Research Policy 54 (2025) 105030

Contents lists available at ScienceDirect

Research Policy

journal homepage: www.elsevier.com/locate/respol

How symmetry between intrafirm knowledge and collaboration structures influences exploratory innovation under conditions of combinability

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A R T I C L E I N F O

Keywords:
Symmetry
Exploratory innovation
Intrafirm collaboration structure
Intrafirm knowledge structure
Combinability

A B S T R A C T

We examine how symmetry between intrafirm knowledge and collaboration structures influences firms' exploratory innovation performance. Symmetry means that the inventors' collaboration structure mimics their knowledge structure, implying that inventors with similar domain knowledge collaborate, whereas inventors with dissimilar domain knowledge do not. We argue and show that intrafirm symmetry is the commonly used form by most firms, as it is intuitive and pays off on average. However, it also comes with an inherent risk for their exploratory innovation performance. To address this, we include a key condition of a firm's technological environment: the ease or difficulty with which its knowledge domains can be combined. Based on a sample of 170 publicly traded semiconductor firms over 23 years, we find a positive association between the symmetry of a firm's collaboration and knowledge structure and its exploratory innovation performance under average combinability. This relationship changes when firms operate under low or high combinability conditions. Both these conditions favor firms that deviate from symmetry by relying on a parallel, isolated configuration or multidisciplinary configuration. Our contribution to the literature lies herein that we show when firms and their managers should pay attention to stimulating and optimizing collaboration, as has been the dominant focus until now, but also, and equally important, when disbanding this standing collaboration among inventors is more effective for a firm's exploratory innovation. Most firms overlook the risk that comes with a symmetric configuration under conditions of low or high combinability and are better off instead through one of two less common, asymmetric configurations of their inventor collaboration and knowledge structures.

1. Introduction

A firm's ability to generate exploratory innovations is at the heart of firm survival, as being skilled in experimentation, risk-taking, and discovery enables it to explore new knowledge domains and renew itself over time (March, 1991). To understand what drives the ability to generate exploratory innovations, a growing body of literature examines the role of intraorganizational collaboration. This literature primarily examines how intrafirm collaboration structures influence the exploratory behavior of inventors (Fleming et al., 2007a; Wang et al., 2014; Yan et al., 2020) and firms (Carnabuci and Operti, 2013; Nan, 2024; Paruchuri and Awate, 2017). A concurrent strand of literature examines how intrafirm knowledge structures such as knowledge decomposability (Yayavaram and Ahuja, 2008; Zakaryan, 2023) or structural knowledge network features (Brennecke and Rank, 2017; Carnabuci and Operti, 2013; Wang et al., 2014) influence exploration.

Despite their different foci, both literatures share the common assumption that a firm's inventors are connected through direct and/or indirect collaboration, which is beneficial for exploration. Following this, the main focus is on optimizing these collaboration and knowledge structures through, for example, structural holes, centrality and/or internal embeddedness (Schillebeeckx et al., 2019; Wang et al., 2014), inventor network connectedness or embeddedness (Brennecke and Rank, 2017; Schillebeeckx et al., 2020), or nearly decomposable knowledge structures (Yayavaram and Ahuja, 2008). Yet, in this way, these literatures ignore the idea that connectivity and collaboration can also hinder innovation. High levels of collaborative integration at the firm level (Carnabuci and Operti, 2013) or global cohesion of inventor networks (Guler and Nerkar, 2012) may potentially harm exploration. This suggests that more connectivity and collaboration is not always a

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https://doi.org/10.1016/j.respol.2024.105030
Received 24 April 2021; Received in revised form 9 May 2024; Accepted 10 May 2024
Available online 6 December 2024

good thing but that *less or even a lack* of collaboration can sometimes benefit exploration as well.[1] This raises the question of when it is effective to stimulate collaboration among inventors and when it is more effective to foster isolation? This question may seem counter-intuitive at first, but it is essential as it takes a fundamental step back and goes beyond the dominant focus on optimizing inventor collaboration by questioning the need to stimulate connectivity and/or optimize collaboration in the first place.[2] Addressing this key question helps us understand when firms and their managers should pay attention to stimulating and optimizing collaboration, as it has been the dominant focus until now, but also, and equally important, when disbanding this standing collaboration among inventors is effective for a firm's exploratory innovation.

The key to answering this question lies in unearthing the implicit assumption made in both strands of literature that the collaboration structure is symmetric to a firm's knowledge structure (e.g., Guler and Nerkar, 2012) and vice versa (e.g., Yayavaram and Ahuja, 2008). Symmetry means that a firm's inventor collaboration structure mimics its knowledge structure, implying that inventors with similar knowledge collaborate, whereas inventors with dissimilar knowledge do not. More recently, however, it has been argued that intrafirm knowledge and collaboration networks can be decoupled and are thus not necessarily symmetric (Brennecke and Rank, 2017; Wang et al., 2014). Relaxing this symmetry assumption between a firm's knowledge and collaboration structure is instrumental in understanding when collaboration is effective for exploratory innovation and when it becomes ineffective, demanding an asymmetric structure.

Let us illustrate this through a simple thought exercise and some practical examples. Symmetry means inventors who work in the same knowledge domain collaborate on an innovation project within a firm, whereas inventors with dissimilar knowledge do not. A key mechanism underlying the symmetry of collaboration and knowledge structure is that collaborating inventors with similar knowledge can quickly develop and share expert vocabularies, references, and information connections. This allows them to exchange knowledge efficiently and develop a mutual understanding (Ertug and Gargiulo, 2018), which furthers explorative innovation (Nooteboom et al., 2007). The same mechanism, however, also means that dissimilar inventors face difficulties when collaborating to create innovations, as it takes time and effort to exchange knowledge and develop a common understanding (Grant, 1996; Nooteboom et al., 2007). This leads to a common form of organization for innovation among many firms that we qualify as a symmetry of collaboration and knowledge structure, meaning that similar inventors collaborate, whereas dissimilar inventors do not.

Yet, there are also arguments that favor deviating from symmetry between collaboration and knowledge structure. For example, studies have demonstrated the merits of a more redundant configuration of similar specialists for innovation that do not collaborate (Caner et al., 2017; Nonaka, 1994), which can be effective for parallel search efforts within the *same knowledge domain* (Lazer and Friedman, 2007; Nonaka, 1994, 1990). Examples such as Google (Groysberg et al., 2009) and Microsoft (Beinhocker, 1999) draw from non-collaborating specialists from the same domain to foster exploration. Another asymmetric configuration is formed by dissimilar inventors who collaborate while specializing in *different knowledge domains*, while similar inventors do not collaborate. Spanning knowledge domains by specialists from different disciplines creates the potential for recombination, furthering exploration (Ben-Menahem et al., 2016). Examples include companies such as IDEO (Hargadon and Sutton, 1997) and the Santa Fe Institute (Fleming, 2004), well-known for collaboration among dissimilar experts.

Of course, firms do generally not fall within these extremes and are more likely to differ in the degree of symmetry, although most firms - as we will argue and show – are primarily biased towards symmetry of collaboration and knowledge structures. Therefore, we expect collaboration and knowledge structure symmetry to be the 'default' form. Yet, what both strands of literature have missed until now and where firms and their managers can go 'wrong' is the inherent risk with a symmetric configuration and that an asymmetric configuration – although seemingly counter-intuitive – can also be highly effective for exploratory innovation. To study this, we take a firm-level perspective as this enables us to disentangle analytically to what degree firms differ in their internal knowledge and collaboration structures and the differential implications this carries for their exploratory innovation performance. This enables us to understand to what degree collaboration among similar inventors benefits exploration (symmetry) and when this becomes ineffective. Moreover, we show when it becomes more effective to collaborate among dissimilar inventors (asymmetry) and when to have no collaboration among similar inventors (asymmetry).

To understand how these symmetric and asymmetric configurations of collaboration and knowledge structures differentially impact exploratory innovation, we include a key condition of a firm's technological environment: the combinability of knowledge domains. Building on a recombinant innovation perspective, we conceptualize innovation as recombining existing knowledge domains (Xiao et al., 2021; Yayavaram and Chen, 2015) and acknowledge that these knowledge domains differ in the ease with which these combine with other domains. The ease or difficulty with which knowledge domains can be combined is crucial for the more risky and uncertain search that exploration represents and influences both the benefits and risks of a specific configuration. Easy-to-recombine domains of technological knowledge demand a different configuration of knowledge and collaboration structure than medium- or difficult-to-combine domains.

