable let us distinguish the collaborators' unique knowledge and captures the level of knowledge heterogeneity provided to the focal inventor from the other members of his or her ego-network. In order to quantify the heterogeneity to which an inventor has access, observing discrepancies between knowledge bases of an inventor and single collaborator (and then aggregating over all dyadic partnerships) is not sufficient. I need to consider differences across multiple collaborators of the focal inventor. In order to achieve this, I extend the measure of Rodan and Galunic (2004) to include in consideration the knowledge flows from focal inventors' collaborators' collaborators. This is important as

previous literature has demonstrated that remote collaborators can generate knowledge spillover benefits for the focal inventor (Ahuja 2000; Gulati and Gargiulo 1999; Zaheer and Bell 2005). Even though such spillovers could potentially extend to remote indirect connections, their benefits erode exponentially with distance (Ahuja 2000). Because the study investigates the role of brokerage that considers inventors with a maximum of two path lengths, this measurement also is constructed by considering inventors with a maximum of two path length.

To create the measurement, I first create the knowledge vectors of each member of a given ego-network. I use the 4-digit technological classes of each inventors' patents during the network period (i.e., the last five years preceding the performing year). Next, I measure the cosine similarity between each dyad in ego-network. Then, based on the angle between a pair of vectors, I create a knowledge distance matrix including all ego-network members (the focal inventor, his or her collaborators and collaborators' collaborators). These matrices let us capture the level of *knowledge heterogeneity* in an ego-network. In order to transform the information in such a matrix into a single measure I compute

$$h_i = \sum_{j=1}^N \frac{d_{ij} * \lambda * U_j}{N * PL_{ij}},$$

where i denotes the focal inventor, j runs over all other scientists in i 's ego-network, N is the size of the ego-network, U_j is the eigenvector centrality of inventor j in this ego-network, d_{ij} is the knowledge distance between inventors i and j , λ is the highest eigenvalue of the matrix, and PL_{ij} denotes the path length between inventors i and j . The measurement is an extension of the original measure Addition of the latter element (PL_{ij}) to the original measure created by Rodan and Galunic (2004). The extension shows up with the addition of the PL_{ij} part. This is inspired by the previous chapter's results and is found necessary to take into account the facility of knowledge transfer between collaborators that are collaborating directly

compared to ones who have not co-signed patents over last five years²⁴. The consideration of the knowledge transfer facilities is another plus of the measurement compared to Herfindahl-Hirschman Index based knowledge heterogeneity measurement which does not take this into account.

The final step in calculating *knowledge heterogeneity* is to standardize h_i by dividing the maximum possible knowledge heterogeneity level in a network of given configuration. This is necessary for meaningful interpretation of estimation results.

Control variables

In order to obtain meaningful results, I control for a number of characteristics in my empirical model. In my setup, it is important to control for variables that provide resource-sharing advantages, knowledge benefits or potential level of knowledge heterogeneity (Perry-Smith and Mannucci 2017). I have two sets of control variables. The first set relates to characteristics of collaboration structure and intensity. The second relates to individual research path and performance.

The first set of controls consists of six variables. I use the number of focal inventor's collaborators (the *number of direct ties*) and the number of inventors indirectly connected to the focal inventor who are the members of focal inventor's ego-network (the *number of indirect ties*) in order to control for inventor's ego-network size. This is important as I need to control for the possibility that the knowledge heterogeneity or deconcentration effect might be simply a function of the network size. In order to control for the strength of focal inventor's connectedness to the members of their ego-network, I use the *average strength of direct*

²⁴ Although the addition of the PL_{ij} is necessary according to the second chapter's conclusion, the results of the previous chapter is valid for more distant inventors. Even so, I have double checked for the robustness of the results without applying no distance weight for the measurement, and the excluding this part provide no qualitative changes in results.

and *indirect ties*.²⁵ In order to control for the team composition within inventor's patent portfolio I use the indicators three variables. *Single firm* is the percentage of the focal inventor's patents that all co-authors come from the same company during the period of five years preceding performance year. *Single Country* is the percentage of the focal inventor's patents that all co-authors live in the same country during the period of five years preceding performance year. And *first inventor* is the share of the patents that the focal inventor was listed first, again during the period of five years preceding performance year.

The second set of controls includes three variables. Here I use the measure of *experience*, which counts the number of years between performance year and the first year the focal inventor appears on one of the patents in EPO database. I also control the level of productivity of an inventor by including the number of patents they have applied for over the last 10 years preceding the performance year (*previous patent count*). The very last control variable I use is patent count during the performance year (*current patent count*).

Estimation and econometric issues

The first thing to notice is that I have a panel structure in my dataset. I can observe patenting behavior of inventors over an extended time period. Therefore, I require an appropriate panel estimator. The descriptive analysis shows that the dependent variable has over dispersed and inflated distribution. Considering the specific features of the data and knowing that the dependent variable takes only whole number values, using a linear model admittedly would create inefficient, inconsistent, and biased coefficients. On the contrary, a (panel) Negative Binomial estimator allows controlling for overdispersion —where the variance is significantly greater than the mean— and inflation which the data exhibits. Being aware of the necessity of a likelihood ratio test to strengthen the estimator's efficiency, I checked for the differences between the

²⁵ The tie strength measurements are constructed as in the second chapter. For technical details on measurement of variables controlling strength of ties, see pg. 53.

coefficients of a random effect modal and fixed-effect modal. Considering the massive number of observations, the test pointed to the necessity for the use of a random effect modal as expected.

Before proceeding to estimation, I need to carefully consider the appropriateness of my measures in boundary cases. In this particular case, consider the brokerage variable. Although this variable does the job for most cases, it is not defined for inventors who do not have any collaborators. Similarly, it takes the maximum value of 1 for inventors who have only one collaborator, which is misleading as these inventors cannot broker an ego-network. Due to these anomalies, following the previous literature (Fleming et al., 2007), I retain for the analysis only cases where focal inventor has at least two collaborators. Additionally, inventors who have no patenting activity in a given year are also excluded from the analysis. Their presence in the dataset would create a bias for in my analysis as they would have no possibility to create new combinations.

This leaves us with 32 092 unique inventors and 80 573 inventor-year combinations that I use to obtain random-effects Negative Binomial estimates (with added year fixed-effects and technology residuals as a replacement of technology fixed-effects²⁶) of my empirical models. Appendix 2.B provides summary

²⁶ Despite I am aware of the necessities and advantages of adding technological fixed effects, I couldn't manage to include them in the models as they are. This is due to the fact that the addition of more than 600 4-digit technologies created computational problems, therefore, the software used for regression analyses (Stata MP-17) could not achieve convergence. I observe the same non-convergence problem for 3-digit and 2-digit technology fixed effects. Therefore, I simply ran a base model that includes only technology fixed effects and create a new variable with the residuals that came out from the model. The new residual variable was included in our main model as a replacement for technology fixed effects. This lets us prevent any bias that may occur in our results without technology-fixed effects. Because the residuals could not be calculated for 4-digit and 3-digit versions for the same reasons of non-convergence the models include the 2-digit technology residuals that provide convergence. Although this choice is done to strengthen our statistical model, I did several robustness checks. To do so, I limited the number of iterations for the calculations of

statistics and pairwise correlations of variables across all retained observations. These statistics indicate some multicollinearity between some of the structural characteristics (i.e., the number of direct and indirectly connected inventors in an ego-network) and knowledge heterogeneity. This is an expected correlation considering the literature discussed above. The same applies to the relationship between the number of direct and indirect ties, as acquiring an indirect connection is only possible through direct connections.

technological residuals at 3- and 4-digit level classes. Then, used the residuals for final estimations. Alternative approaches provide no qualitative changes in results.

RESULTS and DISCUSSION

In order to build the analysis, I estimate four distinct models for each of knowledge heterogeneity variables: *knowledge heterogeneity (matrix-based, from now on this will not be specified again)* and *knowledge heterogeneity hhi-based (Herfindahl-Hirschman Index(hhi)-based)*. I begin with Model 1, which highlights the link between brokerage and the novelty of the inventor's output. This model includes brokerage and control variables, as well as technology residual variables and year-fixed effects. At the next stage, Model 2a and 2b include a stand-alone knowledge heterogeneity term to the Model 1. Finally, Model 3a and 3b are constructed to examine the moderating role of knowledge heterogeneity access. Here I add the interaction term between brokerage and knowledge heterogeneity, to the setup from Model 2a and 2b. These extended models allow us to evaluate the hypotheses put forward in section 2.

Table 2 reports the regression coefficient estimates for variables of interest across all models²⁷. The results from the model b's that include the comprehensive knowledge heterogeneity measure, are considered mainly to test the hypothesis. However, results remain similar for model a's that include the simpler heterogeneity measurement based on Herfindahl-Hirschman Index.

Results from Model 3 estimations allow for the study of the moderating effect of the knowledge heterogeneity. For the sake of interpretation Figure 3 presents predictive margins of the dependent variable for low and high levels of knowledge heterogeneity. I define the low level of heterogeneity as the level at the 5th percentile of the variable distribution in my data. Similarly, I define the high level of it at the 95th percentile of the same distribution.

²⁷ For full regression outputs please see Table 10 and Table 11 in Appendix 2.C.

Results from Table 2 provide strong evidence for all of the hypotheses put forward in my chapter. Model 1 suggests strong support for the first hypothesis, that having disconnected contacts contributes to the novelty of inventor's output. Although I do not test for this, in Model 2a and 2b, first thing to notice is that my results support that an access to heterogeneous knowledge – for both measures– increases the inventor's likelihood to create novel combinations. These findings consistent with the previous literature (Burt 2004; Fleming et al. 2007).

The positive effect of brokerage remains, in Table 2 - Model 2a. Given that I have removed knowledge heterogeneity co-notation from the structural brokerage measure, this result indicates advantages of brokerage beyond those related to knowledge heterogeneity according to Model 2a. However, in Model 2b which includes the more comprehensive knowledge heterogeneity measure, the impact of brokerage diminishes and falls from significance. Moreover, the positive effect of brokage shifts to the negative in both of the Model 3s and do provide similar results for the two alternative heterogeneity measure. The difference of the results in 2nd Models while becoming similar in the 3rd models, supports my concerns about the fact that *hhi-based* heterogeneity measurement limitedly captures the knowledge heterogeneity exposure from a perspective of brokerage advantages. This is why, I observe insignificance of the brokerage in the model 2b while it remains positively significant in model 2a.

Finally, in Model 3s, the interaction variables are positive and significant, confirming the second hypothesis that an inventor within a sparse network and having access to the knowledge heterogeneity performs better than others in novelty. Before discussing results with respect to the second hypothesis, it is important to notice, the results indicate the distinct influence of brokerage and knowledge heterogeneity access on the novelty of inventor's output in addition to the moderating effect of them. Once the interaction variables are included, the stand-alone brokerage variable become negative and significant. This suggests strong support for the last hypothesis that an inventor is less likely to create novel combinations within a sparse collaborative network unless his or her collaborators bring heterogeneous knowledge to the collaboration

network. The negative coefficient of stand-alone brokerage variable indicates the commensal relation of being a broker with knowledge heterogeneity access.

Prior research on the impact of brokerage on inventive activity has been mixed. Studies arguing that brokerage should have positive relation with generated novelty usually equate the structural measure of brokerage with increased combinatory capabilities which, is a concept related to the heterogeneous content of the collaborations (Burt 2004; Nerkar and Paruchuri 2005). Being a broker provide advantages coming from control over the knowledge flow, as well as having benefits associated with higher legitimacy and prestige that increases the implementation power of inventors (Burt 2017; Lee 2010; Rodan and Galunic 2004). As an intermediary study, (Lee 2010), shows the endogenous relation between increased performance and being a broker.

Following contributions, however, claimed the being part of a closed network rather than a sparse one is associated with the higher innovation performance. They point to the potential increase in coordination costs due to necessity to manage cognitively distant collaborators. It also refers to the lack of the shared work-culture emergence across disconnected research groups that brokers usually belong to. On the contrary, a closed network puts inventors in an environment where individuals do not be afraid to seem ridiculous and share their ideas with others more freely (Fleming et al. 2007; Obstfeld 2005; Perry-Smith & Mannucci 2017; Uzzi and Spiro 2005). Them having a common language and shared vision make it easy to communicate and to solve complex problems (Burt 2017).

Our results provide explanations for the two community by clarifying the micro mechanism behind the relationship between brokerage and novelty. I contribute to the brokerage literature and to the ongoing discussion about the influence of brokerage by showing that its effects are moderated by the access to the knowledge heterogeneity. According to my results, although their joint effect on novelty of inventor's

output is positive, the absence of knowledge heterogeneity does dramatically change the brokerage's influence on novelty.

Table 2. Results from panel negative binomial estimation: novelty of inventor's output

VARIABLES	Novelty of Inventor's Output				
	Model 1	Model 2a	Model 2b	Model 3a	Model 3b
Brokerage	0.569*** (0.174)	0.442** (0.173)	-0.106 (0.179)	-2.529*** (0.815)	-0.926*** (0.304)
Knowledge Heterogeneity ^{hhi-based}		2.283*** (0.219)		0.356 (0.536)	
Knowledge Heterogeneity			2.909*** (0.192)		1.481*** (0.470)
Brokerage # Know. Het. ^{hhi-based}				3.829*** (1.023)	
Brokerage # Knowledge Heterogeneity					2.609*** (0.782)
Number of Observations	80 573	80 573	80 573	80 573	80 573
Number of Inventors	32 092	32 092	32 092	32 092	32 092

Notes: Dependent variables are inversely weighted with the number of co-inventors. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

In line with the first literature, brokerage increases the novelty of inventor's output, yet it depends on the availability of diverse knowledge. Opportunities generated by being a broker appear only after a level of knowledge heterogeneity²⁸. As brokers have control over the knowledge flow, between the set of inventors that hold diverse technological expertise, they are more likely to be aware of potential new combinations. Moreover, they take the advantage of their legitimate positioning to push their ideas further easier than

²⁸ Calculations show that the threshold for the level of knowledge heterogeneity to take the advantage of being a broker is approximately 35% which counts up for almost 63% of the observations.

