NETWORK RESOURCE MUNIFICENCE, GEOGRAPHICAL DISPERSION AND INVENTOR PERFORMANCE

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Abstract

This paper explores the variation of knowledge resources embedded in the collaboration networks of corporate inventors. Focusing on the semiconductor industry, we examine the impact of intraorganizational network resource munificence - i.e. the extent to which ego co-inventor networks carry knowledge resources - on inventor performance. Relying on insights from resource dependence theory and the social network perspective, we hypothesize that ego network resource munificence positively influences the innovative performance of inventors above and beyond network structural explanations. Yet, we predict that the geographic dispersion of the ego collaboration network negatively moderates this relationship due to the increased coordination costs of knowledge transfer. We find support for our predictions using a sample of 49,550 inventors employed by 236 companies in the global semiconductor industry over the period 1983 to 2003. Our empirical evidence points to the relevance of a network resource perspective instead of merely considering structural properties, and provide novel insights into how inventors successfully recombine knowledge residing in their ego networks.
INTRODUCTION

How does the intraorganizational social environment impact the innovative success of the individual inventor? A common view in the study of innovation emphasizes how being embedded in interpersonal networks shapes the innovative potential of individuals (Baer, Evans, Oldham, & Boasso, 2015; Brass, Galaskiewicz, Greve, & Tsai, 2004; Phelps, Heidl, & Wadhwa, 2012). In their search for novel and useful solutions to technological problems inventors frequently depend on colleagues (Singh & Fleming, 2009). Peer inventors within the same company provide an inventor with access to useful resources in the innovation process, including relevant knowledge, skills, referrals and support (Fleming, 2007; Singh, 2005). Thus, the social structures in which individual inventors are embedded influence their ability to generate innovations.

To date, research on the role of intraorganizational networks for inventor performance has focused primarily on the optimal structure of social interaction (Baer et al., 2015; Fleming, Mingo, & Chen, 2007; Paruchuri, 2010). To illustrate this point, prior studies focused hitherto on how collaboration network cohesion and brokerage benefit inventor performance (Fleming, Mingo, et al., 2007). In these existing studies, “the structural characteristics of members in an intraorganizational network serve as indicators of quality and richness of knowledge generated by these inventors” (Nerkar & Paruchuri, 2005: 771). Although this dominant structural view on social context increased our understanding tremendously, it relies on the assumption that network structure and position proxy for resource access of the focal individual (Finsveen & van Oorschot, 2008; Lee, 2010). More specifically, network contacts are treated as homogeneous even though network alters likely vary in the knowledge resources that they provide to the focal actor or ego. Except for studies that focused on inventor network diversity (e.g. Tortoriello, McEvily, & Krackhardt, 2015), relevant resources available in such ego networks have largely been ignored.
A recent study by Singh et al. (2016) supports this claim and shows how different knowledge types available from direct and indirect network contacts influence individual innovative outcomes. This means that network structural characteristics alone do not fully explain innovation outcomes at the ego-level. Therefore, our understanding of how intraorganizational networks impact inventor performance remains underdeveloped.

In this study, we depart from the traditional emphasis on network structure and apply a resource dependence perspective on inventors’ ego networks. To do this, we consider the level and use of knowledge resources embedded in collaboration networks of inventors, which we refer to as ego network resource munificence. The overarching argument is that inventors vary in their ability to use the knowledge resources that reside in their collaboration networks to achieve successful recombinant innovation. To examine what drives inventors to generate impactful innovations, we define ego network resource munificence as the ego network of co-inventors whose patented technological knowledge serves as input for ego’s generation of future innovations.

To build our arguments, we combine the resource dependence perspective (Emerson, 1962; Pfeffer & Salancik, 1978) with the social network view (Kilduff & Tsai, 2003) to shed light on how intraorganizational networks impact individual innovativeness in a corporate context (Nerkar & Paruchuri, 2005). Building on Pfeffer & Salancik (1978), we point to agents’ wish to decrease their dependence on resources and therefore resolve or lower uncertainty in their direct intraorganizational environment through collaboration. In the context of innovation, inventors are likely to collaborate with peers in the organization that provide access to valuable resources. We claim that the extent to which inventors depend in their innovative activity on the knowledge resources of colleagues within the organization influences their future innovative performance.
Furthermore, we consider how the geographic dispersion of prior collaborators (Hannigan, Cano-Kollmann, & Mudambi, 2015; Lahiri, 2010; Tzabbar & Vestal, 2015) acts as a contingent factor in the relationship between ego network resource munificence and inventor performance. Knowledge transfer is embedded in collaboration (Fleming, King III, & Juda, 2007), but the cost and effort of transfer of knowledge and skills increase with increases in geographic distance, due to the sticky nature of knowledge (Szulanski, 1996). Consequently, we predict that geographical dispersion of the inventor ego network attenuates the effect of resource munificence on inventor innovative performance.

