Paper to be presented at: DRUID17
NYU Stern School of Business, New York, June 12-14, 2017

TECHNOLOGICAL AND SOCIAL DEFENCES: THE EFFECT ON KNOWLEDGE AND SOCIAL INTERDEPENDENCIES ON INVENTOR OUTWARD MOBILITY

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Abstract

Whereas prior research has examined organizational defenses against the risk associated with knowledge spillover via inventor mobility, we explore defenses that are related to individual knowledge and social capital within the firm. We argue that knowledge and social interdependencies increase an inventor’s value in her current firm, raising the inventor’s opportunity costs associated with founding a new venture or move to a rival firm. At the same time, these interdependencies increase the measurement costs, thereby increasing the obstacle for a prospective entrepreneur to secure external funding and for prospective employers to assess inventor value. We thus challenge existing convention regarding an inventor’s ability “to leave at will” by demonstrating that an inventor’s inclination to leave and her market value vary by the degree of her knowledge.
and social interdependencies.
ABSTRACT

Whereas prior research has examined organizational defenses against the risk associated with knowledge spillover via inventor mobility, we explore defenses that are related to individual knowledge and social capital within the firm. We argue that knowledge and social interdependencies increase an inventor’s value in her current firm, raising the inventor’s opportunity costs associated with founding a new venture or move to a rival firm. At the same time, these interdependencies increase the measurement costs, thereby increasing the obstacle for a prospective entrepreneur to secure external funding and for prospective employers to assess inventor value. We thus challenge existing convention regarding an inventor’s ability “to leave at will” by demonstrating that an inventor’s inclination to leave and her market value vary by the degree of her knowledge and social interdependencies.

Key words: employee mobility, knowledge interdependence, social interdependence, technology entrepreneurship
INTRODUCTION

Technology-rich firms have been referred to as “precarious monopolies” due to costs associated with preventing knowledge spillovers (Zucker et al., 1998). One source of knowledge expropriation, namely employee mobility, particularly concerns organizations that have substantial portions of their R&D capital embodied in their employees (Teece, 1982). Empirical findings focused on the hiring firm support this general thesis that technological (Agarwal et al., 2004), organizational (Tzabbar, 2009), and market (Boeker, 1997) knowledge does indeed leak through firm boundaries and transfer over to other firms through mobile employees. By implication, outward mobility poses a threat to organizations by diffusing their intellectual capital to potential competitors, and in the process, depleting their key knowledge assets one outward employee mobility at a time (Kim and Marshke, 2005).

Given these dire consequences associated with outward mobility, researches have recently focused on organizational litigation practices and knowledge structures, at the firm level, that limits outward flow of skilled labor knowledge (e.g., Agrawal, Ganco, and Ziedonis, 2009; Ganco, 2013; Ziedonis, 2003). Despite increase recognition that the ability for employees to expropriate valuable knowledge vary based on their knowledge and social network positions, we know little about how these individual positions influence their likelihood to leave. Furthermore, although research points out the variance in opportunity costs associated with mobile inventor’s new employment target (i.e., entrepreneurial venture vs. rival firm), most empirical evidence has not provided clear insight on individual propensity to choose one employment arrangement over the other based on what and who they know. Accordingly, a second area in need for contribution is the examination of how individual and social positions
effect their propensity to found a new venture or move to other incumbent firms (e.g., Gambardella, Ganco, and Honoré, 2014).

The purpose of this study is to fill these formidable theoretical and empirical gaps in the literature by examining the effect of inventor knowledge and social network position on their likelihood to found a new venture or move to a new employer. We argue that interdependencies among knowledge components and among internal collaborations have implication for the extent to which individual knowledge base is sticky, causally ambiguous, and embedded within the social relationships within the firm. Building on this logic, we promote the idea that fundamental differences in the interaction process between the elements of knowledge underlying firm creation, as well as that between the purveyors of these knowledge elements, namely the scientists, result in variance in the likelihood for an employee mobility. Specifically, we argue that inventors with high degree of knowledge and social interdependencies are less likely to experience outward mobility relative to their counterparts whose knowledge and social network positions are less interdependent.

Using a unique longitudinal dataset on the career histories of inventors employed at the Intel Corporation, effectively controlling for firm heterogeneity, our competing risk hazard rate model shows that high knowledge and social interdependencies serve as defense mechanisms against inventor mobility and that their effect is significantly higher in preventing inventor starting a spinout relative to mobility to other rival firms. Our study offer further insights into the micro mechanism associated with inventor mobility.