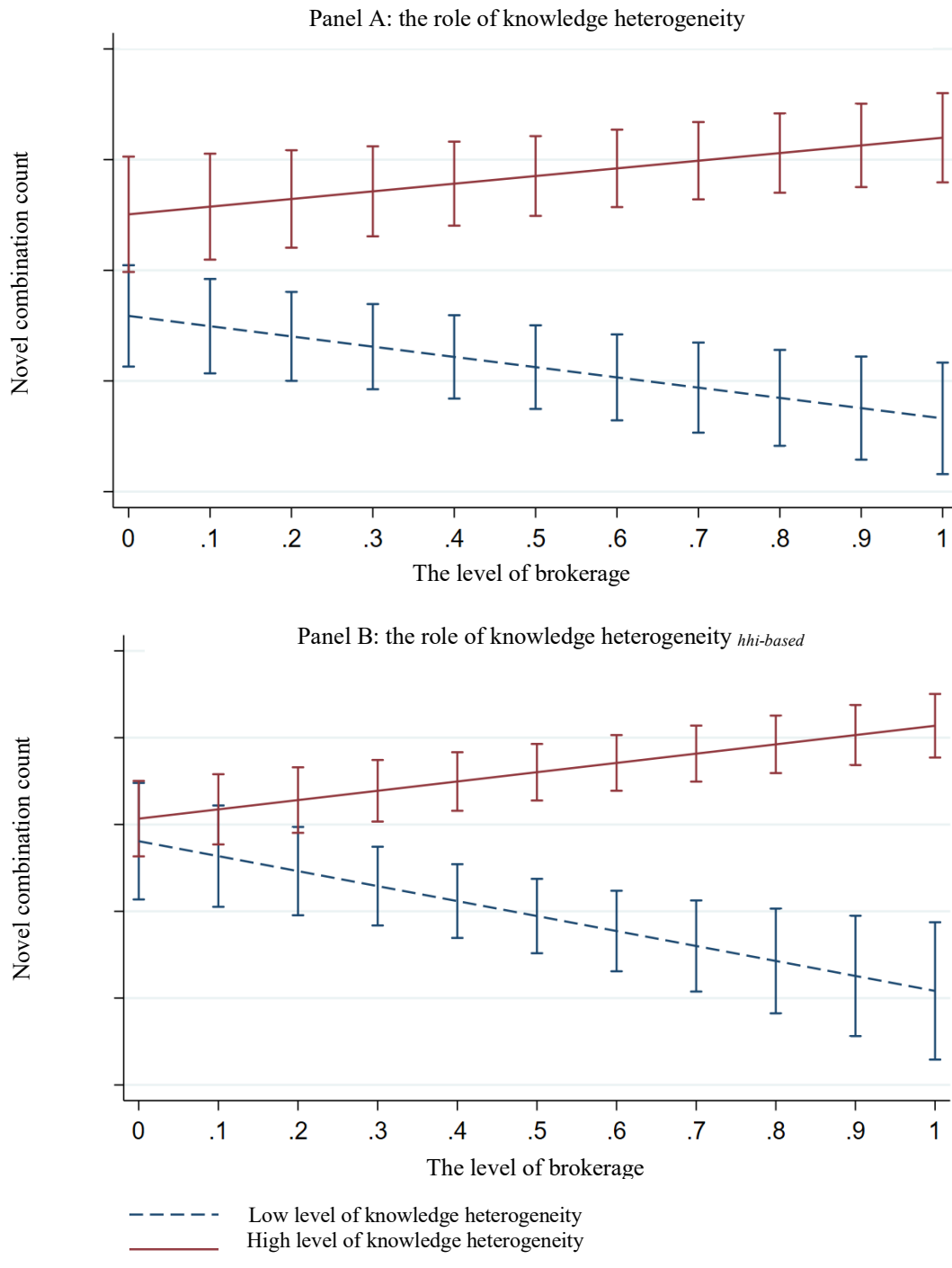
others. Therefore, a combination of the increased combinatory skills and their implementation power increases their performance in terms of the novelty of their output.

In line with the latter interpretation, I see the brokers handicapped by their role which increases the coordination costs. A knowledge homogenous network is a place where there are no chances to take the advantage of control over the knowledge flow as everybody holds redundant knowledge yet still requires time and attention investments. Moreover, a sparse network prevents the emergence of a common language, a shared vision, and most importantly trust environment. However, they are crucial for developing novel technologies that are riskier and more complex projects (Fleming 2001; Mueller et al. 2011). Therefore, low brokerage individuals find themselves embedded in a tenacious collaborative network that motivates them to jump into risky projects and develop more novel combinations (compared to brokers). And thus, they start realizing positive returns of non-sparse networks where their common understanding and shared vision helps for solving complex problems even if they do not have any expertise of it so far.

Results presented in this section are based on panel Negative Binomial estimator, which, I believe, is the most suited procedure for my data set. A robustness check was prompted by the fact that my experience measure applied to EPO dataset generates a small number of extreme values. I have inventors who record 107 years of inventive activities, which is clearly impossible. Given that I do not have access to a complete set of inventor names and have to operate using inventor ID numbers, I cannot fix this anomaly. However, as a sensitivity check I have eliminated all observations recording higher than 40 years of inventive experience from the dataset (this constituted a breaking point in the frequency distribution of the variable) and have re-estimated my models. Results are qualitatively unaltered²⁹.

²⁹ Results, presented in Table 12 and Table 13 in Appendix 2.C

Figure 3 Predictive margins: novelty of inventor's output for two alternative knowledge measurement



Note: Low brokerage is calculated as the level at the 5th percentile of brokerage distribution, while high brokerage is calculated at the 95th percentile of the same distribution. Confidence interval corresponds to 95% confidence level.

CONCLUSION

In this chapter, I have analyzed how brokerage influences the novelty of an inventor's output. More specifically, the study investigates under which circumstances being a broker is beneficial or detrimental for the inventor's creativity by investigating the micro mechanisms behind the relationship. The contribution of my chapter hinges on the separation of brokerage, which constitutes a measure of inventor's positioning within a collaborative network, and knowledge heterogeneity access, which is a measure characterizing the knowledge content available in the focal inventor's surroundings. Naturally, this delineation represents a necessary condition for separating the effects of knowledge content and network positioning of an inventor towards their inventive performance. Results demonstrate that being a broker does not guarantee knowledge heterogeneity access. Therefore, although there is literature assuming heterogeneity is a byproduct of being a broker, it is important to make a distinction between them to better understand the influence of brokerage on inventor's performance.

Our results indicate that both knowledge heterogeneity and brokerage have distinct paths in affecting the creativity of an inventor. In addition, brokerage and knowledge heterogeneity moderate each other's influence. The findings imply that to benefit from the structure of the ego-network, inventors may need both redundancy and non-redundancy of knowledge depending on the connectedness of it. Looking at only the dichotomy between a sparse (where a broker appears) and a closed structure is not enough to explain its effects on the novelty. By bringing the distinction of collaborators' knowledge heterogeneity into the brokerage versus closure debate, I make clear that the maximum creativity of a broker can stem from the dissimilarity of knowledge within his or her network with low levels of structural redundancy. Based on the result of the study, informational advantages associated with brokerage may be maximized when knowledge heterogeneity coexist because the former aids interpretation and the latter safeguards combinatory skills.

More importantly, I demonstrate that the direct effect of brokerage on the novelty of an inventor's output and its effect contingent on the knowledge heterogeneity access go in opposite directions. An inventor may benefit from knowledge heterogeneity at its best only if he is positioned as a gatekeeper within a sparse network. Brokerage always comes with costs that may cause a decrease in performance unless they are compensated by knowledge arbitrage. This is in line with the interpretation that brokering advantages only come from exploiting opportunities presented by knowledge heterogeneity.

A noteworthy feature of my findings is the fact that in existence of knowledge redundancy, an inventor within a closed network does seem to be writing significantly more novel patents. Closure provides advantages regardless of the content of the collaborations. This should be explained uniquely by the structural features of the inventor's collaboration network. First, others do not pay coordination costs as a broker has to pay. Second, it is plausible to expect that developing novel technologies requires the originality, and thus riskier ideas in the collaboration network. A closed network that provides a trusting environment shared vision, and common language among collaborators, helps others to overcome more complex ideas compare to a broker. Inventors may benefit from a structural redundancy within their closed networks only if they can rely on joint third parties whose interpretation, perspective, and language create redundancy yet enable be in agreement to solve more complex problems compare to brokers.

Now, one might ask why the benefits of closed networks diminish when knowledge heterogeneity shows up. It is true that the existence of non-redundant knowledge surely positively affects the novelty as such knowledge constellation increases possibilities for knowledge recombination. Moreover, exploitation of collaborators' potential depends on their willingness to share these ideas and the risks associated with bringing them to fruition. Then, knowing that the willingness is higher in closed networks, it is quite normal to expect higher creativity from an inventor.

However, inventors within closed networks find themselves within more flat, egalitarian environments where there is no structural hierarchy. Therefore, they do not have such legitimate position to push their ideas further as brokers. In addition to this, a broker is the one who knows how to communicate with cognitively distant groups, how to control heterogeneous knowledge and use it for his or her own benefit. On the contrary, inventors within closed networks are less likely to hold such cognitive capabilities. As a result, others do not take advantage of knowledge heterogeneity as much as a broker does and they perform better than a broker only within a network that has more specialized content.

FUTURE IMPLICATIONS

Results in this chapter beg a question of how inventors navigate their collaborations. This is important as inventors can influence (to a certain level) their network positioning, as well as the heterogeneity of knowledge available to them through strategically forming co-inventor relationships. If inventors can affect these two factors separately, they gain larger flexibility in meeting their professional goals. Despite this, there are still those who hold brokerage positions within knowledge redundant networks.

I suspect that my contribution appears as the study focuses on the novelty of inventor's output. This may not be the case for another facet of inventive performance such as the quantity of the inventors' output as well as the usefulness of those inventions. Inventors may have different incentives depending on where they work or where they are in their career path. Therefore, prior research relies on different definitions of inventive performance. In addition, the relationship between the novelty of researcher's invention and the usefulness of generated knowledge is not clear. Some researchers assume that higher novelty implies higher usefulness (Singh and Fleming 2010; Wuchty et al. 2007). Other empirical research, however, shows no relationship between the originality of an idea and its use (Dahlin and Behrens 2005; Nemet and Johnson 2012). I believe that brokers may not benefit from their position in terms of the novelty of their output but for the impact or reuse of their inventions. This motivates us to get the bottom of the question how and to what extent being a broker is beneficial for the impact of his or her inventions and even further does being a broker helps inventors to create an impact with their ideas regardless the novelty of them.

In the light of this additional study, considering that both novelty and impact provide different but important information about the effects of a brokerage position on inventive capacity, I suggest keeping an agnostic viewpoint to analyze whether and according to which conditions brokerage has a positive or negative influence on the capacity of an inventor to produce novel or useful inventions. If it is conceivable that stand-alone brokerage is positively (unlike novelty) associated with its reuse, the moderating role of knowledge

heterogeneity may exhibit different results. Even further, this will make clearer why brokers are willing to pay such coordination costs while creating less novelty compared to non-brokers.

The results of the further analysis may also let us shed light on how to describe a typical inventor's career journey, further, the relationship between performance and brokerage.

CHAPTER 4

COLLABORATION NETWORKS AND THE REUSE OF INVENTORS' OUTPUT: THE INTERPLAY BETWEEN COGNITIVE PROXIMITY AND BROKERAGE

ABSTRACT

This chapter investigates the relationship between brokerage and reuse of inventor's output. The objective of this chapter is twofold. First, it aims to identify differences in the influence of brokerage on the reuse of inventor's output by localized network members and by whole network members. Second, it investigates the potential moderating effect of cognitive proximity in this relationship within the local network setup. To do so, structural advantages brought by brokerage and its accompanying representation of collaborating with cognitively distant inventors are decoupled and their effects on the reuse of broker's ideas are observed. I use panel data of French inventors and examine the within-subject variation over time. The results demonstrate that being a broker is positively associated with the reuse of the inventor's ideas by local network members. Results suggest that being embedded in a network in which members of the network are cognitively proximate generates the conditions conducive to collaborators' understanding and reuse of the broker's ideas. Pinning down the mechanism through how collaboration network structure affects the reuse of inventor's ideas without sacrificing their novelty has important implications. This will inform inventors on how to optimize or adapt their collaborative networks to meet the expectations, as well as help decision makers to design incentive schemes which would maximize organizational performance.

INTRODUCTION

Even though collaborations are generally thought to increase innovation performance (Burt 2004; 2005; Lee et al. 2015; McFadyen and Cannella 2004; Obstfeld 2005; Reagans and McEvily 2003; Rodan and Galunic 2004), there is still controversy over the optimal structure of those collaborations. In particular, the relative benefits of brokerage between otherwise disconnected inventors (Granovetter 1973) and closure where most collaborators have direct connections to each of the others (Coleman 1988) has been at the center of ongoing debate. Most notably, collaboration network structures characterized by brokerage or closure have been shown that they have independent and conditional effects on innovation output (Burt 2017; Carnabuci and Diószegi 2015; Fleming et al. 2007; Quintane and Carnabuci 2016; Tortoriello et al. 2015).

Innovation scholars pointed out, creation of an idea does not guarantee its success which becomes possible with the internal support, alignment and coordinated action. Here, it is important to notice that the creation of an idea and its success have different determinants (Carnabuci and Diószegi 2015; Carnabuci and Opetri 2013). The latter requires the acceptance and reuse of the generated ideas by others (Perry-Smith and Mannucci, 2017).

Aligned with the requirements of a successful innovation outcome, opponents of brokered networks (i.e., proponents of closed networks) has emphasized the importance of a shared vision and understanding for an effective increase in the reuse. Inventors in closed networks are found to be more likely to be fully understood by others and to sell their ideas (Perry-Smith and Mannucci 2017). On the contrary, inventors who collaborate with a broker are assumed to be more likely to differ in their fields and prior knowledge (Fleming et al. 2007; Obstfeld 2005); therefore, they are assumed to have harder time appreciating and understanding of the broker's ideas at least in part. Members of a brokered network are assumed to have

less cognitive proximity which can be defined as the similarities in the way inventors interpret, perceive, and evaluate generated ideas (Boschma 2005; Nootboom 2000).

The handicap of the ongoing debate on brokered versus closed networks is taking structural characteristics as the leading indicator of cognitive proximity or social integration. However, exploring the effects of collaboration networks by solely considering the structure is not enough to bring the ongoing debate between the proponents of network closure and brokerage to a conclusion³⁰. This is due to the fact that an inventor may be located in the center of a very sparse network in which all inventors have a shared vision and/or common language.

Aligned with this concern, a considerable amount of study has shown that the influence of collaboration network structure takes on a new meaning contingent upon the collaborators' attributes and collaboration characteristics. This line of inquiry significantly enhances the social network literature by clarifying various contingencies that co-appear within an unexpected network structure and changes its effect. Studies focusing on the contingency perspective demonstrated the role of various characteristics such as inventor's personality (Anderson 2008), experience (Fleming et al. 2007), culture (Goldberg et al. 2016), perspectives (Schowalter et al. 2020), self-monitoring abilities (Mehra et al. 2001), and cognitive style (Carnabuci and Diószegi 2015).

While the effects of brokerage and notable conditional characteristics have been evidenced by the literature and by the previous chapter of the thesis, cognitive distance of collaborators (i.e., uniqueness of collaborators' possessed knowledge) and structural characteristics (i.e., the level of brokerage) have not been studied jointly. Moreover, although the success of brokers' ideas is well documented (Burt 2004;

³⁰ The need for separation between structure and other attributes of the networks to capture the *pure structural* influence of cohesive and brokered networks is inspired also by the results of the third chapter.

Fleming et al. 2007; Perry-Smith 2006; Perry-Smith and Mannucci 2017), there is still controversies, and less attention has been paid to re-users' social distance to brokers. Considering well-established literature on the importance of social distances for better knowledge spillover and resource sharing (Ahuja 2000; Burt 1991; Singh 2005; Singh and Fleming 2010), it is worthwhile to make a distinction between different spheres of influence and further investigate the mechanism.

This study addresses above-mentioned gap by focusing on the contingency perspective to clarify the micro mechanism behind the relationship between brokerage and reuse of inventor's ideas. To do so, first, it makes a distinction on how the mechanism may vary depending on the focused idea penetration areas (i.e., focusing on the reuse by local inventors comprised of broker's collaborators and collaborators' collaborators, instead of all other inventors). Second, it argues that being in the center of structurally brokered network can be beneficial for the usefulness of an inventor's ideas within the localized sub networks when the crucial benefits of constraint networks (i.e., common language, shared vision, easier acceptance by others and so on) co-appear with the given structure.

