The Differential Impact of Intra-Firm Collaboration and Technological Network Centrality on Employees' Likelihood of Leaving the Firm

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Published in Organization Science: https://doi.org/10.1287/orsc.2021.1535

Abstract

How does an employee's centrality in intra-firm R&D activities affect his/her propensity for outward mobility? Does this proclivity vary by the type of employment the employee seeks: moving to other firms versus founding a new venture? We maintain that to answer these questions we must distinguish between an employee's centrality in the intra-firm collaboration network and his/her centrality in the intra-firm technological recombination network. We utilize the curricula vitae and patent data of corporate inventors at a leading semiconductor company between 1993 and 2012 to test our hypotheses. Contrary to prevailing views, our competing risk model indicates that corporate inventors who are central in the intra-firm collaboration and technological network, and thus have the most opportunities, are less likely to leave the current employer. However, when considering external employment opportunities, their preferences vary. Collaboration central individuals are more likely to start a new venture than to move to another employer. Their skill in developing inter-personal relationships enables them to attract the tangible and intangible resources needed in a new firm. In contrast, inventors whose technological expertise is central to the firm's technology recombination network are more likely to move to another employer than to start a new venture. In an established firm, they can leverage their technological know-how using the resources that a new venture would lack. Our theory highlights the tradeoffs in employees' attempts to take advantage of their internal and external value based on their position within the firm's collaboration and technological networks.

Keywords: Outward mobility; Employee entrepreneurship; Collaboration betweenness centrality; Technological betweenness centrality; Intra-firm networks; Firm-specific human capital; Relational capital.

Acknowledgements
The authors thank Gino Cattani and Haemin Dennis Park for useful comments and suggestions on early versions of this paper, as well as seminar audiences at Bayes Business School, Bocconi University, Drexel LeBow, INSEAD, Maryland, NYU Stern, and SKEMA Business School, and attendees of presentations at the 2017 DRUID Conference, 2017 Strategic Management Conference, and 2018 Academy of Management annual conference. The authors are grateful to the senior editor, Aleksandra Kacperczyk, and the reviewers for their help in improving the manuscript through a most constructive review process. All errors and omissions are ours.

Introduction

In high-tech industries, leading firms are at the greatest risk of losing key knowledge assets through their employees' outward mobility. Their employees are often poaching targets for direct and indirect competitors seeking to expropriate critical knowledge as a way to reduce competitive deficits (Wezel et al. 2006). As repositories of a firm's knowledge, skilled employees such as corporate inventors who are responsible for innovation are commonly believed to have a broad spectrum of employment opportunities (Coff 1999, Godart et al. 2014). Employees' motivations and prospects for seeking external employment options, though, may vary based on their position within the firm's network. For example, individuals who are "in between" others or central in the firm's research and development (R&D) activities, such as boundary spanners, are considered very valuable both internally and externally and are potentially more mobile than others because they serve as system integrators in the intra-firm network (Paruchuri 2010, Paruchuri and Awate 2017). In particular, such a network position enables its holders to access and control unique information, increasing the dependence of others on them and reducing their dependence on others (Brass 1984). Prior works have thus emphasized that firms value them highly (Brass 1984), increasing their opportunity costs in seeking to leave the company (Kacperczyk 2012). However, such individuals are also regarded as having more opportunities to exploit their unique information externally (Cattani and Ferriani 2008, Zou and Ingram 2013).

Despite these considerations, most theoretical advancements and empirical evidence have focused exclusively on how a central position in intra-firm networks enables their holders to achieve internal career advancement and benefits (Tushman 1977). Consequently, there is little theory or empirical evidence to guide us on how employees' internal position affects their propensity for outward mobility. We are also in need of theory about how centrally positioned employees seek to appropriate value, as well as how their opportunity costs in seeking to leave the company depend on the type of external mobility: changing employers or starting a new venture.

The purpose of this study is to help fill these theoretical and empirical gaps. To do so, we build on recent evidence establishing that inventors' positions in a firm's collaboration and technological networks are unlikely to overlap entirely (Brennecke and Rank 2017, Guan and Liu 2016, Wang et al. 2014). The distinction between collaboration and technological networks is critical because individuals who occupy central positions in them are endowed with skills, capabilities and resources that are differently transferable across work contexts. We extend this logic by asking: how do corporate inventors' collaboration and technological centrality in intra-firm R&D activities affect their propensity for outward mobility? Does this propensity vary by the type of employment the inventors seek, meaning, moving to another firm or creating a new venture?

We propose that corporate inventors' positions in each one of these networks reflect their interdependence with other inventors in the firm (i.e., collaboration centrality), and with the firm's technological components (i.e., technological centrality). These factors affect their internal and external value, with varying effects on their opportunity costs in seeking to move to another employer or to start a new venture. Specifically, the inventor's intra-firm *collaboration betweenness centrality*[1] refers to the extent to which the inventor is on the shortest path connecting other colleagues who themselves are not directly connected in the intra-firm collaboration network. At the individual level, collaboration centrality reflects the relational skills and capabilities inventors need to collaborate with others and achieve a central position. At the firm level, central individuals have exclusive access to and control over unique information about who in the intra-firm collaboration network has the information to resolve existing innovative problems (i.e., "who knows what" in the organization), increasing organizational dependence on them (Paruchuri 2010). Given that the positional advantage of central inventors is rooted in the set of relationships they have accumulated within a firm (Mawdsley and Somaya 2016), such individuals have a strong incentive to stay in their unique position. However, when considering external employment options, we argue that central inventors are more likely to start a new venture than move to another

[1] Hereafter, collaboration centrality.

employer. Indeed, moving to another employer would require investing time and effort in rebuilding a stock of relationships. In contrast, an entrepreneurial environment might offer them the opportunity to regain a central position immediately and involve less social friction than moving to another employer where social connections are well established (Cirillo et al. 2018, Wasserman 2003).

Conversely, the inventor's intra-firm *technological betweenness centrality*[2] refers to the extent to which the technological components invented by the inventor, or his/her technological experience, are on the shortest path in the recombination of other technological components in the firm's technology recombination network.[3] Technological centrality is associated with highly specialized tacit knowledge and with expertise about the firm's combinatorial "know-how" and "know-why." Given that the process of knowledge integration crucially depends on such expertise, its holders are highly valued and rewarded internally. Consequently, we predict that a higher level of technological centrality is associated with less likelihood of leaving the current employer. At the same time, among the external employment options, we argue that technologically central inventors are more likely to move to an established employer than to start a new venture. They make this choice because their integration and combinatorial capabilities can be most effectively deployed and utilized in contexts where the complementary know-how, resources and capabilities are available. Typically, this situation is more likely to occur in incumbent firms rather than in new ventures, which have limited know-how and resources.

To test our theory, we created a unique longitudinal dataset using data from public LinkedIn accounts and the U.S. Patent and Trademark Office (USPTO) to build the employment histories and patenting records of 4,416 knowledge workers employed between 1993 and 2012 by a leading firm in the U.S. semiconductor industry. To validate our assumptions, we also conducted interviews with the firm's human resource department and project managers, as well as with employees at various hierarchical levels and types of network centrality. As expected, the competing risk hazard rate model shows that

[2] Hereafter, technological centrality.
[3] In both measures, we refer to the entire intra-firm network as opposed to local networks and/or network components.

central inventors in both collaborative and technological networks are more likely to stay with their existing employer than leave for any other type of employment. However, collaborative central inventors are more likely to start a new venture than to move to another employer. Conversely, technologically central inventors are more likely to move to another employer than to start a new venture. Accordingly, our findings provide nuanced insights into the effect of collaboration and technological centrality on employees' retention and their decisions about moving to another employer versus starting a new venture.

These results add to the extant research in several ways. First, theoretically, by distinguishing between different types of intra-firm networks and types of mobility, our study delves deeper into how employees' human and relational capital improve our understanding of how the opportunity costs and potential for value appropriation vary based on the type of new employment inventors seek. Second, we provide a more nuanced perspective on the resource-based view's arguments about how the "stickiness" of employees' context-specific knowledge shapes their opportunity costs and ability to move to a new employer. Third, whereas network theory has focused on explaining how an individual's position in the intra-firm networks enhances or diminishes his/her internal mobility (e.g., Burt 2007, Fang et al. 2015, Kleinbaum 2012, Seibert et al. 2001), we redirect research efforts by examining their varying effects on two types of outward mobility. Fourth, by establishing that different structural positions are associated with access and control over different type of information, our results suggest that the risk of knowledge leakage and the potential appropriation by other firms also varies. Most critically, while the extant research suggests that the risk of knowledge spillovers following mobility is the greatest in the case of employee entrepreneurship (Campbell et al. 2012), our results show that those who tend to start their own ventures are not those who have critical technological know-how and know-why. More broadly, our results have the potential to expand our understanding of knowledge spillovers by explaining how people's position in various networks may affect the type of knowledge they can take with them when leaving a company. Finally, our results suggest that those who have strong collaborative abilities consider developing their own venture as a better match than moving to new employer. In contrast, those with specific technological know-how capabilities find a move to a new employer to be a better match that will enable them to best utilize their opportunities. As such, our results also provide fresh insights into matching theory (Jovanovic 1979, Lazear and Oyer 2013, Sørensen and Sharkey 2014).

Theory and Hypotheses

In large, complex, high-tech firms, R&D activities are typically organized into autonomous units to allow specialization and adaptation to dynamic technological and innovative environments (Hoegl et al. 2004). Due to specialization, a firm's R&D activities tend to evolve toward nearly decomposable technological structures, where dense clusters of technological elements and expertise are connected by a few interactions between clusters (Brennecke and Rank 2017, Rivkin and Siggelkow 2007). In addition, they also tend to evolve into locally dense collaboration structures, where groups and teams establish their own goals, priorities, communication styles, social codes and subcultures (Kleinbaum and Tushman 2007, Thompson 1967) that create an intra-firm social chasm (Tzabbar and Vestal 2015). Such highly decomposable technological and social structures create a need for integration and coordination. Therefore, the literature has stressed the important role that central employees play in the innovation processes of large organizations, as they connect distinct and otherwise disconnected parts of the intra-firm network (Burt 2004, Kleinbaum and Tushman 2007, Soda et al. 2017).

Prior studies have generally confounded the implications of individual centrality in collaboration and technological networks by treating them as isomorphic (Brennecke and Rank 2017). From a network perspective, the distinction is critical because individuals who occupy central positions in the collaboration network can span colleagues within the same technological domain or between two disconnected technological domains (Wang et al. 2014). In particular, whereas technological centrality arises from recombining technology components, collaboration centrality refers to the relationship between the agents creating an outcome, where some depend on others for exchanges, not the outcome itself. Thus, patterns of collaboration among employees, such as knowledge workers, are conceptually different from patterns of combinations among technological elements of a firm, and they may have different structural features (Guan and Liu 2016, Wang et al. 2014).

To untangle the differences between collaboration and technological centrality[4] we build on the concept of interdependence. Dependence is the result of an interaction between the critical nature of a resource and the existence of alternative providers of such a resource (Casciaro and Piskorski 2005). In contrast, interdependence is a relationship between reciprocally dependent entities such as objects, individuals or technological components. We propose that the inventors' positions in the intra-firm collaboration and technological networks are associated with different kinds of interdependence and reflect different dimensions of individual human capital.

On one hand, collaboration interdependence occurs when individuals are mutually reliant on each other for engaging in an action or obtaining the outcome desired from the action (Pfeffer and Salancik 1978). In this respect, centrality in the collaboration network indicates a high level of interdependence between the inventor and the current employer's human resources, meaning other inventors in the firm. Such centrality consists of knowing "who knows what" in the organization. Employees who achieve a position of centrality in the intra-firm collaboration network become aware of their colleagues' expertise and have control over relevant information on where valuable firm's knowledge resides, and who can exploit it (Zhao and Anand 2013). Thus, regardless of their technological skills and experience, they are capable of promoting or impeding the transfer, coordination and integration of others' skills and expertise across teams and projects (Freeman 1977, Tushman 1977). They also know how to negotiate and bridge differences between different actors in order to assemble and mobilize support for their initiatives (Easley and Kleinberg 2010). Thus, they typically find themselves in a position of influence in the flow of information within the firm (Brass 1984, Casciaro 1998). Clearly, this unique positional advantage increases the dependence of other inventors on them for gaining access to the information and competencies residing in other parts of the network. At the same time, however, the value associated with this relational capital is rooted in the set of relationships that employees have developed within an

[4] We focus on centrality as a structural position in between other parts of the entire intra-firm network (Zhao and Anand 2013). Following Everett and Valente (2016) and Borgatti (2005), we refer to individuals who are central in the entire network of the firm (i.e., global network), not to those who are central in the local network.

organization. Therefore, these relationships have little value to them when moving to other employment contexts (Mawdsley and Somaya 2016).

However, knowing where knowledge resides does not mean also having the necessary know-how and know-why required to use and combine that knowledge. That skill requires a different dimension of human capital and reflects a different notion of interdependence—technological interdependence. The latter "arises when subcomponents significantly affect the contribution of one or more other subcomponents to the functionality of a piece of knowledge" (Sorenson et al. 2006: 995). Accordingly, centrality in the technological network indicates a high level of interdependence between the inventor and the current employer's technological capabilities. Employees who achieve a position of centrality in the intra-firm technological network have unique knowledge about the firm's proprietary technologies and how different technologies are uniquely combined (Yayavaram and Ahuja 2008). In contrast to collaboration networks, to gain prominence in intra-firm technological networks individuals need to master the technological components, expertise or skills that are critical in recombining at least two technological components of the firm (Carnabuci and Bruggeman 2009). Such individuals understand the causal reasoning behind the combination, thus increasing their overall know-how and know-why. In doing so, they can shape the pattern of combinations among technology elements that exists within the current technology base of their employer, helping the organization exploit the benefits of specialization across divisions (Tushman and Nadler 1978). Overall, centrality in the firm's technological network reflects an individual's investment in developing the expertise and skills that are specific to the firm's technology base and, for this reason, are highly valued internally. Simultaneously, the value of this human capital crucially depends on the complementary technological resources available to integrate with inventor knowledge.

We argue that knowledge of "who knows what" and of "what, how and why" are highly valued internally, increasing the likelihood of central inventors remaining with their current employer. However, when it comes to external employment opportunities, the most likely direction of outward mobility can vary by the type of centrality these inventors have. More specifically, in the following sections we elaborate on how an inventor's intra-firm collaboration centrality and technological centrality shape the choice of staying with the current employer and the expected destination of a move to an existing employer vs. entrepreneurship. Implicit in our theoretical framework is the idea that the decision to move and the destination choice are unlikely to be made sequentially. In other words, we maintain that people do not first decide whether to stay or leave and then, given the decision to move, decide on their destination. Rather, the decision to leave the company and the direction of outward mobility are intimately related. Both depend on the expected costs and benefits that the various alternatives offer to the individual.

Collaboration Centrality and Outward Mobility

Staying vs. outward mobility. Inventors with a high level of intra-firm collaboration centrality are more likely to have a broad reach to the far edges of the intra-firm collaboration network, to be better connected with other influential actors and, thus, to potentially receive more and better information than less central individuals (Cross and Cummings 2004). This position gives them an opportunity to access and control critical information about who has the skills, abilities and motivation to resolve existing innovative problems at the firm (Brass 1984). Such knowledge of "who knows what" enables them to play a critical role in fostering greater connectivity and coordination among other firm's members. Connecting various collaboration groups also gives them an opportunity to shape the attitudes, norms and behaviors of others in the organization, and to align them with the firm's expectations (Rogers and Kincaid 1981, Tushman 1977). In addition to their overall visibility, serving in these important roles makes them not only very valuable to their employer but also harder to replace than less central individuals (Burkhardt and Brass 1990). Since the departure of very visible and influential individuals can hurt the morale of other organizational members and increase their motivation to leave (Ballinger and Schoorman 2007), employers try to prevent their leaving by recognizing their value and by rewarding them. For example, the extant research shows that individuals who are in such advantageous network positions are more likely to receive better supervisor ratings (Mehra et al. 2001), enjoy greater intra-firm mobility and receive promotions earlier than their peers (Brass 1984, Gargiulo and Benassi 2000).

At the individual level, the relational capital associated with a high level of collaboration centrality is rooted in the set of relationships an individual has accumulated within a firm. Given its firm-specific nature, this asset is difficult to transfer to another firm (Mawdsley and Somaya 2016). Moreover, the critical nature of the roles central employees play enables them to leverage their value with their current employer relative to any other employment opportunity. Specifically, given that their positional advantage is based on the idiosyncratic and ad-hoc nature of formal collaborations at their current employer, the latter can better assess their contribution to the integration of the intra-firm collaboration network than other prospective employers can. The recognition and opportunities they receive from their current employer motivate them to stay to maintain their unique position with their existing employer (Ballinger et al. 2016, Feeley et al. 2008), and avoid the risk and adjustment costs associated with moving to a new employer or starting a new venture (e.g., Agarwal et al. 2016, Chen 2005, Rocha et al. 2018).

Given the risk and costs associated with mobility, we expect that the perceived value and recognition associated with collaborative centrality outweigh the potential payoff of switching to another employment context:

HYPOTHESIS 1a (H1a). *Inventors with a high level of collaboration centrality are more likely to stay with their current employer then to move to any type of new employment.*

Employee entrepreneurship vs. moving to another employer. While inventors with a high level of collaboration centrality are less likely to leave their current employer, we expect that, when considering external employment opportunities, they will have more benefits and fewer opportunity costs by starting a new venture than moving to another employer. Clearly, they have relational skills and disposition to rebuild a stock of relationships to achieve a central position at any new employment context, but they can also recognize that doing so may involve more investment of time and effort when joining a new employer than when starting a new venture. At a new employer, the mobile inventors would have to first socialize and learn about and participate in the research agenda of their new work context (March 1991). Furthermore, their opportunity to exert their influence on the new employer's research agenda and on the attitudes, norms and behaviors of others in the organization would be limited due to the lack of critical ties in their initial position in the collaboration network (Wanous 1980). In contrast, when these individuals start their own venture, as founders they immediately assume a central and prominent position in the collaboration network. They can also shape the firm's research agenda and behavioral norms, and have a lasting effect on the venture's direction (Agarwal et al. 2004, Cirillo et al. 2014, Wasserman 2003). As such, an entrepreneurial environment is a better match for individuals with such skills. The extant research supports this contention by showing that founders are typically individuals who seek to collaborate and lead (Fang et al. 2015, Ferris et al. 2012, Tocher et al. 2012). Thus, an entrepreneurial context may enable them to replicate the privileged position they enjoyed at their previous employer, albeit on a smaller scale, better than any other external employment context.