THEORETICAL BACKGROUND

The knowledge-based view promotes a ‘democratic notion’ of the firm in which employees undertake specialized activities in the innovation process and learn different things about the
transformation of inputs into outputs (Grant, 1996). Knowledge is perceived as a ‘private good’ that requires discretion in the sharing of employees’ expertise and transformation of tacit knowledge for other employees to learn what an individual has discovered (Kogut and Zander, 1992; Nonaka and Takeuchi, 1995). McKelvey (1982), for instance, describes organizational “competence elements” (comps) as base units of knowledge and skill that make up what the organization knows how to do – the organizational analogue of biological genes. McKelvey (1982) further argues that “comps” are carried in the minds of individuals and that their movement is a vehicle for the transmission of comps.

As repositories of firm knowledge, skilled employees responsible for firm innovation (i.e., inventors) typically have a choice on a wide spectrum starting from remaining with their existing employer, continuing the inventing activities with other employers, or founding a new venture to appropriate the return from their inventing activities as residual claimers. The former choice is likely to provide them with a relatively low-risk career path and resources for their inventing activities, whereas the latter can provide riskier career path yet a potentially lucrative payoff, in terms of both monetary rewards and non-pecuniary benefits (e.g., be own boss, ability to determine the path of their inventing activities, and so on). Faced with such a tradeoff, an inventor is likely to weigh the pros and cons of founding a new venture contingent upon the circumstances of the inventor’s knowledge stock, skillsets, and relationships with others in their current firm.

Skilled workers are believed to be free to leave at will (Coff, 1999). Yet, their ability to do so has been long recognized to be associated with the specificity of their knowledge and on their social relations. Despite this recognition, extent research on employee outward mobility is yet to examine individual positon within an employer knowledge and social network. Drawing
from the literature on technology innovation, we first recognize that development of innovation requires varying degrees of interdependencies among knowledge components (Fleming and Sorenson, 2001; Simon, 1962), residing in inventor’s heads, and among individual carrying those knowledge components (i.e., social interdependencies) (Kogut and Zander, 1996; Mayer and Nickerson, 2005). Furthermore, an inventor’s position within her employer knowledge and social interdependencies has implications on scientists’ mobility choices: remain, move to another incumbent firm, or start a new venture.

**Knowledge and social interdependence**

Knowledge interdependence arises when subcomponents significantly affect the contribution of one or more other subcomponents to the functionality of a piece of knowledge. Interdependent knowledge pieces generally lead to more valuable new knowledge due to causal ambiguity that prevents other firms from imitating the newly created knowledge (Grant, 1996; Sorenson, Rivkin, and Fleming, 2006). However, when subcomponents are highly interdependent, “a change in one may require the adjustment, inclusion or replacement of others for a piece of knowledge to remain effective” (Sorenson et al., 2006: 995). Due to causal ambiguity and difficulty in discerning cause-effect relationships and then successfully generalizing to other context (Gavetti and Levinthal, 2000), interdependencies can enhance stickiness and impair knowledge deficit (Von Hippel, 1994).

Viewing employees as the primary carriers and transmitters of knowledge components and routines in the organization (Kogut and Zander, 1992; Spender, 1996), social interdependence reflects where knowledge is stored and the patterns of knowledge exchange among members. Social interdependence “exists whenever one actor does not entirely control all the conditions necessary for the achievement of an action or for obtaining the outcome desired
from the action.” (Pfeffer and Salancik, 1978: 40). Interdependence characterizes the relationship between the agents creating an outcome, not the outcome itself. The degree of social interdependencies can be determined by the extent of co-invention among scientists in the discovery process, and consequently the degree to which routines are independent from individuals within the firm. Similar to knowledge interdependence, social interdependence creates causal ambiguity in the knowledge building process and reduces the risk of individual discretion over knowledge (Henderson and Cockburn, 1994; Kogut and Zander, 1992).

Implicit in these arguments is that the degree of knowledge and social interdependence underlying a firm’s innovation may have important implications for individual employees to fully comprehend and thus transfer firm knowledge to other context. Such a reduced transferability results in decreased opportunity for inventors to act opportunistically and reduce value of inventor knowledge in the marketplace. An individual inventor’s position within the knowledge and social network might vary significantly. Accordingly, we promote the idea that fundamental differences in the interaction process between the elements of knowledge, as well as that between the purveyors of these knowledge elements, namely the scientists, result in variance in the likelihood for an employee otherward mobility.