The chapter is structured as follows. Section 2 provides an overview of the literature analyzing collaborative networks of brokers, emphasizes the different dynamics of whole and localized sub networks. I summarize the advantages and disadvantages of a focal inventor's local network characteristics and develop hypotheses regarding the way they contribute to the reuse of a broker's ideas. Section 3 describes the empirical setting, data sample and discusses the empirical methodology. Section 4 presents the results; Section 5 concludes and the last one provides future implications.

BROKERED NETWORKS AND REUSE OF INVENTOR'S IDEAS

Aligned with the appearance of alternative perspectives on the inventors' performance, literature investigating the cruciality of social networks demonstrates inconsistencies in the influence of network structure on inventive performance. More specifically, the relative benefits of opposite types of collaborative network structures (i.e., cohesive networks versus sparse networks) are addressed. Being a broker who connects two or more otherwise disconnected inventors, in particular, has been paid attention to.

Being a broker confers several distinct advantages, each of which is helpful during the idea generation and implementation phases which require respectively cognitive flexibilities and a higher legitimacy (Baer 2012; Burt 1991, 2004, 2017; Granovetter 1973; Ibarra and Andrews 1993; Podolny and Baron 1997; Rodan and Galunic 2004).

The latter, idea implementation, is found to be significantly correlated with the level of brokerage. It has been demonstrated that especially brokering managers perform better in their innovation activities because their positioning opens the door to successful project (Rodan and Galunic 2004) and risk management capabilities (Burt 2017). Inventors bridging structural holes are thought to have a higher vision and communication skills as they are working with diverse groups of inventors (Burt 2017; Perry-Smith and Mannucci 2017). Accordingly, they can act like the translators between disconnected collaborators to convince others and sell their ideas (Obstfeld 2005). Due to the lower constraints to which they are subject within their sparse networks they can portray their ideas more freely and easily attract others' attention. In the end, they are expected to have greater visibility and recognition by their pairs to move their ideas further to be implemented and become successful (Burt 2007; Perry-Smith and Mannucci 2017; Rodan and Galunic 2004).

On the contrary, although the strategic advantages attached to knowledge arbitrage capabilities and legitimate positioning are claimed to be helpful for brokers to come up and bring their ideas to a successful conclusion, proponents of cohesive (the opposite of sparse network) networks demonstrate that the benefits of being a broker lose their value for success (Guimerà et al. 2005; Obstfeld 2005; Perry-Smith and Mannucci 2017; Uzzi and Spiro 2005). Researchers counterargue the benefits of being a broker by emphasizing the following detrimental effects. Due to the limited interactions brokered networks prevents the emergence of common language, a shared vision (Fleming et al. 2007; Tortoriello and Krackhardt 2010) and trusting environment (Uzzi 1997). They claim the imperfections of sparse networks as the key decisive factors that help inventors overcome interpretive problems and the potential resistance to their ideas from others to be appreciated and to be reused (Cohen and Levinthal 1990; Obstfeld 2005; Perry-Smith and Mannucci 2017). Some of the researchers, define the success and usefulness of an idea as the repeated use of technological combinations related to implemented ideas. To them, inevitable and detrimental endings of brokered networks are a decelerated knowledge flow and a hampered spread of the combinations that a broker explored (Carnabuci and Operti 2013; Fleming et al. 2007).

Yet, most of these studies focused on the reuse of broker's ideas within larger networks or within whole network that is the entire network. It captures every single inventor, and it does not apply a limitation to the social distance between the focal inventor, namely broker, and any other inventor.

Reuse of broker's ideas within local network

The dynamics of localized sub networks and whole network may vary significantly and change the influence of network structure on the reuse of inventor's ideas. A local network is a subset of whole network and includes a focal inventor and inventors who are clustered together around the broker's close

surroundings. The study considers the focal inventors, their collaborators (the ones with one social distance) and collaborators' collaborators (the ones with two social distance) while talking about local networks³¹.

Studies highlighting the important social (Boschma 2005; Granovetter 1985; Polanyi 1944) and geographical (Ahuja 2000; Burt 2000; Singh 2005) proximities of innovation activities emphasize the enabling structural network characteristics providing them (Boschma 2005; Perry-Smith and Mannucci 2017). First, they claim that there is an association between cohesive network structure, and having trust-based interactions and higher social proximities between inventors (Boschma 2005; Granovetter 1985; Polanyi 1944). Second, being co-located and having arm's length interactions are associated with higher geographical proximity among collaborators (Ahuja 2000; Burt 2000; Singh 2005).

First, with respect to social proximity, it has been shown that embedded and integrated networks facilitate the knowledge exchange and enables the local inventors to monitor each other closely and continuously with a minimum amount of effort (Boschma 2005; Carnabuci and Operti 2013; Fleming 2001; Kaplan and Tripsas 2008). Those non-sparse networks are the ones where literature expects to see an emergence of trusting environment, therefore, more willingness to share the possessed knowledge among network members. Due to many direct connections within the constraint (i.e., closed) networks, by nature, it is easier to communicate and, even further, it is possible to exchange tacit knowledge (Tortoriello and Krackhardt 2010).

Second, with respect to geographical proximity (from a social network perspective), the closer inventors are to each other the more they share, the more they learning from interactions, and the more they benefit from each other's knowledge (Boschma 2005; Garcia et al. 2018). Studies coprocessing this proximity with

³¹ The study determines the local network boundaries being inspired from the second chapter's results.

the social network analysis demonstrate that knowledge spillover benefits provided by indirectly connected collaborators change with a decay frequency proportional to the social distance between inventors (Ahuja 2000; Burt 1991, 2000; Fleming et al. 2007; Singh 2005).

Building on emphasized importance of social and geographical proximities on knowledge spillover benefits and interactive learning, I argue that disadvantages of brokered networks disappear for local networks. This is first, in the local networks the social distance of the collaborators is at maximum path length of 2. Even, most of the collaborators and know the broker as they are part of the same team. Meaning that they work together, mostly know each other in person, or they have common collaborators which is also a sign of common interests and language. Unlike whole network, they can easily access and benefit from broker's knowledge, even further, from their tacit knowledge either directly or through their partners.

In addition, the broker benefits from his position that provides him a better recognition by his or her collaborators. Broker will have the most legitimate position where he or she can easily promote his or her ideas to each of otherwise disconnected inventors. Most importantly broker, the focal inventor of a very sparse network, know how to convince and communicate with many others compare to non-brokers. Their ideas will be more likely to be understood and appreciated by others thanks to their abilities to adapt to different cultures, to multiple work environments and to each collaborator's jargon.

Consequently, I expect that being a broker not only is harmless but also provides strategic advantages such as legitimacy and a higher recognition that are expected to increase the reuse of broker's ideas by local network members. Therefore, the first hypothesis I put forward is:

***Hypothesis 1:** The higher an inventor's brokerage level, the more the inventor's ideas will be reused by local network members.*

Contingent value of brokered networks: the role of cognitive proximity

In addition to social and geographical proximity, cognitive proximity among network members is a well-established driver of innovation success (Balland et al. 2015; Boschma 2005; Nootboom 2000; Shaw and Gilly 2000). Cognitive proximity can be defined as the similarities in the collaborators' perception, interpretation, and evaluation of new knowledge. It implies that inventors possessing a similar prior knowledge are more able to understand and learn from each other (Boschma 2005; Nootboom 2000).

Recalling that reuse of generated ideas depends on users' abilities to understand, appreciate, and accept inventors' ideas, cognitive proximity seems to be a basic need of innovation success. Indeed, the benefits of geographical or social proximities have been claimed to be subject to the existence of cognitive proximity (Garcia et al. 2018). With the lack of it, the generated ideas can be simply seen as ridiculous, crazy, or nonsensical and cannot be reused by others even if they are reachable and valuable enough to be invested in (Burt 2017; Fleming et al. 2007).

The proximity is related to the most common assumption that has been made by researchers focusing on the influence of collaboration networks. The assumption is attached to the level of collaborators' knowledge redundancy. On the one hand, proponents of sparse networks defend the opinion that being a broker increases inventive creativity and success by tapping heterogeneous information from mutually disconnected collaborators (Aral and van Alstyn 2011; Burt 2004). Most of the strategic advantages of a broker (i.e., early awareness of valuable combinations and increased combinatory skills) rely on the assumption that brokers are exposed to heterogeneous knowledge elements through otherwise disconnected collaborators. On the other hand, proponents of non-brokered networks claim that embedded networks and highly integrated collaborations imply a network that consists of redundant knowledge holders. They argue that the members of non-sparse networks have a common language, similar prior knowledge, therefore, higher cognitive proximity. Considering the unveiled importance of proximity on the usefulness of

generated ideas by others, it has been an expected conclusion that social network literature put forward the positive association between closed networks and the reuse of generated ideas.

The study questions the conventional assumption about the strong association between cohesive network structure (i.e., non-brokered network structure) and cognitive proximity among network members and builds on the contingency perspective. To do so, it makes a distinction between the cognitive proximity of the local network members and the network structure (i.e., the level of brokerage). In addition to the projected structural benefits of brokered networks for the local reuse, it is argued that brokers' ideas will be more reused if the members of the local networks (including the broker) hold similar knowledge. This is because the redundancy creates cognitive proximity among inventors, letting them have a common language and understand generated ideas even if they do not have intense interactions or direct connections to the broker. Collaborators' own knowledge will be enough to successfully interpret, therefore, be able to appreciate, adopt and reuse the ideas of brokers. As a result, the second and last hypothesis I put forward is:

Hypothesis 2: The influence of the brokerage on the local reuse of the inventor's ideas is positively moderated by the level of cognitive proximity that appears in the local network.

METHODOLOGY

Setting and data

To test my hypotheses about the role of brokerage on the reuse of inventor's output an empirical study of French inventors is conducted. A single inventor embedded in a collaborative network for a given performance year is focused. As in the previous chapters unit of analysis is an inventor-year pair and as in the third chapter, ego networks are defined as collaborative networks containing focal inventor's collaborators and their collaborator's collaborators. These sub-networks are referred to as *local networks* of a focal inventor. I use co-patenting ties to construct inventors' collaboration networks, whereas inventors' specialty portfolios are used to measure knowledge range, furthermore, cognitive proximities. The study investigates the *reuse* of inventor's output; therefore, the dependent variables consider the reuse of the focal inventor's technological combinations in the future patents up to the fifth year following the performance year. For instance, if the networks are created by using the patents applied between years $t-5$ and $t-1$ – the reuse of inventor's output in year t is measured by using patents applied between year $t+1$ and $t+5$. Therefore, for this chapter the time frame of the analysis is limited to patents that are between the years 1990 and 2015 (instead of 1990 and 2010) to have sufficient data from more recent years to observe patents' reuse.

The model and measures

Dependent variable

Local reuse

In this study, the dependent variable is the reuse of focal inventor's combinations.

The European Patent Office organizes all technology into approximately 650 subclasses and periodically updates and reorganizes them. To construct the variable, I first identified all subclass pairs within each of a focal inventor's patents in a given performance year. This step is done regardless of the novelty of combinations which is controlled with an additional measurement. The variable then counts how many times other inventors reuse the focal inventor's combinations in their patenting activities. Following the literature (Fleming and Sorenson 2004; Singh 2005; Marco 2007) the reuse count considers the patents of other inventors over the five years following the performance year. The variable considers all inventors located in the local network boundaries of the focal inventor. If the focal inventor re-uses his or her combination with a patent in which he or she is a sole inventor, then this use is not taken into account in the variable calculation.

To measure the reuse by local network members of a given year, I consider all patent applications by the focal inventor in a particular performance year and scrutinize the reuse of inventor's combinations by local network members (by collaborators and collaborators' collaborators). The inventors who have a patent(s) in the five years following the performance year, therefore, have a chance to reuse focal inventor's combinations. I simply name this variable as *Local Reuse*.

Independent variables

In this study, I have two independent variables: cognitive proximity within the focal inventor's local network and his or her level of brokerage (i.e., the level of sparseness of his or her network).

Brokerage

The measure of brokerage is defined and constructed as it is used in the previous chapters (see pg. 54).

Cognitive proximity

The second explanatory variable is cognitive proximity. This variable captures the level of knowledge similarity of local network members. Focal inventor's cognitive proximity to the local network is obtained on the basis of the past patenting portfolios of all network members, based again on their inventions during the five years preceding the performance year. The technological expertise of each inventor in the network is described by a vector of length 650, where a cell describes whether an inventor uses a specific subclass. If inventor uses technology, the variable equals 1, else zero. The focal inventor's cognitive proximity available in their local network is calculated as the average cosine similarity of the vectors for each dyad of network members. The decision to include each pair of network members is made because observing discrepancies between the knowledge base of the focal inventor and each other collaborator is not sufficient. Cognitive proximity measure ranges from 0 (fully diverse network) to 1 (fully specialized network). I construct alternative variables³² as a robustness check.

Control variables

To obtain meaningful results, a number of characteristics are included in the empirical model. The control variables are organized on three levels. The network-level set includes the variables related to characteristics of collaboration structure and collaborators. The second set relates to individual-level characteristics of the focal inventor such as research path, previous performance and so on. Last set includes team-level variables to control for the team composition for focal inventor's patenting activities.

³² As an alternative measures of cognitive proximity among local network members, I construct three additional variables. Alternative approaches provide no qualitative changes in results. For detailed explanation of those alternative measurements, see Appendix 3.A.

The network-level set of controls consists of four variables. The number of focal inventor's collaborators (the *number of direct ties*) and the number of inventors indirectly connected to the focal inventor who are the members of focal inventor's local network (the *number of indirect ties*) are calculated to control for inventor's local network size. This is important as I need to control for the possibility that the reuse of the combinations might be simply a function of the network size. In order to control for the effectiveness of inventor's collaborative integration, the *average strength of direct and indirect ties*³³ are constructed.

To control for the team composition within focal inventor's patent portfolio two indicators are used. The first one is the *single firm*. It is the percentage of the focal inventor's patents that all co-authors come from the same company during the period of five years preceding performance year. Second, *single Country* is the percentage of the focal inventor's patents that all co-authors live in the same country during the period of five years preceding performance year.

The inventor-level set includes six variables. Here I use the measure of *first inventor*, which is the share of the patents that the focal inventor was listed first, again during the period of five years preceding performance year. The variable *experience* counts the number of years between performance year and the first year the focal inventor appears in EPO database. To capture the fact that reuse might be a function of the number of patents, I use patent count during the performance year (*current patent count*). I also control the level of productivity of an inventor by including the number of patents he or she has applied for over the last 10 years preceding the performance year (*previous patent count*).

³³ The tie strength measurements are constructed as in the second chapter. For technical details on measurement of variables controlling strength of ties, see pg. 53.

It is also important to notice that the acceptance and reuse by others may vary significantly depending on the novelty of combinations (Mueller et al. 2011; Perry-Smith and Mannucci 2017; Wang et al. 2017). In addition, some researchers assume that higher novelty implies higher value (Singh and Fleming 2010; Wuchty et al. 2007) while others show no relationship between the two (Dahlin and Behrens 2005; Nemet and Johnson 2012). Although a sparse collaborative network structure of a broker is expected to increase his or her creativity, the reuse of the combinations is detached from their novelty. Considering ongoing debate on the relationship between an invention's value and novelty I prefer to control for the *novelty*³⁴ of focal inventor's combinations.