Second, on the rewards side, research suggests that collaboration central individuals prefer and do best in environments that reward more individual than collective performance (Xiao and Tsui 2007). Specifically, when inventors start a new venture, their expected payoff is tightly linked to their individual effort (Nikolowa 2014). In contrast, if they join another existing employer, they typically receive a fixed wage regardless of the market value of their ideas (Cassiman and Ueda 2006). These factors make entrepreneurial environments very attractive to them and a better fit than other external employment contexts. Furthermore, individuals with a high level of collaboration centrality have developed relational and leadership skills that are crucial to mobilize and secure the tangible and intangible resources (Baron and Markman 2000, Ferris and Judge 1991, Ferris et al. 2005) that are particularly relevant when deciding to start a new venture (Cirillo 2019). Accordingly, we maintain that inventors with a high level of collaboration centrality are more likely to derive greater benefits and incur fewer opportunity costs by starting a new venture than joining another company. Accordingly, we hypothesize that:

HYPOTHESIS 1b (H1b). *Among the potential destinations of outward mobility, inventors with a high level of collaboration centrality are more likely to become entrepreneurs than move to another employer.*

Technological Centrality and Outward Mobility

Staying vs. outward mobility. Inventors with intra-firm technological centrality are experts in recombining elements of the company's technologies that would otherwise remain uncombined. While creating such unique recombinations produces value for their employer, it also intertwines the fates of these inventors with that of their firm, making them interdependent, for two reasons. First, the inventors' know-how and know-why are to some extent specific and idiosyncratic to the firm's organizational routines and knowledge base. Their intertwined nature makes the inventors' experience in recombining such firm specific technological components difficult to transfer and imitate (Henderson and Cockburn 1994). The tacitness and context specific aspect of such knowledge also make it harder to leverage and redeploy in other work contexts (Coff and Raffiee 2015). In particular, such knowledge specificity impedes the inventors' ability to develop new inventions independently in a new work context because other complementary technology pieces become less accessible or difficult to replicate outside the current employer (Tzabbar et al. 2015). The difficulty in exploiting their skills across firms, combined with the potential loss of productivity associated with outward mobility, increases their opportunity costs in seeking to leave their current employer (Morris et al. 2017).

Second, the same reasons that make external opportunities less attractive to technologically central individuals also make internal opportunities more attractive to them. Specifically, the more an inventor holds technological components that are highly integrated with the other technological components held by the firm, the greater the firm's dependence is on the inventor's know-how and know-why. This situation makes technologically central individuals valuable within the organization, because their presence insures continual innovative productivity and creativity (Carnabuci and Operti 2013). Indeed, the departure of such central inventors might disrupt the technological integration and creation efforts of their employer more than the departure of those whose technological expertise is less intertwined with the firm's overall technology recombination network (Tzabbar and Kehoe 2014). These considerations increase their perceived value and the employing firm's motivation to retain them (Ahuja et al. 2013, King 2007). Therefore, their potential payoff from switching to a different employment should be smaller than the potential value generated by their internal opportunities. Accordingly, we hypothesize:

HYPOTHESIS 2a (H2a). *Inventors with a high level of technological centrality are more likely to remain with their current employer than to move to any type of new employment.*

Employee entrepreneurship vs. moving to another employer. While technologically central inventors are less likely to leave their current employer, there are several reasons to expect that, when considering external employment opportunities, moving to a new employer will be more advantageous and incur fewer opportunity costs than starting a new venture. As argued above, their know-how and know-why is very idiosyncratic and intertwined with the firm's technological resources. Therefore, their ability to capitalize on their technological expertise in another context depends on the technological resources available in the new work environment. Existing firms are more likely than startups to offer the range of knowledge and resources such inventors would need (Al-Laham et al. 2011). In such environments they could capitalize on their value and reduce their opportunity costs. Thus, they are likely to regard their chances of utilizing their combinatorial and integration skills as better in an existing company than a new venture (Lazear 2009).

Furthermore, the limited technological resources of a new venture may exacerbate the complexity, causal ambiguity and tacitness associated with a central inventor's know-how and know-why (Alnuaimi and George 2016, King 2007, Salomon and Martin 2008). From an external market perspective, there is greater information asymmetry about the inventor's knowledge in entrepreneurial contexts than in other prospective employment contexts (Campbell et al. 2017, Cohen and Dean 2005). This asymmetry increases assessment costs as well as the risk in predicting the true value of the inventor's new inventive efforts (Alnuaimi and George 2016, Kaplan and Murray 2010, King 2007, Salomon and Martin 2008), reducing his/her prospects of securing external investments for the new venture (Park and Tzabbar 2016). In contrast, established organizations may already have the required absorptive capacity to understand and integrate external sources of tacit and causally ambiguous knowledge. As such, existing firms should be able to better utilize and commercially exploit the know-how and know-why of technologically central inventors than new ventures. Accordingly, we hypothesize:

HYPOTHESIS 2b (H2b). *Among the potential destinations of outward mobility, inventors with a high level of technological centrality are more likely to move to another employer than become entrepreneurs.*

Method

Sample

To test our hypotheses, we use data pertaining to the patenting activities and curricula vitae of a sample of inventors employed from 1993 to 2012 by a U.S. firm that led the semiconductor and microprocessor industry during the study period. For confidentiality reasons, we do not identify the firm. This empirical setting is ideal for testing our hypotheses, for several reasons. First, focusing on one firm allows us to control for and eliminate unobserved firm heterogeneity in terms of the firm's value and opportunity for central inventors. Second, the firm's leadership position in the industry enables us to hold constant the market demand for its inventors, reducing unnecessary variance. Considering only inventors, rather than all types of employees, enables us to focus on the internal and external labor market for a relatively homogeneous type of worker. In doing so, we can eliminate not only any unobserved heterogeneity associated with including the mobility of other types of employees but also ensure that the theoretical mechanisms apply equally to the likelihood of inventors' mobility. Third, this firm is among the top North American companies using LinkedIn as a means of developing intra-firm collaborations, encouraging employees' interactions via LinkedIn, and attracting and recruiting new talent.[5] The vast number of the firm's employees with public LinkedIn accounts and patents facilitates the collection of reliable data on career histories. Finally, this firm's research environment also encourages employees to patent. Thus, its employees' patenting activities and intra-firm co-inventions provide a reliable source of data to estimate intra-firm collaboration and technological networks (Paruchuri 2010).

Identifying employees. Using public LinkedIn profiles[6] and patenting activities reported in the United States Patent and Trademark Office (USPTO), we identified engineers and scientists who worked and patented for the firm. In the first stage, using USPTO patent data, we identified 11,992 inventors who

[5] Burgess W. 2015. North America's Most InDemand Employers: 2015. Retrieved May 24, 2017, from https://business.linkedin.com/talent-solutions/blog/trends-and-research/2015/the-most-indemand-employers-in-north-america-for-2015

[6] The data were collected through an approved application to the LinkedIn Vetted API access program.

reported the firm as an assignee on at least one of their patents since the firm's incorporation. This list not only includes inventors who are employed by the firm, but it may also include those of the firm's allied partners when, for example, they collaborate on projects that result in patent co-applications (Hagedoorn 2003). Therefore, to obtain a clean list of only inventors employed by the firm, in the second stage we identified and selected those who had a public LinkedIn profile that reported the firm as one of their employers during their working career, including any job function. In particular, we matched these two sources of data by the person's name, geographical location and employment/patenting dates at the firm. From this set, we dropped those profiles reporting the firm as a contracted job, a client, or a distributor.

Limiting this list to inventors with a LinkedIn profile and USPTO records, and to those employed by the firm during our study period (1993-2012), we successfully matched 4,416 firm employees. Our methodological approach in using both LinkedIn and USPTO data to identify the employees' affiliation and mobility thus corrects two problems that have plagued previous research. First, individuals may appear on the firm's patents not due to formal employment but because a partner firm employed them (Hagedoorn 2003). Second, outward mobility events may be underestimated when inventors do not patent after leaving the focal firm to join other firms (Ge et al. 2016). Taking full account of the LinkedIn data, we then estimated the likelihood of these 4,416 inventors leaving the firm, as well as the targets of their mobility. Appendix A provides further details on our matching algorithm and robustness checks on the selection of the sample.

Focusing on this time period allows us to minimize measurement bias, for two reasons. First, extending our dataset further back than 1993 might include a cohort of inventors with no LinkedIn account.[7] Second, right censoring our dataset in 2012 allows us to control for the impact of an inventor's patents on future inventions, because granted patents typically reach a plateau of forward citations after about six years from the application date (Fleming 2001, Jaffe et al. 1993).

Field research

[7] Although LinkedIn was founded in 2002, our data show that inventors who were hired by the firm after 1992 are more likely to have a public LinkedIn account.

To better understand the phenomena of interest, validate our measurement strategy, interpret our econometric results, and collect important anecdotes on the possible mechanisms that support our theory, we elicited the views of individuals employed at the sampled firm. We gathered evidence from two sources: the human resources department and research and development (R&D) managers involved with the management of R&D processes and employees' careers, and engineers identified as inventors in patent documents at the firm. The semi-structured interviews focused on topics such as the patenting process and decisions, corporate inventors' discretion in the process, and the determinants of internal and external career opportunities. For the sake of conciseness, we provide further details on our interview sample, protocol, open coding, and data in Appendix D.

Measures

We consolidated the patent records and LinkedIn data on an annual basis. For each inventor-year in our sample, we measured the following variables (see Table 1 for a detailed description of each measure and data sources).

[Insert Table 1 here]

Dependent variables. We identified exit events as types of mobility. The first dependent variable, *mobility (any type)*, is a binary indicator set to one when the focal inventor leaves the firm to join another employment context, and zero otherwise. If the LinkedIn profile of the inventor shows two consecutive jobs, first with the firm and then with a different firm, where the time gap is no more than one year, we suppose the inventor left the firm in the starting year of the record. Then, using information on the LinkedIn profile of the inventor, we distinguished between two types of mobility events. If the LinkedIn profile of an inventor cites "founder" as his/her job title at another employer, we suppose the inventor left the firm to start a new venture.[8] Otherwise, we considered that the inventor left the firm to

[8] To ensure data reliability, we also searched for public information on each new venture we detected, and excluded cases of self-employment, meaning, freelance consultants, and misspecifications in the LinkedIn profiles. This list of new ventures born out of employees' entrepreneurship includes both (i) technology spin-offs or corporate venturing spinouts, meaning ventures that are not in conflict with and benefit from the support of their parent firm, and (ii) employee spinouts started by former employees with no agreement and potentially in conflict with their original firm.

join another employer. Accordingly, the second dependent variable, *mobility to another employer*, is a binary indicator set to one when the focal inventor is recruited by another firm, and zero otherwise. The third dependent variable, *entrepreneurship,* is a binary indicator set to one when the focal inventor leaves the firm to either start or join the founding team of a new venture, and zero otherwise. During the timeframe of this study, 1,429 inventors left the firm to join 801 other incumbent firms, and 128 inventors left the firm to start 77 new ventures.

Finally, as a control and a way not to confuse unemployment or retirement with other types of mobility, the third category of outward mobility is *unemployment*, a binary indicator set to one if the inventor leaves the firm to become unemployed, and zero otherwise. If the LinkedIn profile of an inventor shows either a gap of at least one year or no listed employer after the last year of employment at the firm, we deem the inventor to be unemployed the year after the last record at the firm. During the timeframe of this study, 292 inventors left the firm and became unemployed.

For the remaining 2,695 inventors who did not experience any exit event we right-censored the observations at 2012. Given the information we had on the inventors' mode and year of exit, for each inventor, we selected the time period when s/he remained at risk of an exit event during his/her employment at the firm. We divided the inventor observations by year and balanced them to update the covariates. We entered the time dimension in the specification of our econometric model using the logarithm of the number of years since the inventor's first patent with the firm until year t, ln(*Time*). Our final dataset includes 35,344 inventor-year observations.

Independent variables. We relied on the notion of node betweenness (Brass 1984, Freeman 1977) to develop our main independent variables. Generally speaking, a high "betweenness" value indicates a vertex that lies on the shortest paths linking other (loosely connected) vertices of a graph. If this central vertex were removed, the connections between the other vertices would be broken or would become less efficient. In our context, node betweenness represents a good proxy for the extent to which an inventor is on the shortest information path connecting other inventors who themselves are not directly connected (Mehra et al. 2001). Similarly, it is a good proxy to identify those inventors who act as bridges between distinct and otherwise disconnected technological elements within a firm's knowledge recombination network.[9]

Our first independent variable, *collaboration centrality*, measures the extent to which the inventor is on the shortest path connecting other colleagues in the intra-firm collaboration network. To compute this variable, we relied on the intra-firm co-patenting network (Carnabuci and Operti 2013). Specifically, for each year *t* in the duration of our study, we considered all patents the firm filed in [*t-4, t*] and built the corresponding collaboration graph where inventors are linked if they co-authored at least one patent. Since two inventors may appear together on several patents, we weighted these links using the Jaccard coefficient

$$v_k = \frac{a}{a+b+c} \tag{1}$$

where *a* is the number of patents that inventors *i* and *j* have co-authored, *b* is the total number of patents authored by inventor *i* without *j*, and *c* is the number of patents authored by inventor *j* without *i*. This weight captures the strength of the interaction between two inventors. It ranges from 0 (*i* and *j* never co-authored any patent) to 1 (*i* and *j* co-authored all of their patents together).

Using the resulting weighted network, for each inventor, we then computed the value of his/her node betweenness (see Appendix B for details). Since links in our co-invention graph are weighted, we identified the shortest paths as the sequences of edges that minimized the "cost" of connecting two of the firm's inventors, which we assumed to be inversely proportional to the strength of the interaction. Formally, the cost of using the link between inventor *i* and *j* is given by

$$c(e_k) = \frac{1}{v_k} \tag{2}$$

[9] In accordance with Mehra et al. (2001), we chose this measure rather than a more local measure, such as constraint (Burt 2004), because betweenness centrality takes both direct and indirect ties into account (Brass 1984), whereas constraint focuses primarily on the direct ties in an individual's immediate circle of contacts. Local measures are useful when sampling from large populations for which whole network data are unavailable (Burt 2004). This is not so in our case, as our data cover the entire intra-firm network. By capturing an individual's reach in the whole intra-firm network, betweenness centrality also provides a better fit with our theory.

where $c(e_k)$ represents the "cost" of the edge $e_k = (n_i, n_j)$ connecting nodes (i.e., inventors) i and j.[10]

Finally, we normalized the value of the inventor's node betweenness using the minimum and maximum realized values of node betweenness in the network (see Appendix B for details). His/her collaboration (betweenness) centrality thus ranges from zero to a theoretical maximum of one.[11] As an example, Figure 1 illustrates the collaboration (co-inventing) network of the focal firm in 1978-1982.

[Insert Figure 1 here]

In the figure, nodes denote inventors, whereas edges connect inventors who have co-authored patents. The values attached to the edges measure the strength of the interaction between inventors, i.e., v_k in equation (1). The size of the nodes is proportional to the value of betweenness centrality. In other words, inventors with a larger nodal size are on the shortest path connecting other colleagues who themselves are not connected in the intra-firm collaboration network. As an example, inventor A has a collaboration betweenness centrality index of 1, which is the highest value. As a counter example, inventor B exhibits a collaboration betweenness centrality index of 0, which is the lowest value in the firm's collaboration network.

Our second independent variable, *technological centrality*, measures the extent to which the inventor's technological elements are on the shortest path in the recombination of other pieces of technological elements in the firm's stock of knowledge. Following a similar approach, we computed this variable using a three-step procedure. As a first step, for each year t we counted the number of times two (3-digit) U.S. Patent Classification (USPC) classes i and j co-occurred in the patents for which the firm applied in [t-4, t]. We then standardized the raw co-occurrence count by computing a Jaccard coefficient (Yayavaram and Ahuja 2008). Thus, the strength of coupling between two USPCs is

$$v_k = \frac{a}{a+b+c} \tag{3}$$

[10] We assume that, in the collaboration network, the cost of exchanging information between two frequently collaborating inventors is less than the cost of doing so for two inventors who collaborate less frequently.
[11] Whenever an inventor was unproductive in [t-4, t], we multiplied his/her collaboration centrality by a 15 percent yearly decaying component, which compensates for the loss of betweenness centrality over time.

where a is the number of patents co-classified in USPC classes i and j, b is the total number of patents classified in USPC class i but not j, and c is the number of patents classified in USPC class j but not i.

As a second step, using the technology network just described, we computed the value of the normalized node betweenness for each USPC class in the network. Similar to our procedure in the collaboration network, we identified the shortest paths as the sequences of edges that minimized the "cost" of connecting two USPC classes, which we assumed to be inversely proportional to the strength of their coupling, that is, equal to

$$c(e_k) = \frac{1}{v_k} \tag{4}$$

where $c(e_k)$ represents the "cost" of the edge $e_k = (n_i, n_j)$ connecting USPC classes i and j.[12] For example, Figure 2 illustrates the structure of the firm's technology base in 1978-1982. In the figure, the nodes represent technologies (i.e., USPC classes) and their size is proportional to their value of betweenness centrality. Ties connect pairs of classes that have been combined in the firm's patents with tie weights capturing the strength of coupling among classes, i.e., v_k in equation (3), and node size being proportional to the value of betweenness centrality.

[Insert Figure 2 here]

As a third and final step, for each inventor, we computed the weighted value of the betweenness centrality of the three-digit USPC classes in which he/she was active. More formally,

$$Technological\ centrality_{i[t-4,t]} = \sum_k w_{ik[t-4,t]} NB\left(n_{k[t-4,t]}\right) \tag{5}$$

where w_{ik} is the share of patents for which inventor i applied in [t-4, t] and classified in technology k, and $NB(n_k)$ is the normalized betweenness of technology k in the intra-firm technological network (see Appendix B for details). Looking again at Figure 2, the upper panel of it shows the "position" of inventor C in the technological network of the firm by highlighting the vertices corresponding to the technological classes in which s/he was active with a thick black border. The technological centrality of the inventor is

[12] As already noted, we assume that the cost or difficulty of linking two technologies that co-occur frequently is less than the cost of combining two technologies that co-occur less frequently.

just the (weighted) average betweenness centrality of these classes. Thus, in the case of inventor C, technological centrality has a low value, as s/he has been active in relatively peripheral fields in the technological network of the firm (i.e., in fields with a low value of betweenness centrality). In contrast, the position of inventor D in the bottom panel of Figure 2 is characterized by a higher value of technological centrality, as s/he was active in technological fields at the crossroads between otherwise disconnected technological domains (i.e., in fields with a high value of betweenness centrality)

Disentangling collaboration and technological centrality. An important postulate of our theory is that collaboration and technological centrality are not isomorphic. To illustrate this premise and provide a more comprehensive comparison of the two indexes, we cross-plotted their distributions in Figure 3. Although the majority of inventors demonstrate low levels of both collaboration and technological centrality, the distribution also shows employees associated with high levels of collaboration and low levels of technological centrality and, in particular, low levels of collaboration but high levels of technological centrality (i.e., the off-the-diagonal areas). Moreover, almost no employee is associated with high levels of both collaboration and technological centrality. This result provides further evidence that the two measures are not necessarily isomorphic.