Following this recombinant perspective, we theorize how symmetry offers a relatively limited degree of search diversity at the firm level yet effective enough for average combinability. However, this type of diversity falls short and must be adjusted when combinability increases or decreases. This can be accomplished by adjusting the configuration of a firm's knowledge and collaboration structure, by moving away from symmetry towards either of the two asymmetric configurations. As we argue and show, asymmetry through non-collaborating, similar inventors offer within-domain diversity that fits low combinability conditions, whereas asymmetry through collaborating dissimilar inventors offers across-domain diversity that fits high combinability. In this way, we show how different intrafirm knowledge-collaboration configurations impact firm exploratory innovation performance under different levels of combinability. We test our theoretical arguments on 170 publicly traded semiconductor firms over 23 years, drawing on data from

[1] Using network analytical vocabulary, most of the intrafirm's collaboration literature has examined how the connectivity within a firm's network structure's main component (i.e. the lion's share of nodes, such as inventors and their relations, such as collaborations) impacts innovation. This is also reflected in the popular idea of networks as 'small worlds', assuming that the network is fully connected (Baum et al., 2003). Yet, what has been overlooked in this way, is that some inventors are not connected to the main component, and can be qualified as 'isolates'. Or, alternatively, that a firm's network structure is composed of different components (Argyres et al., 2020). For example, a firm with one main component and also one or more isolated components formed by connected inventors that collaborate among themselves but are not linked to the main component, or to the other components (neither directly or indirectly).

[2] Whereas the literature has demonstrated clear benefits of collaboration, inspired by Granovetter (1973)'s seminal study on the strength of weak ties and Burt (1992)'s ideas on the advantage that accrues to individuals if they bridge unconnected groups, these are mostly individual level results. Yet, these advantages do not necessarily aggregate to the organization level (Carnabuci and Operti, 2013; Guler and Nerkar, 2012; Lazer and Friedman, 2007). Still, the value and emphasis placed on collaboration in organizational networks is rooted in the "idea that the more connected we are, the better: silos are to be eliminated, and the boundaryless organization is the wave of the future" (Hargadon and Sutton, 1997; Lazer and Friedman, 2007, p. 667; Phelps et al., 2012).

firms, inventors, and patents.

By introducing the construct degree of symmetry of inventors' knowledge and knowledge structures, we argue and show when the symmetry of collaboration between similar inventors is most effective, but also how most firms turn a blind eye towards its risks, which becomes especially salient under low or high degrees of combinability. Both conditions favor firms that opt for asymmetry by relying on different forms of collaboration or de-stimulating collaboration altogether. In this way, we contribute to the growing literature that so far emphasized how collaboration and knowledge structures independently affect exploratory innovation performance within firms (Carnabuci and Operti, 2013; Wang et al., 2014; Zakaryan, 2023). We contribute to these areas of the literature by showing why some firms innovate better without similar inventor collaboration (asymmetry) or through less common collaboration structures among its inventors (asymmetry), as well as why firms with similar internal inventor collaboration structures can still exhibit persistent differences in their exploratory innovation performance. These are issues that have remained unaddressed until now and have limited a more comprehensive understanding of how the interaction of a firm's collaboration and knowledge structure is associated with a firm's exploratory innovation performance and how this differs under different technological environments.

2. Theory

2.1. Collaboration structures, knowledge structures, and recombinant innovation

Recombination logic lies at the heart of innovation (Fleming, 2001; Rosenkopf and Nerkar, 2001; Schumpeter, 1934; Xiao et al., 2021). A firm and its inventors create innovations based on searching and recombining knowledge domains that may reside in the focal organization (Rosenkopf and Nerkar, 2001; Xiao et al., 2021). Prior work made the point that organizations consist of multiple layers, including a project-team layer (inventor networks in our paper) and a knowledge-base layer (knowledge structure in our paper), and that these different layers jointly affect knowledge creation (Nonaka, 1994, 1990). Despite their early idea, two different strands of literature, one with a focus on collaboration and network structures of inventors and the second one with a focus on knowledge structures of inventors, have developed in isolation from each other with a few exceptions (e.g., Wang et al., 2014 at the individual level).

The first literature has emphasized that firms vary in collaboration and network structures among inventors, with consequences for their recombinant search activities and their ability to generate innovations (Carnabuci and Operti, 2013; Guler and Nerkar, 2012). The second literature has emphasized that firms vary in their knowledge structure and shows how the variation of internal knowledge patterns influences firms' ability to generate valuable innovations (Brennecke and Rank, 2017; Yayavaram and Ahuja, 2008; Yayavaram and Chen, 2015). In this context, Yayavaram and Ahuja (2008, p. 338) claim: "patterns in individual interactions would be reflected in the patterns of couplings of knowledge elements in which the individuals or the research units have expertise", implying that a firm's knowledge and collaboration structure may follow the same organizing principle and mirror each other. This implicit assumption also underlies most prior studies, namely that inventors with similar knowledge collaborate, whereas inventors with dissimilar knowledge do not (e.g., Guler and Nerkar, 2012), and vice versa (e.g., Yayavaram and Ahuja, 2008). More recently, however, it has been argued that these structures can be decoupled and may not necessarily be symmetric (Brennecke and Rank, 2017; Wang et al., 2014). Therefore, we relax this symmetry assumption and follow recent research showing that knowledge and collaboration structures within a firm need not be similar (Guan and Liu, 2016; Wang et al., 2014).

In line with this idea, we complement the literature on collaboration structures, from which we use the construct of collaboration distance, with the one on knowledge structures these inventors operate in (Brennecke and Rank, 2017), and use the construct of knowledge distance among inventors. By combining knowledge distance with collaboration distance among inventors, we introduce the construct of symmetry that indicates to what extent firms differ in their inventors' internal knowledge and knowledge structures and the differential implications this carries for their exploratory innovation performance.

2.1.1. Baseline: Symmetry between inventor collaboration and knowledge structures

For theorization purposes, we discuss three intrafirm configurations whereby we acknowledge that 'pure' symmetric or asymmetric configurations are exceptional and, in practice, more a matter of degree, in line with our measurement of the degree of symmetry along a continuum.

We start our theorization by discussing a configuration in which inventors of an organization are symmetrical in the firm's internal knowledge and collaboration structure. In such a situation, inventors with similar knowledge collaborate, whereas inventors possessing dissimilar knowledge do not collaborate or only to a limited degree. Due to cognitive proximity, inventors with similar knowledge find it generally easy to understand each other's language and expertise (Boland and Tenkasi, 1995; Nooteboom et al., 2007). By operating in the same domain, the similarity between inventors yields more cooperation, trust, and social cohesiveness (Harrison et al., 2002; Locke and Horowitz, 1990), enhancing an 'in-group' orientation. Such an in-group orientation also means a stronger focus on the inventor's domain knowledge and serves the build-up of a common, specialized language and shared cognition that supports their knowledge exchange (Boland and Tenkasi, 1995; Cohen and Levinthal, 1990; Lawrence and Lorsch, 1967). Consequently, knowledge similarity eases communication, speeds up mutual understanding, and facilitates the subsequent build-up of knowledge-based trust (Gulati, 1995). Trust facilitates collaboration among inventors, contributing to knowledge transfer success (Szulanski, 1996) and supporting them in their exploration of domains new-to-the firm.

The process of recombinatory search for exploratory innovation is uncertain and executed by boundedly rational inventors who are guided by their experience of prior accumulated knowledge (Fleming, 2001; Fleming and Sorenson, 2004). Because of this, firms tend to search in the vicinity of what they already know (Levinthal and March, 1993). This means that when inventors search new-to-the-firm domains, which is riskier and more uncertain, they predominantly search for new combinations in related domains at the expense of searching into distant, unrelated domains (Nelson and Winter, 1982; Tushman and Anderson, 1986). This makes firms search primarily through inventors that specialize and work together with inventors with similar expertise. This builds on the idea that a deep, specialized understanding of a knowledge domain advances the knowledge frontier (Caner et al., 2017; Kaplan and Vakili, 2015; Taylor and Greve, 2006).

Yet, firms also have to infuse novelty when searching for new domains. This requires some inclusion of more distant domains through collaboration with inventors who are dissimilar from these domains but on a limited scale. This builds on the notion that diverse perspectives promote exploration (Hargadon and Sutton, 1997; Kaplan and Vakili, 2015). Combining these contrasting perspectives – the role of local, related domain search versus distant, unrelated domain search –implies a predominantly symmetric configuration. Such a configuration is rooted in the idea that inventors with similar knowledge collaborate and simultaneously allow room for limited collaboration with relatively dissimilar inventors (Boland and Tenkasi, 1995; Hoever et al., 2012). Together, symmetry hits the sweet spot of mutual understanding and novelty that benefits the exploration of domains new to the firm (Nooteboom et al., 2007).