The very last individual-level control variable is *self-reuse*. To make sure that the reuse is not biased because of the self-reuse I construct the variable. A simple count of reuse of focal inventor's combinations in his or her future patents is used as a measure of *self-reuse*. The patents where the reuse appears, and the broker is the solo-author are not considered for the calculations.

Econometric issues and estimation

A panel dataset where it is possible to observe patenting behavior of inventors over an extended time period is structured. Therefore, a panel data estimator is required to be used. The descriptive analysis shows that the dependent variable has an overdispersed and an inflated distribution. Also, it takes only integer values. Considering the specific features of the variable itself and its distribution, it is preferred to use panel data specific Negative Binomial estimator. This is done to prevent the estimation of inefficient, inconsistent, and biased coefficients. Moreover, the estimator lets me control for overdispersion—where the variance is quite bigger than the mean—and inflation which the data exhibits. Despite the high number of observations, I

³⁴ For technical details on measurement of variables controlling *novelty* of combinations, see Appendix 3.A.

double-checked for the differences between the coefficients of a random effect modal and a fixed-effect modal by using a likelihood ratio test. As expected, the test pointed to the use of a random effect modal.

Before proceeding to estimation, inventors who did not work with two or more collaborators are identified as these inventors cannot become brokers within their network, therefore, are misleading the analysis. Following the previous literature (Fleming et al. 2007), I use only cases where the focal inventor has at least two collaborators. Additionally, inventors who have no patenting activity in a given year are also excluded from the analysis. As they do not generate any combinations which can be reused by others, they create a noise between the ones who have generated the combinations with no reuse and the ones who do not generate any combinations at all. Therefore, their inclusion would have easily created a bias for the reuse of inventor's ideas and for the analysis. I use 32 092 unique inventors and 80 573 inventor-year combinations to obtain random-effects Negative Binomial estimates (with added year fixed-effects and technology residuals as a replacement of technology fixed-effects³⁵) of empirical models. Table 14³⁶ provides descriptive statistics and pairwise correlations of main variables across all retained observations.

³⁵ Despite I am aware of the potential bias deriving from ignored technological fixed effects, I couldn't manage to include them in the models as they are. This is due to the fact that the addition of almost 650 4-digit technologies created computational problems (i.e., conformability and non-achieved convergence errors) that appeared in the software used for regression analyses (Stata MP-17). As a solution, I simply run a base model that includes only technology fixed effects and create a new variable with the residuals that came out from the model. The variable then is included in the main models as a replacement for technology fixed effects. This lets me prevent any bias that may occur in the results without technology-fixed effects. Because the residuals could not be calculated for 4-digit and 3-digit versions because of the same errors the models include the 2-digit technology residuals that provide convergence. This choice is done to strengthen our statistical model.

³⁶ Please see Appendix 3.B

These statistics indicate some multicollinearity between some of the structural characteristics such as the number of direct and indirectly connected inventors, and the number of collaborators and local reuse. This is an expected correlation considering the literature discussed above about the ease of interactive learning and knowledge sharing for the shorter social distances. The same applies to the relationship between the number of direct and indirect ties, as acquiring an indirect connection is only possible through direct connections.

RESULTS AND DISCUSSION

In order to build analyses, I estimate three distinct models. To test the reuse of inventor's combinations by local network members. I begin with Model 1, which highlights the link between the focal inventor's level of brokerage and the reuse by the local network. This model includes brokerage and control variables including the novelty of the inventor's output, as well as technology residual variables and year-fixed effect. In the next stage, Model 2 appends a stand-alone cognitive proximity term to Model 1. Although I do not question the relationship between cognitive proximity and reuse by local network members, its inclusion in the second model creates an added value for the sake of interpreting the influence of network structure by decoupling the assumed knowledge benefits of brokerage. Therefore, second model is used for hypothesis testing. Finally, Model 3 is constructed to examine the moderating role of cognitive proximity among local network members. Here I add the interaction term between brokerage and cognitive proximity, to setup from Model 2. The extended model allows us to evaluate the hypothesis 2 put forward in section 2.

Table 3. Reuse of inventor's output by local network members

VARIABLES	Local Reuse		
	Model 1	Model 2	Model 3
Brokerage	0.0801*** (0.0309)	0.0735** (0.0319)	-0.504*** (0.0756)
Cognitive Proximity		-0.0233 (0.0284)	-0.562*** (0.0701)
Brokerage # Cognitive Proximity			0.977*** (0.116)
Number of Observations	80,573	80,573	80,573
Number of Inventors	32,092	32,092	32,092

Note: Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 3³⁷ report the regression coefficient estimates for variable of interests across all models explaining the reuse of focal inventor's ideas by local network members. Results provide strong evidence for both hypotheses.

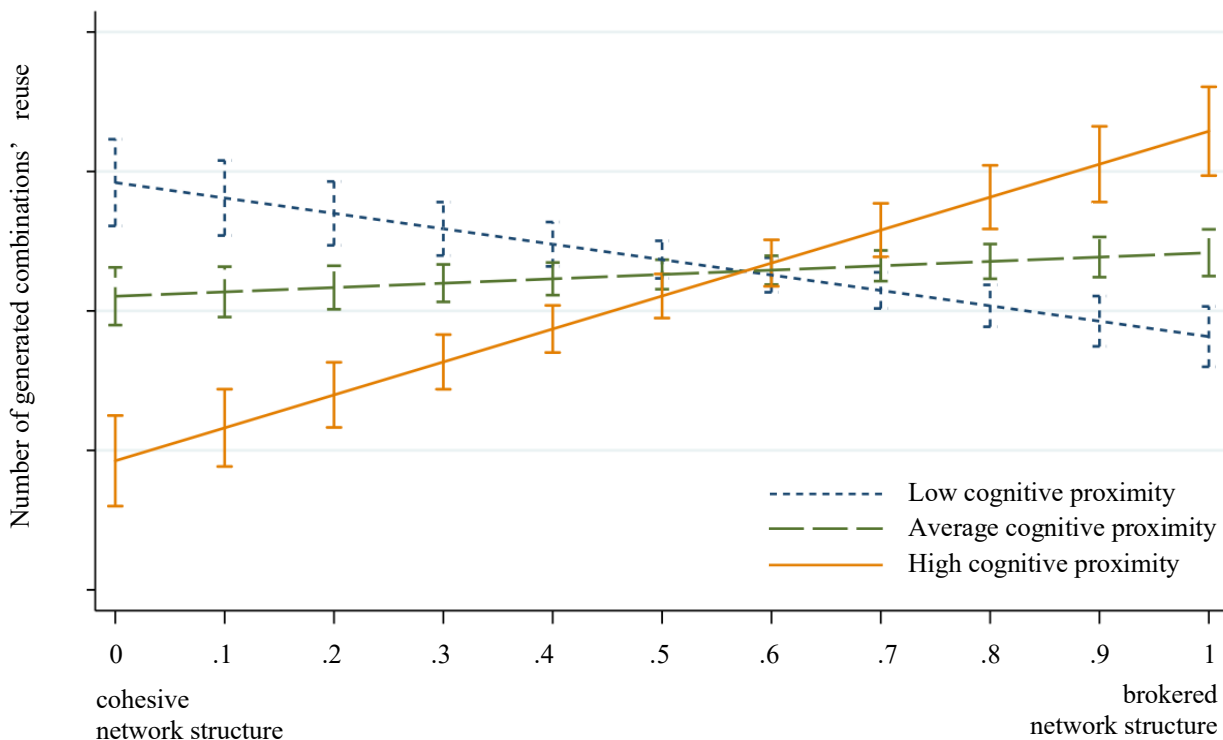
First of all, results from Model 1 and 2 suggests strong support for the first hypothesis, that the higher an inventor's brokerage level, the more the inventor's ideas will be reused by local network members. Inventors located in local networks are very close to the brokers even further may have direct connections to the broker. First, because they have already chose worked together, the trust argument is apparently weakened. And second, the knowledge diffusion is way faster compared to larger networks. Building on these arguments, unlike literature demonstrating the dark side of brokered networks for the innovation success³⁸, results indicate that for local networks this is not the case. And again, the study emphasizes the strategic advantages of brokerage beyond those related to non-redundant knowledge exposure (i.e., the sparseness of the network structure) are positively influencing the reuse of inventor's ideas. Shorter social distance between collaborators and broker help inventors to overcome the obstacles of sparse networks. In addition, brokers enjoy their unique gatekeeper positioning where they can have good reputation and higher legitimacy. Their working with different groups of inventors, and ability to communicate with larger audience is a huge plus for the reuse their ideas by local neighbors.

³⁷ For full regression outputs please see Table 16, and for all robustness checks related to local reuse please see Table 17 in Appendix 3.D. Results in Table 17 are robust to changes in measurement and consistent with the discussed results in section 4.

³⁸ Although I do not hypothesis for the reuse of broker's ideas within whole networks, I conduct additional analysis to see the robustness of my dataset with literature showing that brokered networks are detrimental for the diffusion of generated ideas within whole networks. The results are aligned with the literature. For the details of additional analysis, see Appendix 3.C.

Second, results from Model 3 estimations allow for the study of the moderating effect of the cognitive proximity and evidence the second hypothesis, that the sparseness of a broker's network and having cognitive proximity among local network members jointly increases the reuse of the broker's ideas by local network members. For the sake of interpretation Figure 4 presents predictive margins of the dependent variable for low (10th percentile of the variable distribution), average, and high (90th percentile of the variable distribution) levels of cognitive proximity.

Figure 4. Predictive margins: reuse of inventor's output by local network members



Note: Confidence interval corresponds to 95% confidence level

Before discussing results with respect to the last hypothesis, it is important to notice, the results indicate the distinct influence of brokerage and cognitive proximity on the reuse of inventor's output in addition to the moderation of them. Although I do not test for this, the insignificance of cognitive proximity in Model 2 and then its positive significance only within brokered networks is worthwhile to be discussed. Results

from Model 3 demonstrates that unless the inventor is part of loosely embedded network, cognitive proximity can be harmful. This transition reminds the cost of embedded networks where inventors need to interact with each other and spend their time and attention on many redundant collaborators (Mueller and Kamdar 2011; Perry-Smith and Shalley 2003; Uzzi 1997). Yet, considering the standard deviation of the coefficients (see in Figure 4) for the mean of brokerage appears in the analyzed dataset, I do not see a significant difference in the reuse of inventors' ideas contingent upon the level of cognitive proximity.

With respect to the core question of the study, prior research on the reuse of broker's innovation activity has been mixed. The results of this study provide explanations for the two community (i.e., proponents of brokered or embedded networks) by clarifying the micro mechanism behind the relationship between brokerage and success of inventor's output. I demonstrate that the influence of network structure is contingent upon the cognitive proximity of local network members. According to the results, although the interaction variable is positive and significant confirming their joint benefits on the reuse of inventor's idea, the absence of cognitive proximity does dramatically change the influence of brokerage.

On the one hand, although I do not hypothesis for the relationship between brokered networks and the reuse of inventor's output by larger network members, the results of the robustness checks are in line with the literature supporting the non-brokered networks (see Appendix 3.C). If the broker has no common knowledge with any other inventors whom he is collaborating with, sparseness of the network creates only obstacles and decreases the reuse of inventors' ideas. As argued in section 2, this is due to the fact that highly disconnected network hinders the emergence of trusting environment, therefore, willingness to share possessed knowledge, slow down the knowledge flow which hampers interactive learning and emergence of knowledge convergence (Burt 2017; Coleman 1988; Reagans and McEvily 2003; Uzzi 1997). Now, knowing that the influence of brokerage is positive in the first two models, the result of a remarkable study comes to the mind. Boschma (2005) has provided a critical assessment about the importance of main proximities' co-appearance to increase innovation performance. For instance, geographical proximity hinge

upon the cognitive proximity among actors because even if the actors are next to each other they cannot communicate. This provides a is a potential explanation of my results. Although the broker has the shortest social distance to his or her collaborators within local networks in which inventors live in a cognitive world of their own, structural convenience is not enough to increase the reuse of the inventor's output.

On the other hand, being part of a more specialized knowledge clique generates the conditions conducive to collaborators understanding and reusing broker's ideas more than ever. By digging into the micro mechanisms of the relationship, I observe that local network members possessing common knowledge boost the benefits of being a broker on the reuse of inventor's combinations by local network. Strategic opportunities generated by being a broker appears after a level of cognitive proximity among inventors and continue to gradually increase. Knowing that cognitively proximate collaborators do not provide knowledge advantages as much as knowledge heterogeneous networks to be aware of more valuable combinations, I claim that this significant increase in the positive influence of being a broker erupt from strategic advantages such as prestige, legitimacy, and communication skills which led to a higher acceptance and recognition by others. Thus, having lesser communication costs thanks to common language and shared understanding among the local network members provides additional advantages.

To sum up, if a broker collaborates with inventors differ in their domain and prior knowledge – as it is assumed in the literature – their ideas are less likely to be reused by the members of their local networks. Moreover, it appears that being a broker does not guarantee a higher knowledge diversity among the collaborators and this, also, is consistent with the contingency perspective. Finally, following the distinction between brokerage and knowledge, the study proves that being a broker becomes beneficial more than ever especially for inventors who are cognitively capable of understanding each other's ideas.

CONCLUSION

The study contributes to the social network and innovation literature and develop a deeper understanding of the brokerage's influence on inventor's success while controlling for the novelty of their output. It explores micro-mechanisms behind the relationship between brokerage and the reuse of inventor's ideas and the conditional influence of cognitive characteristics on the relationship. It enlarges my understanding to what extend sparseness of collaboration networks hinders the reuse of generated ideas and provide scenarios in which convergence of technology expertise among collaborators may help to overcome the obstacles of a brokered network. The main contributions of the chapter hinge on the two separations: First one is between the reuse of broker's ideas by localized network members instead of all active inventors. Second one is the distinction between brokerage, which constitutes a structural measure of inventor's positioning, and cognitive proximity of the collaborators including broker and the ones at maximum of 2 path length to the focal inventor.

A noteworthy feature of the findings is the fact that both brokered and cohesive networks provide advantages contingent upon the cognitive proximity level among local network members. On the one hand, the chapter contributes to the ongoing debate on closure versus brokerage by showing that the detrimental effect of brokered networks can be overcome through knowledge redundancy of collaborators. Even further brokering the network might be conditionally an advantageous position to increase the reuse of an inventor's ideas without sacrificing novelty. On the other hand, closed networks become advantageous for unique knowledge holders. This time, the high intensity of interactions appears in their networks helps them to overcome consequences of cognitive distance.

The study highlights that there is always a trade of every second network structure and knowledge specialty of inventors to achieve the same success. Yet, the best of these two scenarios points that being a broker

where a high level of cognitive proximity exist is the most fruitful environment to increase the reuse of inventor's ideas within his or her local network.