[Insert Figure 3 here]

Control variables. We controlled for several variables that might affect an inventor's propensity for and direction of mobility. Prior literature suggests that experienced inventors may be in a better position to obtain a new job (Hoisl 2007) or take advantage of entrepreneurial opportunities (Gambardella et al. 2014), especially if they are coming from a high status firm (Rider 2012, Tan and Rider 2017) such as the firm we studied. To account for the opportunity and motivation to leave, we controlled for inventors' capabilities, indicated by the number of *inventor's prior patents*, the *impact of inventor's patents* (i.e., yearly mean of forward citations the inventor's prior patents received), the *inventor's specialization* (i.e., a Herfindahl index of the distribution of inventor's prior patents across USPCs) and the *inventor's tenure* in the firm at his/her first patent (i.e., the number of years from recruitment to first patent at the firm).

Since employees' experience with mobility can also affect their opportunity and motivation to leave, we followed prior research and accounted for inventors' mobility and entrepreneurial experiences (Ge et al. 2016, Nanda and Sørensen 2010, Raffiee and Feng 2014, Tzabbar 2009). Specifically, we controlled for their *prior geographical mobility* (i.e., number of prior residency changes across US states), *prior firm mobility* (i.e., number of different employers in their prior career history) and *prior entrepreneurship* (i.e., number of new ventures they founded in the past). Taking full advantage of the LinkedIn data, we also searched for and measured *peers' entrepreneurship* experiences (i.e., number of new ventures founded by other focal firm's employees—both inventors and non-inventors—in the past).

Since starting a new venture is a risky career choice that also depends on external opportunities, we controlled for the intensity of venture capital (VC) investments in the information and communication technologies (ICT) industry in the inventor's state (*VC deals in state*). Taking full advantage of the LinkedIn data, we also controlled for their managerial job title (i.e., *manager*), the number of prior *job positions* at the firm and educational *degree* (*MBA* and *PhD*) to control for their skills and abilities.

In addition, we considered that an employee's internal and external opportunities might also vary based on the employee's area of employment. Thus, we used a phrase-based classification of job titles (as reported in LinkedIn) to match employees' job functions with their departments or job areas at the firm by year. We first created a taxonomy of five departments at the firm—*software*, *engineering*, *manufacturing*, *corporate services* and *others*[13]—based on job postings on the firm's jobs and careers website. Then, for each department, we created a vocabulary of the most frequent keywords appearing in the job descriptions and derived all possible pairwise combinations of these keywords. Finally, we matched this resulting list with the job title descriptions reported in the LinkedIn profiles of the firm's employees. From this match we built a measure of similarity between employees' job titles (as reported in their LinkedIn profile) and job postings at the firm, which we used to create dummies for the firm's departments.

[13] We use this category as a baseline.

Finally, we acknowledge that inventors can leave their employer for reasons unrelated to opportunity costs and that personal motivations might determine involuntary mobility, neither of which we can fully capture with our data. To partially offset this possible source of bias, we collected additional data from Factiva and Thompson SDC on several restructuring and strategic repositioning events experienced by the firm during the time period of this study. Thus, we included controls on *CEO change*, *plant closures*, *unit divestitures* and organizational *restructuring*.

Statistical Approach

In the context under examination, inventors have three alternatives: stay with the current employer, move to another existing employer or start a new venture. Implicit in our theory is that the decision to leave the company cannot reasonably be separated from the decision concerning the employment destination. In other words, we believe it is not appropriate to model outward mobility as a two-step process: first, the decision to move, and given this decision, the choice of the destination. Rather, the choice of staying or leaving the company is most likely made by comparing the costs and benefits of all potential alternatives relative to remaining with the current employer, and the alternative that is selected is the one that yields the most (expected) utility. For these reasons, we treated the three alternatives plus the risk of being laid off[14] as competing options (Sørensen and Sharkey 2014). Accordingly, we adopted Jenkins' (1995) extension of Prentice and Gloeckler's (1978) competing risk discrete time duration model as our estimation framework.[15] We used three models with a Weibull hazard function to derive the predicted

[14] Strictly speaking, unemployment is not a choice (at least in general). Yet, it can be considered as one of the competing events in the career of an inventor.

[15] Among the alternative modeling frameworks, we discarded the nested logit approach (McFadden 1984) because, as argued in the text, we believe that the decision to leave and the choice of the employment destination are unlikely to be made sequentially. Likewise, we discarded the conditional logit model (McFadden 1973). Whereas this approach has been widely used to model the choice among alternatives, it is not suitable in our context as it focuses on the effects of destination-specific characteristics. Another alternative specification is the multinomial logit model. Unlike the conditional logit model, the multinomial logit model focuses on the effects of the individual characteristics of the decision makers on the decision to move and on the mobility destination. Thus, it is a reasonable choice for our study. Although we performed some robustness checks using the multinomial logit model, our preferred estimation framework is the one reported in the text because research has shown it to be appropriate when the data generating process occurs in continuous time but the observed survival times are grouped into intervals (Narendranathan and Stewart 1993). In our case the choice of staying or leaving the company occurs in near-continuous time, but we censored survival times at discrete, annual intervals.

hazard of an inventor's exit by a move to another employer, entrepreneurship, and unemployment. The hazard rate function for inventor *i* at time *t* takes the proportional hazard form $\theta_{it} = \theta_0(t) \bullet X'_{it}\beta$, where $\theta_0(t)$ is the baseline hazard function and X_{it} is a series of time-varying covariates summarizing observed differences across inventors. The discrete time formulation of the hazard of a move to another employer, entrepreneurship, or unemployment for inventor *i* in year *t* results from the complementary log logistic function

$$h_t(X_{it}) = 1 - exp\{-exp(X'_{it}\beta + \theta(t))\} \quad (6)$$

where $\theta(t)$ is the baseline hazard function related to the hazard rate $h_t(X_{it})$ of a move to another employer, entrepreneurship, or unemployment in year *t*.

Results

Table 2 provides the descriptive and correlation statistics. The variance inflation factors (VIFs) are less than 10 and the mean VIF is 1.15, indicating that multicollinearity is not present in the data set.

[Insert Table 2 here]

Table 3 presents estimates of the effect of collaboration centrality, technological centrality and controls on the hazard rate of moving to any new employment relative to staying at the current employer (Columns 1-4) and, as a benchmark, *unemployment* (Column 5). Overall, the coefficient of collaboration centrality reflects a decrease in the likelihood of leaving the firm ($p < 0.01$, Column 4). In particular, one standard deviation increase in collaboration centrality is associated with about a 9 percent lower likelihood of mobility of any type ($[e^{-1.181*(0.021+0.062)}-1] \times 100 = -9.33\%$) relative to staying at the firm, supporting Hypothesis 1a. As expected in Hypothesis 2a, the coefficient of technological centrality is also associated with a decrease in the likelihood of leaving the firm ($p < 0.001$, Column 4). At one standard deviation above the mean, technological centrality is associated with a 19 percent decrease in the likelihood of leaving relative to staying with the existing employer ($[e^{-0.525*(0.223+0.177)}-1] \times 100 = -18.94\%$), supporting Hypothesis 2a.

[Insert Table 3 here]

Hypotheses 1b and 2b deal with whether higher values of our centrality constructs increase the likelihood of moving to an existing employer *relative to* starting a new venture. To test them, we proceeded as follows. First, we estimated the effect of our centrality constructs on the hazard rate of joining *an existing employer* relative to staying with the current employer (Table 4, Columns 1-4). Second, we estimated the effect of our centrality constructs on the hazard rate of starting a new venture (*entrepreneurship)* relative to staying with the current employer (Table 4, Columns 5-8). Finally, we tested whether the estimated coefficients were different by conducting a Wald test (Table 5). As Table 5 indicates, when comparing the coefficients of collaboration centrality between mobility to an existing employer (b = -1.879; p <0 .01) and mobility to entrepreneurship (b = 2.085; p <0 .01), the difference between the two coefficients was statistically significant ($p < 0.001$; two-sided Wald test). Thus, individuals with more collaboration centrality are significantly more likely to start a new venture than move to another employer, supporting Hypothesis 1b. Similarly, when comparing the coefficients of technological centrality between mobility to an existing employer (b = -0.383; p <0 .01) and mobility to entrepreneurship (b = -2.157; $p < 0.01$) the difference between the two coefficients was statistically significant ($p < 0.001$; two-sided Wald test). Thus, individuals with more technological centrality are significantly less likely to start a new venture than move to another employer, supporting Hypothesis 2b.

[Insert Tables 4 and 5 here]

To further investigate these relationships, we plotted the marginal effects separately for collaboration centrality (Figure 4, left-hand graph) and technological centrality (Figure 4, right-hand graph).[16] The dotted lines in each graph represent the predicted probability of staying with the current employer. The solid lines represent the predicted probability of moving to *an existing employer*. The dashed lines represent the predicted probability of starting a new venture (*entrepreneurship)*. As shown, the probability of staying with the current employer increases as collaboration and technological betweenness centrality increase. Furthermore, the probability of staying is greater than the likelihood of

[16] To compute the marginal effects, we kept all of the other covariates fixed at their median values.

any type of mobility at all levels of collaboration and technological centrality. Results regarding external employment options vary by the type of centrality, in line with our predictions. Specifically, the probability of starting a new venture becomes higher than that of moving to a new employer as collaboration centrality increases. Conversely, individuals with a high level of technological betweenness centrality are more likely to move to another employer than start a new venture.

[Insert Figure 4 here]

Overall, our results indicate that individuals who occupy central positions in the intra-firm technological and collaboration networks are better matched with their existing employer than with any other external employment context. When considering external options, however, those who are in a central collaboration position may have a relatively greater propensity to start a new venture than to move to other existing employers. In contrast, those who are central in the technological network have a better match with other employers than with entrepreneurship.

Finally, we also found some important results associated with our control variables regarding the choice of the mobility destination relative to staying with the current employer. Table 3 shows that inventors' technological specialization and prior mobility experience reduce their likelihood of leaving their current employer. Similarly, Table 4 indicates that inventors' inventing capabilities, reflected in the average impact and number of their patents, increase the likelihood of *entrepreneurship*. In addition, consistent with prior research, we found that peers' prior entrepreneurship experience increases the likelihood of the inventors engaging in *entrepreneurship*. In contrast, it also reduces their likelihood of a move to *another employer*. Furthermore, individuals with managerial positions, MBA and PhD degrees are also more likely to move to another employer. Organizational changes associated with a CEO change increase the likelihood of a move to *another employer* and *entrepreneurship*. However, unit divestitures reduce these likelihoods. Finally, plant closures are associated with a reduction in the likelihood of inter-firm mobility, whereas organizational restructuring is positively associated with it.

Robustness check

For a robustness check, we measured *exit mode*—a multinomial variable that equals zero for survival, meaning staying at the firm, one for a move to another employer, two for entrepreneurship, and three for unemployment. We used this factor as a dependent variable in a multinomial logit competing risks model (Jenkins 2004). To help with the interpretation of Hypotheses 1b and 2b on the varied effects of collaboration and technological centrality on the two types of mobility, we considered a *move to another employer* as the base outcome of the multinomial logit model. As Table 6 shows, the results provide robust support for our hypotheses. Specifically, the coefficient of collaboration centrality is associated with an increase in the likelihood of *entrepreneurship* relative to moving to *another employer* ($p < 0.001$, supporting Hypothesis 1b). Furthermore, the coefficient of technological centrality is associated with a decrease in the likelihood of *entrepreneurship* relative to moving to *another employer* ($p < 0.05$, supporting Hypothesis 2b).

[Insert Table 6 here]

Finally, in order to control for the non-independence of some of the mobility events in our data, such as the possibility that inventors can join the same new employer in the same year, we ran our main complementary log-log model by clustering standard errors by new employer. The results in Table C1 in Appendix C confirm our prior estimates.

Additional analyses

We conducted several additional analyses testing alternative explanations and mechanisms. For reasons of space, they are fully reported in Appendix C.

Brokerage and Status. Since global centrality, as reflected in our measure, and local centrality, as reflected in Burt's brokerage, may overlap, it is unclear whether a global or a local brokerage position drives our results. Furthermore, since centrality is also associated with status and influence, power may serve as an alternative explanation. To account for these possibilities more directly, we tested the effects of Burt's brokerage (2004, 2007) (i.e., local centrality) and Bonacich's centrality, which is commonly used as a measure of power and status (Nerkar and Paruchuri 2005) (see Tables C2 and C3 in Appendix C).[17]

Counter to our findings regarding betweenness centrality, Burt's brokerage is not associated with a significant effect on the likelihood of leaving relative to staying. Consistent with our findings, instead, inventors who score high on Burt's brokerage are more likely to become entrepreneurs than move to another employer ($p = 0.001$, two-sided Wald test). However, this effect is statistically weaker than that we estimated for betweenness centrality ($p = 0.033$, two-sided Wald test). Regarding power and status, Bonacich's centrality measure reduces inventors' likelihood of leaving the firm compared to staying. Contrary to our findings on betweenness centrality, however, its effect on employees' propensity to move to another employer is not statistically different from that of starting a new venture. In terms of comparing the magnitude, the effect of collaboration betweenness centrality on the likelihood of leaving relative to staying (see Table 3, Column 4) is statistically stronger than that of the brokerage measure ($p = 0.056$, two-sided Wald test) and of Bonacich's power measure ($p = 0.065$, two-sided Wald test).

Overall, we believe these results provide support to our argument that a high level of betweenness centrality in the collaboration network is associated with preferential access to the information flowing through the whole network. We maintain that it is this privileged position, rather than localized brokerage or status, that explains the propensity to move and the most likely destination.

Co-mobility. We claimed that collaboration central inventors are more likely to become entrepreneurs than move to another employer (i.e., H1b). Building on prior research documenting that moving in teams leads to higher rents than moving solo (Marx and Timmermans 2017), one of our premises is that founders can transfer prior ties to new ventures more easily, for example, by recruiting corporate colleagues for the founding team. To examine this assertion more explicitly, we compared the effect of collaboration centrality on inventors' likelihood of leaving the firm in teams for any type of external employment opportunity. Consistent with our arguments and related research, the results (see

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[17] We thank our reviewers for these suggestions.

Table C4 in Appendix C) show that inventors with a high level of collaboration centrality are more likely to co-found a new venture with corporate colleagues than to co-move with them to another employer (p = 0.006; two-sided Wald test).

Involuntary mobility. Our theory on centrality assumes that inventors have a choice. However, it is possible that some of the moves in our data are a result of involuntary mobility. To account for these possibilities, we controlled for a change in CEO, restructuring and plant closures as possible factors resulting in involuntary moves. It is also possible that involuntary mobility is associated with poor individual performance or with occupying peripheral positions in the intra-firm network. To exclude this possible source of bias in our results, we examined the effect of the interaction between the inventors' productivity measures (i.e., their patenting productivity and impact) and our centrality measures.[18] The results in Table C5 in Appendix C indicate that inventors' patents and impact do not significantly moderate the relationship between centrality measures and mobility.

Discussion and Conclusion

We tested how an employee's centrality in the intra-firm collaboration and technological networks was associated with his/her propensity for staying with the current employer or leaving, and how this propensity varied depending on whether the employee moved to another firm or founded a new venture. Contrary to the prevailing views that employees' positions in the collaboration and technology networks are isomorphic and potentially have similar effects on their mobility, we argued and demonstrated that the most likely destination of outward mobility depends on the type of network considered. Higher degrees of centrality, either collaborative or technological, are associated with a reduction in the likelihood of leaving the current employer, albeit through different mechanisms. However, when it comes to external destinations, employees who are central in the intra-firm collaboration network are more likely to start a new venture than to move to another employer. In contrast, employees who are central in the intra-firm technology network, and whose departure might be most disruptive to the recombination efforts of the

[18] We thank one of our reviewers for this suggestion.

firm, are more likely to move to another employer than to start a new venture. As such, our results also provide novel insights into the push and pull forces that drive inventors' decisions to remain with their current employers, move to a rival firm, or start a new venture.

Our arguments and findings contribute to several streams of research. First, with regard to theory, we related individuals' positions in both the collaboration and technology networks to different types of critical information. In doing so, we align our intra-firm collaboration and technological centrality measures with the concepts of relational and human capital (Mawdsley and Somaya 2016), respectively. Specifically, we argued that collaboration centrality is related to information about who knows what in the organization (i.e., where knowledge resides, and the unexploited opportunities associated with it). Centrality in the technological network, on the other hand, is associated with the tacit know-how and know-why of the firm's technology recombination efforts. In the context of external mobility, each position is associated with opportunities and costs, although through different mechanisms. The trade-off depends not only on the type of centrality but also on the direction of the mobility. In showing that inventors' opportunities vary by the type of centrality and type of employment, we validated and extended prior research suggesting that inventors' positions in knowledge building efforts determine their internal and external value (Paruchuri 2010), and that collaboration and technology networks should be decoupled (Brennecke and Rank 2017, Guan and Liu 2016, Wang et al. 2014). The results of our robustness check comparing several measures of centrality also confirm the varying effect of power or status, measured with Bonacich's method, brokerage, measured with Burt's method, and boundary spanning (i.e., betweenness centrality), although they are all associated with occupying a central position.

Second, in highlighting the distinctions between collaborative and technological centrality in the context of outbound mobility, our theory and findings have the potential to expand the resource-based view in several ways. First, we associate different structural positions with different skills and abilities at the individual level, and context specific skills at the firm level. We discuss how these skills and abilities at different levels affect the internal and external value of the employees and the costs they incur when leaving the company. We also discuss how their ability to appropriate such value and the costs associated with mobility vary across employment contexts. Second, while the resource-based view treats the firm specificity of people's knowledge in general terms, with no clear indication about how it can be measured, our results support the contention that the degree of "stickiness" associated with firm specific knowledge is a function of both people's structural position and the external options they consider. Our findings illustrate collaboration and technological centrality as nuanced mechanisms for creating stickiness and retention of employees, through different mechanisms. Specifically, we argued and demonstrated that while both types of centralities reduce the likelihood of moving to another employer, when considering external options, collaboration central individuals are more likely to start a new venture than move to another employer, whereas the opposite is true for those with technological centrality. In doing so, we also demonstrated that not all types of context-specific relational and human capital increase the opportunity costs of moving equally (Kacperczyk 2012, Lazear 2009, Mawdsley and Somaya 2016, Morris et al. 2017).