Therefore, we expect as a baseline that a configuration of symmetry of collaboration and knowledge structure – meaning inventors with similar knowledge collaborate, whereas inventors with dissimilar knowledge do not or only to a limited extent – positively impacts its exploratory innovation performance. This suggests the following baseline hypothesis:

Baseline Hypothesis 1. Symmetry between the intrafirm inventor collaboration and knowledge structure is positively associated with a firm's exploratory innovation performance.

2.1.2. Risks of symmetry for exploration innovation: Combinability as moderator

Although symmetry can pay off for firms, on average, this configuration has a risk too. A symmetric configuration comes with a strong in-group orientation among similar collaborating inventors. This brings along the risk that they perceive inventors from other domains as less relevant, trustworthy, or cooperative (Stephan and Stephan, 1985; Tsui et al., 1995) and feeds the development of stereotypes and prejudices (Boland and Tenkasi, 1995; Milliken and Martins, 1996). Inventors from different knowledge domains not only find it difficult to share ideas but also tend to view one another's central issues of expertise and interests as esoteric or even meaningless (Boland and Tenkasi, 1995; Brown and Duguid, 1991). This observation resonates with the social categorization literature findings that group diversity negatively affects cross-group processes and performance (McGrath and Gruenfeld, 1993; Milliken and Martins, 1996).

As a consequence, a symmetric configuration increases both cognitive and social barriers to the build-up of mutual understanding across different inventor groups and severely inhibits the process of reaching out to and incorporating the perspectives of inventors from distant domains, which makes their knowledge recombination more difficult (Boland and Tenkasi, 1995; Carnabuci and Operti, 2013; Milliken and Martins, 1996). Hence, the symmetry of collaboration and knowledge structures of inventors carries the risk of driving a vicious feedback loop, where collaboration among similar inventors feeds out-group biases, further strengthening their in-group orientation, and so on. Such a vicious loop can stifle communication and knowledge exchange across groups of knowledge-distant inventors. As a consequence, a symmetric configuration diminishes inventors' motivation to invest time and energy into negotiating shared meaning and reconciliation of differences in meanings (Carlile, 2002; Grant, 1996; Yayavaram and Chen, 2015), which may negatively affect a firm's exploratory innovation performance.

This risk of symmetry is amplified or attenuated by a key environmental condition, namely technological combinability. Technological combinability builds on a recombinant innovation perspective and suggests that technological knowledge domains differ in the ease with which these can be combined with other domains (Fleming and Sorenson, 2004; Yayavaram and Chen, 2015). Low combinability refers to a situation where a firm will find it challenging to recombine a particular knowledge domain, as this has not or seldom occurred in the universe of recombinations. In contrast, high combinability means a technological environment where the recombination of knowledge domains has often occurred in the universe of recombinations, and the number of available recombinations becomes depleted. This ease or difficulty is especially relevant given the uncertain search process that the exploration of new domains involves and influences both the effectiveness and risk of a symmetric configuration.

Our baseline hypothesis assumes, ceteris paribus, average combinability. Average combinability implies that knowledge components have already been combined before by the 'universe' of firms and inventors (Yayavaram and Chen, 2015). Already combined domains ease communication and speed up the building of mutual understanding among similar inventors, yet it may come at the expense of collaboration and knowledge exchange among dissimilar inventors. This suggests that average combinability fits a symmetric configuration and mitigates its risk. However, the risk of symmetry dramatically increases when combinability is either low or high. Under both conditions, we expect that firms with a configuration that deviates from the symmetry of both structures will be better positioned to explore successfully, enabling them to create the type of search diversity needed. The lack of symmetry between collaboration and knowledge structures may express itself in different configurations that we again discuss for theorization purposes. *Parallel, isolated perspectives* is one archetype where a firm creates within-domain diversity by means of a configuration of non-collaborating inventors who possess similar knowledge, which fits low combinability. *Creative leaps* is the other archetype where a firm creates across-domain diversity by collaborating inventors with dissimilar knowledge, which fits high combinability. We discuss each in turn.

2.1.2.1. Asymmetrical configuration of non-collaborating, similar inventors: Parallel, isolated perspectives. Low combinability means that knowledge domains have never been combined before or only a few times. Such a technological environment is highly differentiated, meaning a low degree of coherence among these different domains, which makes them difficult to combine for exploratory innovation. An example is the very early stage of a newly emerging technology or product life cycle, like the 'era of ferment' (Anderson and Tushman, 1990; Tushman and Anderson, 1986). This phase is characterized by many newly emerging designs that yield a high degree of technological uncertainty due to the low degree of combinability of the technological environment. Here, a symmetric configuration offers too limited search diversity as a firm must be able to evaluate many possibilities for recombining knowledge domains and conduct a trial-and-error search to assess their potential value (Dosi, 1982; Gilsing and Nooteboom, 2006). Deviating from symmetry through non-collaborating inventors with similar knowledge creates the necessary within-domain diversity through two mechanisms.

First, a firm with a configuration of non-collaborating, similar inventors can be seen as an intrafirm structure with relatively independent inventors who process information and solve problems in a particular domain in parallel (Lazer and Friedman, 2007). The parallel nature of such an intrafirm structure provides two distinct advantages. First, parallel sets of inventors with similar expertise can process large amounts of information (Sandelands and Stablein, 1987) and spend more time on solving problems in a specific domain (Streeter, 1992) to move the knowledge frontier. This increased capability allows inventors to explore more alternatives or alternate routes for problem-solving (Streeter, 1992), elevating the volume of exploratory solutions. To illustrate this, Nonaka (1994, 1990) refers to encouraging internal rivalry and competition among Japanese product development teams in which managers "divide the product-development team into competing groups that develop different approaches to the same project and then argue over the advantages and disadvantages of their proposals" (Nonaka, 1994). So, a configuration of parallel sets of inventors with similar expertise can enhance exploratory innovation through an evolutionary process of internal variation, selection, and retention of methodologies or knowledge within the organization (Birkinshaw and Lingblad, 2005; Galunic and Eisenhardt, 2001). This enables a firm to engage in trial-and-error search when exploring domains that are new-to-the firm.

Second, this configuration also enables a firm to maintain isolated perspectives by avoiding the natural convergence of its members as a product of the close exchange of knowledge (Lazer and Friedman, 2007). The isolation of sub-groups within the organization favors the preservation of alternative perspectives, even though the sub-groups have similar fields of expertise (i.e. "bisociation" cf. Zahra and George, 2002). When similar inventors do not collaborate but search separately, this attenuates the risk that their shared mental models and cognitive filters ignore or fail to recognize the value of their new findings, in contrast to established R&D teams of similar inventors that may be quicker to resist or reject unfamiliar, new combinations that conflict with their dominant beliefs (Ahuja and Lampert, 2001; Yayavaram and Chen, 2015). This enables non-collaborating inventors to deeply understand how their specific recombination of knowledge components performs (Kaplan and Vakili, 2015).

As a result, this configuration offers more capacity for search and reduces the risk of cognitive myopia, elevating both the number of exploratory solutions and their novelty value. Multiple related approaches to finding a solution or a design can help when technologies lack combinability and where a configuration of isolated inventors with similar expertise enables a firm to search in a fragmented, differentiated technological environment (Caner et al., 2017; Kaplan and Vakili, 2015). This allows a firm to consider many similar alternatives (Rhee and Kim, 2015), providing different but related interpretations for emerging opportunities. Still, the similar specialization of inventors ensures an in-depth understanding of recombination choices. Thus, a configuration that deviates from symmetry in which inventors with similar knowledge work independently, yet in parallel, offers the within-domain diversity to support a firm when recombining in a technological domain with low combinability.

2.1.2.2. Asymmetrical configuration of collaborating inventors with dissimilar knowledge: Creative leaps. In contrast, high combinability means a technological environment where the recombination of knowledge domains often occurs in the 'universe' of recombinations. In such a technological environment, different technological domains are easy to recombine. To explore effectively then, a different form of diversity is required, namely one that enables a firm to take a multidisciplinary approach building on intrafirm structures of dissimilar expertise. Multidisciplinarity is the dominant approach to developing innovations by going beyond the established order through 'thinking out of the box' and looking for technical solutions beyond the status quo. This is, for example, at the end of the era of 'incremental change' of a technology or product life, with growing indications of exhaustion as the potential for further refinements gets depleted because most combinations have been tried, whereas the number of untried combinations declines (Anderson and Tushman, 1990; Candiani et al., 2022; Dosi, 1982; Fleming, 2001; Tushman and Anderson, 1986). Or, when an established community of inventors accepts or sees a particular recombination as mature and fails to consider new architectures or opportunities for untried applications (Ahuja and Lampert, 2001; Fleming, 2001; Henderson, 1995). Here, long 'knowledge jumps' are required to push the innovation frontier (Adner and Levinthal, 2002; Fleming, 2001; Gilsing and Nooteboom, 2006; Tushman and Anderson, 1986). Deviating from symmetry through collaboration among dissimilar inventors creates the necessary across-domain diversity.