We test our arguments on a sample of 49,550 inventors employed by 236 companies in the global semiconductor industry over the period 1983 to 2003. In this industry, individuals’ ability to generate novel and useful technologies is essential to long-term performance of the companies they are active in (Carnabuci, Operti, & Kovács, 2015; Hall & Ziedonis, 2001; Lim, 2004). Our findings show the relevance and importance of network resource munificence above and beyond structural ego network characteristics following the current dominant structural view in individual-level network research. Our findings resonate with the claim that the source of intraorganizational power does not rely only on “an actor’s locational centrality within a network of workflow relations” but also “an actor's capacity to control the resources on which others depend” (Astley & Sachdeva, 1984: 105). We also contribute to the broader literature on the microfoundations of corporate innovation showing that the generation of innovations will depend in part on the knowledge resources embedded in individuals’ ego collaboration networks within the organization. The extent to which employees use the munificent resources available in their ego networks fosters inventor performance, yet the benefits abate with increasing geographic dispersion of the ego network.
THEORETICAL BACKGROUND

Recombinant Innovation and Collaboration Networks

We follow the common perspective in the study of innovation to conceptualize innovation as the recombination of existing and new knowledge components (Fleming & Sorenson, 2004; Schumpeter, 1934). The agents engaged in this recombination process – inventors – search for solutions to problems that they or their superiors at the research and development (R&D) department of incumbent corporations identify (Caner, Cohen, & Pil, 2016). The opportunities within organizations for such recombinant innovation rely in part on the interaction among inventors (Toh & Polidoro, 2013). Two or more individuals know more than one and working together might prove an important mode for establishing new combinations of knowledge. Prior research discussed how the innovation process is an inherent social process in which individuals collectively solve problems and generate novel combinations (Hargadon & Sutton, 1997; Marengo, Dosi, Legrenzi, & Pasquali, 2000; Perry-Smith & Mannucci, 2017).

The innovation literature reports an increasing tendency to innovate as a collective in modern-day society (Wuchty, Jones, & Uzzi, 2007). A greater reliance on interpersonal interaction is necessary, because the level of complexity of the underlying problem-solving process has changed dramatically. Due to the “burden of knowledge” – which refers to the steadily increasing educational burden as a result of continuous accumulation of technological progress – the nature of innovation has changed (Jones, 2009). Most notably, innovation requires growing specialization and interaction among inventors (Jones, 2009; Luo & Wood, 2017). The empirical context in this study, the global semiconductor industry, is no exception in this regard. While the late 20th century was still characterized by an exponential growth of computational capacity following Moore’s Law (Fleming, 2001; Moore, 1998), technological progress in the semiconductor industry has
reached a point of saturation, indicated by a stalling growth of computer chip performance (Simonite, 2016). Consequently, organizing for corporate recombinant innovation involves encouraging collaborative behavior among inventors (Singh & Fleming, 2009).

Due to the growing importance of interaction among inventors, one strand of research underlines the interpersonal collaboration relationships among knowledge workers within companies (Guler & Nerkar, 2012; Nerkar & Paruchuri, 2005; Phelps et al., 2012). In this line of innovation research, inventors are considered the key knowledge workers within companies and the co-invention patterns among them resemble collaborative interaction. Prior literature established both quantitatively and qualitatively that patent collaboration ties involve intense interaction during and after working on a R&D project that led to one or more patents (Fleming, King III, et al., 2007; Singh, 2005). Such interpersonal collaboration ties stimulate knowledge transfer among inventors and serve as an efficient means of searching for relevant knowledge in the innovation process due to boundedly rational behavior of agents (Singh et al., 2016).

The intraorganizational network approach is dominated by the structural view on social capital, which postulates that the structural configuration of intraorganizational networks impact the behavior and performance of individuals and even organizations as a whole (Grigoriou & Rothaermel, 2017; Guler & Nerkar, 2012; Kilduff & Tsai, 2003; Liu, 2014; Paruchuri & Awate, 2017; Tasselli, Kilduff, & Menges, 2015). The structure of links to potential resource providers might take several forms, most notably cohesive networks and networks rich in structural holes (Burt, 2004, 2005; Coleman, 1988). This structural network view also proved important in the context of intraorganizational networks of inventors (Fleming, 2007; Guler & Nerkar, 2012; Nerkar & Paruchuri, 2005; Paruchuri & Awate, 2017). For example, Fleming et al. (2007) showed how both ego network brokerage and cohesion positively impact the development and use of
inventor-generated innovations depending on individual characteristics. The leading assumption in these studies is that certain network configurations are advantageous for individuals as they proxy for resource access (Finsveen & van Oorschot, 2008; Rodan & Galunic, 2004; Tortoriello et al., 2015). However, maintaining links to resource providers within the organization does not necessarily mean that scarce resources flow from one individual to another within the organization in an unrestricted manner (Ghosh & Rosenkopf, 2015; Singh et al., 2016).