The study is one of the contributors to literature building on the contingency perspective. Following this stream of research (Brass and Borgatti 2019; Carnabuci and Diószegi 2015) many other things can be tested such as the experience within firms, managerial abilities, coming from different working culture, being a broker within versus between teams, firms and so on. One of the outstanding questions is that how an inventor increases his or her innovative performance in terms of both novelty and success while he or she is in a very sparse but knowledge redundant network. I would expect that a broker's creativity within knowledge redundant network is lower than another broker located in knowledge heterogeneous network, as redundancy decreases the combinatory capabilities. However, the study investigates the reuse of broker's ideas under the condition of the novelty of broker's ideas *being equal*. This means a broker can be as creative as independently of knowledge heterogeneity access. Here, the study hints at the importance of different cultures, perspectives, experiences, and any other contributors of a valuable collaboration. There are studies demonstrating the importance of bridging perspectives, cultures, or the importance of social integration to increase the inventive performance (Brass and Borgatti 2019; Chua 2018; Goldberg et al. 2016; Schowalter et al. 2020). Therefore, although in the beginning, observing similar creativity for the inventors who are exposed to significantly different levels of knowledge heterogeneity is seen as a counterintuitive result, I claim that this is due to the fact that the ones bridge cognitively proximate disconnected collaborators enjoy their position by being exposed to different perspectives, approaches and working cultures. These diversities help them to be specialized in a particular area and exploit it at its best, even further, help them to be able to apply the technology in multiple contexts.

FUTURE IMPLICATIONS

In general, the study motivates us to further investigate the network evolution of inventors and actually how and where to start building structurally sparse versus cohesive networks. In addition to the structure, the study begs for further studies on the trade of between several proximities including structural proximity such as cultural and cognitive ones. It would have created an added value if I could understand and provide some managerial implications which to start with and which proximity to add in the next steps for constant innovative performance and knowledge spillover within local networks. Another conclusion of this kind of study would provide a comprehensive understanding on how to guide inventors during their career journey. This could shape at which stage and which incentive (to collaborate more interactively and to upskill or to reskill themselves to increase their cognitive abilities) to offer to the employees.

CHAPTER 5

GENERAL CONCLUSION

Inventive performance has been extensively studied over the last decades by both practitioners and scholars as it is agreed that the ability for technological change and innovation performance are drivers of competitive advantage and sustainable growth. Since the acceptance of a significant association between collaboration networks and knowledge spillover benefits, legitimacy, trust, and so on, researchers have widely acknowledged the importance of collaboration networks on the inventors' performance. However, the theoretical and empirical arguments of the potential influence of inventors' collaboration networks on their performance are not yet clearly established in the literature and provide contradictory conclusions and managerial implications, therefore, invite scholars to further clarify the processes and conditions under which collaboration networks deliver value to inventors' performance.

The main purpose of this dissertation is to investigate the role of collaboration network features, the mechanisms through which they affect individuals' inventive performance, and question the extent to which collaboration network structure is advantageous. My research makes an effort to define the influence of structural and relational characteristics and explores their contribution to French inventors' performance. Then, the study combs through the utilities of collaborative network structure by questioning very well-accepted assumptions in the literature. It aims to introduce a distinction between collaboration networks' structure and assumed attributes of network members such as their knowledge portfolio and cognitive proximity.

The dissertation presents three essays on the influence of collaboration network characteristics and the dichotomy between cohesive and brokered networks from different theoretical angles focusing on the rate of, the novelty of, and the usefulness of their output, namely inventions. More specifically, in the first essay of my dissertation, I argue that in order to better understand how and to what extent collaboration network characteristics influence inventors' performance I need to distinguish structural and relational features of

collaboration networks and I propose four general sources of increased performance: maintaining direct connections, increasing network size through indirect connections, bridging network, and strengthening relationships. I also provide theoretical arguments on the differences between those sources based on the potential benefits they provide, their relative contribution to inventors' performance, and their interplay with each other, and I statistically test the explanatory power of the framework with four features of collaboration networks. In the second essay, I seek evidence for the unlikely co-appearance of structure-content couples, namely, brokered network structure-knowledge heterogeneity of network members. Building on the distinction between content and structure of the networks, I expand on the contingency perspective and explore the moderating influence of accessible knowledge heterogeneity within inventors' networks on the relationship between bridging networks and the novelty inventors' output. In the final essay, I adopt a novel stance toward analyzing the value of brokered network structure arguing that their utility should take into account not only their direct influence on the diffusion of inventors' ideas but also its association with others' cognitive capabilities and their reachability to the bridge holders, termed brokers. The fourth chapter accentuates the counterintuitive appearance of cognitively proximate collaborators within brokered network structure or cognitively distant collaborators within the cohesive network structure.

Together, the three essays of my dissertation provide intriguing perspectives on the collaborating strategies and contingencies. My research demonstrates that collaboration networks provide advantages under certain conditions. It demonstrates that to increase inventors' performance their very close connections matter. In addition to the importance of quick accessibility through social proximity, the brokered structure is demonstrated to be the most important influencer of inventive performance. However, the research shows that a given structure is not a valid indicator of the other features of the collaboration networks. It reveals that brokered networks do not guarantee access to knowledge heterogeneity as well as cohesive networks do not guarantee cognitive proximity within networks, and finally, the contribution of the network structure

is significantly dependent on the co-appearance of other features of the networks. The results of my dissertation contribute to collaboration networks literature and the ongoing debate on “cohesive versus brokered networks” with new findings on the value and utility of their structural, relational, and content features and raise interesting theoretical questions for future research, which I cover in the sections that follow.

CONTRIBUTIONS

The first contribution of my thesis is that focal inventors can *only* profit from their local networks which are composed of focal inventors, their collaborators, and collaborators’ collaborators. This enlightens us about how the boundaries of ego networks for inventor level analyses need to be defined. The study demonstrates that even within the same network, the benefits provided to the focal inventor by the collaborators and inventors who are indirectly connected differ significantly. More importantly, the benefits of indirectly connected collaborators do not substitute the benefits of collaborators to the focal inventor. The study provides evidence that having strong relationships reinforce the focal inventor’s performance and that highly integrated connections have a bigger influence on the inventor's performance than the number of collaborators. It shows that the most important feature that will improve and contribute to the performance of focal inventors in every aspect of it (i.e., quantity and novelty of their output, and usefulness of their inventions by local network members) is the brokered structure of local networks.

The following contributions of the thesis hinges on the separation of collaboration networks’ structure and assumed attributes of collaborators. Digging into the micro-mechanisms behind the inventors’ performance the thesis focuses on the most important feature of the collaboration networks – structural non-redundancy– and questions the most common assumptions in the literature. I argue that looking at being the focal inventor within a brokered network can be advantageous in which to an extent and depending on the appearance of assumed byproduct features.

First of all, the distinctions allow us to understand that the structure of the network may hint at but does not guarantee the heterogeneity of shared knowledge or the cognitive proximity among collaborators. The findings demonstrate that the appearance of either available knowledge heterogeneity within networks or cognitive proximity of collaborators and network structure (bridging versus bonding structure) are not dependent on each other's existence, yet they moderate each other's influence on inventors' performance. Therefore, although there is literature assuming heterogeneity and cognitively distant collaborators are byproducts of being focal inventors within brokered network structure, it is a must to make a distinction between them to better understand the influence of any mentioned features on inventor's performance.

Second of all, by bringing distinctions between knowledge heterogeneity and brokered network structure, high cognitive proximity among collaborators, and cohesive network structure into the brokered versus cohesive networks debate, the thesis makes clear that both structures have their unique yet contingent advantages. On the one hand, the study contributes to the Burt's social capital and structural hole theories. It makes clear that the maximum creativity of the focal inventor within a brokered network structure stems from the provided knowledge heterogeneity by collaborators. Strategic advantages associated with being a broker are maximized if and only if collaborators possess unique knowledge. In addition to the benefits of being a broker on the creativity of inventors, their ideas are also more likely to be recognized and reused by collaborators under the condition of holding similar expertise and being cognitively proximate. Those findings support the literature on the advantages of being the focal inventor within brokered networks by enhancing our understanding on its contingent value for inventors' performance. On the other hand, by contributing to Coleman's (1998) argument on the benefits of cohesive networks (non-brokered networks) the thesis put forward that inventors within a cohesive network are better performers in terms of the novelty and reuse of their output more than brokers unless collaborators possess unique knowledge or similar technological expertise.

With the study, I raise awareness that while there is a trade-off in being within brokered and cohesive network structure, their assumed byproducts are not exclusive to a given structure. The study highlights that the advantages achieved with certain structural characteristics (i.e., brokered, and cohesive networks) appears contingent upon other features of collaborators. There is a tradeoff between cohesive and brokered network structures for inventors' performance. Yet, the best of these two scenarios points that focal inventors who have cognitively proximate collaborators and exposed to heterogeneous knowledge within a brokered networks are the best performers in terms of both creativity and the impact of their inventions on others' future studies.

The study makes contributions to my understanding of the optimum network features and their implications by exploring the interplay between an individual's collaborative network characteristics and their performance. It also enlarges our understanding to what extent sparseness of collaboration networks hinders the inventors' performance and provide scenarios in which convergence of technology expertise among collaborators and accessible knowledge heterogeneity help to overcome the obstacles of a brokered networks. Considering all the findings of the three main essays of the thesis, the most fruitful environment of a focal inventor is in which he or she holds strong connections with collaborators from different groups of inventors who provide complementary knowledge elements and are also cognitively proximate to the focal inventor. The combination of all these features allows the focal inventors to profit from all the strategic advantages of bridging the network to increase their inventive performance.

However, it is not so easy to create a network that holds all the mentioned features at once. Also, inventors are not always expected and promoted to produce both novel and useful patents at the same time or the same stage of their careers. Contrarily, they may choose to focus on one aspect of their performance by focusing on the essentials of the targeted outcome (i.e., quantity, novelty, and reuse of their inventions). For instance, if they would like to increase their creativity, it is enough that they focus on and maintain their connections with heterogeneous knowledge providers to increase their combinatory skills, knowledge

arbitrage advantages, therefore, the novelty of their output. Another example of this approach is that a manager who tries to increase the reuse of generated ideas by broker inventors within localized networks needs to put them with cognitively and socially proximate inventors to ease their communication and diffusion of the novel ideas.

To sum up, my dissertation provides evidence that adopting the distinction among multiple features of collaboration networks and questioning their widely accepted indications for each other in investigating the association between collaboration network features and multiple facets of inventive performance will allow scholars to address not only the questions of which structure will influence the outcome, but also the interplay between structure and determinants (i.e., social, and cognitive proximity, and knowledge heterogeneity access) of inventive performance. Together, the relational and structural features of collaboration networks and attributes of network members provide a more rigorous theoretical base, on which to estimate the mechanisms through which they deliver value and the ways in which context change their added value. The contingency perspective in my research strengthens the argument that each of the variables has a distinct contribution that is influenced differently by the other features. Most importantly, the findings of the thesis serve as a foundation for future research ideas that can vastly improve our understanding of how and the extent to which collaborations and collaboration networks matter, social capital management strategies, and the determinants of invention performance at different levels of analyses.

LIMITATIONS AND FUTURE RESEARCH

Several limitations of my dissertation merit discussion. From a theoretical standpoint, the use of the EPO database is certainly one of the main limitations of the three essays because patents do not reflect all collaborative initiatives taking place among inventors. Therefore, collaboration networks of inventors considered represent only the observable dimension of collaborative relationships among actors. The

addition of other types of data could deepen my understanding of the collaboration network features' contribution to inventors' performance. For instance, data from social media networks such as LinkedIn and surveys could be helpful to better observe all collaborations and define the attributes of collaborators such as their motive to collaborate or their hierarchical level.

In addition, the three essays try to do their best on controlling the organizational boundaries, however, an analysis of a more focused setup would have been helpful to better explore the influence of inter-organizational collaborations. Moreover, it could let us observe the differences between organizations and their influence on the construction of collaboration networks of inventors. For instance, depending on the exploration or exploitation strategies and business plans of the organizations they could choose whether to share their knowledge with other actors in the ecosystem. In the same vein, three essays control for the variance among technologies used for inventions, however, focusing on one part of inventions related to specific technologies (such as focusing AI, AgTech, or FoodTech) or focusing on a specific product (such as drones or plant-based meats) would help for further investigations. For instance, it could provide in-depth explanations why some firms are better to adopt new technologies or why their innovation performance is better than others.

Besides, while only collaborations among inventors have been investigated in the thesis, other types of collaborators, in particular, industry-science collaborations as well as intra- and inter-sectoral collaborations are also important to interpret the role of collaboration networks on inventors', therefore, firms', and regions' innovation performance.

Moreover, the thesis motivates us to further investigate the network evolution of inventors and actually how it is important to keep the network evolving over time. Because *sparse - knowledge heterogeneous* networks are the most creative ones while *sparse - knowledge homogenous* or *cohesive - knowledge heterogeneous* networks are the most fruitful to increase the reuse of generated ideas by local network members. Meaning

that, an inventor as a broker first needs knowledge heterogeneity to generate novel ideas and then knowledge convergence among his/her very close network to be cited or to be replicated in the future. As a matter of fact, answering whether inventors need to shift from brokered to cohesive networks or shift from knowledge heterogeneous networks to more specialized ones would be a worthwhile contribution to the innovation literature and would provide managerial implications.

Even further, the question to be investigated can go beyond the evolution of networks and change in the network characteristics. It may be about the smart activation of the necessary part of the network as has been highlighted in the literature (Perry-Smith and Mannucci 2017). Then, building on this theoretical study, the followed question is who is capable of maintaining all their collaborations while they continue to invest their attention and time to a dedicated part of it. This needs to be further investigated by observing the inventor's additional advantages such as their positioning within the organizational hierarchy, being a manager versus being a newcomer. This can be a part of an investigation of inventors' career journey their innovation activities during the journey by specifically questioning when and how to bridge or bond the relationships, further, which one to start with to the journey.

From an empirical standpoint, a significant future study would be constructing hypergraphs instead of graphs. It would define the collaborative relationships at the team level or triadic relationships other than a dyadic approach which is used for three essays of the dissertation and could be useful to provide alternative explanations of redundancy or social capital within networks.

Another drawback of my dissertation is that across the studies I am unable to account for causality in the mechanism. Although I conduct longitudinal analysis for all three essays, I could only claim by observing the existing collaboration network characteristics. By applying a dynamic model approach and how those collaborations emerge and change over time and how they explain network features is a question that begs for further studies.

In addition, although this is only for the purpose of robustness analysis, the study is using the Burt's constraint measurement which does consider collaborators with a maximum of two path length while observing its effect on the reuse by any other inventor (for global network analysis, see Appendix 3.C). Although this is chosen to contribute to an ongoing debate which apply the same approach and measurement, it may not be the best strategy to capture the network structure's influence for reuse within larger networks. It would be insightful to see a complementary study which investigates the mechanism with other centrality measurements such as original betweenness centrality measure.

One of the very last promising future study ideas is related to the limitation on whole network measurement that gives a new lease of study. A very important future implication of the study would be its application for multi-level analysis and then replicating the whole network perspective by also using local networks of small actors. For instance, local networks of a global network can be defined by economic actors such as departments, universities, and firms. The global network would represent a regional network that includes all those local networks. This would help us to better understand why some regions are better benefiting from each other's core knowledge to increase both their own and regional innovation performance. In this set, it would make sense to assign one knowledge vector to each local network and observe the cognitive proximity or alignment of whole network members that are the local networks including scientists and inventors. This approach would make both theoretical and empirical contributions to the literature as well as help to better explain firm or regional level performances by relying on inventors' actions or investigating the influence of network-based innovation policies on all types of actors' collaboration networks, further, their performance.