A configuration of collaborating inventors with dissimilar knowledge offers a company access to heterogeneous bodies of knowledge and expertise possessed by inventors who jointly engage in problem-solving and recombination (Ben-Menahem et al., 2016). In this case, the firm can draw on disparate knowledge and expertise to create novel recombinations of knowledge elements (Fleming, 2001; Hargadon and Sutton, 1997; Rodan and Galunic, 2004). Diversity in internal knowledge sources fosters the organization's ability to choose among different technological paths to solve technological problems (Katila and Ahuja, 2002). Accessing and using these heterogeneous internal members allows the organization to recombine unrelated technological elements (Laursen, 2012; Van Der Vegt and Bunderson, 2005). When there is high combinability, the number of opportunities for recombination quickly depletes, making those marginal changes to the knowledge domains involved in the recombination lead to marginal changes in overall performance. Thus, the firm will have to make large jumps. Knowledge diversity among collaborating inventors facilitates a firm to engage in creative leaps necessary for exploring new knowledge areas (Amabile, 1996; Rodan and Galunic, 2004) and spot opportunities that move beyond the status quo.

Having disparate ideas in-house, in close social proximity, allows the organization to make such leaps. The variety of 'thought worlds' stemming from knowledge diversity challenges established cognitive schemas and cause-effect understandings, which offers insights to adjust and broaden these and, in this way, enables firms to identify new opportunities for more creative combinations (Dougherty, 1992). Such a configuration increases the probability that a different approach to solving a given technological problem will emerge or new opportunities are identified that have been filtered or ignored by inventors' established mental models (Ahuja and Lampert, 2001).

So, the second archetypical configuration deviating from symmetry in which dissimilar inventors collaborate, offers the cross-domain diversity through creating diverse perspectives among collaborating inventors (Hargadon and Sutton, 1997; Kaplan and Vakili, 2015). This configuration supports a firm when recombining under high combinability, as it offers the opportunity for major leaps out of the existing status-quo. In sum, this means that deviation from the symmetry of collaboration and knowledge structures benefits innovation under low and high combinability conditions, as it enables a firm to elevate the degree of diversity and adjust it into a more effective type. This implies that sticking to the default symmetry configuration between collaboration and knowledge structure, with its lower type of diversity than either of the two asymmetric forms, becomes a liability for a firm's exploratory innovation performance. Hence, our baseline prediction of the more common symmetrical configuration between a firm's collaboration and knowledge structure and its positive relationship with innovation is negatively moderated when firms explore under low or high combinability conditions. We, therefore, posit the following hypothesis:

Hypothesis 2. The positive association of symmetry between the intrafirm inventor collaboration structure and knowledge structure and a firm's exploratory innovation performance is moderated by the combinability of a firm's technological environment in such a way that (a) a firm with collaborating inventors who possess dissimilar knowledge performs well under high combinability conditions and (b) a firm with non-collaborating inventors who possess similar knowledge performs well under low combinability conditions.

3. Data and methods

The longitudinal empirical setting used to test our hypotheses is the global semiconductor industry from 1980 to 2006. There are several reasons for this choice. The semiconductor industry is an innovative setting in which global companies patent their technologies with the United States Patent and Trademark Office (USPTO) and involves significant investment in corporate R&D (Carnabuci et al., 2015; Hall and Ziedonis, 2001; Lim, 2004; Yayavaram and Ahuja, 2008). Also, firms in the semiconductor industry compete in a dynamic technological environment (Yayavaram and Ahuja, 2008). Semiconductor products involve "hundreds of interwoven design and process steps" (Lim, 2004, p. 292). Finally, this sector has proven a valuable context for studying intrafirm knowledge (Yayavaram and Ahuja, 2008) and collaboration structures (Carnabuci and Operti, 2013; Guler and Nerkar, 2012).

We used the WRDS Compustat database to identify relevant semiconductor companies, which includes firms trading on the U.S. stock market. We selected SIC industry code 367 "Electronic Components and Accessories" firms and matched these firm records to NBER patent data using the global company key (GVKEY) (Hall et al., 2001). To identify inventors, we combined the NBER patent and citation data with Harvard Dataverse project data (Li et al., 2014). We consulted the USPTO online database on all relevant patents to obtain accurate information. We were careful to manually incorporate changes in ownership structures for the firms involved in our final sample.

Patents are used widely in innovation studies due to the detailed information on the inventions (Griliches, 1990; Savage et al., 2020). They describe the type of technology involved, relevant inventors, patent assignee, date of patent filing and granting, the prior art on which the patent builds, future inventions that build on the focal patent, and inventors' country of origin. This provides the necessary information to test our hypotheses. Our final sample consists of 170 semiconductor firms from 1984 to 2006.

3.1. Dependent variable

3.1.1. Number of explorative patents

We follow Gilsing et al. (2008) to measure firms' technological exploration. This measure relies on the patent classes linked to a firm's patents. Specifically, we measure the Number of Explorative Patents as the number of a firm's patents applied for in year t within patent classes it did not apply for in the previous five years (Gilsing et al., 2008).

3.2. Independent variables

3.2.1. Deviation from symmetry

As argued theoretically, deviation from symmetry describes the lack of symmetry between these knowledge and collaboration structures of a firm's inventors in orientation and magnitude. We take the following three steps to measure the extent to which the firm's knowledge and collaboration structures are symmetric versus asymmetric. First, we separately identified the firm's collaboration and knowledge structures. Whereas the collaboration structure refers to the internal collaboration network of inventors, the knowledge structure refers to a firm's internal structure of combinations among knowledge elements. Except the study by Wang et al. (2014), these two organizational dimensions are assumed to be symmetric in most network-related management and innovation literature. That is, the properties of knowledge similarity are implied by collaboration proximity and vice-versa. Second, we measure the distance between inventors in the collaboration network to characterize the firm's collaboration structure. This structure describes the set of inventors working for the firm during a three-year window and the collaborative ties among them based on the frequency of co-authorship of patents (Carnabuci and Operti, 2013; Fleming et al., 2007b; Guler and Nerkar, 2012). Prior research shows that co-patenting among inventors involves substantial technological interaction among them, even several years after a collaboration (Fleming et al., 2007a), and drives significant knowledge exchange among inventors (Carnabuci and Operti, 2013; Nerkar and Paruchuri, 2005; Singh, 2005; Sorenson et al., 2006). Third, we identify the knowledge structure as a *knowledge network* that describes the set of different technologies used by the firm during a three-year window and how these technologies are combined by the firm based on their co-occurrence in the firm's patents (Wang et al., 2014; Yayavaram and Ahuja, 2008; Yayavaram and Chen, 2015). We use the USPTO patent classification system to approximate knowledge components or technologies (Carnabuci et al., 2009), considering primary and secondary classifications (Wang et al., 2014; Yayavaram and Ahuja, 2008) at the first subclass level (main-line subclasses). Prior research shows that pairings among firm knowledge elements and the resulting network structure significantly influence invention value and firm performance (Fleming and Sorenson, 2001; Yayavaram and Ahuja, 2008).

Taken together, these three steps enable us to calculate the degree of deviation from symmetry of the intrafirm collaboration and knowledge network structures in the following way. We use the firm's knowledge and collaboration network to position its inventors. Following our theoretical model, firms can include inventors who are proximate to or distant from each other. The set of possible paths within these networks, and the frequency of co-invention or co-occurrence to weigh those paths, describe the distances among all the elements in each network. While inventors are the nodes in the collaboration network, the knowledge network consists of technological subclasses as nodes. Thus, we position inventors in the knowledge network according to their knowledge expertise. Specifically, we weigh the distances among technological subclasses drawn on by inventors during the previous three years based on their co-occurrence.

Distances among inventors along these two dimensions allow us to identify inventors who reduce the symmetry in the two structures. We first define perfect symmetry between the two structures as a positive correlation between distances on both structures, which cannot be increased by removing any component. Consequently, symmetry can be weakened by inventors disproportionately close to other inventors in one structure (i.e., knowledge or collaboration structure) compared to their distance in the other structure (i.e., collaboration or knowledge structure).

To measure the firm's deviation from symmetry, we calculate the average deviation from symmetry between collaboration and knowledge distances of those firm's inventors who reduce the symmetry. An inventor is considered to reduce the firm's symmetry if the correlation between distances among inventors increases when that inventor is removed from the set. Such inventors are disproportionally far from other inventors in one of the two structures compared to the other. Some inventors may display disproportionately large collaboration distances relative to their knowledge distances, or they may be disproportionately distant from other inventors in the knowledge structure relative to the collaboration structure.