Third, prior studies have related individuals' positions in the collaboration network to their mobility within the firm (Burt 2004, Kleinbaum 2012). We extended this line of work by examining its effects on outward mobility. Indeed, a central position in both networks serves as a strong pull for inventors to stay with their existing employers rather than move to another employer. However, our theory and results provide a nuanced view of these effects. Contrary to prevailing views, we showed that the same mechanisms that reduce the likelihood of an inventor's move to another employer also increase his/her preference to start a new venture rather than join another employer. Specifically, individuals' centrality in the collaboration network increases their propensity to prefer to start their own venture rather than to move to a new employer. Furthermore, recognizing technological centrality as a critical mechanism that reduces the likelihood of an employee's entrepreneurship is an important topic to study and can have important policy implications for selecting and nurturing entrepreneurs and entrepreneurial ventures. By implication, these results extend our understanding of the effect of centrality on career choices as reflected in the decision to stay with an existing employer, leave for another employer or start a new venture.

Fourth, we complement the growing evidence that a firm's risk of losing an employee may vary depending on the direction of his/her move (Campbell et al. 2012). Specifically, while the extant research suggests that the risk of knowledge spillovers following mobility is the greatest in the case of employee entrepreneurship (Campbell et al. 2012), our results show that those who tend to start their own ventures are not those who have critical technological know-how and know-why. Furthermore, prior research argues and demonstrates that much of the knowledge a new employer appropriates from an inventor it hires away is associated with the mobile inventor's own knowledge (e.g., Tzabbar et al. 2005). However, our research suggests that the type of knowledge transferred also depends on the mobile inventor's position within the technological and collaborative network. As such, our results have the potential to expand our understanding of knowledge spillovers by providing a nuanced view on how people's position in various networks may affect the type of knowledge they bring with them to a new employer.

Finally, our arguments and findings have the potential to expand matching theory (Jovanovic 1979, Lazear and Oyer 2004), which posits that workers seek to maximize their value appropriation by identifying jobs that best fit their skills and abilities, and that firms seek employees with skills and abilities that fit the local work environments (Sørensen and Sharkey 2014). Specifically, the theory suggests that there are no "good" workers and "good" employers, but only a good match between individual human capital and the work environment (Jovanovic 1979, Lazear and Oyer 2013). The theory also assumes that, *"imperfect information exists on both sides of the market about ... optimal assignments"* (Jovanovic 1979: 974). With more information, there is greater possibility for an employer to reward a worker who is a good match with the company. In line with this theory, our argument contends that decisions about whether to stay or leave are a result of the match between an employee's skills and abilities, and the employment context. Specifically, our theory and results suggest that as individuals become more central in their respective network, their match with the current employer grows. Thus, they can appropriate more value from their knowledge and abilities with their current employer than any other employment opportunity. When external options are considered, we show that those who have strong abilities to collaborate consider developing their own venture as a better match than moving to a new employer. In contrast, those with specific technological know-how capabilities find a move to a new employer to be a better match that will enable them to best utilize their opportunities.

As any study does, this work contains several limitations that inform interpretations of the results and open up avenues for future studies. First, we rely on a single firm and one type of employee (i.e., inventors). While this empirical design aligns well with our interest in investigating outward mobility from a leading firm, and also enables us to account for firm, labor market and employee heterogeneity, it has inherent limitations regarding its generalizability. Future research could determine whether we can generalize the mechanisms described in this study to other firms, industries and geographical contexts.

Second, different causes of mobility may influence the direction of mobility. Common to other studies using secondary data, we cannot clearly and cleanly differentiate between voluntary and involuntary turnover. Nonetheless, one could speculate that not accounting for potential involuntary mobility might bias our results. To address this possibility, we added several controls and examined the differences in the likelihood of mobility based on both network centrality and inventor productivity. While our results did not show significant differences between strong and weak performers in their likelihood of leaving, providing further credence to our results, we recognize this limitation and encourage future research to assess the potential bias for involuntary turnover.

Third, our study uses co-inventing network data and patent classes' recombination to measure collaboration and technological centrality, respectively. Although filing for patents is an important activity to protect intellectual property in technology-based industries, it is more applicable to explicit technology domains. Consistent with Singh (2005: 767), we also acknowledge that constructing our network measures using only information drawn from patents underestimates the effects of networks on mobility because patents reflect only a small portion of all relevant intra-firm network ties. Future studies could examine whether our mechanisms work in a similar fashion to protect more tacit knowledge, such as managerial capabilities or artistic endeavors. It is possible that collaboration centrality plays a larger role in such instances because knowledge transfer is likely to become an even more social process. However, it remains for future research to confirm our speculation.

Finally, we could not measure people's motivations and decisions to invest in human capital and fully separate them from other individuals' mobility intentions. However, our goal was not to prove causality. Rather, our theoretical and empirical approach sought to show that, considering and possibly correcting for alternative explanations, significant differences exist between employees' positions in collaboration and technological networks and their relationship with different employment options. In addition, our theory—which also finds support in the interview data—predicts that employees and prospective employers cannot fully assess the value of people's investments in context-specific skills, both for current and future employment contexts. Furthermore, as Lazear (2009) suggested, context-specific knowledge may possibly overlap with industry-specific knowledge, thus influencing the perceived value and opportunity associated with the former.

Conclusion. Our theory and results provide a more nuanced insight into employees' retention, mobility, and their creation of new ventures. Scholars and practitioners can gain a new understanding about how inventors' positions may enhance or reduce their likelihood of outward mobility. Our finding that inventors who connect various technologies in the firm are less likely to leave the company should be useful for employers. Furthermore, managers and practitioners should realize that there are methods other than litigation that can limit the opportunity and motivation of inventors to leave with critical knowledge. Instead, managers should realize that encouraging the development of context-specific knowledge and capabilities is a strong pull encouraging central employees to stay.

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Table 1. Descriptions of the Main Measures and Data Sources

Variable	Measure	Source
1. *Mobility (any type)* $_{t+1}$	1{employee leaves for another employment—i.e., either to join another firm or to start a new venture—in year t+1}; 0 otherwise.	LinkedIn
2. *Mobility to another employer* $_{t+1}$	1{employee leaves to join another firm in year t+1}; 0 otherwise.	LinkedIn
3. *Mobility to entrepreneurship* $_{t+1}$	1{employee leaves to start a new venture in year t+1}; 0 otherwise.	
4. *Unemployment* $_{t+1}$	1{employee leaves in year t+1 and does not join any other firm for at least 12 months}; 0 otherwise.	LinkedIn
5. *Collaboration centrality* $_{[t-4,\, t]}$	Normalized betweenness centrality computed on inventor's co-patenting with respect to all of the firm's co-patenting in [t-4, t].	USPTO
6. *Technological centrality* $_{[t-4,\, t]}$	Normalized betweenness centrality computed on inventor's USPC combinations with respect to the firm's USPC combinations in [t-4, t].	USPTO
7. *ln(Time* $_{t}$*)*	ln(1 + # years since inventor's first patent with the firm until year t)	USPTO
8. *Inventor's tenure at first patent*	Inventor's tenure at the firm at the time of his/her first patent with the firm.	LinkedIn
9. *Inventor's patents* $_{t}$	# inventor's patents granted by USPTO until year t.	USPTO
10. *Inventor's impact* $_{t}$	Mean of forward citations to inventor's patents in year t.	USPTO
11. *Inventor's specialization* $_{t}$	Herfindahl index of distribution of inventor's prior patents across USPCs	USPTO
12. *Prior geographic mobility* $_{t}$	# inventor's changes in residence prior to year t.	USPTO
13. *Prior firm mobility* $_{t}$	# inventor's changes in employer prior to joining the firm until year t.	LinkedIn
14. *Prior entrepreneurship* $_{t}$	# inventor's new ventures prior to joining the firm until year t.	LinkedIn
15. *Peers' entrepreneurship* $_{t}$	# firm's employees' new ventures in year t-1.	LinkedIn
16. ln(*VC deals in state* $_{t}$)	ln(1 + # VC deals in ICT ventures inventor's state in year t)	Thomson
17. *Manager* $_{t}$	1{inventor has a managerial position in year t}; 0 otherwise.	LinkedIn
18. *Job positions* $_{t}$	# inventor's job changes in the firm prior to year t.	LinkedIn
19. *Job title (software)* $_{t}$	1{software job category in year t}; 0 otherwise.	LinkedIn
20. *Job title (engineering)* $_{t}$	1{engineering job category in year t}; 0 otherwise.	LinkedIn
21. *Job title (manufacturing)* $_{t}$	1{manufacturing job category in year t}; 0 otherwise.	LinkedIn
22. *Job title (corporate services)* $_{t}$	1{corporate services job category in year t}; 0 otherwise.	LinkedIn
23. *Degree(MBA)*	1{inventor earned an MBA degree}; 0 otherwise.	LinkedIn
24. *Degree(PhD)*	1{inventor earned a PhD degree}; 0 otherwise.	LinkedIn
25. *CEO changes* $_{t}$	1{the firm changed CEO in year t}; 0 otherwise.	Factiva
26. *Plant closure* $_{t}$	1{the firm announced a plant closure in year t}; 0 otherwise.	Factiva
27. *Unit divestiture* $_{t}$	# units the firm divested in year t.	SDC
28. *Restructuring* $_{t}$	1{the firm announced corporate restructuring in year t}; 0 otherwise.	Factiva

Table 2. Descriptive Statistics and Correlations

Variable	Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10
1. *Mobility (any type)* $_{t+1}$	0.040	0.197	0	1										
2. *Mobility to another employer* $_{t+1}$	0.037	0.188	0	1	.95									
3. *Mobility to entrepreneurship* $_{t+1}$	0.004	0.060	0	1	.29	-.01								
4. *Unemployment* $_{t+1}$	0.008	0.091	0	1	-.02	-.02	-.01							
5. *Collaboration centrality* $_{[t-4,\ t]}$	0.021	0.062	0	1	-.02	-.02	.01	-.01						
6. *Technological centrality* $_{[t-4,\ t]}$	0.223	0.177	0	1	.00	.01	-.02	-.00	.07					
7. ln(*Time* $_{t}$)	1.493	0.803	0	2.996	-.02	-.02	-.01	-.00	.08	-.18				
8. *Inventor's tenure at first patent*	3.352	3.815	0	31	.00	.01	-.02	.03	-.05	.01	-.04			
9. *Inventor's patents* $_{t}$	6.057	11.766	1	299	-.01	-.02	.01	-.00	.27	.04	.23	-.11		
10. *Inventor's impact* $_{t}$	6.043	9.316	0	144	.00	-.01	.02	.01	.04	-.01	.05	-.01	.04	
11. *Inventor's specialization* $_{t}$	0.185	0.318	0	1	-.02	-.02	.00	-.01	.04	.10	-.58	-.01	-.00	.01
12. *Prior geographic mobility* $_{t}$	0.106	0.410	0	8	-.01	-.01	-.00	.00	.12	.01	.16	-.07	.30	.08
13. *Prior firm mobility* $_{t}$	0.876	1.372	0	13	.04	.05	-.01	.06	-.00	.00	-.10	-.01	.02	.00
14. *Prior entrepreneurship* $_{t}$	0.016	0.142	0	6	.00	.00	.00	.01	-.00	-.01	-.02	-.01	-.00	.02
15. *Peers' entrepreneurship* $_{t}$	20.540	6.474	3	31	.01	.01	.01	.01	.00	-.04	.13	-.01	.02	-.07
16. ln(*VC deals in state* $_{t}$)	0.539	1.539	0	7.265	.01	.00	.01	.00	.02	-.01	.00	-.06	.08	.02
17. *Manager* $_{t}$	0.233	0.423	0	1	.06	.07	-.00	.01	-.03	.05	.04	.16	-.03	.04
18. *Job positions* $_{t}$	0.279	0.762	0	9	-.02	-.02	-.01	.04	.00	-.06	.27	.05	.06	.03
19. *Job title (software)* $_{t}$	0.261	0.439	0	1	.00	.01	-.02	.01	-.06	-.07	-.01	.03	-.08	.05
20. *Job title (engineering)* $_{t}$	0.065	0.247	0	1	.00	-.00	-.00	-.01	.04	-.03	-.02	-.02	.03	-.03
21. *Job title (manufacturing)* $_{t}$	0.187	0.390	0	1	.00	.01	-.01	-.01	-.03	.06	-.04	.05	-.06	-.04
22. *Job title (corporate services)* $_{t}$	0.017	0.130	0	1	.00	.00	-.00	-.00	-.02	-.00	.02	.01	-.02	.03
23. *Degree(MBA)*	0.068	0.251	0	1	.03	.03	.01	.01	-.02	.03	-.03	.05	-.03	-.00
24. *Degree(PhD)*	0.198	0.398	0	1	.03	.04	-.01	.01	.08	.08	-.08	-.02	.08	-.05
25. *CEO change* $_{t}$	0.111	0.314	0	1	.04	.04	.01	.01	.03	.05	-.07	.00	-.01	.03
26. *Plant closure* $_{t}$	0.109	0.311	0	1	-.02	-.02	.00	-.00	.01	-.03	.06	.00	.01	-.01
27. *Unit divestiture* $_{t}$	1.467	1.500	0	4	.01	.01	-.01	.01	-.01	.06	.08	.01	.02	-.05
28. *Restructuring* $_{t}$	0.082	0.274	0	1	.04	.05	-.00	.02	-.00	.12	.03	.01	.01	-.04

	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27
12. *Prior geographic mobility* $_{t}$	-.03																
13. *Prior firm mobility* $_{t}$	.03	.03															
14. *Prior entrepreneurship* $_{t}$	.01	-.01	.20														
15. *Peers' entrepreneurship* $_{t}$	-.10	.02	.01	.01													
16. ln(*VC deals in state* $_{t}$)	-.01	.08	.03	.01	.02												
17. *Manager* $_{t}$	-.05	.00	.18	.06	.00	-.02											
18. *Job positions* $_{t}$	-.14	-.01	.10	.06	.04	.00	.26										
19. *Job title (software)* $_{t}$	-.03	-.01	.07	-.01	-.00	-.03	.22	.07									
20. *Job title (engineering)* $_{t}$	.02	-.00	.04	.03	.01	.02	-.04	.03	-.16								
21. *Job title (manufacturing)* $_{t}$	.01	-.05	-.07	-.01	-.00	.00	-.11	-.03	-.28	-.13							
22. *Job title (corporate services)* $_{t}$	-.02	.01	.01	.04	.01	.02	.07	.09	-.08	-.04	-.06						
23. *Degree(MBA)*	-.00	-.02	.01	.06	-.00	.01	.22	.08	.02	-.01	-.01	.09					
24. *Degree(PhD)*	.07	.00	.13	-.00	.02	.02	.01	.04	-.10	.10	.01	-.03	-.04				
25. *CEO changes* $_{t}$	.04	.00	-.00	-.00	.00	-.00	.00	-.03	-.00	-.01	.01	.01	.01	-.01			
26. *Plant closure* $_{t}$	-.02	.01	-.00	.00	-.03	.00	-.00	.03	.00	.01	-.00	-.01	-.01	.01	.17		
27. *Unit divestiture* $_{t}$	-.06	-.00	-.00	-.00	.25	.01	-.00	.02	-.00	.01	.01	-.01	-.00	.01	-.11	-.28	
28. *Restructuring* $_{t}$	-.05	-.00	.00	-.00	.48	.01	.00	.00	-.00	.00	.01	.00	.00	.01	-.11	-.10	.50

Note. N = 35,344. All correlations above |.01| are significant at $p < 0.05$.

Table 3. Complementary Log-Log Regressions: The Hazards of Employees' Exit

Exit by:	*Mobility (any type)* $_{t+1}$				*Unemp.* $_{t+1}$
	1	2	3	4	5
Collaboration centrality $_{[t-4,\,t]}$		-1.308*		-1.181*	-2.321
		(0.60)		(0.59)	(1.74)
Technological centrality $_{[t-4,\,t]}$			-0.551***	-0.525***	-0.145
			(0.16)	(0.16)	(0.11)
ln(*Time* $_t$)	-0.104*	-0.097*	-0.126**	-0.119**	0.069***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.01)
Inventor's tenure at first patent	-0.008	-0.009	-0.009	-0.009	0.001
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Inventor's patents $_t$	-0.003	-0.001	-0.002	-0.001	0.005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Inventor's impact $_t$	0.001	0.002	0.001	0.002	-0.284
	(0.00)	(0.00)	(0.00)	(0.00)	(0.24)
Inventor's specialization $_t$	-0.537***	-0.517***	-0.541***	-0.523***	0.087
	(0.11)	(0.11)	(0.11)	(0.11)	(0.14)
Prior geographic mobility $_t$	-0.093	-0.089	-0.089	-0.086	0.271***
	(0.08)	(0.08)	(0.08)	(0.08)	(0.03)
Prior firm mobility $_t$	0.102***	0.101***	0.099***	0.098***	0.073
	(0.02)	(0.02)	(0.02)	(0.02)	(0.22)
Prior entrepreneurship $_t$	-0.235	-0.232	-0.238	-0.235	-0.012
	(0.18)	(0.18)	(0.18)	(0.18)	(0.01)
Peers' entrepreneurship $_t$	-0.009*	-0.009*	-0.011*	-0.011*	0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)
ln(*VC deals in state* $_t$)	0.017	0.017	0.015	0.015	-0.254
	(0.02)	(0.02)	(0.02)	(0.02)	(0.15)
Manager $_t$	0.643***	0.641***	0.667***	0.664***	0.307***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.05)
Job positions $_t$	-0.303***	-0.303***	-0.307***	-0.307***	-0.043
	(0.05)	(0.05)	(0.05)	(0.05)	(0.14)
Job title (software) $_t$	-0.054	-0.058	-0.070	-0.073	-0.551†
	(0.07)	(0.07)	(0.07)	(0.07)	(0.29)
Job title (engineering) $_t$	-0.056	-0.051	-0.073	-0.068	-0.222
	(0.12)	(0.12)	(0.12)	(0.12)	(0.18)
Job title (manufacturing) $_t$	0.108	0.105	0.121	0.118	-0.442
	(0.07)	(0.07)	(0.07)	(0.07)	(0.40)
Job title (corporate services) $_t$	0.053	0.045	0.058	0.050	0.217
	(0.20)	(0.20)	(0.20)	(0.20)	(0.21)
Degree(MBA)	0.311***	0.311***	0.313***	0.314***	0.215
	(0.09)	(0.09)	(0.09)	(0.09)	(0.14)
Degree(PhD)	0.381***	0.391***	0.397***	0.405***	0.567***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.17)
CEO changes $_t$	0.648***	0.654***	0.665***	0.670***	-0.118
	(0.07)	(0.07)	(0.07)	(0.07)	(0.21)
Plant closure $_t$	-0.392***	-0.392***	-0.393***	-0.392***	0.003
	(0.10)	(0.10)	(0.10)	(0.10)	(0.05)
Unit divestiture $_t$	-0.087***	-0.088***	-0.086***	-0.086***	0.834***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.25)
Restructuring $_t$	1.025***	1.029***	1.086***	1.086***	-0.445
	(0.11)	(0.11)	(0.12)	(0.12)	(0.39)
Constant	-3.083***	-3.079***	-2.912***	-2.915***	-4.991***
	(0.12)	(0.12)	(0.13)	(0.13)	(0.30)
Log likelihood	-5,758	-5,755	-5,752	-5,749	-1,606
Chi-square	495.0	501.0	508.1	513.9	207.2

Note. N = 35,344. Robust standard errors (in parentheses) clustered by employee; Unemp, unemployment.
*** $p < .001$; ** $p < .01$; * $p < .05$; † $p < .1$.