**Ego Networks and Knowledge Resources**

Our conceptual scaffold builds upon three main insights from the social network literature. First, we wish to disentangle network structure from network resource use, because structural properties can at most proxy for the resources potentially available within interpersonal networks. Instead, we follow the so-called pipe and pool perspective (Podolny, 2001; Singh et al., 2016; Tortoriello et al., 2015) to argue that relationships can function as pipes to access resources from the pools of network contacts. Only recently the literature attempted to disentangle relationships from resource providers (Singh et al., 2016; Tortoriello et al., 2015). This is important because even in the context of intraorganizational innovation, knowledge and information contained in these pools is sticky and unequally distributed (Grant, 1996; Szulanski, 1996). Second, we follow the assertion that relation asymmetry is present in inventors’ collaboration networks within organizations (Gargiulo, Ertug, & Galunic, 2009). Asymmetric relations are usually neglected, even though “asymmetric relations (...) are common in ties that arise from the division of labor and the heterogeneous distribution of resources among specialized actors” (Gargiulo et al., 2009: 302). Inventors vary in their ability to draw from the resources embedded in their collaboration ego networks. Accordingly, we posit that the extent to which knowledge resources in co-invention networks are utilized vary. Finally, we follow the view that individuals within organizations are not aware of all
the relevant knowledge within the organization. The study by Friedkin (1983) showcases that there is a horizon to network observability in such a way that employees are aware of colleagues’ activities they directly communicate with. We therefore limit our study to examining inventors’ ego collaboration networks. With these assumptions in mind, we attempt to provide a more nuanced and complete view on the role of collaboration networks for inventor performance by putting forward how inventors depend on the knowledge resources that reside among their past collaborators within the company.

**Resource Dependence Perspective on Intraorganizational Collaboration Networks**

The resource dependence theory originally explained how organizations and their managers attempt to decrease the uncertainty present in the external environment through a variety of organizational responses (Pfeffer & Salancik, 1978). We alternatively apply the resource dependence view on the internal organization to explain how control over internal knowledge resources impacts inventor performance. Such a view implies “situationism” – the pressures and constraints that inventors face emanate from the social situation in which they are located. The main argument we like to put forward is that inventors rely on their colleagues to reduce the uncertainty of resource access and control within the organization. Resource access and use subsequently lead to power and status differences or power imbalance (Kehoe & Tzabbar, 2015; Pfeffer & Salancik, 1978; Tzabbar & Kehoe, 2014). Paradoxically, the resource dependence perspective predicts that agents tend to reduce uncertainty through partnership formation, yet, this simultaneously places agents in a network of social relationships and interdependencies (Blau, 1964; Emerson, 1962; Pfeffer & Salancik, 1978). Thus, resource dependence thinking implies that inventors are embedded in social networks characterized by mutual dependence. The extent to which an inventor relies on other colleagues depends on the importance of the resources that these
peers hold and the level of discretion with which the focal inventor can use such resources. In the subsequent sections we build on the resource dependence view to explain how inventors are being influenced by the most important intraorganizational network resource in the context of innovation – knowledge.

HYPOTHESES

Ego Network Resource Munificence

Firm-internal collaboration relationships offer inventors multiple benefits in their quest to innovate (Allen & Cohen, 1969; Carnabuci & Operti, 2013). In network terms, the alters of the ego inventor might be useful to bounce off ideas and can offer different mental models to address similar problems (Singh et al., 2016). Direct contacts can also be a source of referrals that may foster experimentation with subsequent potential avenues for knowledge recombination (Singh, Hansen, & Podolny, 2010). Arguably, however, the most important resource is the access to and use of knowledge embodied by the inventors whom the focal inventor recently collaborated with. We introduce the concept of ego network resource munificence, which in our context refers to the level and use of knowledge resources residing in the ego collaboration network of the inventor. Given that inventors depend on alters’ provision of knowledge resources to successfully recombine knowledge, we posit that higher levels of network resource munificence improves the ability of the ego inventor to innovate successfully. We provide two main reasons for this prediction.

Knowledge repository. Collaboration relationships are strong ties that involve intense communication between inventors (Fleming, King III, et al., 2007; Singh, 2005). Focal inventors gain knowledge from the other inventors they collaborate with (Singh et al., 2016; Singh & Fleming, 2009). Such knowledge comprises an understanding of the problems that co-inventors solve, the methods they apply to solve them and knowledge areas that inspire these solutions.
In other words, inventors gather information about knowledge components to be recombined (Nerkar & Paruchuri, 2005). In his study on Hewlett-Packard’s thermal ink-jet invention, Fleming (2002) provides an example of how two collaborating inventors – the wide-ranging empiricist John Vaught and the narrow analyst Dave Donald – provided each other with complementary skills and knowledge:

“At the time of their ink-jet invention, Donald had only a limited awareness of previous ink-jet technologies. Where Vaught had a tendency to take things ‘very far, very fast’ (…), Donald was the consummate engineer: methodical, informed and very aware of details. Judged by their invention of the prototype ink-jet, the juxtaposition of skills and personalities proved to be fruitful.” (Fleming, 2002: 1065)

As this example illustrates, the knowledge gained from collaborators increases the technological space from which focal inventors filter, select and modify relevant knowledge to advance novel recombinations into own innovations. Thus, the recombinant innovation potential depends on the resource munificence embedded in the ego collaboration network of the focal inventor.