APPENDICIES

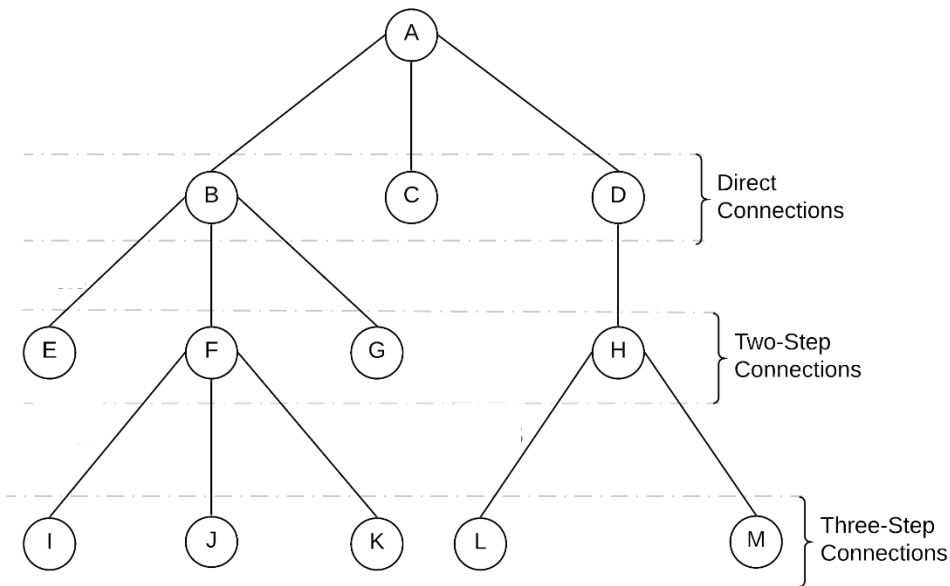
APPENDIX 1

Appendix 1.A

An Example on how to construct indirect connections variables:

To explain all indirectly connected inventor measurements with an example a hypothetical ego network as in the Figure 5 is illustrated. The focal inventor (A) of hypothetical ego network in the figure has 3 direct (B, C, D), 4 two-steps (E, F, G, H), and 5 three-steps (I, J, K, L, M). Let's assume that while two-steps collaborators produced 2, 4, 1 and 3 patents respectively, three-step connections produced 4, 3, 1, 5, and 8 patents respectively. In this case the network size (N) is equal to 13, *indirect 1st connections* are 4 (E, F, G, H), and *indirect connections – count* are 9 (E, F, G, H, I, J, K, L, M). *Indirect connections – distance weighted* will be equal to $2.23 = ((1-7/13) * 4 + (1-12/13) * 5)$ and *indirect connections - distance and information weighted* is equal to $6.23 = ((6/13) * (2+4+1+3) + (1/13) * (4+3+1+5+8))$.

Figure 5. Inventor A's ego network

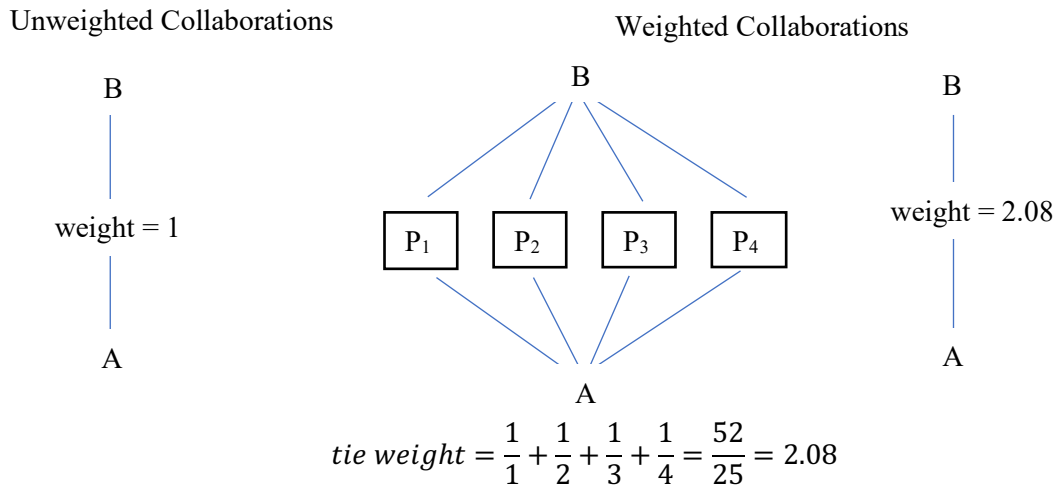


An example to tie measurements in weighted and unweighted networks:

First, for the unweighted collaboration relationships, a link occurs (i.e., weight = 1) if inventor *A* is a co-inventor of inventor *B* at least in one patent which is written in given five-year window and there is no link otherwise (i.e., weight = 0).

Second, for weighted ties I used Newman's (2001) approach to account for the strength of collaborative integration. An example for measurement of tie weights explained with an example in Figure 6. In this example, inventors *A* and *B* have collaborated for four patents, labeled *P*₁, *P*₂, *P*₃, and *P*₄ which had respectively 2, 3, 4, and 5 inventors. The tie between *A* and *B* accordingly accrues weights 1, 1/2, 1/3, and 1/4 from the four patents, for a total weight of 2.08.

Figure 6. An example to tie measurements in weighted and unweighted networks



Appendix 1.B

Table 4. Summary statistics (means, standard deviations, N = 227 679)

Variables	Mean	S.D.
(1) quantity of inventor's output	1.17	2.946
(2) number of direct collab.	7.25	6.88
(3) indirect 1st connections	22.32	50.63
(4) indirect connections – count	6870.9	40422.3
(5) ind. collab. - distance weighted	1384.6	9764.9
(6) ind. collab. - distance & information weighted	14049.7	90532.3
(7) brokerage	.531	.207
(8) technology diversity	17.90	27.89
(9) avg. strength of direct ties	.898	.965
(10) avg. strength of 1st order indirect ties	.933	.957
(11) avg. strength of indirect ties	.9	.777
(12) previous patent count	8.91	15.69
(13) experience	6.26	6.05
(14) first inventor	.304	.366
(15) single country	.8	.352
(16) single firm	.835	.318

Table 5. Pairwise correlations (N = 227 679)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) quantity of inventor's output	1.00														
(2) number of direct collab.	0.21	1.00													
(3) indirect 1st connections	0.15	0.58	1.00												
(4) indirect connections – count	0.06	0.30	0.56	1.00											
(5) ind. collab. - distance weighted	0.05	0.27	0.55	0.95	1.00										
(6) ind. collab. - distance & information weighted	0.06	0.28	0.54	0.98	0.97	1.00									
(7) brokerage	0.12	0.31	0.11	0.05	0.04	0.04	1.00								
(8) technology diversity	0.12	0.40	0.65	0.62	0.65	0.64	0.15	1.00							
(9) avg. strength of direct ties	0.23	-0.04	-0.01	-0.01	-0.01	-0.01	0.22	0.04	1.00						
(10) avg. strength of 1 st indirect ties	0.18	0.09	0.10	0.03	0.03	0.03	0.07	0.14	0.35	1.00					
(11) avg. strength of indirect ties	0.13	0.06	0.07	0.04	0.03	0.05	0.07	0.14	0.28	0.76	1.00				
(12) previous patent count	0.27	0.49	0.30	0.16	0.14	0.15	0.29	0.26	0.43	0.26	0.17	1.00			
(13) experience	0.02	0.16	0.09	0.06	0.05	0.05	0.13	0.08	0.09	0.05	0.04	0.31	1.00		
(14) first inventor	0.03	-0.06	-0.06	-0.03	-0.02	-0.03	0.20	-0.03	0.09	-0.01	-0.02	0.05	0.02	1.00	
(15) single country	0.00	-0.18	-0.20	-0.18	-0.15	-0.17	0.10	-0.20	0.13	0.04	0.02	0.00	0.02	0.07	1.00
(16) single firm	0.04	-0.02	0.04	0.03	0.02	0.03	0.12	0.02	0.10	0.08	0.05	0.06	-0.02	0.05	0.09

Appendix 1.C

Table 6. Results from panel negative binomial estimation: quantity of inventor's output – model 1&2

VARIABLES	<i>inventor's performance - quantity of inventor's output</i>				
	1	2a	2b	2c	2d
number of collaborators	0.00889*** (0.000598)	0.00964*** (0.000656)	0.00927*** (0.000599)	0.00905*** (0.000598)	0.00912*** (0.000598)
indirect 1 st connections		-0.0002*** (7.65e-05)			
indirect connections – count			-6.39e-07*** (1.00e-07)		
ind. collab. - distance weighted				-3.4e-06*** (4.10e-07)	
ind. collab. - distance & information weight.					-3.1e-07*** (4.48e-08)
direct collab. # indirect 1 st collab.					
direct collab. # indirect collab.					
direct collab. # ind. collab. dist. weight.					
direct collab. # ind. collab. dist. & inf. weight.					
brokerage					
avg. strength of direct ties	0.0515*** (0.00362)	0.0423*** (0.00369)	0.0441*** (0.00367)	0.0443*** (0.00367)	0.0442*** (0.00367)
avg. strength of 1 st order indirect ties		0.0519*** (0.00350)			
avg. strength of indirect ties			0.0616*** (0.00411)	0.0609*** (0.00412)	0.0617*** (0.00411)
technology diversity	0.00242*** (0.000112)	0.00254*** (0.000138)	0.00294*** (0.000151)	0.00327*** (0.000158)	0.00306*** (0.000154)
previous patent count	0.00358*** (0.000251)	0.00344*** (0.000251)	0.00374*** (0.000248)	0.00368*** (0.000249)	0.00372*** (0.000249)
experience	-0.0409*** (0.000905)	-0.0407*** (0.000903)	-0.0409*** (0.000902)	-0.0409*** (0.000902)	-0.0409*** (0.000902)
first inventor	0.199*** (0.0102)	0.204*** (0.0101)	0.203*** (0.0101)	0.203*** (0.0101)	0.203*** (0.0101)
single country	0.0715*** (0.0115)	0.0679*** (0.0114)	0.0672*** (0.0114)	0.0699*** (0.0114)	0.0677*** (0.0114)
single firm	0.0996*** (0.0125)	0.0953*** (0.0125)	0.100*** (0.0125)	0.0998*** (0.0125)	0.100*** (0.0125)
technology residuals	0.0998*** (0.000537)	0.0992*** (0.000537)	0.0995*** (0.000536)	0.0994*** (0.000536)	0.0995*** (0.000536)
year dummies	YES	YES	YES	YES	YES
constant	-0.877*** (0.0277)	-0.917*** (0.0278)	-0.939*** (0.0279)	-0.944*** (0.0279)	-0.940*** (0.0279)
observations	227,679	227,679	227,679	227,679	227,679
number of inventors	32,092	32,092	32,092	32,092	32,092

Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table 7. Results from panel negative binomial estimation: quantity of inventor's output – model 3

VARIABLES	<i>inventor's performance - quantity of inventor's output</i>			
	3a	3b	3c	3d
number of collaborators	0.0110*** (0.000683)	0.00968*** (0.000626)	0.00924*** (0.000621)	0.00930*** (0.000625)
indirect 1 st connections	0.000295*** (8.29e-05)			
indirect connections – count		-4.57e-07*** (1.31e-07)		
ind. collab. - distance weighted			-3.05e-06*** (5.45e-07)	
ind. collab. - distance & information weight.				-2.84e-07*** (5.80e-08)
direct collab. # indirect 1 st collab.	-1.27e-05*** (1.88e-06)			
direct collab. # indirect collab.		-4.99e-09** (2.39e-09)		
direct collab. # ind. collab. dist. weight.			-1.03e-08 (9.50e-09)	
direct collab. # ind. collab. dist. & inf. weight.				-9.53e-10 (1.04e-09)
brokerage				
avg. strength of direct ties	0.0437*** (0.00369)	0.0444*** (0.00367)	0.0444*** (0.00368)	0.0443*** (0.00368)
avg. strength of 1 st order indirect ties	0.0511*** (0.00351)			
avg. strength of indirect ties		0.0615*** (0.00411)	0.0609*** (0.00412)	0.0616*** (0.00411)
technology diversity	0.00243*** (0.000134)	0.00291*** (0.000151)	0.00325*** (0.000160)	0.00305*** (0.000155)
previous patent count	0.00348*** (0.000251)	0.00375*** (0.000248)	0.00368*** (0.000249)	0.00373*** (0.000248)
experience	-0.0409*** (0.000904)	-0.0410*** (0.000902)	-0.0409*** (0.000902)	-0.0410*** (0.000902)
first inventor	0.206*** (0.0101)	0.203*** (0.0101)	0.204*** (0.0101)	0.203*** (0.0101)
single country	0.0740*** (0.0115)	0.0694*** (0.0115)	0.0709*** (0.0115)	0.0686*** (0.0115)
single firm	0.0953*** (0.0125)	0.100*** (0.0125)	0.0998*** (0.0125)	0.100*** (0.0125)
technology residuals	0.0989*** (0.000538)	0.0994*** (0.000537)	0.0993*** (0.000537)	0.0994*** (0.000537)
year dummies	YES	YES	YES	YES
constant	-0.938*** (0.0280)	-0.943*** (0.0280)	-0.946*** (0.0280)	-0.942*** (0.0280)
observations	227,679	227,679	227,679	227,679
number of inventors	32,092	32,092	32,092	32,092

Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table 8. Results from panel negative binomial estimation: quantity of inventor's output – model 4

VARIABLES	<i>inventor's performance - quantity of inventor's output</i>			
	4a	4b	4c	4d
number of collaborators	0.00791*** (0.000724)	0.00694*** (0.000672)	0.00661*** (0.000663)	0.00659*** (0.000669)
indirect 1 st connections	0.000321*** (8.05e-05)			
indirect connections – count		-4.19e-07*** (1.30e-07)		
ind. collab. - distance weighted			-2.92e-06*** (5.38e-07)	
ind. collab. - distance & information weight.				-2.71e-07*** (5.75e-08)
direct collab. # indirect 1 st collab.	-1.07e-05*** (1.83e-06)			
direct collab. # indirect collab.		-2.48e-09 (2.36e-09)		
direct collab. # ind. collab. dist. weight.			-2.07e-09 (9.19e-09)	
direct collab. # ind. collab. dist. & inf. weight.				1.20e-10 (1.02e-09)
brokerage	0.272*** (0.0202)	0.269*** (0.0202)	0.268*** (0.0201)	0.270*** (0.0202)
avg. strength of direct ties	0.0369*** (0.00377)	0.0378*** (0.00376)	0.0379*** (0.00376)	0.0377*** (0.00376)
avg. strength of 1 st order indirect ties	0.0524*** (0.00351)			
avg. strength of indirect ties		0.0622*** (0.00411)	0.0616*** (0.00412)	0.0623*** (0.00411)
technology diversity	0.00233*** (0.000134)	0.00280*** (0.000151)	0.00314*** (0.000160)	0.00294*** (0.000155)
previous patent count	0.00354*** (0.000254)	0.00383*** (0.000250)	0.00377*** (0.000251)	0.00381*** (0.000251)
experience	-0.0415*** (0.000907)	-0.0416*** (0.000906)	-0.0415*** (0.000906)	-0.0416*** (0.000906)
first inventor	0.180*** (0.0103)	0.178*** (0.0103)	0.178*** (0.0103)	0.177*** (0.0103)
single country	0.0543*** (0.0115)	0.0504*** (0.0116)	0.0518*** (0.0116)	0.0494*** (0.0116)
single firm	0.0779*** (0.0126)	0.0834*** (0.0126)	0.0833*** (0.0126)	0.0833*** (0.0126)
technology residuals	0.0989*** (0.000539)	0.0995*** (0.000538)	0.0994*** (0.000538)	0.0995*** (0.000538)
year dummies	YES	YES	YES	YES
constant	-1.015*** (0.0286)	-1.020*** (0.0286)	-1.023*** (0.0286)	-1.020*** (0.0286)
observations	227,679	227,679	227,679	227,679
number of inventors	32,092	32,092	32,092	32,092

Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1

APPENDIX 2

Appendix 2.A

Herfindahl-Hirschman Index

The Herfindahl-Hirschman Index (HHI) is a common measure of market concentration and is used to determine market competitiveness (Matsumoto et al. 2012; Rhoades 1993). The higher a market's concentration and the lower its competition the closer the market is to a monopoly.