The number of inventors in this situation, the direction of their deviation from symmetry, and the magnitude of each deviation describe the level and type of deviation from having symmetric structures. We average these inventor-level measurements at the organization level. For a firm f in year y with n inventors, we define the degree of deviation from symmetry as the average deviation of those inventors who decrease the symmetry weighted by the number of deviating inventors over the total number of the company's inventors, where d is distance, c is collaboration, k is knowledge, v is the number of inventors breaking symmetry, and V is the total number of inventors (*i,j*, and *a* are subscripts for operating with sums across the n inventors – for example, the sum on i of numbers from 1 to n, or such $i = 1, 2, \dots$ n is equal to $1 + 2 + .. + n$).

$$\text{Deviation from symmetry}_{f,y} = \frac{v_{f,y}}{V_{f,y}} \sum_a \frac{\sum_i \frac{\left(d^c_{a,i} - d^k_{a,i}\right)}{n}}{\#a}$$
$$\text{such that} \begin{cases} \text{corr}\left(d^c_{i\neq a,j\neq a}, d^k_{i\neq a,j\neq a}\right) > \text{corr}\left(d^c_{i,j}, d^k_{i,j}\right) \\ a, i, j = 1 \dots n \end{cases} \tag{1}$$

According to this measure, if no inventors reduce the symmetry (correlation), the degree of deviation from the symmetry of the organization is zero (i.e., it is symmetric). Our measure ranges theoretically from −1 (perfectly asymmetric organization in which dissimilar inventors collaborate with each other) to +1 (perfectly asymmetric organization in which similar inventors are isolated from one another), with zero referring to complete symmetry. Our measure characterizes an organization as showing a positive (negative) deviation from symmetry if some inventors are disproportionately far from (close to) others in the collaboration structure compared to their distance to other inventors in the knowledge structure. The measurement was tested with simulations and contrasted empirically with real organizational structures observed in our data sample.

3.3. Moderating variable

3.3.1. Combinability

To measure the level of combinability types of a firm's technological environment, we follow the approach of Yayavaram and Chen (2015) and Fleming and Sorenson (2001). Building on Yayavaram and Chen (2015)'s approach, we average the level of combinability of a firm's inventions. We measure the combinability of the technological environment *c* that a firm *f* navigates during year *y* as the average of the ease of combination ($E_{c,y}$) of the N_f technological subclasses linked to the firm inventions produced during the focal year weighted by the number of patents in each class ($n_{f,c}$) (eq. 2):

$$C_{f,y} = N_f \left(\sum_{c=1}^{N_f} E_{c,y} n_{f,c} \right) \quad (2)$$

A low score for C indicates that the focal firm generates inventions by combining technologies that are not often combined with any other (i.e. low combinability). A high score indicates that the focal firm focuses on technological subclasses, which tend to be used in combination with numerous others. We refer to this measure in the regression as *combinability,* and it indicates the easiness of different technologies to be combined and therefore the types of challenges that the firm faces when innovating. It is computed using the universe of patent data, and therefore, it can be considered exogenous to the firm (Yayavaram and Chen, 2015).

3.4. Control variables

We include a range of organizational-level control variables to specify the effects of the explanatory variables on innovation performance. We control the firm's technological experience using the total number of patents awarded to a firm before the focal year; this avoids concerns related to a firm's innovation capabilities (Carnabuci and Operti, 2013; Moreira et al., 2018). To account for the possibility that our main independent variable *deviation from symmetry* comes from a disproportionately high number of inventors in a narrow set of technological classes or vice versa, we include the ratio of *inventors/classes* as a control. We also control for the firm's *technological breadth* by calculating the Herfindahl index for the distribution of patents in technological subclasses. *Age* controls for the number of years since the firm's first patent (Carnabuci and Operti, 2013), and firm size is based on *sales* volume. We also control for the resources the firm assigns directly to R&D by calculating *R&D intensity* as the share of R&D expenses divided by the firm's total assets. Following the composite index approach in Tyler and Caner (2016), we control for *slack resources* since they might be to groups of similar inventors that search for solutions in parallel, which could be considered redundant. We measure firm *slack* as the sum of standardized available slack (ratio of current assets to current liabilities), absorbed slack (ratio of working capital to sales), and potential slack (ratio of equity to debt). We measure the firm's level of *geographical dispersion* using a Blau index based on share of inventors resident in a U.S. state or some other country using inventors' home addresses (Hannigan et al., 2015; Tzabbar and Vestal, 2015). Finally, the average *number of (patent) claims* in the firm's patent portfolio is included to control for the firm's strategy regarding patenting scope, which might affect innovation quality (Keijl et al., 2016; Lanjouw and Schankerman, 2004).

The descriptive statistics of the variables and their correlations are presented in Tables 1 and 2. Table 1 reports the correlations among the variables included in the regression analysis. Table 2 presents the means, standard deviations (SD), and minimum and maximum values of the variables. Note that our independent variable – deviation from symmetry – shows substantial variation with a mean of 0.039 and a SD of 0.043, with minimum and maximum values of −0.095 and 0.170. Fig. 1 shows the distribution of our main independent variable *deviation from symmetry*. This supports two key claims we put forward. Symmetry is the default, as most firms are organized around symmetry. That is, 954 observations of a total of 1397 observations fall within plus and minus one standard deviation range from the mean, which is 68 %. At the same time, substantial interfirm heterogeneity exists in the degree to which firms' knowledge and collaboration structures are symmetrical or deviate from symmetry.

To explore whether we have any potential issue with multicollinearity, we rely on the Variance inflation factors (VIFs). To compute the Variance inflation factors (VIFs), we used the "collin" command in Stata. The VIFs suggested minimal multicollinearity in our models presented in Table 3 (minimum VIF = 1.04, maximum VIF = 2.46).

3.5. Model specification and estimation

Given the skewed nature of the dependent variable, *Number of Explorative Patents*, and the independent variables structured by firms and years, we estimate a robust Poisson quasi-maximum likelihood with conditional panel model with fixed effects given its robustness to overdispersion in comparison with alternative models as negative binomial (Wooldridge, 1999). The panel structure of our data allows us to control for time-invariant characteristics specific to the firm as well as time variation in the number of citations across firms. The dependent variable also requires a Poisson model to account for discrete, non-negative values and over-dispersion.

4. Results

We followed a step-wise estimation procedure to check the stability of the coefficients. Table 4 (model 1–4) reports the robust Poisson quasi-maximum likelihood estimator results with conditional fixed effects (Wooldridge, 1999). The first estimation of the model includes only the controls. We use a step-wise approach to include our variables of interest across the models. We use the results of the fully specified model 4 of Table 4 to test our hypothesized relationships.

Hypothesis 1 predicts that the symmetry between the intrafirm inventor collaboration and knowledge structure is positively associated with a firm's exploratory innovation. Given the nature of our variable with 0 referring to a perfectly symmetrical intrafirm configuration we include both *deviation from symmetry* and *deviation from symmetry squared* to examine whether the optimal value is close to 0. Note that we hypothesized a linear positive effect, but we must assess whether a curvilinear effect exists due to the variable characteristics (ranging from −0.095 and 0.170, with 0 being symmetrical). We find support for our hypothesis that intrafirm symmetry benefits exploration. The *deviation from symmetry* ($p = 0.05$) is positively related to the *number of explorative patents,* while the *deviation from symmetry squared* has a negative effect ($p = 0.001$).[3] Fig. 2 visualizes the inverted-U-shaped relationship with the optimal value close to 0, which means symmetry.

Hypothesis 2 predicts a moderation effect of combinability of a firm's technological environment in such a way that (a) a firm with collaborating inventors who possess dissimilar knowledge performs well in high combinability situations and (b) a firm with non-collaborating inventors who possess similar knowledge perform well in low combinability situations. To interpret our findings, we visualize the marginal effect of the interaction between *deviation from symmetry* and *combinability* on *number of explorative patents*. Fig. 3 supports our second hypothesis, as deviation from symmetry performs best in low and high combinability situations. Specifically, firms with collaborating inventors who possess dissimilar knowledge perform well in high combinability situations, while firms with non-collaborating inventors who possess similar knowledge perform well in low combinability situations. Symmetry between a

[3] Note that we follow Haans et al. (2016) to further explore the nature of the inverted-U shaped relationship. The first condition specified by Haans et al. (2016) is satisfied; both the linear and quadratic terms of deviation from symmetry are significant, and in the direction we expected. The second condition stipulates that the confidence interval for the extreme point must be within the independent variable's range. Our results show that the extreme point is 0.0482 with the 95 % confidence interval to be [−0.0162, 0.0877]. This falls within the range of our variable. A third and final condition is that the slopes at the distribution's lower and upper end points should be sufficiently steep and with different signs. The slopes are sufficiently steep and the overall test for curvilinearity is significant. Hence, our results support our claim that the optimal level is located close to symmetry between the intrafirm inventor collaboration and knowledge structure.