**Knowledge transfer.** Ego network contacts are direct co-working contacts whom encourage the transfer of tacit knowledge (Hansen, 1999; Singh et al., 2016; Sorenson, Rivkin, & Fleming, 2006). Also, alter inventors may be used to discuss the potential uses of prior inventions or recombinations and offer sincere evaluations of innovations in development. In addition, focal inventors can ask them for help and insight, thus acting as a support system (Fleming, King III, et al., 2007). In this context, Sorenson et al. (2006) state:

“Direct, single-step connections provide the most obvious and valuable links between inventors and those attempting to receive and build on knowledge because they permit two-way communication. The recipient can therefore interactively query the original source of
the knowledge to correct errors or to fill gaps in the original transmission.” (Sorenson et al., 2006: 999)

This example explains that having alter-specific collaborative experience may act as a lubricant for sticky knowledge (Reagans & McEvily, 2003; Sorenson et al., 2006; Szulanski, 1996). Inventors with highly munificent ego collaboration networks within the organization may thus capitalize on these resources for their own innovation projects. Taken together, we predict that:

*Hypothesis 1: The higher the resource munificence in an inventor’s ego collaboration network, the higher the inventor’s innovative performance.*

**Ego Network Geographical Dispersion**

The extent to which the ego network resources are dispersed over geographical space and time is an important determinant of an inventor’s ability to integrate and transform alters’ knowledge into own innovations (Forman & Zeebroeck, 2012; Singh, 2008). *Ego network geographical dispersion* is defined as the degree to which the knowledge resources embodied by recent prior collaborators of ego are dispersed over multiple geographical locations. We expect the impact of ego network resource munificence on inventor performance to vary depending on the degree of the ego network’s geographical dispersion. Two main mechanisms guide this prediction.

*Resource awareness and search.* A widely dispersed ego collaboration network indicates large geographical distances among the focal inventor and its collaborators. Increasing distance reduces opportunities for serendipitous and spontaneous informal talk (Allen, 1977; Boh, Ren, Kiesler, & Bussjaeger, 2007). Chance and frequent encounters with past collaborators are important for the knowledge recombination process as such chance meetings smoothen subsequent communication and awareness of relevant knowledge resources (Allen, 1977; Allen & Fustfeld, 1975; Kim, 2018). A collegial collocated environment might prove crucial for knowledge
Awareness and innovation search as Fleming (2002) explains:

“Simple physical proximity increased the probability of unplanned meetings and non-professional friendships in cafeterias and at Christmas parties or softball games. Such friendships and the close availability of diverse resources greatly aid wide recombinant search.” (Fleming, 2002: 1074)

Thus, a low degree of geographical dispersion of the ego network – and the resources embedded among ego’s collaborators – will facilitate picking up signals of relevant knowledge for inventors’ recombinant innovation efforts. Resource munificent ego networks will therefore have a higher impact on ego’s innovative performance when the geographical dispersion is relatively low.

Interaction and coordination. Collocated past collaborators are more likely to transfer knowledge to each other compared to more distant network contacts (Kim, 2018; Singh, 2005). Due to frequent face-to-face interaction and a shared institutional context such individuals are more likely to share common conventions and mental schemes – also called common ground – which in turn facilitates knowledge absorption (Malmberg & Maskell, 2006; O’Leary & Cummings, 2007; Tzabbar & Vestal, 2015). In particular tacit knowledge is more likely to be shared over shorter spatial distances (Cramton, 2001; Hannigan et al., 2015; Sorenson et al., 2006). Decoding tacit knowledge over high geographical distance is possible, yet costly. Transfer of knowledge resources is also more difficult across large distances, because of increasing time zone separation. Changing work routines might be necessary in these cases, for instance using virtual means of interaction (Cramton, 2002). Transfer of tacit knowledge through such virtuals means is difficult and information flow might distort along the way (Cramton, 2002). Spatial dispersion among collaborators will attenuate the likelihood of contextual knowledge transfer (Cramton, 2001). Overall, an inventor will likely face coordination costs when he or she intends to acquire,
assimilate and recombine knowledge from resource munificent collaborators residing in different geographical locations. Moreover, discussion and support from alter inventors is less effective at a distance.

For these reasons, we expect that ego network geographical dispersion will lessen the effect of resource munificence on inventors’ recombinant innovation success\(^1\). We thus hypothesize:

*Hypothesis 2: The positive effect of ego network resource munificence on the inventor’s innovative performance is negatively moderated by the level of geographic dispersion of the ego collaboration network.*

**METHODS**

**Empirical Setting**

To understand how knowledge resources in ego networks influence inventor performance we use the global semiconductor industry over the period 1983 to 2003 as our empirical setting. In this industry firms manufacture electronic and electrical equipment and components, including electron tubes, printed circuit boards, electronic capacitors, resistors, coils and other inductors (Anand & Khanna, 2000; Hall & Ziedonis, 2001; Kelley, Ali, & Zahra, 2013; Lim, 2004). Several reasons motivated the choice for this industry. The semiconductor industry is driven by technological intensity (Macher, Mowery, & Hodges, 1998) and companies in this industry regularly file patents to protect the intellectual property generated by inventors (Ganco, 2013; Hall & Ziedonis, 2001; Lim, 2004). This industry has also proven a fruitful context for studying collaboration networks among inventors (Carnabuci & Operti, 2013; Paruchuri & Awate, 2017). Overall, this industry fits our research (Huggins & Thompson, 2014) purposes well as information

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\(^1\) We are aware that geographical dispersion could be correlated with novelty, which is important for the ideation and development of innovation (Huggins & Thompson, 2014). However, due to awareness and knowledge transfer constraints we claim geographical dispersion will diminish the impact of network resource munificence on inventor performance.
enclosed in patents allow us to track inventors over the course of their careers and measure their technological profiles and co-invention networks.