HHI takes value between 0 and 1. A value close to unity indicates strong technological concentration, the polar case being unity, where all the patents applied by members of an ego network belong to one technological field. In other words, all collaborators have specialized in one technology and do not access to a wide range of knowledge. On the contrary, a value close to zero represents availability of more heterogeneous knowledge and lesser concentration of the technology expertise in the ego network. Therefore, the final step in calculating knowledge deconcentration is a linear transformation by subtracting HHI from 1. This step is necessary for the interpretation of heterogeneity rather than concentration of knowledge available in the ego network.

For instance, if an ego network with 5 patents uses only one technology the HHI of this ego network will be equal to $1 = (5/5)^2$. This first illustrated network is fully concentrated on one technology field, and the HHI will be equal to 1. An alternative example to this is an ego network with, again, 5 patents use Technology 1 (T1), Technology 2 (T2) and Technology 3 (T3), respectively in 5, 3 and 2 of these 5 patents. In this case, the HHI of the illustrated ego network would be $0.38 = ((5/10)^2 + (3/10)^2 + (2/10)^2)$. In this second illustrated network, there are many dominated technologies unlike in the first illustrated network.

Appendix 2.B

Table 9. Summary statistics and pairwise correlations (means, standard deviations, $N = 80\ 573$)

Variables	Mean	S. D.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) novelty of inventor's output	.036	.51	1.00												
(2) knowledge heterogeneity	.281	.19	0.02	1.00											
(3) knowledge heterogeneity <small>hhi-based</small>	.731	.22	0.02	0.65	1.00										
(4) brokerage	.555	.21	0.01	0.33	0.15	1.00									
(5) number of direct collab.	8.13	8.44	-0.01	0.22	0.23	0.36	1.00								
(6) number of indirect collab.	26.82	64.16	-0.01	0.20	0.18	0.14	0.58	1.00							
(7) avg. strength of direct ties	1.01	1.11	0.027	0.07	0.04	0.25	-0.01	-0.01	1.00						
(8) avg. strength of indirect ties	1.02	1.01	0.021	0.19	0.19	0.11	0.09	0.08	0.36	1.00					
(9) current patent count	3.31	4.18	0.073	0.06	0.09	0.15	0.26	0.18	0.33	0.28	1.00				
(10) previous patent count	10.86	20.25	0.00	0.19	0.14	0.34	0.53	0.30	0.43	0.26	0.34	1.00			
(11) experience	5.78	6.29	0.00	0.14	0.11	0.23	0.24	0.11	0.13	0.08	0.1	0.34	1.00		
(12) first inventor	.326	.36	0.013	0.04	-0.02	0.21	-0.06	-0.06	0.10	-0.01	0.02	0.06	0.04	1.00	
(13) single country	.81	.34	0.006	-0.03	-0.09	0.09	-0.18	-0.21	0.13	0.05	-0.01	-0.00	0.02	0.08	1.00
(14) single firm	.85	.30	0.001	0.01	-0.02	0.12	-0.01	0.04	0.09	0.08	0.05	0.06	-0.02	0.04	0.08

Appendix 2.C

Table 10. Results from panel negative binomial estimation: novelty of inventor's output

VARIABLES	<i>novelty of inventor's output</i>		
	model 1	model 2	model 3
number of collaborators	-0.00258 (0.00720)	-0.000309 (0.00737)	-0.00319 (0.00759)
average strength of direct ties	-0.0410 (0.0348)	-0.0354 (0.0342)	-0.0328 (0.0342)
number of indirect connections	-0.00746*** (0.00156)	-0.0155*** (0.00195)	-0.0154*** (0.00194)
average strength of indirect ties	-0.169*** (0.0358)	-0.299*** (0.0411)	-0.291*** (0.0409)
current patent count	0.0679*** (0.00530)	0.0699*** (0.00525)	0.0698*** (0.00526)
previous patent count	-0.00162 (0.00233)	0.000391 (0.00240)	-0.000122 (0.00245)
experience	-0.00587 (0.00621)	-0.0111* (0.00643)	-0.0121* (0.00649)
first inventor	0.145* (0.0871)	0.139 (0.0871)	0.136 (0.0870)
single country	0.0976 (0.104)	0.0800 (0.103)	0.0713 (0.103)
single firm	0.144 (0.113)	0.208* (0.114)	0.205* (0.114)
technology residuals	0.208*** (0.0158)	0.240*** (0.0157)	0.243*** (0.0155)
brokerage	0.569*** (0.174)	-0.106 (0.179)	-0.926*** (0.304)
knowledge heterogeneity		2.909*** (0.192)	1.481*** (0.470)
brokerage # knowledge heterogeneity			2.609*** (0.782)
constant	-4.249*** (0.262)	-5.000*** (0.284)	-4.637*** (0.305)
year dummies	yes	yes	yes
number of observations	80,573	80,573	80,573
number of inventors	32,092	32,092	32,092

notes: dependent variables are inversely weighted with the number of co-inventors. standard errors in parentheses. significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 11. Results from panel negative binomial estimation (considering knowledge heterogeneity based on hhi)

VARIABLES	<i>novelty of inventor's output</i>		
	model 1	model 2	model 3
number of collaborators	-0.00258 (0.00720)	-0.00802 (0.00737)	-0.0108 (0.00751)
average strength of direct ties	-0.0410 (0.0348)	-0.0391 (0.0345)	-0.0375 (0.0344)
number of indirect connections	-0.00746*** (0.00156)	-0.0109*** (0.00174)	-0.0110*** (0.00174)
average strength of indirect ties	-0.169*** (0.0358)	-0.247*** (0.0386)	-0.245*** (0.0386)
current patent count	0.0679*** (0.00530)	0.0685*** (0.00525)	0.0682*** (0.00525)
previous patent count	-0.00162 (0.00233)	0.000314 (0.00235)	0.000312 (0.00237)
experience	-0.00587 (0.00621)	-0.0103 (0.00644)	-0.0110* (0.00648)
first inventor	0.145* (0.0871)	0.150* (0.0872)	0.149* (0.0870)
single country	0.0976 (0.104)	0.140 (0.103)	0.133 (0.103)
single firm	0.144 (0.113)	0.200* (0.114)	0.200* (0.114)
technology residuals	0.208*** (0.0158)	0.227*** (0.0155)	0.230*** (0.0153)
brokerage	0.569*** (0.174)	0.442** (0.173)	-2.529*** (0.815)
knowledge heterogeneity <small>hhi-based</small>		2.283*** (0.219)	0.356 (0.536)
brokerage # know. heterogeneity <small>hhi-based</small>			3.829*** (1.023)
constant	-4.249*** (0.262)	-6.150*** (0.329)	-4.727*** (0.485)
year dummies	YES	YES	YES
number of observations	80,573	80,573	80,573
number of inventors	32,092	32,092	32,092

Notes: Dependent variables are inversely weighted with the number of co-inventors. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 12. Results from panel negative binomial estimation - lower than 40 years of experience

VARIABLES	<i>novelty of inventor's output</i>		
	model 1	model 2	model 3
number of collaborators	-0.00295 (0.00721)	-0.000520 (0.00739)	-0.00338 (0.00760)
average strength of direct ties	-0.0413 (0.0348)	-0.0354 (0.0342)	-0.0328 (0.0342)
number of indirect connections	-0.00745*** (0.00157)	-0.0155*** (0.00195)	-0.0154*** (0.00194)
average strength of indirect ties	-0.168*** (0.0358)	-0.298*** (0.0411)	-0.291*** (0.0409)
current patent count	0.0679*** (0.00530)	0.0699*** (0.00525)	0.0698*** (0.00526)
previous patent count	-0.00198 (0.00236)	0.000157 (0.00243)	-0.000341 (0.00247)
experience	-0.00163 (0.00713)	-0.00846 (0.00707)	-0.00969 (0.00709)
first inventor	0.144* (0.0871)	0.139 (0.0871)	0.136 (0.0870)
single country	0.0966 (0.104)	0.0794 (0.103)	0.0708 (0.103)
single firm	0.147 (0.114)	0.210* (0.114)	0.206* (0.114)
technology residuals	0.208*** (0.0158)	0.239*** (0.0157)	0.243*** (0.0155)
brokerage	0.558*** (0.175)	-0.113 (0.179)	-0.928*** (0.304)
knowledge heterogeneity		2.904*** (0.192)	1.484*** (0.470)
brokerage # knowledge heterogeneity			2.595*** (0.782)
constant	-4.267*** (0.263)	-5.009*** (0.284)	-4.646*** (0.305)
year dummies	YES	YES	YES
number of observations	80,448	80,448	80,448
number of inventors	32,051	32,051	32,051

Notes: Dependent variables are inversely weighted with the number of co-inventors. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

**Table 13. Results from panel negative binomial estimation - lower than 40 years of experience
(considering knowledge heterogeneity based on hhi)**

VARIABLES	<i>novelty of inventor's output</i>		
	model 1	model 2	model 3
number of collaborators	-0.00295 (0.00721)	-0.00824 (0.00739)	-0.0110 (0.00752)
average strength of direct ties	-0.0413 (0.0348)	-0.0393 (0.0345)	-0.0376 (0.0344)
number of indirect connections	-0.00745*** (0.00157)	-0.0109*** (0.00174)	-0.0110*** (0.00174)
average strength of indirect ties	-0.168*** (0.0358)	-0.247*** (0.0386)	-0.245*** (0.0386)
current patent count	0.0679*** (0.00530)	0.0685*** (0.00525)	0.0683*** (0.00525)
previous patent count	-0.00198 (0.00236)	7.74e-05 (0.00238)	8.86e-05 (0.00240)
experience	-0.00163 (0.00713)	-0.00761 (0.00710)	-0.00846 (0.00710)
first inventor	0.144* (0.0871)	0.150* (0.0872)	0.149* (0.0871)
single country	0.0966 (0.104)	0.139 (0.103)	0.132 (0.103)
single firm	0.147 (0.114)	0.202* (0.114)	0.202* (0.114)
technology residuals	0.208*** (0.0158)	0.227*** (0.0155)	0.230*** (0.0153)
brokerage	0.558*** (0.175)	0.435** (0.173)	-2.524*** (0.815)
knowledge heterogeneity <small>hhi-based</small>		2.278*** (0.219)	0.358 (0.536)
brokerage # know. heterogeneity <small>hhi-based</small>			3.814*** (1.023)
constant	-4.267*** (0.263)	-6.155*** (0.329)	-4.738*** (0.485)
year dummies	YES	YES	YES
number of observations	80,448	80,448	80,448
number of inventors	32,051	32,051	32,051

Notes: Dependent variables are inversely weighted with the number of co-inventors. Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

APPENDIX 3

Appendix 3.A

Alternative cognitive proximity measurements

Three additional measurements are constructed as alternatives to the main cognitive proximity measure.

The first one, *cognitive proximity 2*, is a simple average of the cosine similarity of vectors as in the main measurement. However, the alternative version does not include vector dyads unless the focal inventor is one of the two. Again, the measurement is obtained on the basis of the past patenting portfolios of all network members, based on their inventions during the five years preceding the performance year. The technological expertise of each inventor in the network is described by a vector of length 650, where a cell describes whether an inventor uses a specific subclass. It equals 1 if the inventor uses the technology, else zero. The cognitive proximity is calculated as the average cosine similarity between the focal inventor's vector and the vectors of each other network member. The measurement does not capture the similarities between the network members and only considers the average cognitive proximity of local network members to the focal inventor. The alternative measure ranges from 0 (fully diverse network) to 1 (fully specialized network).

For the second one, *cognitive proximity 3*, Herfindahl-Hirschman Index (HHI) is used. HHI a common measure of market concentration (Matsumoto et al. 2012; Rhoades 1993). In my study the higher a network's knowledge concentration and specialization the higher the cognitive proximity within the network is. HHI takes value between 0 and 1. A value close to unity indicates strong technological concentration, the polar case being unity, where all the patents applied by members of a local network belong to one technological field. In other words, all collaborators have specialized in one technology and

do have the highest possible cognitive proximity. On the contrary, a value close to zero represents availability of a wide range of knowledge and lesser specialized technology expertise in the local network.

For instance, if a local network with 10 patents uses only one technology the HHI of this local network will be equal to $1 = (10/10)^2$. This first illustrated network is fully concentrated on one technology field, and the HHI will be equal to 1. An alternative example to this is a local network with, again, 10 patents use Technology 1 (T1), Technology 2 (T2) and Technology 3 (T3), respectively in 10, 6 and 4 of these 10 patents. In this case, the HHI of the illustrated local network would be $0.38 = ((10/20)^2 + (6/20)^2 + (4/20)^2)$. In this second illustrated network, there are many dominated technologies unlike in the first illustrated network which leads to a more cognitive distance among the local network members.

The last alternative measure, *cognitive proximity 4* of the variable let us distinguish the collaborators' common and unique knowledge and captures the level of cognitive proximity within focal inventor's local network. To construct the measurement, I used the generated technology vectors of each member of a given local network. Next, I measure the cosine similarity between each dyad in local network. Then, based on the knowledge similarities between pairs of vectors, a knowledge matrix for the full local network is created. These matrices let me capture the level of cognitive proximity of local network members more from a network perspective. In order to transform the information in such a matrix into a single measure I compute

$$cp_i = \sum_{j=1}^N \frac{\lambda * C_j}{N},$$

where i denotes the focal inventor, j runs over all other inventors in i 's local network, N is the size of the local network, C_j is the eigenvector centrality of inventor j in this network, and λ is the maximum eigenvalue of the matrix. I, then, standardize cp_i by dividing the maximum possible cognitive proximity in a network of given configuration. This is necessary for meaningful interpretation of estimation results.

Being that the results are robust to changes in measurement, I use the variable that is simpler and comprehensive enough to cover the compatibilities of all local network members' knowledge portfolios.