Table 4. Complementary Log-Log Regressions: The Hazards of Employees' Exit

Exit by:	*Mobility to another employer* $_{t+1}$				*Mobility to entrepreneurship* $_{t+1}$			
	1	2	3	4	5	6	7	8
Collaboration centrality $_{[t-4,\, t]}$		-1.978**		-1.879**		1.789*		2.085**
		(0.71)		(0.70)		(0.81)		(0.78)
Technological centrality $_{[t-4,\, t]}$			-0.419**	-0.383*			-2.058**	-2.157**
			(0.16)	(0.16)			(0.65)	(0.67)
ln(*Time* $_t$)	-0.085†	-0.075†	-0.102*	-0.092*	-0.211	-0.229†	-0.278*	-0.298*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.13)	(0.13)	(0.13)	(0.13)
Inventor's tenure at first patent	-0.000	-0.001	-0.000	-0.001	-0.110**	-0.110**	-0.113***	-0.113***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)
Inventor's patents $_t$	-0.006†	-0.003	-0.005	-0.002	0.008*	0.006†	0.009**	0.008*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Inventor's impact $_t$	-0.001	-0.001	-0.001	-0.001	0.017**	0.017**	0.017**	0.017**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Inventor's specialization $_t$	-0.560***	-0.531***	-0.563***	-0.535***	-0.271	-0.309	-0.283	-0.322
	(0.12)	(0.12)	(0.12)	(0.12)	(0.34)	(0.35)	(0.34)	(0.35)
Prior geographic mobility $_t$	-0.056	-0.054	-0.054	-0.052	-0.372	-0.407†	-0.345	-0.385†
	(0.08)	(0.08)	(0.08)	(0.08)	(0.23)	(0.24)	(0.23)	(0.23)
Prior firm mobility $_t$	0.121***	0.121***	0.119***	0.118***	-0.168*	-0.167†	-0.172*	-0.170*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.09)	(0.09)	(0.09)	(0.09)
Prior entrepreneurship $_t$	-0.299	-0.296	-0.302	-0.298	0.444	0.433	0.420	0.409
	(0.19)	(0.19)	(0.19)	(0.19)	(0.37)	(0.39)	(0.39)	(0.40)
Peers' entrepreneurship $_t$	-0.017***	-0.017***	-0.018***	-0.018***	0.049**	0.049**	0.042**	0.042**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.02)
ln(*VC deals in state* $_t$)	0.010	0.010	0.009	0.009	0.060	0.061	0.055	0.057
	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.05)	(0.05)	(0.05)
Manager $_t$	0.679***	0.676***	0.698***	0.692***	0.207	0.208	0.278	0.285
	(0.07)	(0.07)	(0.07)	(0.07)	(0.26)	(0.26)	(0.26)	(0.26)
Job positions $_t$	-0.304***	-0.304***	-0.307***	-0.307***	-0.255	-0.255	-0.272	-0.272
	(0.05)	(0.05)	(0.05)	(0.05)	(0.20)	(0.21)	(0.20)	(0.21)
Job title (software) $_t$	0.027	0.022	0.015	0.011	-0.886***	-0.873***	-0.935***	-0.920***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.26)	(0.26)	(0.26)	(0.26)
Job title (engineering) $_t$	-0.006	0.001	-0.019	-0.012	-0.396	-0.406	-0.440	-0.457
	(0.12)	(0.12)	(0.12)	(0.12)	(0.40)	(0.40)	(0.40)	(0.39)
Job title (manufacturing) $_t$	0.198*	0.195*	0.209**	0.205**	-0.817**	-0.805**	-0.801**	-0.787**
	(0.08)	(0.08)	(0.08)	(0.08)	(0.29)	(0.29)	(0.29)	(0.29)
Job title (corporate services) $_t$	0.123	0.112	0.127	0.115	-0.522	-0.508	-0.537	-0.516
	(0.20)	(0.21)	(0.20)	(0.21)	(0.71)	(0.71)	(0.71)	(0.71)
Degree(MBA)	0.297**	0.298**	0.298**	0.298**	0.557†	0.564†	0.596†	0.602†
	(0.10)	(0.10)	(0.10)	(0.10)	(0.31)	(0.31)	(0.32)	(0.32)
Degree(PhD)	0.445***	0.458***	0.456***	0.468***	-0.296	-0.323	-0.237	-0.267
	(0.06)	(0.06)	(0.06)	(0.06)	(0.25)	(0.25)	(0.26)	(0.26)
CEO changes $_t$	0.663***	0.672***	0.676***	0.683***	0.488*	0.473*	0.557*	0.543*
	(0.08)	(0.08)	(0.08)	(0.08)	(0.23)	(0.23)	(0.24)	(0.24)
Plant closure $_t$	-0.420***	-0.419***	-0.420***	-0.420***	-0.175	-0.177	-0.196	-0.198
	(0.11)	(0.11)	(0.11)	(0.11)	(0.27)	(0.27)	(0.27)	(0.27)
Unit divestiture $_t$	-0.075**	-0.076**	-0.074**	-0.075**	-0.182*	-0.182*	-0.175*	-0.175*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.08)	(0.08)	(0.08)	(0.08)
Restructuring $_t$	1.133***	1.139***	1.179***	1.181***	-0.152	-0.152	0.052	0.062
	(0.12)	(0.12)	(0.12)	(0.12)	(0.46)	(0.46)	(0.46)	(0.46)
Constant	-3.178***	-3.172***	-3.047***	-3.052***	-5.521***	-5.527***	-4.931***	-4.919***
	(0.13)	(0.13)	(0.14)	(0.14)	(0.44)	(0.44)	(0.48)	(0.48)
Log likelihood	-5,327	-5,322	-5,324	-5,319	-804.3	-803	-798.1	-796.3
Chi-square	552.1	564.5	558.4	570.0	110.2	114.4	124.0	127.6

Note. N = 35,344. Robust standard errors (in parentheses) clustered by employee; Unemp, unemployment.
*** $p < .001$; ** $p < .01$; * $p < .05$; † $p < .1$.

Table 5. Differential Impact of Centrality across Mobility Types

	Wald tests on coefficients difference
β(*Collaboration centrality*[Mobility to another employer]) < β(*Collaboration centrality*[Mobility to entrepreneurship])	$p = 0.0002$
β(*Technological centrality*[Mobility to another employer]) > β(*Technological centrality*[Mobility to entrepreneurship])	$p = 0.0103$

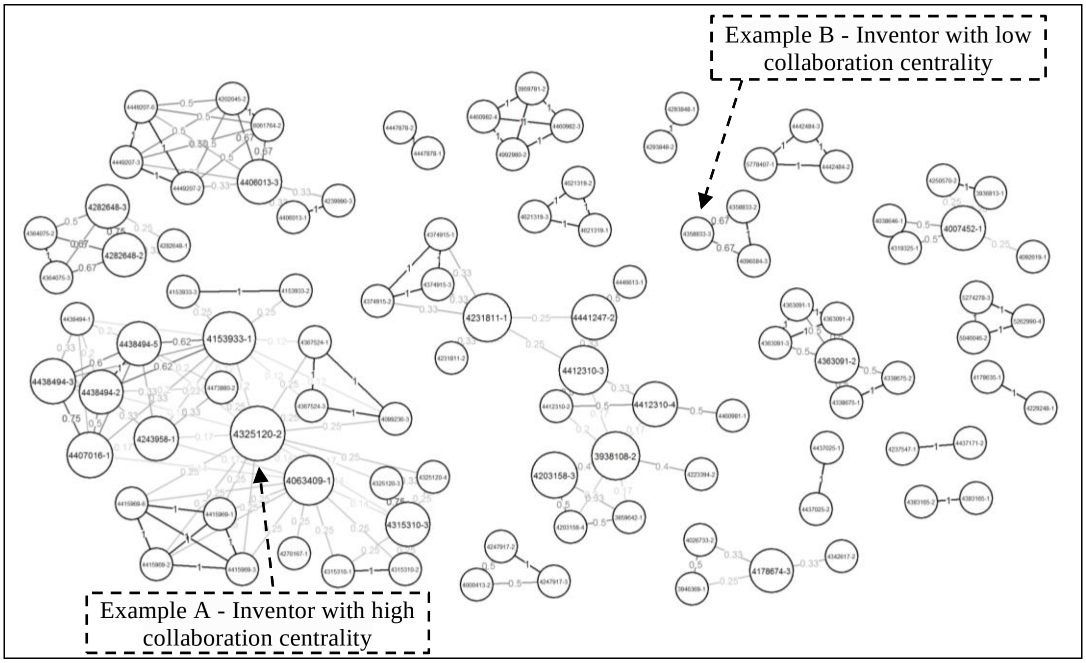
Note. Coefficient estimates from models 4 and 8 in Table 4.

Table 6. Results of Multinomial Logit Competing Risks Models

	1					
Exit mode:	0{Staying at the firm $_{t+1}$}		2{Entrepreneurship $_{t+1}$}		3{Unemployment $_{t+1}$}	
Collaboration centrality $_{[t-4,\ t]}$	1.938**	(0.72)	3.987***	(1.06)	-0.470	(1.89)
Technological centrality $_{[t-4,\ t]}$	0.408*	(0.16)	-1.777*	(0.69)	-0.069	(0.42)
ln(*Time* $_t$)	0.099*	(0.05)	-0.206	(0.14)	-0.055	(0.12)
Inventor's tenure at first patent	0.000	(0.01)	-0.112**	(0.03)	0.069***	(0.02)
Inventor's patents $_t$	0.002	(0.00)	0.010*	(0.00)	0.003	(0.01)
Inventor's impact $_t$	0.001	(0.00)	0.019**	(0.01)	0.006	(0.01)
Inventor's specialization $_t$	0.553***	(0.12)	0.206	(0.37)	0.243	(0.26)
Prior geographic mobility $_t$	0.056	(0.08)	-0.333	(0.24)	0.140	(0.17)
Prior firm mobility $_t$	-0.129***	(0.02)	-0.291***	(0.09)	0.153***	(0.03)
Prior entrepreneurship $_t$	0.302	(0.20)	0.705	(0.45)	0.353	(0.29)
Peers' entrepreneurship $_t$	0.018***	(0.01)	0.060***	(0.02)	0.006	(0.01)
ln(*VC deals in state* $_t$)	-0.010	(0.02)	0.049	(0.05)	-0.006	(0.05)
Manager $_t$	-0.710***	(0.07)	-0.395	(0.27)	-0.928***	(0.17)
Job positions $_t$	0.310***	(0.05)	0.028	(0.22)	0.615***	(0.08)
Job title (software) $_t$	-0.008	(0.07)	-0.931***	(0.27)	-0.058	(0.16)
Job title (engineering) $_t$	0.021	(0.13)	-0.442	(0.41)	-0.545†	(0.31)
Job title (manufacturing) $_t$	-0.207**	(0.08)	-0.992***	(0.30)	-0.426*	(0.19)
Job title (corporate services) $_t$	-0.108	(0.21)	-0.624	(0.75)	-0.567	(0.49)
Degree(MBA)	-0.322**	(0.10)	0.301	(0.33)	-0.086	(0.24)
Degree(PhD)	-0.488***	(0.07)	-0.734**	(0.26)	-0.247	(0.15)
CEO change $_t$	-0.715***	(0.08)	-0.137	(0.25)	-0.101	(0.19)
Plant closure $_t$	0.432***	(0.11)	0.215	(0.29)	0.294	(0.23)
Unit divestiture $_t$	0.078**	(0.03)	-0.101	(0.08)	0.078	(0.06)
Restructuring $_t$	-1.225***	(0.13)	-1.104*	(0.48)	-0.322	(0.28)
Constant	3.018***	(0.14)	-1.841***	(0.50)	-1.915***	(0.33)
Log likelihood	-7,701					
Chi-square	963.5					

Note. N = 35,344. Dependent variable is *exit mode*. The base outcome is "move to another employer" (i.e., *exit mode* = 1). Robust standard errors (in parentheses) clustered by employee.
*** $p < .001$; ** $p < .01$; * $p < .05$; † p < .1.

Figure 1. Collaboration Network of the Firm in 1978-1982



Note. Eighteen isolated inventors (without any link) are not shown.

Figure 2. Technological Network of the Firm in 1978-1982

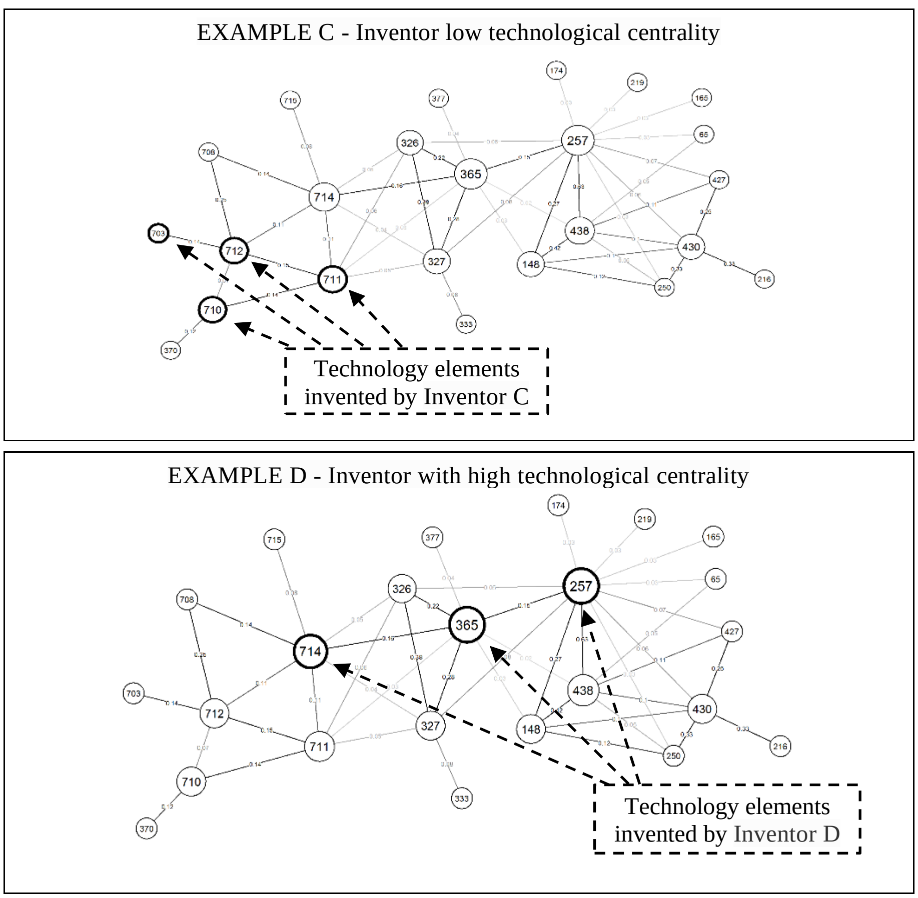
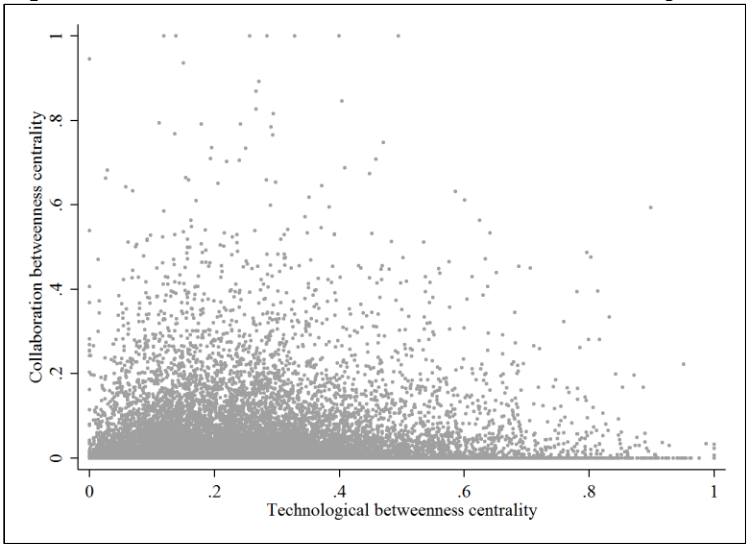
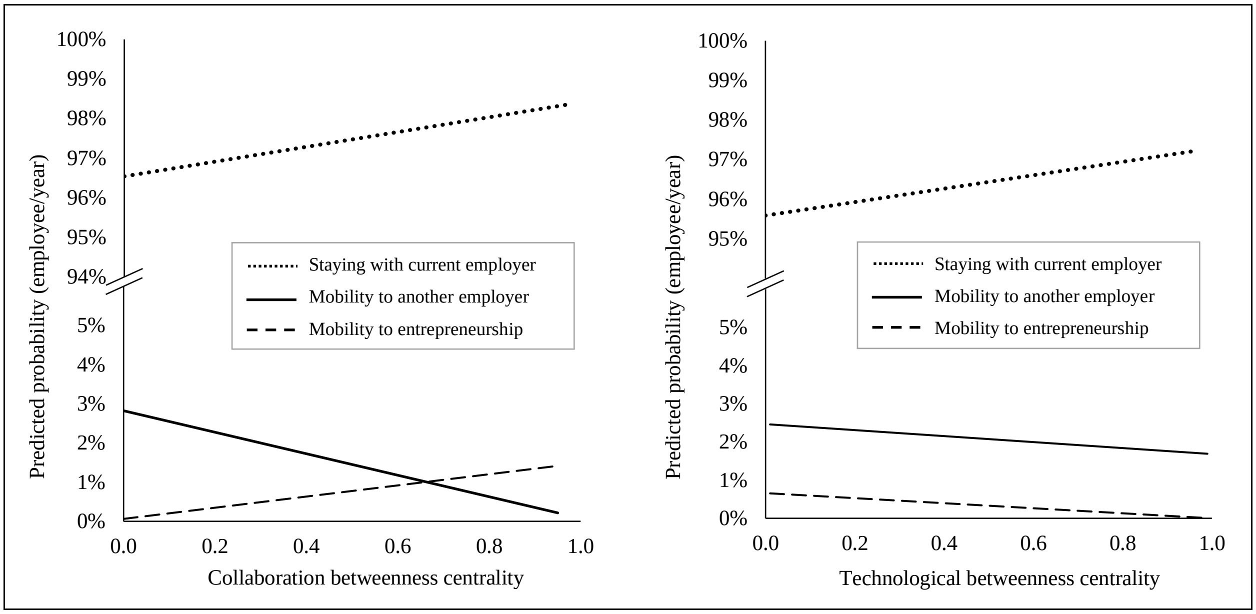


Figure 3. Distribution of Collaboration and Technological Centrality in our Sample



Note. Distribution of combinations of collaboration and technological centrality in the inventor-year data.