**Sample**

As a starting point we selected all firms within the global semiconductor industry using the WRDS Compustat database (standard industry classification 367 or “Electronic Components and Accessories”) with at least one USPTO patent as observed in the NBER patent dataset (Hall, Jaffe, & Trajtenberg, 2001). In addition, we matched the public firm, patent and citation data with the Harvard Dataverse inventor-level data (Li et al., 2014). We supplemented and corrected this data with our self-developed automated online consultation of the USPTO website to update and check the source patent data. Our final unbalanced longitudinal sample consists of 105,668 inventor-year observations. This sample relies on 236 unique semiconductor companies that employ 49,550 unique inventors whom generated patents in the period 1983 to 2003. Companies with their head office outside the U.S. employ around 30 percent of the inventors in our sample and most inventors reside in the major cities of North America, Europe and East Asia (See Figure 1).

[Insert Figure 1 around here]

**Variables**

The unit of analysis for the variables is the individual inventor. Our independent variables cover inventor information that relates to her prior experience and performance, the prior ego co-invention network and company characteristics. The dependent variable was measured for each inventor-year observation and all the independent variables preceded the dependent variable in time. We measured several of the variables over multi-year windows, because the patent application process might introduce time lags.

**Dependent variable**
**Forward citation counts.** To measure inventor performance or success we use the total number of forward citations received by the patents generated by the focal inventor using a five-year moving window (t+1 to t+5). Forward citations are commonly used to proxy technological importance and social value and correlate with inventor innovativeness and firm value (Albert, Avery, Narin, & McAllister, 1991; Fischer & Leidinger, 2014; Hall, Jaffe, & Trajtenberg, 2005; Lee, 2010; Trajtenberg, 1990).

**Independent variables**

To construct the ego collaboration networks we rely on the co-invention behavior of inventors. A collaborative relationship between inventors forms when they appear together on a patent application (Fleming, Mingo, et al., 2007; Nerkar & Paruchuri, 2005; Singh et al., 2016; Singh, 2005). In social network terms, the inventors represent nodes and co-invention indicates a tie between these nodes. Even though working together on a project that leads to a patent is temporary, prior literature showed that the interpersonal relationship persists long after the actual collaboration (Fleming, 2007; Fleming, King III, et al., 2007). We use three-year moving windows in creating the collaboration networks, following a common approach in inventor network studies (Carnabuci & Operti, 2013; Nerkar & Paruchuri, 2005; Singh et al., 2016). The criterion for inclusion of inventors in the overall collaboration network – or network boundary – is semiconductor company membership, similar to prior studies (Singh et al., 2016). The intraorganizational co-invention ties among inventors serve as main input for measuring the two main independent ego network variables.

**Ego network resource munificence.** To operationalize collaboration network munificence we use a modified version of the procedure developed by Carnabuci & Operti (2013). For each firm-year observation, we first build the co-inventor network, where a tie $c_{ij}$ indicates the sum of
number of patents inventors \(i\) and \(j\) co-created during a three year-moving window \((t-2\) to \(t)\). Then, we focus on the inventor-level to trace whether the focal inventor cites patents from her collaborators or direct ties until year \(t\). Thus, we build an inventor-citation network across all inventors within the firm where \(v_{ijt}\) indicates the number of patents inventor \(i\) has cited from inventor \(j\) until year \(t\), applying a decay function based on the years elapsed between the time of citation and \(t\). We row-normalize \(v_{ijt}\) (i.e., divide each cell by the sum of each row) of the citation network matrix transforming it into a proportional tie \(w_{ijt}\), expressing the share of citations that inventor \(i\) makes to patents generated by inventor \(j\), over the total number of citations made by \(i\). Finally, we measure the ego-network resource munificence of inventor \(i\) in year \(t\), \(M_{it}\), as the sum of patents produced by the \(n\) focal inventor’s direct collaborators \(p_{jt}\) weighted by \(w_{ijt}\) (See Equation 1). We thus consider both the level of resource munificence present in the ego network and the extent to which the focal inventor recently used her alters’ knowledge resources as reflected in prior patents. Our measure differs from the operationalization by Carnabuci & Operti (2013) in two ways. We measured ego network resource munificence focusing on the resource munificence residing in the collaboration network instead of the spillover network as a whole, and we apply the measure at the interpersonal level instead of the interfirm level. See Figure 2 for an example of our measure.

\[
(1) \quad M_{it} = \sum_{j=1:n} w_{ijt} p_{jt}
\]

\[
M_{At} = w_{ABt} p_{Bt} + w_{ACT} p_{Ct} + w_{ADt} p_{Dt}
\]

\[
M_{At} = \frac{v_{ABt}}{v_{ABt} + v_{ACT} + v_{ADt}} p_{Bt} + \frac{v_{ACT}}{v_{ABt} + v_{ACT} + v_{ADt}} p_{Ct} + \frac{v_{ADt}}{v_{ABt} + v_{ACT} + v_{ADt}} p_{Dt}
\]

[Insert Figure 2 around here]
**Ego network geographical dispersion.** For the focal inventor $i$, we considered the ego network formed by her collaborators and herself. We then identified the location of the patents generated by these alter inventors during the time window. By combining available information on the state and country for each of the patents, we calculated geographical dispersion following the approach of Hannigan et al. (2015) as one minus the sum of the squares of the share of all inventors in each state-country (see Equation 2). Specifically, we measure the geographic dispersion of the ego collaboration network of focal inventor $i$ in year $t$, $D_{it}$, as the share of direct alter inventors $p_{jt}$ in country-state $n$. The higher the value of this index, the more geographically dispersed the ego collaboration network. This measure is bounded between 0 and asymptotically to 1 as the direct contacts of the focal inventor are dispersed across more state-countries.