HYPOTHESES

Knowledge interdependence and inventor mobility

We view new knowledge creation as a process of recombining existing knowledge pieces (Fleming, 2001; Sorenson et al., 2006). When newly created knowledge solution does not depend on the recombination from interactions among knowledge components, it is more “decomposable” as compared with other solutions with high interdependencies (Nickerson and Zenger, 2004). In a decomposable knowledge recombination landscape, a knowledge piece is
easier to be transferred and recombined with other knowledge pieces and is thus more vulnerable because an inventor who acts as the repository of the knowledge can leave and carry with her gamut of information that could be conducive to subsequent knowledge creation elsewhere. In contrast, firms with a knowledge portfolio involving high-degree of interdependencies among knowledge components that are non-decomposable are less likely to be hindered by inventor outward mobility as an individual piece of knowledge is less valuable unless it is recombined with other pieces (Macher, 2006). Causal ambiguity combined with a myriad of potential combinations to any solution will surround interdependent knowledge pieces with a protective barrier for easy transfer and loss for the focal firm (Sorenson et al., 2006).

Consistent with this logic, given the ease of knowledge transferability associated with low knowledge interdependence, individuals with innovative portfolio involving low-degree of knowledge interdependencies have a greater external value. This is because such inventors act as the repository of the knowledge that can leave, carrying their gamut of information required to carry out inventive activities independently. Such an ability is extremely valuable for a rival firm or other prospect employers and for mobile inventors who seek to start their own technology-based venture. This is because prospect employers or resource providers (e.g., venture capitalist) have a greater ability to assess the potential outcomes of their inventive activities and also the marginal contribution of the inventor on knowledge building efforts reducing the overall uncertainty associated with the inventor’s inventing capabilities. Internally, such an inventor is less valuable for the employers as others are less dependent on their knowledge to advance firm knowledge recombination.

Conversely, when an inventor’s individual knowledge stock is highly interdependent, the inventor is likely to be more valuable to the employing firm. This is because of the tacit
experience necessary to recombine individual knowledge with other knowledge stocks within the firm. Absence of an inventor whose knowledge stock is highly interdependent with the firms’ knowledge stock will have a greater negative impact on new knowledge creation outcome as compared with absence of an inventor whose knowledge stock is less interdependent with the firm’s overall knowledge stock. Accordingly, such tacit understanding is critical for firm knowledge recombination purposes making inventor more internally valuable.

From a market perspective, when an inventor’s knowledge stock is interdependent to that of the employing firm, the inventor’s ability to develop new inventions independently in a new employment arrangement can be severely hindered. This is because other interdependent knowledge pieces become less accessible when the inventing activity is taken outside the firm. Individuals with such non-decomposable knowledge are less valuable in the free market decreasing such an inventor likelihood to find alternative employment arrangement such as founding new ventures or moving to rival firms (Macher, 2006). Furthermore, due to the causally ambiguous inventor knowledge base prospect employers face greater challenges in assessing the marginal contribution of the inventor’s effort and knowledge stock to the overall outcome of inventing activities and the riskiness of investing in inventing activities involving high degree of knowledge interdependence. With such an increase in measurement costs prospect employers and external investors incur, the market interest and external employment opportunity of such inventors decrease. Accordingly, we expect:

Hypothesis 1a. Knowledge interdependence of an inventor’s knowledge stock with that of the inventor’s firm will reduce the inventor’s likelihood of outward mobility.

Based on the logic above we argue that the negative effect associated with inventor knowledge interdependence and outward mobility is particularly strong for inventors seeking to start a new technology venture (i.e., spinout). Unlike mobility into a new employer who can
benefit from inventor general inventing capabilities, inventors contemplating to found a new venture commonly depend on their specialized inventing capabilities to secure external funding.

In starting a new venture, resource acquisition is one of the most critical challenges that entrepreneurs face in commercializing viable ideas into products (Shane, 2003; Stinchcombe, 1965). This is because there is a high degree of uncertainty and information asymmetry between entrepreneur and potential external investors in terms of entrepreneurs’ managerial and technological capabilities as well as the knowledge pieces that can be commercialized into new products or services. Therefore, external investors, such as angels and venture capitalists, closely scrutinize entrepreneurs’ managerial and technological capabilities to carry out their entrepreneurial endeavor (Lee, Lee, and Pennings, 2001). At the same time, those investors also examine the knowledge stock of the new ventures to assess its probability of leading to a commercially successful products (Kaplan, Sensoy, and Strömberg, 2009).

Knowledge interdependence of prospective entrepreneurs will create a significant barrier in investors’ ability to assess the true value of the entrepreneurs and their knowledge. When an entrepreneur possesses knowledge pieces that are interdependent with those of their former firm, external investors will incur not only greater measurement costs in assessing the human capital of the entrepreneurs but also greater risks in predicting the outcome of the commercialization effort by the new ventures. In contrast, when a new venture possesses knowledge pieces that do not depend on other knowledge pieces, external investors can more easily evaluate the prospective entrepreneurs and the risk of recombining less interdependent knowledge pieces goes down, because they are more likely to be able to predict the outcome of such recombination effort. In sum, the opportunity costs for investors who possess highly interdependent knowledge are greater as compared to their counterparts whose knowledge is less interdependent as
knowledge interdependencies increases barrier to entrepreneurial entry. Therefore, inventors with highly interdependent knowledge are less likely to be involved with an entrepreneurial venture because they perceive tough challenges in securing resources and their odds of successful commercialization are low.