Table 1
Correlation coefficients.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Number of Explorative Patents	1.000											
(2) Deviation from Symmetry	0.218*	1.000										
(3) Combinability	0.112*	−0.014	1.000									
(4) Technological Experience	0.304*	0.200*	0.060*	1.000								
(5) Inventors/Classes	0.332*	0.319*	−0.166*	0.497*	1.000							
(6) Technological Breadth	0.313*	0.281*	0.220*	0.255*	0.007	1.000						
(7) Age	0.156*	0.191*	0.003	0.531*	0.260*	0.258*	1.000					
(8) Sales	0.428*	0.210*	0.033	0.696*	0.571*	0.272*	0.377*	1.000				
(9) R&D Intensity	−0.041	−0.100*	−0.163*	−0.064*	−0.109*	−0.098*	−0.182*	−0.127*	1.000			
(10) Slack	−0.107*	−0.060*	−0.127*	−0.072*	−0.066*	−0.071*	−0.086*	−0.106*	−0.140*	1.000		
(11) Geographical Dispersion	0.100*	0.227*	−0.150*	0.135*	0.272*	0.155*	0.131*	0.140*	−0.045	−0.096*	1.000	
(12) Number of Claims	−0.022	−0.086*	−0.133*	−0.037	−0.004	−0.107*	−0.055*	−0.073*	0.113*	0.050	0.017	1.000

* $p < 0.05$.

Table 2
Descriptive statistics.

Variables	Mean	SD	Min	Max
Number of explorative patents	21.224	44.410	0.000	530.000
Deviation from symmetry	0.039	0.043	−0.095	0.170
Combinability	2.577	0.525	1.416	4.635
Technological experience	600.815	1658.021	2.000	13,987.000
Inventors/classes	1.212	0.679	0.200	4.784
Technological breadth	0.934	0.051	0.627	0.991
Age	15.448	10.464	4.000	92.000
Sales	1354.178	3290.375	0.390	38,826.000
R&D intensity	0.119	0.116	0.000	1.179
Slack	0.060	0.504	−1.203	4.145
Geographical dispersion	0.143	0.182	0.000	0.738
Number of claims	18.693	7.772	3.000	82.800
	1.397 observations			

firm's collaboration and knowledge structure is most effective under conditions of moderate combinability, whereas asymmetry is most effective under conditions of low combinability (similar inventors not collaborating) and high combinability (dissimilar inventors collaborating). The marginal effects also show economic significance. Fig. 3 shows that the marginal effect of the number of explorative patents ranges between 12 and 17 exploratory patents. On average, companies in our sample generate 21 explorative patents, which suggests that aligning the degree of intrafirm symmetry with environmental combinability is highly worthwhile for managers to pursue.

We also conduct various robustness checks. First, we use two alternative specifications to model our dependent variable in models 5 and 6, using the negative binomial conditional fixed-effects and the negative binomial with firm dummies as fixed effects. The findings are largely consistent with our main models. In model 7, we use an alternative dependent variable, the number of explorative citations inspired by Phelps (2010), and the findings are similar. In model 8, we juxtapose our main findings with the number of exploitative patents and find no significant effects. Finally, we also examine in model 9 whether firm inventive performance (sum of all forward citations received by a firm's patented inventions in a five-year moving window) is affected by deviation from symmetry. Our findings show that intrafirm symmetry drives exploratory, high-quality innovation, while deviation from symmetrical

Table 3
The VIF values.

Variables	VIF
Deviation from symmetry	1.25
Combinability	1.21
Technological experience	2.46
Inventors/classes	1.91
Technological breadth	1.35
Age	1.50
Sales	2.37
R&D intensity	1.15
Slack	1.09
Geographical dispersion	1.17
Number of claims	1.04
Mean VIF	1.50

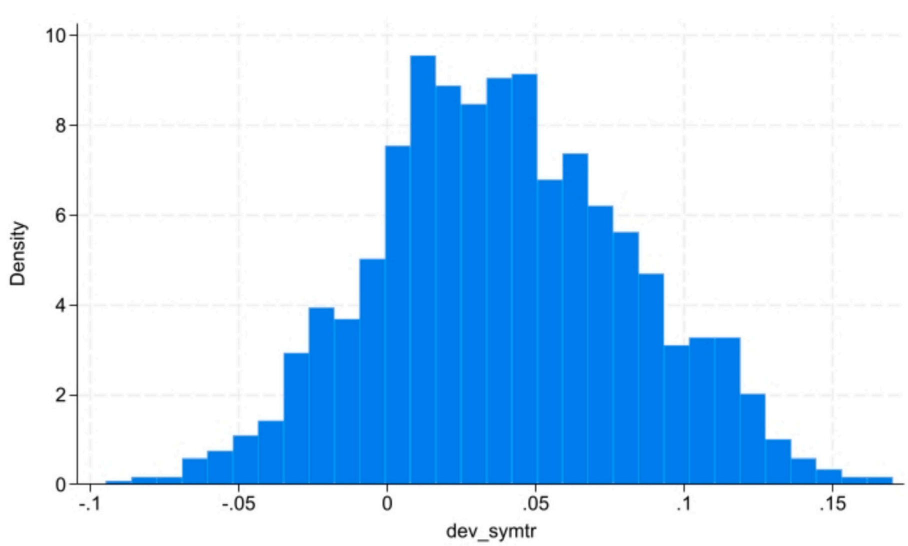

Fig. 1. The distribution of variable deviation from symmetry.

Table 4
Robust Poisson quasi-maximum likelihood estimator with conditional fixed effects model for number of explorative patents (Five-year moving window).

	1	2	3	4	5	6	7	8	9
Model	xtpoisson,fe	xtpoisson,fe	xtpoisson,fe	xtpoisson,fe	xtnbreg, fe	xtnbreg, i.firm	xtpoisson, fe	xtpoisson,fe	xtpoisson,fe
Variables	Explorative patents	Explorative patents	Explorative patents	Explorative patents	Explorative patents	Explorative patents	New citations	Exploitative patents	Forward citations
Deviation from symmetry		−1.097	3.586*	16.73***	8.652***	8.775***	16.96**	7.666	18.73***
		(1.088)	(2.018)	(5.623)	(3.202)	(3.222)	(7.551)	(13.54)	(6.271)
Deviation from symmetry squared			−37.13**	−32.49**	−15.30	−24.43***	−36.49	−24.65	−53.85**
			(15.15)	(14.19)	(9.406)	(9.143)	(23.48)	(39.10)	(21.90)
Deviation from symmetry x combinability				−5.100**	−2.787**	−2.667**	−6.537**	−4.761	−6.562**
				(2.153)	(1.132)	(1.162)	(2.943)	(4.528)	(2.561)
Combinability	−0.793**	−0.790**	−0.785**	−0.518	−0.177**	−0.538***	−0.340	−0.223	−0.375
	(0.391)	(0.384)	(0.389)	(0.337)	(0.0804)	(0.101)	(0.361)	(0.368)	(0.376)
Technological experience	−0.000113***	−0.000115***	−0.000113***	−0.000121***	−0.000107***	−0.000124***	−8.10e-05***	−4.56e-05**	−0.000116***
	(2.64e-05)	(2.59e-05)	(2.54e-05)	(2.68e-05)	(2.76e-05)	(2.00e-05)	(1.25e-05)	(2.01e-05)	(1.84e-05)
Inventors/ classes	−0.156	−0.161	−0.177	−0.200	−0.244***	0.213***	0.203	0.343	0.130
	(0.181)	(0.183)	(0.185)	(0.184)	(0.0574)	(0.0784)	(0.245)	(0.272)	(0.257)
Technological breadth	19.38***	19.62***	19.24***	18.69***	6.897***	14.11***	15.93***	14.34**	9.587*
	(5.552)	(5.410)	(5.372)	(5.420)	(0.925)	(1.260)	(5.586)	(6.180)	(5.391)
Age	−0.0335	−0.0327	−0.0336	−0.0329	−0.00310	−0.0650***	0.0149	0.0500	0.0239
	(0.0291)	(0.0295)	(0.0293)	(0.0295)	(0.00459)	(0.00690)	(0.0352)	(0.0379)	(0.0403)
Sales	5.67e-05***	5.63e-05***	5.58e-05***	5.77e-05***	1.76e-05	4.09e-05***	3.26e-05**	7.72e-06	3.63e-05***
	(1.51e-05)	(1.53e-05)	(1.55e-05)	(1.59e-05)	(1.45e-05)	(1.03e-05)	(1.34e-05)	(1.45e-05)	(1.39e-05)
R&D intensity	−1.398	−1.368	−1.363	−1.551	−1.285***	−0.637	−3.932**	−5.680**	−4.683***
	(1.101)	(1.108)	(1.093)	(1.107)	(0.347)	(0.447)	(1.814)	(2.456)	(1.710)
Slack	−0.148	−0.153	−0.144	−0.144	−0.0933	−0.0547	−0.295	−0.552*	−0.620**
	(0.145)	(0.148)	(0.147)	(0.147)	(0.0649)	(0.0739)	(0.198)	(0.315)	(0.273)
Geographical dispersion	−0.808	−0.757	−0.765	−0.834	−0.402**	0.0450	−0.957	−1.584**	−0.914
	(0.672)	(0.663)	(0.671)	(0.659)	(0.195)	(0.245)	(0.680)	(0.662)	(0.829)
Number of claims	0.0453***	0.0446***	0.0454***	0.0457***	0.0152***	0.0227***	0.0764***	0.0941***	0.0834***
	(0.0130)	(0.0129)	(0.0131)	(0.0130)	(0.00333)	(0.00370)	(0.0182)	(0.0305)	(0.0200)
Constant					−5.198***	−11.83***			
					(0.865)	(1.288)			
Observations	1397	1397	1397	1397	1397	1397	1397	1310	1397
Number of firms	170	170	170	170	170	170	170	144	170