\[
(2) \quad D_{it} = \sum_{n=1}^{N} p_{jt}^2
\]

**Control variables**

To rule out alternative explanations for our findings, we control for a variety of inventor-, ego network-, and firm-level variables. At the inventor-level we include first a measure called inventor专利 experience to control for the focal inventor’s innovation experience using the cumulative number of patents until the focal year (Fleming, Mingo, et al., 2007). This measure controls for the productivity and career stage of the inventor – a common predictor of inventor performance (Lee, 2010). Another source of important experience is the extent to which an inventor accumulated a broad knowledge base over time (Fleming, Mingo, et al., 2007; Singh et al., 2016). To capture inventor breadth experience we count the number of unique subclasses attached to the focal inventor’s patents until the focal year (Fleming, Mingo, et al., 2007). Another generally known predictor of inventor performance is inventor mobility because an inventor accumulates a variety of human and social capital through job-hopping (Corredoira & Rosenkopf, 2010; Ganco,
We control for inventor mobility using the number of assignees that appear on the patents of the focal inventors up to focal year \( t \). Inventors that work with more recent technologies tend to perform better (Fleming, Mingo, et al., 2007; Nerkar, 2003; Singh et al., 2016). We follow the common procedure within patent-based studies to control for the average of the patent numbers that the focal inventor used as backward citation. The USPTO assigns sequential numbers to granted patents and therefore higher values of this control variable indicate using knowledge that is more recent (Nerkar, 2003; Wang, Van De Vrande, & Jansen, 2017). We label this variable prior art age.

To rule out another set of competing explanations, we control for several characteristics of the focal inventor’s ego collaboration network. We include ego network constraint to control for the prominent structural network explanation brokerage (Burt, 1992, 2005; Paruchuri & Awate, 2017). We follow Burt (2004) to construct the network constraint index. Higher values of this index indicate that the focal inventor is more constrained and hence brokers less widely (i.e. is embedded in a more cohesive collaboration ego network). Higher average tie strength offer the focal inventor superior opportunities to transfer knowledge from her collaborators (Guler & Nerkar, 2012; Hansen, 1999). Accordingly, we control for ego network tie strength. Inventors with a large ego network might perform better than their lesser endowed counterparts, due to their higher exposure to knowledge resources. These individuals might also be simply more prolific in maintaining collaborations. We thus control for the number of direct co-inventors in the focal inventor’s ego network, which we label ego network size. At the ego network-level, we also control for the number of external ties to the focal inventor’s direct contacts who do not share a co-invention tie with the focal inventor. The variable ego network external ties controls for the presumably heterogeneous resources that direct contacts of the focal inventor can access (Fleming,
Finally, we include firm-level controls as firm factors might shape inventor success due to the intraorganizational resource availability. We control for firm size because larger semiconductor companies might offer more technological opportunities for recombinant innovation. In contrast, we control for firm age as inventors in older firms might be constrained by accumulated firm routines and myopia (Levinthal & March, 1993; Sørensen & Stuart, 2000). We control for the financial situation of a firm by including ROA and net income of the company (Hess & Rothaermel, 2011; Hitt, Hoskisson, Johnson, & Moesel, 1996). The variable R&D intensity controls for the resources that companies directly assign to R&D (Helfat, 1994), which may encourage inventor performance. Semiconductor companies vary in their formal structure and thus we control for firm-level geographical dispersion, similar to the ego network measure. Firm geographical dispersion captures the extent to which a firm exhibits a geographic multi-unit structure (Lahiri, 2010). The final variable included in our analyses, foreign country, controls for the geographical location of a firm’s head office. This dummy variable takes the value 1 when a firm originates from outside the U.S.

Model Specification and Estimation

The dependent variable is a positive and discrete count variable. A number of potential count models are at our disposal. However, given the skewed or overdispersed nature of inventor performance – as measured by the number of forward citations in five-year moving windows – we rely on negative binomial models. To analyze the longitudinal data we specifically use random-effects negative binomial models (Hausman, Hall, & Griliches, 1984) because our key independent variables are change-related measures and the unbalanced nature of our inventor-year data would lead to omitting many data points (Awate & Mudambi, 2017; Yayavaram & Chen, 2015). This
allows us to include both varying and time-invariant covariates. The basic equation in our analysis is:

\[ (3) \ Y_{it+1 \ to \ 5} = \beta_0 + B_1X_{i,t} + B_2X_{i,t} \times Z_{i,t} + B_3Z_{i,t} + v_{i,t} \]

where \( Y_{it+1 \ to \ 5} \) is the sum of all forward citations received by focal inventor \( i \) in year \( t+1 \ to \ 5 \), \( X_{it} \) are lagged independent variables, \( Z_{it} \) are lagged control variables and \( v_{i,t} \) is the error term.