Figure 4. Marginal Effects of Collaboration and Technological Centrality



Note. Marginal effect of unemployment not shown here.

Supplementary material for review

Contents:

Appendix A. Tests of the match between LinkedIn data and USPTO patents

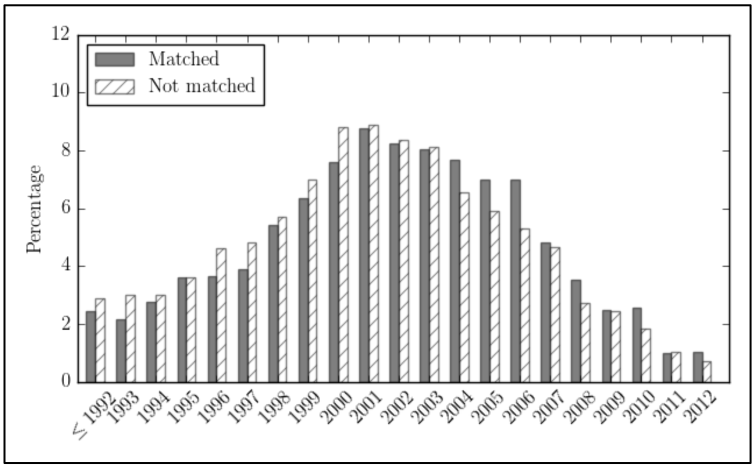
As noted in the paper, we found a raw match between the LinkedIn data and USPTO patents for 4,416 inventors, that is, about 47% of all of the firm's inventors. It is reasonable to assume that this percentage represents an upper bound of the share of inventors who actually had a LinkedIn profile, and that the vast majority of the remaining 53% never subscribed to this social network. We needed additional controls to ensure the representativeness of our sample.

First, to ensure the quality of our match, we considered the 515 cases in which the firm's inventors reported their patents in their LinkedIn profiles. Using this subset, we determined that our matching algorithm had a rate of false positive matches (Type 1 error) less than 3%, meaning that it correctly assigned a LinkedIn profile to an inventor in more than 97% of cases.

Second, we assessed to what extent the sample of matched inventors included more recent cohorts, under the assumption that younger people have more incentives or simply a greater propensity than relatively older people to set up a LinkedIn profile. Ideally, we would like to compare the age profile across the two subsets. However, while we can estimate the ages of the matched inventors from their educational data, there is no way to retrieve this information for the unmatched ones. As a second-best solution, therefore, for each subset of inventors we computed the distribution by year of application for the first patent at the USPTO.[19] As Figure A1 shows, the sample of matched inventors appears to include individuals with a relatively more recent patenting history than the sample of unmatched inventors. At the same time, the two distributions look quite similar. A simple Mann-Whitney-Wilcoxon rank sum test (-0.11, p-value 0.91) confirmed that the two distributions do not differ significantly. As a consequence, with the caveat that the date of the first patent does not correspond to the age of the inventor, we can reasonably conclude that our sample of matched inventors is not significantly different from the subset of unmatched inventors, as far as entry into patenting is concerned.

[19] Note that the 11,195 examined inventors (4,416 matched, plus 6,779 unmatched) applied for their first patent while at the firm between 1993 and 2012 (inclusive). To calculate the date of their first patent at the USPTO, we did not limit ourselves just to the patents applied for while they were at the firm, but also considered all patents by an inventor at any company.

Figure A1. Matched and Unmatched Inventors by Application Year of the First Patent



However, other factors might differentiate matched and unmatched inventors. In particular, highly productive inventors and those with a greater propensity to change jobs might have more incentives to signal their skills and abilities through professional social networks such as LinkedIn. To test these effects, we compared the two groups by means of the (cumulative) number of patents for which the inventor filed at the USPTO—as a proxy for his/her innovative productivity—and the (cumulative) number of assignees for which the inventor had made patents—as a proxy for his/her propensity to move across firms. Table A1 reports no statistical differences between the two groups, both in terms of productivity and propensity to move.

Table A1. Sample of the Firm's Inventors: Public LinkedIn Profiles, Patents and Mobility

	Firm's inventors with a LinkedIn profile (N = 4,416)			Firm's inventors without a LinkedIn profile (N = 7,576)			
	Mean	*Std.dev.*	*95% CI*	*Mean*	*Std.dev.*	*95% CI*	*T-test on mean difference*
Inventors' total patents	7.415	14.629	[6.984; 7.846]	7.529	22.748	[7.126; 8.041]	$p = 0.766$
Inventors' total mobility events (patent records)	0.706	0.012	[0.683; 0.728]	0.723	0.012	[0.700; 0.747]	$p = 0.321$

We therefore ran additional, more sophisticated empirical analyses that confirmed this initial finding. In particular, we estimated a simple logit regression model in which the dependent variable takes the value of 1 if we matched the inventor to a LinkedIn profile and 0 otherwise. We also included additional regressors, such as a series of dummy variables for the year in which the inventor filed his/her first patent at the USPTO, and two dummy variables capturing the ethnicity of the two most important groups of non-US inventors—Chinese and Indian inventors[20]—to account for the fact that these individuals might have more incentives to compile an online CV to overcome problems of asymmetric information. Table A2 shows the results of the logit estimation. For ease of interpretation, we report the marginal effects next to the estimated coefficients.

Table A2. Probability of Having a Matched LinkedIn Profile (Logit Regression)

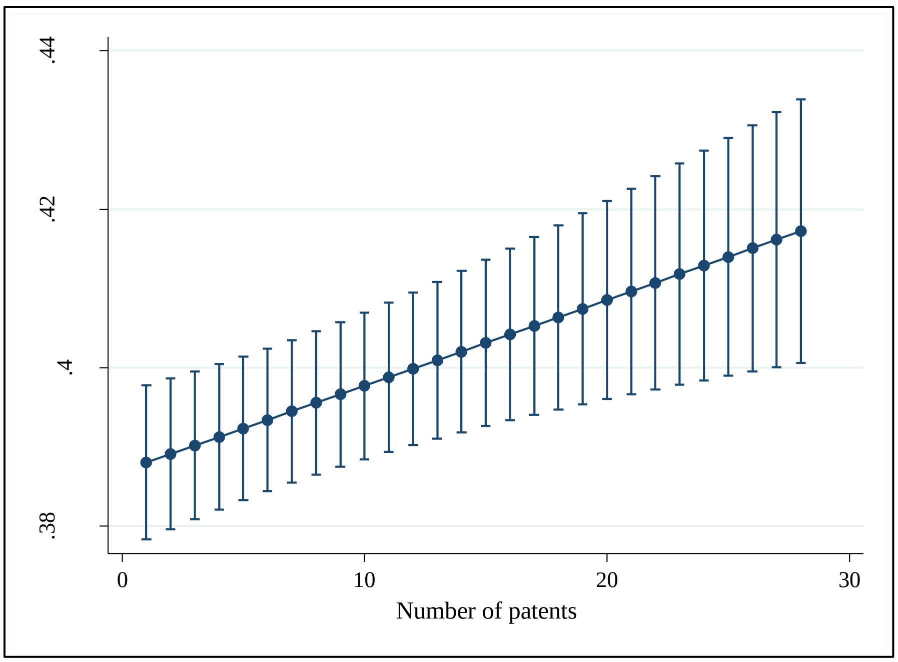
Dependent variable:	*LinkedIn*			
	Coef.	*Std. err.*	*dy/dx*	*Std. err.*
Number of assignees	- 0.06**	(0.01)	-0.01	(0.00)
Number of patents	0.00**	(0.00)	0.00	(0.00)
Ethnicity (Indian)	0.09†	(0.05)	0.02	(0.01)
Ethnicity (Chinese)	0.28**	(0.07)	0.06	(0.01)
First patent at USPTO:				
Before 1993	- 0.42†	(0.24)	-0.10	(0.05)
1993	- 0.68**	(0.24)	-0.16	(0.05)
1994	- 0.44†	(0.23)	-0.10	(0.05)
1995	- 0.35	(0.23)	-0.08	(0.05)
1996	- 0.59*	(0.23)	-0.14	(0.05)
1997	- 0.58*	(0.23)	-0.13	(0.05)
1998	- 0.41†	(0.22)	-0.09	(0.05)
1999	- 0.46*	(0.22)	-0.11	(0.05)
2000	- 0.51*	(0.22)	-0.12	(0.05)
2001	- 0.38†	(0.21)	-0.09	(0.05)
2002	- 0.38†	(0.22)	-0.09	(0.05)
2003	- 0.38†	(0.22)	-0.09	(0.05)
2004	- 0.22	(0.22)	-0.05	(0.05)
2005	- 0.22	(0.22)	-0.05	(0.05)
2006	- 0.11	(0.22)	-0.02	(0.05)
2007	- 0.35	(0.22)	-0.08	(0.05)
2008	- 0.13	(0.23)	-0.03	(0.05)
2009	- 0.35	(0.24)	-0.08	(0.05)
2010	- 0.05	(0.24)	-0.01	(0.05)
2011	- 0.41	(0.28)	-0.09	(0.06)
2012	*Baseline*			
Constant	- 0.02	(0.21)		
Observations	11,195			
Log-likelihood	-7,459.2			
LR Chi-square	98.55			

Note. The dependent variable is *LinkedIn*.
** $p < .01$; * $p < .05$; † $p < .1$.

[20] To identify the inventors' ethnicity, we matched first and last names with the IBM InfoSphere Global Name Management© database.

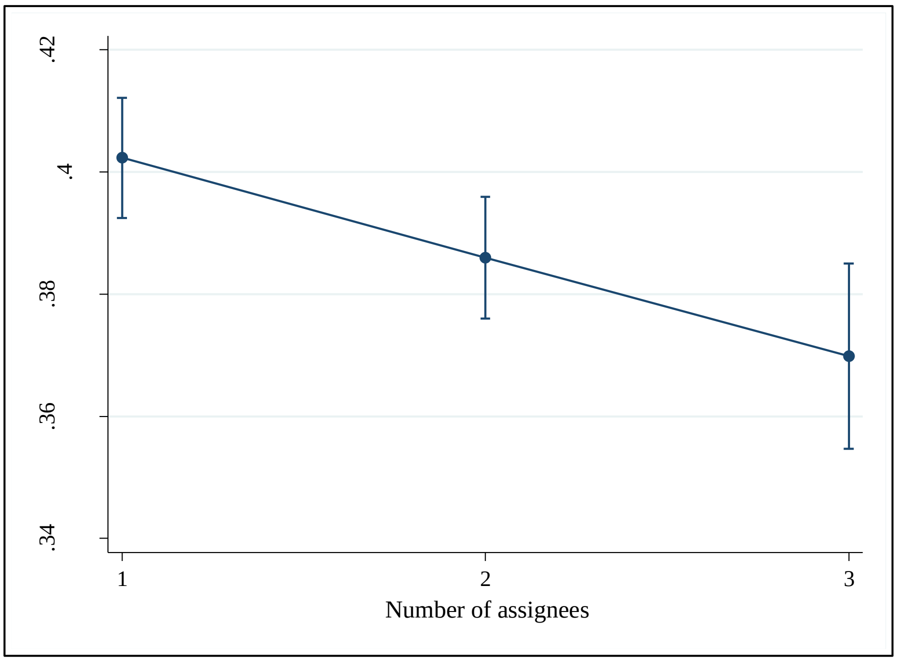
The positive and statistically significant coefficient on the number of patents suggests that our sample of matched inventors might be biased towards more productive inventors. However, the magnitude of the coefficient, as well as the marginal effect, is rather small. To help interpret the results, Figure A2 illustrates how the predicted probability that an inventor is matched with a LinkedIn profile *and* included in our sample changes when the number of patents goes from 1 (5th percentile) to 28 (95th percentile), keeping all other variables at their means. The probability ranges from 0.39 for an inventor with just 1 patent to 0.42 for an inventor with 28 patents. Hence, even though the effect is statistically significant, its magnitude looks sufficiently small to ensure that the sample of inventors we used in the main regressions of this paper is not systematically biased towards highly prolific inventors.

Figure A2. Predicted Probability of Being Matched with a LinkedIn Profile and Included in Our Sample as the Number of Patents Increases from 1 to 28 (5th and 95th Percentiles)



Similar arguments hold for the number of assignees (our proxy for the propensity to move). The coefficient is statistically significant and, quite surprisingly, has a negative sign. However, the magnitude of the effect looks reasonably small. Figure A3 plots the predicted probability that we matched an inventor with a LinkedIn profile and included him/her in our sample as the number of assignees goes from 1 (5th percentile) to 3 (95th percentile), keeping all other variables at their means. The probability of being matched with a LinkedIn profile *and* included in our sample is equal to 0.40 for an inventor who filed for patents for just one assignee (i.e., the firm in our study) and 0.37 for an inventor who filed for patents for three different assignees. Once again, even though this finding signals that our sample might be slightly biased towards relatively *less* mobile inventors, the magnitude of the bias looks small enough to guarantee that it did not affect the results of our analysis in a significant way.

Figure A3. Predicted Probability of Being Matched with a LinkedIn Profile and Included in Our Sample as the Number of Assignees Increases from 1 to 3 (5th and 95th Percentiles)



As far as the other variables are concerned, it is interesting to note that both the coefficients for Chinese and Indian inventors are positive and statistically significant, thereby confirming our assumption that signaling through social networks might be important for this group of inventors. In particular, the probability of being matched with a LinkedIn profile and included in our sample is equal to 0.45 for Chinese inventors, compared to a probability of 0.39 for an average non-Chinese inventor. Finally, the coefficients for the dummy variables capturing the year of the first patent at the USPTO suggest that inventors who started their patenting career during the 1990s may be slightly under-represented in our sample compared to those who began patenting during the 2000s.

Appendix B. Notion of node betweenness

In this appendix, we provide a formal definition and our intuition for the use of the betweenness centrality measures. Consider a *valued* and *undirected* network G that consists of three sets of information: 1) a set of g nodes $N = \{n_1, n_2 \dots n_g\}$; 2) a set of m edges $E = \{e_1, e_2 \dots e_m\}$; and 3) a set of values $V = \{v_1, v_2 \dots v_m\}$ attached to the edges (Wasserman and Faust 1994). Each edge connects a pair of distinct nodes. For example, the edge $e_k = (n_i, n_j)$ connects nodes n_i and n_j, while the value v_k attached to the edge measures the *strength* of the relation between this pair of nodes.[21] In such a generic network, one can define the *cost* of using a given edge e_k as the inverse of the value v_k attached to it (Newman 2001). Thus, the *cost* of edge e_k is equal to $1/v_k$.[22] Using these definitions, the *shortest path* between two nodes is defined as the path (i.e., the sequence of edges needed to connect them) that minimizes the sum of the *costs* of its constituent edges.[23]

The notion of the shortest path is the underlying metric used in the computation of node betweenness. Broadly speaking, the latter represents the number of shortest paths among all pairs of nodes in the network that pass through a given node (Freeman 1979). Formally, node betweenness is defined as:

$$B(n_i) = \sum_{s \neq t \in N} \frac{\sigma_{st}(n_i)}{\sigma_{st}} \tag{B1}$$

where σ_{st} is the total number of shortest paths between nodes n_s and n_t, and $\sigma_{st}(n_i)$ is the number of shortest paths passing through node n_i out of σ_{st}. This measure ranges from a theoretical minimum of 0, when node n_i is not on any shortest path, to a theoretical maximum of 1, when node n_i is on all of the shortest paths connecting all pairs of inventors. Given that we calculated this measure repeatedly over different time periods, with a varying number of nodes and edges, we standardized edge betweenness by computing the following quantity:

[21] As we discuss below, in our setting, the value v_k refers either to the frequency of contacts between two inventors (collaboration network), or to the frequency of co-occurrences of two technologies (technological network).
[22] The cost of linking two disconnected nodes, for which $v_k = 0$, is equal to infinity.
[23] Note that, in general, there may not be a unique shortest path between two nodes. There may be two or more shortest paths, which may or may not share some edges.

$$NB(n_i) = \frac{B(n_i) - min[B(n)]}{max[B(n)] - min[B(n)]} \quad \text{(B2)}$$

where $min[B(n)]$ and $max[B(n)]$ are, respectively, the minimum and maximum realized values of node betweenness in the network. Thus, the normalized value of node betweenness ranges from 0, when $B(n_i)$ is equal to the minimum observed value, to 1, when $B(n_i)$ is equal to the maximum observed value. The expression reported in equation (B2) is our measure of collaboration betweenness centrality.

The intuition for the use of node betweenness as our basic measure of collaboration and technological betweenness centrality can be explained in this way. If a network contains groups or clusters of nodes (e.g., clusters of inventors or clusters of technologies, in our setting) densely connected within them, but loosely connected with one another, then the nodes connecting these clusters will have a high value of node betweenness, because they provide the only link to nodes in the different clusters. To put it differently, by removing these nodes, the different clusters would be separated from one another. As a consequence, nodes that occupy these positions act "in-between" otherwise unconnected nodes (Mehra et al. 2001).