Novelty

According to previous studies, number of new combinations represents the extent to which an invention is novel (Fleming et al. 2007; Jung and Lee 2016; Verhoeven et al. 2016; Arts and Fleming 2018). Consistent with the literature, the number of new subclass pairs within each of a focal inventor's patents is used as a measure of *novelty* of inventor's output. For this, I identified the first appearance of a previously uncombined pair of subclasses in each patent. I assign the combinations as novel by comparing them with pairwise combinations appear in all previous patents in EPO database. I then summed this indicator measure for each pairwise combination of the focal inventor during the performance year. Although new combinations are taken as a measure of novelty, I check if there are patents with no new combinations but with single new technology. The descriptive analysis showed that only 3 out of all used patents (from 1995 to 2010) have included new and solo technological subclass. In the end, I am confident about the performance of the novelty measurement which relies on the number of new combinations.

Appendix 3.B

Table 14. Summary statistics and pairwise correlations

<i>Means, Standard deviations, N = 80 573</i>																		
Variables	Mean	S. D.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	
(1) global reuse	119884	229159	1															
(2) local reuse	70.41	273.41	0.44	1														
(3) cognitive proximity	0.60	0.24	0.22	0.07	1													
(4) brokerage	0.56	0.21	-0.04	0.08	-0.29	1												
(5) number of direct collab.	8.13	8.44	0.27	0.47	-0.17	0.36	1											
(6) number of indirect collab.	26.82	64.16	0.18	0.51	-0.14	0.14	0.58	1										
(7) avg. strength of direct ties	1.01	1.11	0.06	0.12	-0.07	0.25	-0.01	-0.01	1									
(8) avg. strength of indirect ties	1.02	1.01	0.09	0.19	-0.21	0.11	0.10	0.08	0.36	1								
(9) novelty	0.01	0.25	-0.01	0.00	-0.01	0.01	-0.01	-0.01	0.02	0.02	1							
(10) self-reuse	5.97	25.47	0.39	0.57	0.05	0.08	0.26	0.16	0.17	0.17	0.00	1						
(11) current patent count	3.31	4.18	0.29	0.41	-0.04	0.15	0.26	0.18	0.33	0.28	0.04	0.44	1					
(12) previous patent count	10.86	20.25	0.15	0.32	-0.15	0.34	0.53	0.30	0.43	0.26	0.00	0.20	0.34	1				
(13) experience	5.78	6.29	0.08	0.09	-0.12	0.23	0.24	0.11	0.13	0.08	0.00	0.06	0.10	0.34	1			
(14) first inventor	0.33	0.36	-0.07	-0.06	-0.03	0.21	-0.06	-0.06	0.10	-0.01	0.01	-0.01	0.02	0.06	0.04	1		
(15) single country	0.81	0.34	-0.10	-0.14	0.02	0.10	-0.18	-0.21	0.13	0.05	0.00	-0.04	-0.01	0.00	0.02	0.08	1	
(16) single firm	0.85	0.30	-0.01	0.05	0.00	0.12	-0.01	0.04	0.09	0.08	0.00	0.03	0.05	0.06	-0.02	0.04	0.08	
(17) forward citation	7.46	17.7	0.11	0.14	0.01	0.03	0.10	0.10	0.02	0.02	0.01	0.13	0.28	0.07	-0.01	0.00	-0.08	0.02

Appendix 3.C

Success of broker's ideas within whole network

Whole network represents the entire network that captures every single inventor, and it does not apply a limitation to the social distance between the focal inventor, namely broker, and any other inventor. In a network that consists of all active inventors without questioning their distance to the focal inventor, having high-intensity connections, that is observed within cohesive networks, is emphasized to provide the following advantages to increase the success of the broker's ideas. First, inventors' engagement with one another directly is higher in cohesive networks and conducive to a more seamless diffusion of generated ideas. Second, the members of non-sparse networks are assumed to be more likely to possess highly overlapped knowledge which makes it easier to learn diversifying information through frequent interactions. Therefore, by agreeing with proponents of cohesive networks, the study build on the assumption that inventors' ideas are more likely to be useful for others if they are embedded in cohesive networks. Consequently, the baseline hypothesis I tested is:

Baseline hypothesis: *The higher an inventor's brokerage level, the less the inventor's ideas will be successful (i.e., being reused and being cited by others) within whole networks.*

In addition to the opposing views about the influence of sparse network structure, counterparties provide non identical perspectives in terms of innovation success. Here, there is no harm to emphasize the differences between using an idea to take inspiration for future inventive activities and using the generated combination in an exact way by replicating it. The latter requires an excellent understanding of the generated technology combination to be able to use it in another context. To do so, inventors need to know the generated combinations very well and be able to refine them to solve new problems and develop novel applications. Even though there are remarkable studies on the success of individual's ideas such as Fleming et al. (2007), the influence of being a broker still remains unclear and cannot be generalized for all contexts.

In addition to this generalizability issue, it is worthwhile to investigate the consistency of its effect for multiple facets of innovation usefulness (i.e., innovation success). And last, studies focusing on the innovation success and the influence of being a broker generally do not question whether the knowledge content of a brokered network is non-redundant or whether disconnected actors have different fields of expertise.

Global reuse

To measure the reuse by global network members of a given year, I consider all patent applications by the focal inventor in a particular performance year and scrutinize the reuse of inventor's combinations by others. Networks that contain all active inventors appear in European Patent Office worldwide patent statistical database are referred to as *global* or *whole networks*. Naturally, global network members can be at any social distance to focal inventor. Those members are the inventors who have a patent(s) in the five years following the performance year, therefore, have a chance to reuse focal inventor's combinations. I simply name this variable as *Global Reuse*.

As a matter of fact, the estimator's performance begged for robustness analyses. Moreover, considering the alternative perspectives of innovation success (i.e., citing versus replicating the generated combinations) I see an added value for an alternative and very well-established proxy of usefulness of generated combinations. Therefore, I construct an alternative variable to use as a robustness check for reuse of inventor's ideas by global network members. The variable considers future citations to the focal inventor's patents of a given year. The variable is named as *forward citations*. It considers all patents applied by the focal inventor in a particular performance year and scrutinizes forward citations received by these patents. Forward citation count is another accepted measure of invention's reuse (Harhoff et al. 1999; von Wartburg et al. 2005; Perry-Smith and Mannucci 2017). The variable is again measured over the five years following the patent application date.

Results

In order to build analyses, I estimate two models respectively. To test the reuse of inventor's combinations by all active network members (i.e., *forward citation* and *global reuse*) I begin with Model 1, which highlights the link between the focal inventor's level of brokerage and the reuse by the whole network. This model includes brokerage and control variables including the novelty of the inventor's output, as well as technology residual variables and year-fixed effect. In the next stage, Model 2 appends a stand-alone cognitive proximity term to Model 1. Although I do not question the relationship between cognitive proximity and reuse³⁹, its inclusion in the second model creates an added value for the sake of interpreting the influence of network structure by decoupling the assumed knowledge benefits of brokerage. Therefore, second models are used for hypothesis testing.

Table 15 reports the regression coefficient estimates for variable of interests across all models explaining the reuse of focal inventor's ideas by whole network members. The results from Model 2s provide similar and strong evidence aligned with the literature showing that having disconnected contacts decreases the likelihood of the reuse of broker's combinations. Literature provides opposite insights on the brokered networks' influence on alternative reuse measurements tested in this study. Although the coefficients of brokerage are qualitatively consistent starting from Model 1, once the distinction between broker's *assumed*

³⁹ The study does not choose to measure the global member's cognitive proximity or observe its moderation on the analyzed mechanism. This is due to the fact that the global network constructed based on EPO database provides 1 global network of active thousands of inventors. Therefore, first, it is obvious that the knowledge matrix could not provide a good output because a massive number of inventors would create too much convergence among their knowledge vectors. Second, I could have only 1 cognitive proximity measurement for this whole network which consists of all analyzed local networks. And addition of an interaction variable with a constant value of cognitive proximity could not be a valid approach and more importantly would not change the conclusion of my results.

knowledge advantages and its structural influence is made, the significance of coefficients increases for *Forward Citation Count*. Therefore, the study is convincing enough to conclude that regardless the broker's strategic advantages relying on assumed knowledge heterogeneity access, his or her limited interactions decreases the reuse of his or her combinations by inventors placed in anywhere in the whole network. As proponents of closed networks argue, sparseness of broker's network prevents the emergence of trusting environment, decelerate the knowledge flow, and hinder others from realizing previously used combinations. The study claims that this is not about the common language or ability to understand each other's ideas as well as bias against novelty because it controls for the broker's collaborators' cognitive proximity and the novelty of their ideas.

Table 15. Reuse of inventor's output by global network members

VARIABLES	<i>forward citation count</i>		<i>global reuse</i>	
	model 1	model 2	model 1	model 2
number of collaborators	-0.00955*** (0.000824)	-0.00956*** (0.000825)	-0.0270*** (0.000754)	-0.00351*** (0.000645)
average strength of direct ties	-0.0734*** (0.00546)	-0.0733*** (0.00546)	-0.164*** (0.00544)	-0.160*** (0.00588)
number of indirect connections	6.27e-05 (8.46e-05)	5.81e-05 (8.53e-05)	0.000642*** (2.52e-05)	0.000940*** (2.29e-05)
average strength of indirect ties	-0.0704*** (0.00493)	-0.0709*** (0.00507)	-0.170*** (0.00508)	-0.0930*** (0.00535)
current patent count	0.0326*** (0.000779)	0.0326*** (0.000780)	-0.00274*** (0.00101)	0.0115*** (0.000642)
previous patent count	0.000346 (0.000327)	0.000348 (0.000327)	0.0145*** (0.000193)	0.00864*** (0.000198)
experience	-0.0160*** (0.000926)	-0.0161*** (0.000927)	-0.0429*** (0.00103)	0.00902*** (0.000729)
first inventor	-0.0196* (0.0116)	-0.0195* (0.0116)	-0.0441*** (0.0111)	-0.0430*** (0.0122)
single country	-0.0403*** (0.0127)	-0.0401*** (0.0127)	-0.686*** (0.0108)	-0.630*** (0.0122)
single firm	0.0230* (0.0139)	0.0231* (0.0139)	-0.710*** (0.0116)	-0.633*** (0.0129)
technology residuals	0.0106*** (7.95e-05)	0.0106*** (7.95e-05)	2.57e-06*** (1.35e-08)	2.70e-06*** (1.34e-08)
self-reuse	-0.001518*** (0.0000112)	-0.00341*** (0.000016)	-0.0149182*** (0.000214)	-0.001527*** (0.00012)
novelty	0.0673*** (0.0117)	0.0673*** (0.0117)	0.0838*** (0.0123)	0.0801*** (0.0124)
cognitive proximity		-0.0117 (0.0240)		1.724*** (0.0282)
brokerage	-0.0437* (0.0229)	-0.0464** (0.0236)	-1.165*** (0.0220)	-0.705*** (0.0240)
constant	-0.148*** (0.0317)	-0.149*** (0.0318)	2.255*** (0.0208)	1.477*** (0.0223)
year dummies	YES	YES	YES	YES
number of observations	80,573	80,573	80,573	80,573
number of inventors	32,092	32,092	32,092	32,092

Note: Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Appendix 3.D

Table 16. Reuse of inventor's output by local network members

VARIABLES	<i>local reuse</i>		
	model 1	model 2	model 3
number of collaborators	0.00900*** (0.000637)	0.00901*** (0.000637)	0.00887*** (0.000632)
average strength of direct ties	-0.000362 (0.00514)	-0.000236 (0.00514)	-0.00113 (0.00514)
number of indirect connections	0.000319*** (4.78e-05)	0.000316*** (4.81e-05)	0.000357*** (4.80e-05)
average strength of indirect ties	0.103*** (0.00470)	0.102*** (0.00473)	0.101*** (0.00475)
current patent count	0.0176*** (0.000645)	0.0176*** (0.000645)	0.0175*** (0.000643)
previous patent count	-0.000651*** (0.000184)	-0.000655*** (0.000184)	-0.000514*** (0.000183)
experience	-0.000422 (0.00113)	-0.000426 (0.00113)	3.93e-05 (0.00113)
first inventor	-0.111*** (0.0173)	-0.110*** (0.0173)	-0.108*** (0.0173)
single country	-0.293*** (0.0180)	-0.292*** (0.0180)	-0.289*** (0.0180)
single firm	0.0654*** (0.0210)	0.0658*** (0.0210)	0.0632*** (0.0210)
technology residuals	0.000801*** (1.18e-05)	0.000802*** (1.18e-05)	0.000791*** (1.19e-05)
self-reuse	-0.000266*** (9.08e-05)	-0.000272*** (9.12e-05)	-0.000189** (9.13e-05)
novelty	0.0331** (0.0159)	0.0331** (0.0159)	0.0316** (0.0159)
brokerage	0.0801*** (0.0309)	0.0735** (0.0319)	-0.504*** (0.0756)
cognitive proximity		-0.0233 (0.0284)	-0.562*** (0.0701)
brokerage # cognitive proximity			0.977*** (0.116)
constant	-0.513*** (0.0385)	-0.496*** (0.0438)	-0.158*** (0.0592)
year dummies	YES	YES	YES
number of observations	80,573	80,573	80,573
number of inventors	32,092	32,092	32,092

Note: Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 17. Robustness checks for alternative cognitive proximity measurements –reuse of inventor's output by local network members

VARIABLES	<i>local reuse</i>		
	<i>alternative 1</i>	<i>alternative 2</i>	<i>alternative 3</i>
number of collaborators	0.00902*** (0.000636)	0.00840*** (0.000662)	0.00917*** (0.000637)
average strength of direct ties	-0.000619 (0.00513)	0.00696 (0.00506)	-0.000294 (0.00514)
number of indirect connections	0.000343*** (4.83e-05)	0.000234*** (4.95e-05)	0.000323*** (4.87e-05)
average strength of indirect ties	0.102*** (0.00473)	0.0838*** (0.00501)	0.0993*** (0.00479)
current patent count	0.0176*** (0.000641)	0.0178*** (0.000652)	0.0175*** (0.000646)
previous patent count	-0.000556*** (0.000183)	-0.000573*** (0.000185)	-0.000550*** (0.000183)
experience	-4.56e-05 (0.00113)	-0.000921 (0.00110)	6.46e-05 (0.00112)
first inventor	-0.108*** (0.0173)	-0.0895*** (0.0171)	-0.106*** (0.0173)
single country	-0.290*** (0.0180)	-0.242*** (0.0177)	-0.284*** (0.0180)
single firm	0.0637*** (0.0210)	0.0946*** (0.0206)	0.0641*** (0.0210)
technology residuals	0.000792*** (1.19e-05)	0.000831*** (1.19e-05)	0.000797*** (1.19e-05)
self-reuse	-0.000201** (9.13e-05)	-0.000412*** (9.24e-05)	-0.000237*** (9.15e-05)
novelty	0.0322** (0.0159)	0.0269* (0.0161)	0.0315** (0.0160)
brokerage	-0.414*** (0.0820)	-0.307*** (0.0485)	-0.813*** (0.104)
cognitive proximity	-0.418*** (0.0702)	-2.389*** (0.0976)	-0.874*** (0.0856)
brokerage # cognitive proximity	0.786*** (0.120)	1.111*** (0.174)	1.164*** (0.137)
constant	-0.240*** (0.0607)	0.00251 (0.0442)	0.162** (0.0757)
year dummies	YES	YES	YES
number of observations	80,573	80,573	80,573
number of inventors	32,092	32,092	32,092

Note: Standard errors in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

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