**Descriptive statistics and correlations**

Table 1 reports the descriptive statistics of the variables included in our study. Table 2 presents a correlation matrix for the variables. Multicollinearity does not appear to be an issue. Each of the individual variance inflation factor (VIF) values do not exceed the value 3 and the average value is below 2. Thus, the VIF values are well below the commonly accepted threshold of 10 (Belsley, Kuh, & Welsch, 1980). To check for the stability in the coefficients we followed a stepwise estimation procedure.

[Insert Table 1 and 2 around here]

**RESULTS**

Table 3 reports the results of the random-effects negative binomial count models. Model 1 presents the base model with only the controls included. Model 2 adds the ego network resource munificence. Model 3 adds the ego network geographical dispersion. Finally, in model 4 we add the interaction between ego network resource munificence and geographical dispersion of the ego collaboration network.

[Insert Table 3 around here]

We use model 4 from Table 3 to interpret our findings. We find a consistent positive and statistically significant effect of ego network resource munificence (p<0.000). This offers support for Hypothesis 1, which states that *The higher the resource munificence in an inventor’s ego*
collaboration network, the higher the inventor's innovative performance. In other words, we find a positive and significant effect of resource munificence beyond network structural explanations that dominate the inventor network literature. This finding proves our overarching argument that the knowledge resources present in individuals’ ego networks are important in the context of innovation. We also corroborate Hypothesis 2, *The positive effect of ego network resource munificence on the inventor’s innovative performance is negatively moderated by the level of geographic dispersion of the ego collaboration network*. The coefficient of the interaction between ego network resource munificence and ego network geographical dispersion is negative and significant (p<0.001). Our results thus seem to support our theoretical prediction that geographical dispersion attenuates the impact of resource munificence present in a focal inventor’s ego collaboration network.

The coefficients of the control variables are mostly in line with the existing theoretical predictions. While the interaction effect of ego network geographical dispersion is negative, the main effect is positive and significant, which indicates that focal inventors with spatially dispersed collaboration networks might benefit from the unique information they have acquired through their direct contacts in distant locations (Liu, 2014; Tzabbar & Vestal, 2015). We observe a negative effect of general technological experience, yet inventor experience breadth is positively associated to inventor success. Together with the finding that inventor mobility positively influences inventor performance, we assume experience diversity promotes success (Dokko, Wilk, & Rothbard, 2009), rather than length of experience. Using recent technologies also benefits an inventor’s performance. The effects of the ego network variables all have the expected direction except network constraint. Burt’s constraint index positively impacts inventor success, which is in contrast with the prior empirical literature on network brokerage (Burt, 2005). Instead, our study
is in line with prior work on the benefits of network cohesion (Coleman, 1988; Obstfeld, 2005) and might be driven by individual or industry context (Fleming, Mingo, et al., 2007). Larger ego networks and higher average tie strength seem to foster inventor performance, while the initial positive effect of external ties fades in terms of significance in regression models 2-4. The firm-level control variables sketch the picture that inventors employed in large and old companies might suffer from increased competition and myopic managerial behavior. In addition, firms characterized by a geographical multi-unit structure negatively impact inventor performance beyond the positive effect of inventors’ ego network geographical dispersion. The findings hence add to the existing inconclusive results regarding the impact of geographic dispersion on innovation quality (Lahiri, 2010; Singh, 2008; Tzabbar & Vestal, 2015). R&D intensive and financially healthy companies foster inventor performance, while being located outside the US negatively correlates with the number of forward citations that inventors receive.

**ROBUSTNESS CHECKS**

One concern that might affect the estimation of the random-effects regression models is unobserved heterogeneity. We added prior inventor performance to address this issue (Lee, 2010). Another issue that might affect our results is network autocorrelation (Uzzi & Spiro, 2005). Using inventor collaboration data could pose a problem because some of the ego network variables might be the same for co-inventing inventors. Our network variables originate from an initial bipartite structure, which might lead to biased estimates. Observations of collaborating inventors could be dependent on each other – which violates the basic independence assumption in statistical modeling (Fleming, Mingo, et al., 2007). We use a common strategy to address network autocorrelation by randomly sampling our initial sample (Fleming, Mingo, et al., 2007; Lee, 2010). The findings for the main variables in these subsamples were in line with our primary estimations.
and are available upon request.

**DISCUSSION AND CONCLUSION**

This study offered a refined explanation to the existing literature on the question why social context influences individual-level innovation. We complement the current network structural focus by showing how resource munificence present in inventors’ ego collaboration networks impact the generation of valuable innovations. Our results suggest that network resource munificence positively influences inventor performance while controlling for important alternative explanations, including individual-level ability, ego network and firm characteristics. Specifically, the availability of knowledge resources combined with actual knowledge resource use determines the innovative performance of inventors employed in the global semiconductor industry. Conditional on having a resource munificent collaboration network, however, we document how ego network geographical dispersion dissipate the effect of resource munificence on inventor success. These arguments and evidence provide an additional explanation as to why social context drives individual-level variation in innovative outcomes; heterogeneity in availability and use of network resources impact innovative performance.

The theoretical implications of our study advocate the need to further explore how individuals are dependent on resources available in the intraorganizational environment (Kehoe & Tzabbar, 2015; Paruchuri & Awate, 2017; Pfeffer & Salancik, 1978). We show how individuals utilize knowledge resource opportunities through recent collaborative experience with peers. With our focus on individuals’ immediate social context, we join a growing body of literature distinguishing between structural and compositional network characteristics (Rodan & Galunic, 2004; Singh et al., 2016). We do not downplay the importance of structural characteristics, but instead claim that network structure partially determines the extent to which inventors are socially
autonomous or constrained in their ability to access and integrate resources (Gabbay & Zuckerman, 1998). The resources embedded in these intrafirm networks merit future research attention.