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Appendix C. Robustness checks and additional analyses

Table C1. Complementary Log-Log Regressions: Standard Errors Clustered by New Employer

Dependent variable:	Mobility to another Employer $_{t+1}$				Mobility to entrepreneurship $_{t+1}$			
	1	2	3	4	5	6	7	8
Collaboration bet. centrality $_{[t-4,\ t]}$		-1.978**		-1.879*		1.789*		2.085**
		(0.75)		(0.74)		(0.79)		(0.78)
Technological bet. centrality $_{[t-4,\ t]}$			-0.419**	-0.383*			-2.058**	-2.157**
			(0.15)	(0.15)			(0.72)	(0.74)
ln(*Time* $_t$)	-0.085	-0.075	-0.102†	-0.092†	-0.211	-0.229	-0.278†	-0.298*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.15)	(0.15)	(0.15)	(0.15)
Inventor's tenure at first patent	-0.000	-0.001	-0.000	-0.001	-0.110**	-0.110**	-0.113**	-0.113**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.04)	(0.04)
Inventor's patents $_t$	-0.006†	-0.003	-0.005	-0.002	0.008**	0.006*	0.009***	0.008**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Inventor's impact $_t$	-0.001	-0.001	-0.001	-0.001	0.017**	0.017**	0.017**	0.017**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Inventor's specialization $_t$	-0.560***	-0.531***	-0.563***	-0.535***	-0.271	-0.309	-0.283	-0.322
	(0.12)	(0.12)	(0.12)	(0.12)	(0.36)	(0.36)	(0.36)	(0.36)
Prior geographic mobility $_t$	-0.056	-0.054	-0.054	-0.052	-0.372	-0.407	-0.345	-0.385
	(0.08)	(0.08)	(0.08)	(0.07)	(0.25)	(0.26)	(0.25)	(0.26)
Prior firm mobility $_t$	0.121***	0.121***	0.119***	0.118***	-0.168*	-0.167*	-0.172*	-0.170*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.08)	(0.08)	(0.08)	(0.08)
Prior entrepreneurship $_t$	-0.299†	-0.296†	-0.302†	-0.298†	0.444	0.433	0.420	0.409
	(0.18)	(0.18)	(0.18)	(0.18)	(0.36)	(0.38)	(0.38)	(0.39)
Peers' entrepreneurship $_t$	-0.017**	-0.017**	-0.018**	-0.018**	0.049*	0.049*	0.042*	0.042*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
ln(*VC deals in state* $_t$)	0.010	0.010	0.009	0.009	0.060	0.061	0.055	0.057
	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.06)	(0.06)	(0.06)
Manager $_t$	0.679***	0.676***	0.698***	0.692***	0.207	0.208	0.278	0.285
	(0.07)	(0.07)	(0.07)	(0.07)	(0.27)	(0.27)	(0.27)	(0.27)
Job positions $_t$	-0.304***	-0.304***	-0.307***	-0.307***	-0.255	-0.255	-0.272	-0.272
	(0.06)	(0.06)	(0.06)	(0.06)	(0.21)	(0.21)	(0.21)	(0.21)
Job title (software) $_t$	0.027	0.022	0.015	0.011	-0.886**	-0.873**	-0.935**	-0.920**
	(0.08)	(0.08)	(0.08)	(0.08)	(0.32)	(0.32)	(0.32)	(0.32)
Job title (engineering) $_t$	-0.006	0.001	-0.019	-0.012	-0.396	-0.406	-0.440	-0.457
	(0.13)	(0.13)	(0.13)	(0.13)	(0.39)	(0.39)	(0.39)	(0.39)
Job title (manufacturing) $_t$	0.198*	0.195*	0.209**	0.205*	-0.817**	-0.805**	-0.801**	-0.787**
	(0.08)	(0.08)	(0.08)	(0.08)	(0.29)	(0.29)	(0.29)	(0.29)
Job title (corporate services) $_t$	0.123	0.112	0.127	0.115	-0.522	-0.508	-0.537	-0.516
	(0.21)	(0.21)	(0.21)	(0.21)	(0.71)	(0.71)	(0.71)	(0.71)
Degree(MBA)	0.297**	0.298**	0.298**	0.298**	0.557†	0.564†	0.596†	0.602†
	(0.10)	(0.10)	(0.10)	(0.10)	(0.33)	(0.33)	(0.34)	(0.34)
Degree(PhD)	0.445***	0.458***	0.456***	0.468***	-0.296	-0.323	-0.237	-0.267
	(0.08)	(0.08)	(0.08)	(0.08)	(0.26)	(0.26)	(0.26)	(0.26)
CEO change $_t$	0.663**	0.672**	0.676**	0.683**	0.488	0.473	0.557†	0.543
	(0.24)	(0.24)	(0.24)	(0.24)	(0.33)	(0.33)	(0.34)	(0.34)
Plant closure $_t$	-0.420**	-0.419**	-0.420**	-0.420**	-0.175	-0.177	-0.196	-0.198
	(0.14)	(0.14)	(0.14)	(0.14)	(0.36)	(0.36)	(0.36)	(0.36)
Unit divestiture $_t$	-0.075**	-0.076**	-0.074**	-0.075**	-0.182†	-0.182†	-0.175†	-0.175†
	(0.02)	(0.02)	(0.02)	(0.02)	(0.10)	(0.10)	(0.10)	(0.10)
Restructuring $_t$	1.133***	1.139***	1.179***	1.181***	-0.152	-0.152	0.052	0.062
	(0.13)	(0.14)	(0.14)	(0.14)	(0.56)	(0.56)	(0.56)	(0.56)
Constant	-3.178**	-3.172**	-3.047**	-3.052**	-5.521***	-5.527***	-4.931***	-4.919***
	(0.99)	(0.98)	(0.98)	(0.98)	(1.15)	(1.15)	(1.16)	(1.16)
Log likelihood	-5,327	-5,322	-5,324	-5,319	-804.3	-803	-798.1	-796.3
Chi-square	513.9	519.7	522.9	527.9	133.9	139.1	184.2	177

Note. N = 35,344. Robust standard errors (in parentheses) clustered by new employer; bet., betweenness.
*** $p < .001$; ** $p < .01$; * $p < .05$; † $p < .1$.

Table C2. Correlations: Collaboration Betweenness Centrality, Bonacich's Power Centrality and Burt's Brokerage

Variable	1	2	3	4	5	6
1. *Mobility (any type)* $_{t+1}$						
2. *Mobility to another employer* $_{t+1}$	.95					
3. *Mobility to entrepreneurship* $_{t+1}$	.29	-.01				
4. *Unemployment* $_{t+1}$	-.02	-.02	-.01			
5. *Collaboration betweenness centrality* $_{[t-4,\, t]}$	-.02	-.02	.01	-.01		
6. *Collaboration Bonacich's power centrality* $_{[t-4,\, t]}$	-.02	-.02	.00	-.01	.41	
7. *Collaboration Burt's brokerage* $_{[t-4,\, t]}$	-.01	-.01	.01	-.01	.34	.44

Note. N = 35,344. All correlations above |.01| are significant at $p < 0.05$.

Table C3. Robustness Checks: Bonacich's Power Centrality and Burt's Brokerage

Exit by:	Mobility (any type) $_{t+1}$		Mobility to another employer $_{t+1}$		Mobility to entrepreneurship $_{t+1}$	
	1	2	3	4	5	6
Collaboration Bonacich's power centrality $_{[t-4, t]}$	-0.126*		-0.129*		-0.072	
	(0.05)		(0.06)		(0.08)	
Collaboration Burt's brokerage $_{[t-4, t]}$		-0.077		-0.122*		0.479**
		(0.05)		(0.05)		(0.18)
Technological bet. centrality $_{[t-4, t]}$	-0.567***	-0.505**	-0.436**	-0.349*	-2.061**	-2.403***
	(0.16)	(0.16)	(0.16)	(0.16)	(0.65)	(0.71)
ln(*Time* $_t$)	-0.127**	-0.138**	-0.105*	-0.122**	-0.274*	-0.213
	(0.04)	(0.04)	(0.05)	(0.05)	(0.13)	(0.14)
Inventor's tenure at first patent	-0.008	-0.009	0.000	-0.000	-0.112***	-0.115***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)
Inventor's patents $_t$	0.002	-0.001	-0.000	-0.002	0.010***	0.005
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Inventor's impact $_t$	0.002	0.001	-0.001	-0.001	0.017**	0.018**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Inventor's specialization $_t$	-0.521***	-0.541***	-0.544***	-0.563***	-0.265	-0.289
	(0.11)	(0.11)	(0.12)	(0.12)	(0.34)	(0.34)
Prior geographic mobility $_t$	-0.105	-0.084	-0.072	-0.047	-0.344	-0.408†
	(0.08)	(0.08)	(0.08)	(0.08)	(0.23)	(0.24)
Prior firm mobility $_t$	0.097***	0.097***	0.118***	0.116***	-0.173*	-0.165†
	(0.02)	(0.02)	(0.02)	(0.02)	(0.09)	(0.09)
Prior entrepreneurship $_t$	-0.231	-0.227	-0.295	-0.283	0.420	0.392
	(0.18)	(0.18)	(0.19)	(0.19)	(0.39)	(0.40)
Peers' entrepreneurship $_t$	-0.011*	-0.011*	-0.018***	-0.018***	0.042**	0.044**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)
ln(*VC deals in state* $_t$)	0.014	0.017	0.009	0.011	0.053	0.053
	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.05)
Manager $_t$	0.658***	0.664***	0.689***	0.692***	0.271	0.308
	(0.07)	(0.07)	(0.07)	(0.07)	(0.26)	(0.26)
Job positions $_t$	-0.309***	-0.309***	-0.309***	-0.309***	-0.274	-0.261
	(0.05)	(0.05)	(0.05)	(0.05)	(0.20)	(0.21)
Job title (software) $_t$	-0.077	-0.070	0.009	0.015	-0.944***	-0.922***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.26)	(0.26)
Job title (engineering) $_t$	-0.073	-0.066	-0.019	-0.008	-0.438	-0.504
	(0.12)	(0.12)	(0.12)	(0.12)	(0.40)	(0.40)
Job title (manufacturing) $_t$	0.118	0.120	0.207**	0.208**	-0.804**	-0.790**
	(0.07)	(0.07)	(0.08)	(0.08)	(0.29)	(0.29)
Job title (corporate services) $_t$	0.051	0.051	0.120	0.115	-0.536	-0.504
	(0.20)	(0.20)	(0.21)	(0.21)	(0.71)	(0.71)
Degree(MBA)	0.312***	0.307***	0.296**	0.288**	0.595†	0.629*
	(0.09)	(0.09)	(0.10)	(0.10)	(0.32)	(0.31)
Degree(PhD)	0.413***	0.407***	0.471***	0.473***	-0.221	-0.305
	(0.06)	(0.06)	(0.06)	(0.07)	(0.26)	(0.26)
CEO changes $_t$	0.666***	0.669***	0.676***	0.681***	0.561*	0.529*
	(0.07)	(0.07)	(0.08)	(0.08)	(0.24)	(0.24)
Plant closure $_t$	-0.396***	-0.394***	-0.424***	-0.423***	-0.197	-0.190
	(0.10)	(0.10)	(0.11)	(0.11)	(0.27)	(0.27)
Unit divestiture $_t$	-0.087***	-0.086***	-0.076**	-0.074**	-0.176*	-0.175*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.08)	(0.08)
Restructuring $_t$	1.090***	1.088***	1.183***	1.183***	0.056	0.046
	(0.12)	(0.12)	(0.12)	(0.12)	(0.46)	(0.46)
Constant	-2.872***	-2.819***	-3.007***	-2.902***	-4.908***	-5.543***
	(0.13)	(0.15)	(0.14)	(0.15)	(0.48)	(0.53)
Log likelihood	-5,747	-5,750	-5,320	-5,321	-797.9	-794.2
Chi-square	517.3	508.8	564.8	560.8	131.5	127.5

Note. N = 35,344. Robust standard errors (in parentheses) clustered by employee; bet., betweenness.
*** $p < .001$; ** $p < .01$; * $p < .05$; † $p < .1$.

Table C4. Additional Analysis: Individual vs. Collective Mobility

Exit by:	Mobility (in team) to another employer $_{t+1}$ (*Co-mobility*)	Mobility (in team) to entrepreneurship $_{t+1}$ (*Co-founding*)	β[*Co-mobility*] - β[*Co-founding*] = 0
	1	2	*Wald test*
Collaboration bet. centrality $_{[t\text{-}4,\ t]}$	-0.583	3.087**	p = 0.0069
	(0.98)	(1.03)	
Technological bet. centrality $_{[t\text{-}4,\ t]}$	-0.809*	-2.565**	p = 0.0810
	(0.32)	(0.89)	
ln(*Time* $_t$)	0.056	-0.509**	
	(0.09)	(0.18)	
Inventor's tenure at first patent	-0.003	-0.081*	
	(0.01)	(0.04)	
Inventor's patents $_t$	-0.006	0.010	
	(0.01)	(0.01)	
Inventor's impact $_t$	-0.019*	0.008	
	(0.01)	(0.01)	
Inventor's specialization $_t$	-0.697**	-0.318	
	(0.22)	(0.43)	
Prior geographic mobility $_t$	0.116	-0.153	
	(0.13)	(0.32)	
Prior firm mobility $_t$	0.143***	-0.144	
	(0.03)	(0.11)	
Prior entrepreneurship $_t$	-0.156	0.056	
	(0.35)	(0.89)	
Peers' entrepreneurship $_t$	-0.031**	0.062**	
	(0.01)	(0.02)	
ln(*VC deals in state* $_t$)	0.011	0.004	
	(0.03)	(0.07)	
Manager $_t$	0.589***	-0.007	
	(0.12)	(0.35)	
Job positions $_t$	-0.306***	-0.805†	
	(0.09)	(0.44)	
Job title (software) $_t$	-0.027	-0.426	
	(0.13)	(0.32)	
Job title (engineering) $_t$	-0.417	-0.075	
	(0.25)	(0.48)	
Job title (manufacturing) $_t$	0.170	-0.429	
	(0.13)	(0.36)	
Job title (corporate services) $_t$	-0.303	-0.335	
	(0.46)	(1.02)	
Degree(MBA)	-0.172	0.804*	
	(0.20)	(0.39)	
Degree(PhD)	0.552***	-0.275	
	(0.11)	(0.34)	
CEO changes $_t$	1.446***	0.723*	
	(0.12)	(0.34)	
Plant closure $_t$	-1.261***	-0.830†	
	(0.26)	(0.47)	
Unit divestiture $_t$	-0.212***	-0.286*	
	(0.05)	(0.12)	
Restructuring $_t$	2.101***	0.140	
	(0.25)	(0.70)	
Constant	-3.998***	-5.556***	
	(0.28)	(0.64)	
Log likelihood	-2,020	-482.1	
Chi-square	332.1	71.8	

Note. N = 35,344. Robust standard errors (in parentheses) clustered by employee; bet., betweenness.
[a] *Co-mobility* and *Co-founding* are binary indicators set to one when the inventor moves to the new employment—either another firm or founding a new venture—with other corporate inventors, and zero otherwise.
*** $p < .001$; ** $p < .01$; * $p < .05$; † $p < .1$.

Table C5. Robustness Check: Inventor Productivity

Exit by:	Mobility (any type) $_{t+1}$							
	1		2		3		4	
Collaboration bet. centrality $_{[t-4,\ t]}$	-1.349*	(0.67)	-1.479†	(0.82)	-1.182*	(0.59)	-1.183*	(0.59)
Collaboration bet. centrality $_{[t-4,\ t]}$***Inventor's patents* $_t$	0.014	(0.02)						
Collaboration bet. centrality $_{[t-4,\ t]}$***Inventor's impact* $_t$			0.039	(0.06)				
Technological bet. centrality $_{[t-4,\ t]}$	-0.523***	(0.16)	-0.526***	(0.16)	-0.533**	(0.17)	-0.558**	(0.19)
Technological bet. centrality $_{[t-4,\ t]}$***Inventor's patents* $_t$					0.002	(0.02)		
Technological bet. centrality $_{[t-4,\ t]}$***Inventor's impact* $_t$							0.005	(0.02)
ln(*Time* $_t$)	-0.118**	(0.04)	-0.118**	(0.04)	-0.119**	(0.04)	-0.119**	(0.04)
Inventor's tenure at first patent	-0.009	(0.01)	-0.009	(0.01)	-0.009	(0.01)	-0.009	(0.01)
Inventor's patents $_t$	-0.002	(0.00)	-0.001	(0.00)	-0.001	(0.00)	-0.001	(0.00)
Inventor's impact $_t$	0.002	(0.00)	0.001	(0.00)	0.002	(0.00)	0.000	(0.00)
Inventor's specialization $_t$	-0.522***	(0.11)	-0.522***	(0.11)	-0.523***	(0.11)	-0.522***	(0.11)
Prior geographic mobility $_t$	-0.084	(0.08)	-0.088	(0.08)	-0.086	(0.08)	-0.086	(0.08)
Prior firm mobility $_t$	0.098***	(0.02)	0.098***	(0.02)	0.098***	(0.02)	0.098***	(0.02)
Prior entrepreneurship $_t$	-0.235	(0.18)	-0.238	(0.18)	-0.235	(0.18)	-0.237	(0.18)
Peers' entrepreneurship $_t$	-0.011*	(0.00)	-0.011*	(0.00)	-0.011*	(0.00)	-0.011*	(0.00)
ln(*VC deals in state* $_t$)	0.016	(0.02)	0.016	(0.02)	0.015	(0.02)	0.016	(0.02)
Manager $_t$	0.664***	(0.07)	0.663***	(0.07)	0.664***	(0.07)	0.664***	(0.07)
Job positions $_t$	-0.308***	(0.05)	-0.308***	(0.05)	-0.307***	(0.05)	-0.307***	(0.05)
Job title (software) $_t$	-0.073	(0.07)	-0.073	(0.07)	-0.073	(0.07)	-0.073	(0.07)
Job title (engineering) $_t$	-0.068	(0.12)	-0.068	(0.12)	-0.068	(0.12)	-0.069	(0.12)
Job title (manufacturing) $_t$	0.118	(0.07)	0.118	(0.07)	0.118	(0.07)	0.118	(0.07)
Job title (corporate services) $_t$	0.050	(0.20)	0.051	(0.20)	0.050	(0.20)	0.049	(0.20)
Degree(MBA)	0.313***	(0.09)	0.314***	(0.09)	0.314***	(0.09)	0.314***	(0.09)
Degree(PhD)	0.405***	(0.06)	0.407***	(0.06)	0.405***	(0.06)	0.405***	(0.06)
CEO change $_t$	0.670***	(0.07)	0.670***	(0.07)	0.670***	(0.07)	0.670***	(0.07)
Plant closure $_t$	-0.392***	(0.10)	-0.393***	(0.10)	-0.392***	(0.10)	-0.392***	(0.10)
Unit divestiture $_t$	-0.086***	(0.02)	-0.086***	(0.02)	-0.086***	(0.02)	-0.086***	(0.02)
Restructuring $_t$	1.086***	(0.12)	1.088***	(0.12)	1.086***	(0.12)	1.088***	(0.12)
Constant	-2.914***	(0.13)	-2.913***	(0.13)	-2.913***	(0.14)	-2.908***	(0.14)
Log likelihood	-5,749		-5,749		-5,749		-5,749	
Chi-square	514.1		514.3		514.0		514.0	

Note. N = 35,344. Complementary Log-Log Regressions; robust standard errors (in parentheses) clustered by employee; bet., betweenness.
*** $p < .001$; ** $p < .01$; * $p < .05$; † $p < .1$.

Appendix D. Interview protocol

To interpret the econometric results further and understand the mechanisms that explain our findings, we elicited the views of individuals employed at the sampled firm. We gathered evidence from two sources. First, we interviewed two managers employed at the firm and involved with (i) human resource management, technical personnel training and career development, and (ii) research and development (R&D) and project management. Second, we randomly selected 30 employees from the firm's R&D workers on LinkedIn and emailed them with a request for an interview. Five of them replied positively to our invitation. Among these, four interviewees are also represented in our quantitative analysis and exhibited both low and high levels of collaboration and technological centrality at the firm during the time period of our study. Table D1 describes our final interview sample. At the time of the interview, three interviewees were still working at the firm, whereas the remaining four had moved to join other firms in the same industry.