*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

configurations outperforms symmetry under low and high combinability conditions.

5. Discussion

Since the early work of Burns and Stalker (1961) and Allen and Cohen (1969), many studies have examined how intrafirm collaboration structures or knowledge structures influence innovation outcomes in general (Schillebeeckx et al., 2020; Argyres et al., 2020; Brennecke and Rank, 2017; Carnabuci and Operti, 2013; Guler and Nerkar, 2012; Yan et al., 2020; Yayavaram and Ahuja, 2008), and exploration in particular (Nan, 2024; Wang et al., 2014; Zakaryan, 2023). The implicit yet strong assumption in these strands of literature is that collaboration and connectivity among a firm's inventors is beneficial for exploration. In this paper, we question this idea and take a step back by studying when firms and their managers should pay attention to optimizing collaboration and connectivity among inventors, directly and/or indirectly, for boosting firms' exploratory innovation performance, yet equally important, when it is effective to disband standing collaboration among inventors and foster isolation?

To address these questions, we go back to the early and seminal idea by Nonaka (1994, 1990), who argued that organizations consist of multiple layers, including a project-team layer (here, inventor collaboration structure) and a knowledge-base layer (here, knowledge structure), to study how they jointly affect firm exploratory innovation performance. Based on this idea, we have combined collaboration distance from the literature on inventor collaboration and networks with knowledge distance from the literature on knowledge structures. Following these two dimensions, we distinguish between symmetric and asymmetric configurations of collaboration and knowledge structures.

Building on a recombinant innovation perspective, we include a key condition of a firm's technological environment, namely the combinability of knowledge domains. We argue that easy-to-recombine domains of technological knowledge demand a different configuration of knowledge and collaboration structure than medium- or difficult-to-combine domains. Our baseline prediction is that a symmetric configuration is the default form for most firms and is, on average, effective for exploratory innovation. Symmetry means that inventors who work in

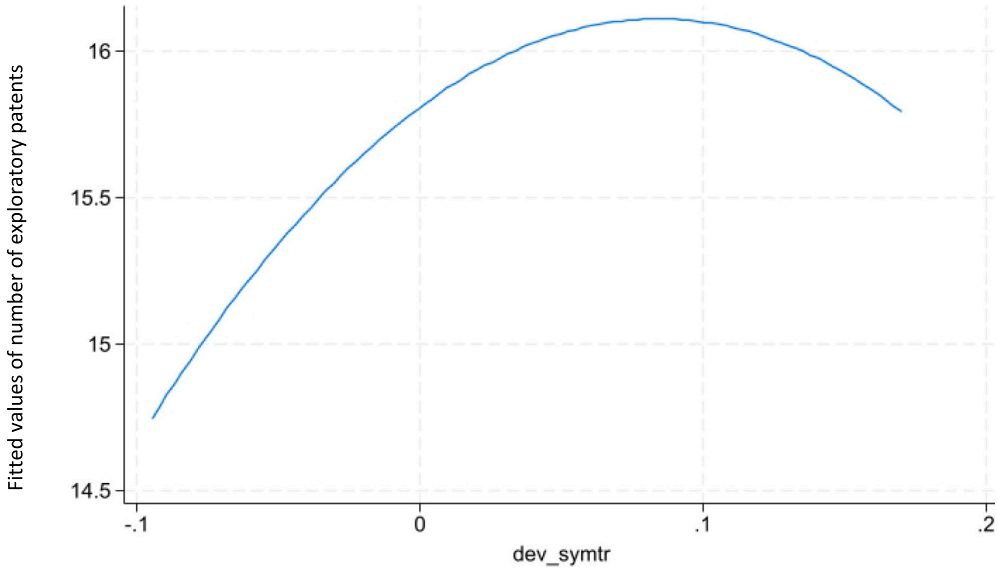

Fig. 2. The effect of deviation from symmetry on number of explorative patents.

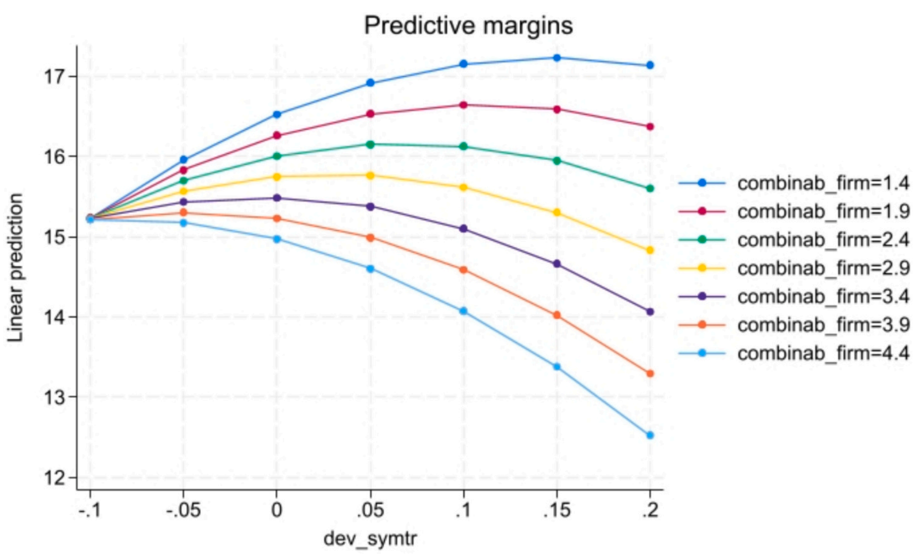

Fig. 3. The effect of deviation from symmetry on number of explorative patents moderated by combinability.

the same knowledge domain collaborate on recombinatory search and innovation, whereas inventors with dissimilar knowledge do not or only to a limited extent. Symmetry offers a relatively limited degree of search diversity at the firm level, yet effective enough for average combinability. Based on a sample of 170 publicly traded semiconductor firms over the period from 1984 to 2006, we find strong evidence supporting this idea. In fact, we show that about 68 % rely on a symmetric configuration of their inventors' collaboration and knowledge structure. The fact that the majority of firms, *over two-thirds* of them even, rely on symmetry makes sense as it is both intuitive, with cognitively close inventors who collaborate and distant ones not or much less, and also effective, as it yields a solid exploration innovation performance on average. Note that while we hypothesized a positive effect of symmetry on firm exploration, the nature of our primary independent variable – deviation from symmetry – led us to assess whether a curvilinear effect exists. We show that the most beneficial intrafirm collaboration-knowledge configuration for exploratory innovation is close to a symmetrical structure.

However, we also argue and show that most firms overlook the risk of a symmetric configuration. Whereas it stimulates collaboration among similar inventors that strengthens an in-group orientation, it can also feed out-group biases at the expense of communication and knowledge exchange across groups of more distant inventors. This risk increases considerably under conditions of low or high combinability. Under both these conditions, a symmetric configuration severely limits a firm's potential for recombinatory search and weakens its ability to create exploratory innovations. Here, instead, two asymmetric configurations are more effective. As we argue and show, asymmetry through non-collaborating, similar inventors offers within-domain diversity that fits low combinability conditions, whereas asymmetry through collaborating dissimilar inventors offers across-domain diversity that fits high combinability.