Of course, another explanation for the variation in inventors’ ability to absorb knowledge resources from their direct contacts resides in individuals’ innate ability, personality traits and accumulated experience (Cohen & Levinthal, 1990; Fleming & Sorenson, 2004; Tasselli et al., 2015). Our work emphasizes that not only resource availability is important, but also the active use of knowledge resources obtained through collaborative experience with alters within the organization. Individuals might learn from learning-by-doing and actively using knowledge possessed by their colleagues (Schilling, Vidal, Ployhart, & Marangoni, 2003). This study thus resonates recent calls to further explore individuals’ use of knowledge resources that reside in the intraorganizational environment (Singh et al., 2016; Toh & Polidoro, 2013).

Our study also contributes to the existing literature on geographical dispersion of R&D-based innovation (Alcácer & Zhao, 2012; Allen, 1977; Funk, 2014; Lahiri, 2010; Singh, 2008; Tzabbar & Vestal, 2015). Our findings resonate the call by resource dependence theorists that the spatial character of social action and structure merits attention (Pfeffer & Salancik, 1978: xx). Building on the common argument that face-to-face interaction and collocation foster the transfer of tacit and sticky knowledge we found how the positive effect of resource munificence abate with increasing geographical dispersion of ego network contacts. In addition, our research underlines the need for future research on the spatial dispersion of innovation activity due to our contrasting findings with regard to ego network geographic dispersion and firm-level geographic dispersion (cf. Lahiri, 2010; Singh, 2008; Tzabbar & Vestal, 2015).
Finally, with this study we also intend to contribute to the broader literature on the knowledge-based view (KBV) and absorptive capacity (Cohen & Levinthal, 1990; Grant, 1996; Kogut & Zander, 1992; Volberda, Foss, & Lyles, 2010). We highlight that the collaborative context that surrounds innovation affects individual-level recombinant innovation. With our focus on recombinant innovation in the context of the semiconductor industry, we intend to contribute to the microfoundations movement in strategy and innovation (Felin, Foss, & Ployhart, 2015).

Limitations and future research

Our study has some limitations. The current archival data research design allows us to capture inventors, their ego networks and the network resource use in a large-scale fashion over time. Yet, this choice also limits us in various ways. For instance, we cannot capture information regarding inventor’s demographic background or job position. Using patent data also means that our research design could suffer from success bias. Even though our focus on a R&D intensive industry partially alleviates such concerns, we cannot rule out that we only capture relatively prolific inventors. Furthermore, we analyze collaborative behavior of individuals based on co-invention patterns, but we are not able to consider other types of interpersonal relationships, such as advice or friendship ties, which have proven relevant in the context of corporate innovation (Brennecke & Rank, 2017; Carnabuci & Dioszegi, 2015; Perry-Smith, 2006). Another limitation that arises from our specific choice to use archival data is that we cannot distinguish motivational factors and strategic intent. For instance, it might be that certain inventors opportunistically connect with resource-rich colleagues. Nor do we know whether R&D managers assign inventors to projects in such a way that they alter the collaboration networks and composition of dispersed inventor teams. These issues of course raise the question to what extent our research might suffer from endogeneity concerns (Bascle, 2008). This is an important issue to address in future research.
Managerial implications

From a managerial perspective, our research points to important areas for reflection. A manager should be mindful of the distribution of knowledge resources and skills across her subordinate innovation professionals. To unlock the full potential for recombinant innovation (Fleming, 2004, 2007), managers could assign resourceful or high-powered inventors to act as mentors or motivate them to collaborate widely with intrafirm peers (Tzabbar & Kehoe, 2014). This would require managers to apply a resource dependence lens to their current human capital pool. Another way that managers should interpret our findings is that geographical barriers might hamper innovation performance and that existing collaborative structures between different geographical locations within the same company might not suffice in driving recombinant innovation. Other mechanisms to enhance knowledge resource exchange could be explored such as short-term intrafirm rotation or mobility (Choudhury, 2017).

Conclusion

To conclude, we view the network resource lens applied here as a promising avenue for future research on social context and corporate innovation. Our study showed how inventors might unlock knowledge resources that reside in their intraorganizational collaboration networks and may subsequently encourage future innovation success. Nevertheless, we also note that these collaborative ties among innovation professionals might not be sufficient to defeat issues pertinent to crossing distant locations. Consequently, intrafirm social and geographical factors deserve our continued attention in the context of innovation.
REFERENCES


APPENDIX

Figure 1. Geographic Dispersion of Inventors Active in the Semiconductor Industry from 1983 to 2003
Figure 2. Ego Network Resource Munificence
Table 1. Descriptive Statistics

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*p < 0.01
Table 3. Results of Random-Effects Negative Binomial Models Predicting Inventor Innovative Performance Measured as Forward Citation Counts (5-year window)

Random-effects Negative Binomial Model of Forward citation counts (5 year windows)

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*** p<.001 **<.005 *.01 <.05 N=105,668

Standard deviation in parentheses