Table D1. Interview Sample

Interviewee	Interviewee's role(s) at the firm	Tenure at the firm	Inventor's collaboration betweenness centrality	Inventor's technological betweenness centrality	Interviewer(s)
Employee 1	Technical Training Specialist (HR Manager)	11 years	-	-	Author1, Author2
Employee 2	Project Manager (R&D Manager)	9 years	-	-	Author1, Author2
Employee 3	Design Engineer; Senior Logic Design Engineer	12 years	-	-	Author2
Employee 4	Affiliate Researcher; Program Manager; Senior Supplier Development	21 years	Lower than average	Higher than average	Author1, Author2
Employee 5	Staff Engineer; Principal Engineer; Senior Principal Engineer	22 years	Higher than average	Higher than average	Author2
Employee 6	Principal Engineer	12 years	Higher than average	Lower than average	Author2
Employee 7	Power Management Architect	7 years	Lower than average	Lower than average	Author 1

Note. The names of the interviewees and the firm are anonymous.

Once the interview was agreed, we emailed the interviewees (i.e., both managers and R&D workers) a brief summary of our findings and asked about their reactions and views in light of their experience at the firm. Thus, we conducted telephone interviews of about 90 minutes each using a focused (semi-structured) interview technique.

The first part of the interviews focused on the firm's R&D environment and employees' value and opportunities. Our discussion was informal and focused on topics such as the patenting process and decisions, corporate inventors' discretion in the process and the determinants of internal and external career opportunities. Table D2 presents our interview protocol for this first part.

The second part of the interviews focused on the interviewees' impressions about the graphical representations of the employees' position (betweenness centrality) in the intra-firm collaboration and technological networks (see Table D3). We showed these graphs to the interviewees, both managers and R&D workers, and asked them for their insights on the mobility and/or career opportunities of employees in these representations.

All interviews were recorded and transcribed. We then read the interview transcripts, open coded them and engaged in discussions to assess the convergence and divergence in the major empirical concepts that emerged. Tables D4 and D5 show examples of some major concepts that emerged from the coding.

Table D2. Interview Protocol – Part 1

Questions for HR and R&D managers

1. Can you describe how a research project is initiated and how employees are selected for a project?
2. What drives collaboration decisions between inventors/engineers who are not on the same team/unit?
3. What drives collaboration decisions between inventors/engineers who are not in the same technology?
4. How much discretion do employees have in the process of such collaboration decisions?
5. Does [firm name] encourage collaboration across technology clusters, projects and teams?
6. Does [firm name] encourage inventors to patent their inventions? If so, how?
7. How important are publications and patents in the decision to promote an individual?
8. Does [firm name] have technologies that the management considers more strategic than others?
9. How are individuals selected to work on technology classes central to [firm name]?
10. How often are your employees a poaching target for other firms?
11. How does [firm name] protect itself from having its key inventors poached by competitors and avoid the turnover of key inventors?
12. Do you have examples of employees being approached by competitors during the past five years? If they left [firm name], what do you believe contributed to their decision to leave?
13. What does the labor market seek in [firm name]'s employees? What does it value the most?
14. Does connecting various unconnected knowledge clusters within [firm name] provide someone promotion opportunities? And does it increase his/her value in the labor market? If so, why?
15. Does connecting various unconnected groups of scientists or inventors within [firm name] provide promotion opportunities? And does it increase his/her value in the labor market? If so, why?
16. Can you think of an example of a [firm name] employee spinout? If so, what do you believe contributed to the employee's decision to spinout (i.e., to start his/her own venture)?
17. To what extent does an employee's firm-specific knowledge (e.g., knowledge about [firm name]'s R&D processes, routines and core technologies) change his/her chances of being poached by competitors? In addition, what about his/her chances of creating a spinout?
18. Are individuals with more [firm name]-related patents more attractive in the labor market than others?
19. Does an employee's position in the [firm name]'s collaboration network determine his/her chances for a spinout?
20. Who is more likely (a) to receive fast promotion and (b) to leave [firm name]? Those who work in [firm name]'s core technology or those who work on non-core technology? Those who span different collaboration clusters or those who span different knowledge clusters?

Questions for knowledge workers (i.e., corporate inventors)

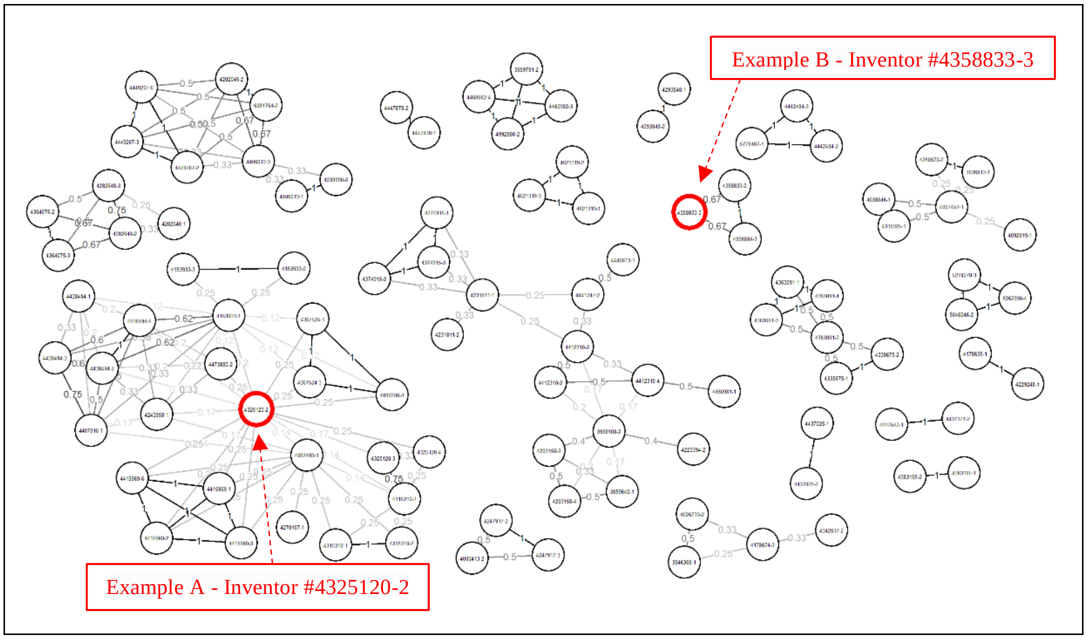
21. During your tenure at [firm name], how many times have you been approached by other companies? If so, why do you believe they have approached you?
22. Do you know someone who was poached by other firms? If so, why do you believe he/she was approached?
23. Can you think of an example of a [firm name] employee spinout? If so, what do you believe contributed to their decision to spinout?
24. How many times have you been promoted during your tenure at [firm name]? If so, what do you believe were the main reasons for the promotion?
25. How much value do you believe [firm name] places on (a) the professional relationships and (b) the knowledge and skills you have developed within the firm?
26. Do you believe you connect various unconnected individuals in [firm name]? If so, does it provide an opportunity to get promoted within [firm name]? Does it increase your attractiveness in the labor market? If so, why?
27. Does [firm name] value more your general knowledge or that specific to [firm name]'s R&D activity?
28. Does the labor market value more your general knowledge or that specific to [firm name]'s R&D activity?
29. Do you believe you connect various unconnected knowledge clusters in [firm name]? If so, does it provide an opportunity to get promoted within [firm name]? And does it increase your attractiveness in the labor market? If so, why?

Table D3. Interview Protocol – Part 2

The objective of the last part of this interview is to solicit your opinion about the preliminary findings of this project. Using patent data, we derived the structure of [firm name] employees' co-patenting activity to define employees' *collaboration* and *technological betweenness centrality* in the firm, as follows.

[Firm name] inventor's *collaboration betweenness centrality* is reflected in the extent to which he/she is at the crossroads of otherwise disconnected groups of researchers and/or provides the shortest path of connection to them. We relied on their patent co-inventing network as an indication of their intra-firm collaboration networks in the past five years. As an example, Figure D1 illustrates the graph for the collaboration (co-invention) network of [firm name] in 1978-1982.

Figure D1. Collaboration (i.e., co-patenting) network of [firm name] in 1978-1982



In the graph, nodes (i.e., circles) denote [firm name]'s inventors. The inventor's ID number is shown within the node. The values attached to the edges (i.e., links) measure the strength of the collaboration between inventors, as formalized in patent applications.

The graph maps the collaboration betweenness centrality of two [firm name]'s inventors between 1978 and 1982. As an example, inventor #4325120-2, who successfully applied for four patents at [firm name] in the period, has a collaboration betweenness centrality index of 1, which is the highest value. As a counter example, inventor #4358833-3 exhibits a collaboration betweenness centrality index of 0, which is the lowest value in [firm name]'s collaboration network.

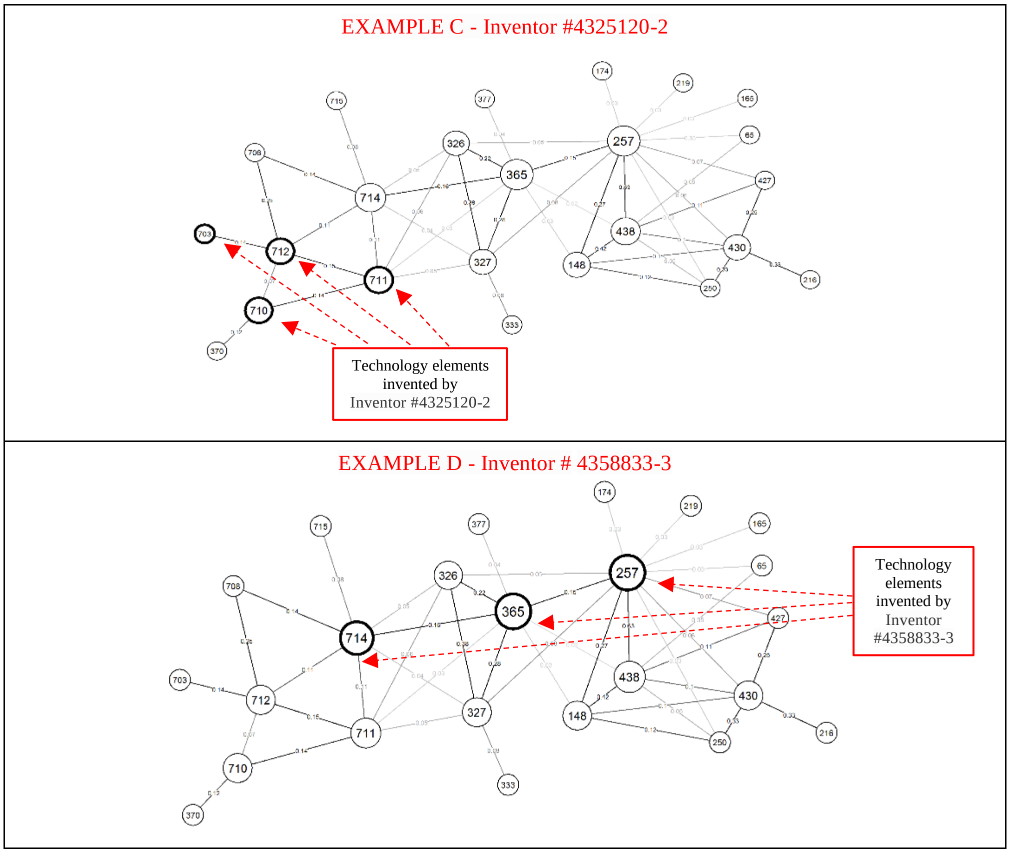
Comparing these two inventors (i.e., examples A and B):

30. Who is more likely to get promoted at [firm name], and why?
31. Who is more likely to move and/or be attractive to a competitor, and why?
32. Who is more likely to start his/her own venture, and why?

Table D3 (cont'd). Interview protocol – Part 2

[Firm name] inventor's *technological betweenness centrality* is reflected in the extent to which he/she has technology components, expertise or skills that are critical in recombining at least two other technology components or expertise of the firm's knowledge stock. As a first step, we counted the number of times two U.S. Patent Classification (USPC) classes co-occurred in the firm's patents in the past five years. This is illustrated in Figure D2, where nodes (i.e., circles) represent USPC classes, and ties between nodes (i.e., links) connect pairs of classes that have been combined in the firm's patents. Then, using the technology network just described, we computed the technological betweenness centrality of each inventor. As an illustration, Figure D2 maps the overall technology structure of the firm between 1978 and 1982 and the classes in which two inventors were active.

Figure D2. Technology recombination network of [firm name] in 1978-1982



The thicker nodes indicate the USPC classes in which the two inventors were active, while the weights on the solid lines indicate the strength of coupling between technological classes. The size of the vertices is proportional to the value of the technological betweenness centrality index of the corresponding technological class. As the figure illustrates, inventor #4325120-2 engaged in technologies that were relatively low in technological betweenness centrality. In contrast, inventor #4358833-3 was active in fields that spanned different technology domains and had a higher technological betweenness centrality total in [firm name]'s portfolio of patents.

Comparing these two inventors (i.e., examples C and D):

33. Who is more likely to get promoted at [firm name], and why?
34. Who is more likely to move and/or be attractive to a competitor, and why?
35. Who is more likely to start his/her own venture, and why?

Table D4. Examples of Interviews Open Coding: Collaboration Centrality

Theme	Selection of representative quotes	Collaboration centrality associates with…
Influence on collaborations and R&D agenda of the firm	"*The example A* [referring to Table D3] *will have an opportunity for having bigger impacts, get involved in projects of bigger scope and will be able to have bigger impacts on the success of these projects … and he will have a higher visibility because the contribution resulted in a bigger project success.*" (Employee 5)	Impact on the R&D activity of the firm and visibility in the collaboration network
	"*A lot of the way the grade structure works in these companies is about your scope of influence internal to the organization … Usually, one of the key criteria for getting to a certain level is to have a scope of influence beyond the team that you work in. So I think, especially for getting promoted, it's hugely important*." (Employee 6)	Scope of influence and promotion opportunities
Extensive reach	"*Example A* [referring to Table D3] *is going to be more likely to have problems* [speaking of inter-firm mobility] *because if the graph also represents your fame and stature, more people are going to know who you are, and when you leave, then it's worse, and people talk about it more because you're more well known. And then people are more concerned about it, and then it becomes a bigger issue potentially*." (Employee 6)	Stigma from inter-firm mobility
	"*If you go just look at a lot of the criteria for promotion … you have to go get some project to happen, … it needs to be a complex project that gets multiple teams involved ... like your scope of influence, it is much easier for managers to measure and see because they see your... Like your graph, for example, they can see, oh, this engineer is dealing with all these groups, and getting all these things done. That's kind of a more, a very visible metric of the influence of that person.*" (Employee 6)	Intra-firm visibility and likelihood of getting involved with complex projects that involve multiple teams
Internal promotion opportunities	"*We're definitely measuring people by influence, and influence means connecting with other people, leaving marks, not just professional marks but also personal marks, being a go-to person for people, being the focal point for professional consultation. So this is, yes, part of the criteria.*" (Employee 1)	Human resources evaluation criteria for promotion
	"*If you were one of these team leaders, and you were successful in getting your colleagues to all deliver to what was necessary, and all of those necessary pieces fit together as a puzzle to solve the challenge that was given, then that was viewed very highly, in terms of you being competent to move up higher into a higher management position.*" (Employee 4)	Internal promotion opportunities
	"*The person with the more complex graph is going to be the person more likely to get promoted.*" (Employee 6)	
Uncertainty of employee's individual value in the external job market	"*I would say … people in the smaller group of individuals* [referring to example B in Table D3] *are more likely to leave … let's say you're working with a* [firm name]*'s supplier. If there is a* [firm name]*'s guy that comes up with the solution, then that company is going to look at that individual and say, 'Wow, this guy just solved the problem that* [firm name] *was hammering on me for, I want to hire this guy away.' I saw that happen a number of times.*" (Employee 4)	Peripheral or more isolated individuals are better identified by prospective employers, which assign them more certain value

Note. This is an extract from our interviews' open coding process. The names of the interviewees, firms and technologies are anonymous for privacy reasons.

Table D5. Examples of Interviews Open Coding: Technological Centrality

Theme	Selection of representative quotes	Technological centrality associates with…
Firm's "know-how" and "know-why"	"*Software engineers or hardware engineers in general are not unique; all of our competitors look for them as well. But if we deep-dive into specific profiles like, for example, front-end engineers, BIOS engineers that we're looking for to handle the CPU components that we're building, not every competitor would benefit from these type of engineers because it's only unique to the CPU world. So, competitors like* [firm α] *would compete with us on these engineers, but others like* [firm β], [firm γ], *other companies might not use our engineers that are going out because they were experienced in our technology that is sometimes not really relevant to our competitors. But the other topics, like I mentioned, the artificial intelligence, autonomous cars, all the topics of the future are really necessary, people are really looking for this type of profiles.*" (Employee 1)	Technological interdependencies. Other firms would not poach them because they do not necessarily value this expertise
Uncertain value of individual's technological expertise in the external job market	"*Someone is going to want experience, someone who's had experience doing that specific thing … and in some ways too, being a more senior person, being that expert, if you're not going to be doing management, you're going to be doing something technical. Generally, they're hiring you because of your specific experience, I would say … a technology that is a match is definitely something that people would go after … in my case, … as soon they had the opportunity for me to work there* [i.e., at firm γ], *they just created a position for me… It would be interesting to go look at the top Linux kernel maintainers and go see what companies they actually work for, the ones that work full-time, and then what kind of positions they have in those companies because they were basically pulled out based on their knowledge*." (Employee 6)	Little external market value. Prospective employers can value and open positions more easily for tenured experts in stand-alone technologies than for technology spanners
Interdependence with other firm's technologies and intra-firm value	"*I think the connection between the different technologies is more valuable for the firm because it shows the person is flexible and dynamic, and can then transition from one technology to another, in comparison to people that are specializing just in one specific area, which is valuable but … I'm not sure how they will be competitive*." (Employee 1) "*Where things get investigated and just get patented defensively, but if things are tied together, then it's likely that person is working on some key technologies that have more value, if you don't weigh every patent equally conceptually*." (Employee 6)	Employee's technological expertise on how to combine firm's technologies. This is more valued and protected by the employer.
Intra-firm career opportunities	"*I think example D* [referring to Table D3] *will be more likely because typically, most of the advancements happen in the intersection of adjacent technologies. So, if technologies are adjacent which means many times the purpose is to combining them together into a single thing to create something much bigger than sum of the two. I think that will have a bigger impact than having two different technologies that are not related to each other. They're not used over each other; such opportunities don't exist if technologies are so different that they don't set across each other's path in regular projects and products. So I think example D clearly will have much more opportunity to have a bigger impact to the company and as a result he'll be promoted.* [...] *somebody who knows or understands adjacencies is typically better equipped to innovate and create a bigger impact.*" (Employee 5)	Recombining different technologies provides better intra-firm career opportunities because of a stronger impact on the firm's products

Note. This is an extract from our interviews' open coding process. The names of the interviewees, firms and technologies are anonymous for privacy reasons.