In this way, we inform both the literature on intrafirm collaboration and knowledge structures in the following way. We provide an understanding of why easy-to-recombine domains of technological knowledge demand a different configuration of knowledge and collaboration structure compared to medium- or difficult-to-combine domains. Firms with equal configurations of inventor collaboration and knowledge structures can still exhibit persistent differences in their exploration performance, as this depends on the conditions of technological combinability under which they operate. For example, when two firms both rely on an asymmetric configuration of dissimilar inventors who collaborate, the one operating under conditions of high combinability will see its exploratory innovation performance soar. In contrast, the one under average or low combinability will see its performance decline. In this way, we offer a more comprehensive understanding of when firms and their managers should pay attention to optimizing collaboration, as has been the dominant focus until now, but also when the configuration of a firm's knowledge and collaboration structure must be adjusted for its exploratory innovation performance, by reducing collaboration and connectivity, and/or create isolation among inventors, when combinability either increases or decreases.

Second, we also contribute to an emerging distinction being made in the literature between two views on recombination, namely the tension view and the foundational view (Kaplan and Vakili, 2015). Proponents of the dominant tension view argue that the recombination of more distant and diverse knowledge tends to promote innovation (Hargadon and Sutton, 1997), whereas the contrasting foundational view argues that immersion in a single or very few knowledge domains is a prerequisite for pushing the knowledge boundaries (Jones, 2009; Kaplan and Vakili, 2015; Simonton, 1999). Our study suggests the differential organizational design implications for each route and how these are contingent upon combinability conditions. Under low combinability, a configuration of non-collaborating, similar inventors that specialize and focus on deep search suggests that a foundational approach is most effective. In contrast, under high combinability a configuration of collaborating, dissimilar inventors suggests that a tension approach is most effective. The default configuration of symmetry is mostly in line with the foundational view, although our findings show it carries some tension characteristics, too, because firms rely herein on collaboration with dissimilar inventors to a limited extent.

Our study has some limitations which suggest directions for new research. First, our data enable observation of emergent collaborative and knowledge patterns in companies but do not allow us to identify how organizations and their managers coordinate the actions of inventors. Knowing whether and how inventors become aware of expertise overlaps with colleagues in other parts of the firm would be helpful. We also did not observe communication channels other than collaborative ties proxied by co-invention. An open question remains about the extent to which (R&D) managers are aware and try actively to alter their firms' overall collaboration and knowledge configurations. While we are doubtful that firms know all the combinations of knowledge elements and collaboration structures among their inventors, we cannot rule out managerial influence.

Another limitation is related to our data. We build on prior research on recombinant innovation in high-tech sectors to legitimize our use of patents. Although the semiconductor industry is characterized by high R&D intensity and high patenting rates (Kapoor and McGrath, 2014), patent data may not capture all the relevant social networks and communications channels (cf. Guler and Nerkar, 2012). Future research could investigate different types of social relationships to capture informal forms of organization using survey data (Brennecke and Rank, 2017). Another research direction worth pursuing is considering other related innovation outcomes related to exploratory innovation. For instance, Carnabuci and Operti (2013) showed how intrafirm collaboration structures might impact recombination creation versus reuse. Another option might be to investigate whether companies pursue novel combinations using new or existing knowledge (Schoenmakers and Duysters, 2010) instead of our focus on the number of exploratory patents based on patent classes. We invite future research to study how deviation from symmetry may influence different innovation-related outcomes at the inventor, team, and firm-level. A limitation of our current research design is that we cannot rule out endogeneity concerns. Despite our fixed-effect estimations, unobserved factors, such as strategic intent, might drive both internal structures among inventors and firm innovation.

5.1. Implications for firms and their managers

When articulating practical implications from our study, two different views can be taken regarding the role of managers and why their firm has a mostly symmetric combination of collaboration and knowledge structure or deviates from symmetry instead. On the one hand, a more deterministic view suggests less or limited room for agency by R&D leaders, for example, when a firm's internal structure may come from the interdependencies present in the technological architecture determined by the technological environment (cf. mirroring hypothesis, Colfer and Baldwin, 2016). Or, when an organizational structure and design emerges due to (changes in) the external environment, such as the degree of environmental turbulence and/or complexity that may determine intrafirm structures (Huber and Glick, 1993). All in all, this reflects a more deterministic understanding of why firms deviate from a symmetrical configuration or why they would stick to a symmetric configuration even though it may be sub-optimal.

On the other hand, a more voluntaristic perspective suggests that R&D managers have more agency to change internal structures. The basic idea here is that managers and leadership matter for organizational change (Nadler and Tushman, 1990). Managers or inventors may, for instance, change the routines within firms and act as sources of change, including structure (Feldman and Pentland, 2003; Yi et al., 2016). Yet, the performance effects of such changes to structural configurations are uncertain. To address such uncertain choices therefore, firms and their (R&D) managers may rely on imitating 'best-practices' as adopted by other firms. Yet, best-practices carry a risk of a 'one-size-fits-all' approach, which may not necessarily fit with the context of the firm that adopts it. As a consequence, imitating others by adopting their best-practices may turn out to be sub-optimal or even detrimental when there is a misfit with a firm's specific context (Bikhchandani et al., 1992). This is exactly where the contribution of our study comes in, and its added value to firms and their managers. We offer them guidance and insights on both the need to become aware of the potential risks of deviation from symmetry and how to change it for the better, informed by the idiosyncratic context (i.e., combinability) of the firm in question.

More specifically, this means that, for exploration, managers should be aware of their firm-internal collaboration and knowledge structures and their natural intuition or even bias to resort to a symmetrical organization of the two. While knowledge-collaboration symmetry is effective under moderate combinability, this becomes a liability under low or high combinability conditions. Yet, whereas deviation from symmetry can be somewhat counter-intuitive for managers, the benefits of asymmetry between collaboration and knowledge structure become evident under conditions other than moderate combinability. This means that firms and their managers should de-bias themselves by raising their awareness of the type of combinability of the technological environments in which they innovate, and also become more aware of the potential benefits and risks of organizing around relatively isolated inventors with the same expertise and/or diverse, collaborating inventors.

One of the two asymmetric configurations, which we would call multidisciplinarity, has been identified as an essential organizing principle in creativity and innovation (Ben-Menahem et al., 2016; Hargadon and Sutton, 1997). The other asymmetric form, represented by a more redundant internal organization, provides an exciting avenue for managers to explore. While organizing parallel efforts might be bold and costly (Sargut and McGrath, 2011), it offers the opportunity for "having multiple experiments allows you to take a few risks without betting the farm" (Beinhocker, 1999, p. 100). Parallel or duplicate organizing is not new. For instance, the "Japanese approach" to innovation involves multiple product development teams competing internally to find the best solution to a technological problem (Nonaka, 1994). Moreover, in the context of Google, a manager noted that one should "not … eliminate all replication of effort, as sometimes it makes sense to tackle a challenge from multiple vantage points" (Groysberg et al., 2009, p. 12). During the 1980s, Microsoft pursued several operating systems in parallel (Beinhocker, 1999). Francisco Jariego, former director of Telefonica's R&D unit in Madrid, in a personal interview with one of the authors of this study stated that: "I actively defend redundancies in our organization because I believe that Telefonica's capacity to succeed lies there" (Interview, Nov. 29, 2011). In sum, our findings suggest that when managers aim to organize parallel search processes, they should be mindful that to produce meaningful deviations of alternative solutions, a "common base of knowledge and capabilities" is key (Beinhocker, 1999, p. 103).

Deviation from symmetry in which dissimilar inventors collaborate is more frequent in the literature on innovation strategy and management (Ben-Menahem et al., 2016; Fleming, 2004). Examples include IDEO (Hargadon and Sutton, 1997) and the Santa Fe Institute (Fleming, 2004), which is a common form of organization in the pharmaceutical sector (Ben-Menahem et al., 2016). It can also be a costly organizing principle due to elevated communication costs in facilitating cross-domain knowledge transfer (Ben-Menahem et al., 2016). Our study suggests that collaboration among inventors offers high communication bandwidth and allows for fruitful recombinations of knowledge in high combinability environments. Managers should be mindful of collaboration among their R&D professionals and not underestimate the importance of making creative leaps in high combinability situations.

To conclude, our study underscores the necessity to explore further how the degree of firm-internal symmetry explains inter-firm variation in the ability to generate exploratory innovation. We hope our paper will inspire more investigations into how firms' internal and external environments simultaneously influence the creation of innovation.

CRediT authorship contribution statement

Arjan Markus: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Formal analysis, Conceptualization. **Juan Antonio Candiani:** Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Victor A. Gilsing:** Writing – review & editing, Writing – original draft, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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