Hypothesis 1b. The decrease likelihood of outward mobility associated with inventor’s knowledge interdependencies is stronger when such inventors seek to found a new venture.

Social interdependence and inventor mobility

Similar to knowledge interdependence, the degree of social interdependencies can be determined by the extent of co-invention among scientists in the discovery process. We promote the idea that fundamental differences in the interaction process between the purveyors of these knowledge elements, namely the inventors, result in variance in the likelihood for an employee to change employer and/or start a new venture. Social interdependence creates several defenses reducing the opportunities for inventors’ outward mobility.

One such defense at the firm level is through transforming individual knowledge, expertise, and skills into social knowledge that is accessible to managers and other employees (Kogut and Zander 1992). To aggregate individual know-how to social know-how, organizations need to increase the degree of interdependencies among its members (Reagans and McEvily, 2003). Organizations that promote connectedness can facilitate a freer flow of information enabling firm members to tap into the firm-wide knowledge base (Tzabbar, Silverman, and Aharonson, 2015) resulting in lower decomposability of knowledge. High degree of social interdependence, and the decomposability associated with it, also limits the value of individual knowledge in the market. This is because, when social interdependence is high, inventor ability to contribute to innovative productivity is influenced by the knowledge of other inventors in an
inventing team, due to the complementary skill-sets of the inventing team members (Nahapiet and Ghoshal, 1999; Nickerson and Zenger, 2004; Zander and Kogut, 1995). Such interdependence increases causal ambiguity limiting the ability of external prospect to assess individual contribution to knowledge building activities.

Over time, when high social interdependence involves frequent interaction among members, it increases mutual learning (Reagans and McEvily, 2003), which enables aggregation of individual knowledge to social knowledge in such a way that individuals have no discretional right on the knowledge (Henderson and Cockburn, 1994; Kogut and Zander, 1992). When others in the organization possess knowledge, individual knowledge value internally and externally diminishes significantly.

Strong relationships among firm members provide the encouragement and social support decreasing the likelihood for an individual to act opportunistically (Granovetter, 1985). Indeed, connectedness reportedly strengthen the link among members of the R&D staff, which in turn increases social cohesion by pulling the incumbent scientists together, and helps ensure a unified R&D effort (Sheremata, 2000), the pursuit of common initiatives (Reagans and Zuckerman, 2001), and the development of common ground and a shared language (Srikanth and Puranam, 2011). Social interdependence also increases individual commitment and sense of belonging to the group (Harrison, Mohammed, McGrath, and Florey, 2003), reducing the likelihood for an individual to act opportunistically.

Furthermore, similar to information asymmetry and causal ambiguity problems associated with knowledge interdependence, high social interdependence increases the measurement costs for external evaluators in assessing the quality of an individual inventor, because it becomes more difficult to assess how much credit to give to the inventor for prior
inventions among various inventors who are socially embedded. Socially interdependent inventors are thus more likely to face greater challenges in attracting interest from rival firms or from entrepreneurial resource providers to found a new venture.

In contrast, the productivity of investors who are not socially interdependent with other investors in a firm can claim the credit for their output and can more easily signal their quality to the external labor market or obtain entrepreneurial resources to found a new venture. Furthermore, when social interdependencies are kept to a minimum, individual and firm knowledge are not widely diffused, there are likely to be fewer interdependencies of information and ideas among scientists (Eisenhardt and Bourgeois, 1988). In such a context, there is greater reliance on individual scientists to act as repositories of knowledge rather than an organization-wide memory (Kogut and Zander, 1992). Finally, when an individual has low levels of social interdependencies, the individual has more discretion on the use of the knowledge (Brown and Duguid, 2001; Burt, 1992), resulting in higher knowledge decomposability.

Taken together, we predict that the degree of an inventor’s social interdependence will be negatively associated with the inventor’s likelihood of outward mobility and founding a new venture.

Hypothesis 2a. Social interdependence of an inventor with other inventors in the firm will reduce the inventor’s likelihood of outward mobility.

Hypothesis 2b. Social interdependence of an inventor with other inventors in the firm will reduce the inventor’s likelihood of founding a new venture.

METHODS

Data

To test our hypotheses, we use data pertaining to the patenting activities and curricula vitae of a sample of inventors employed by the Intel Corporation over the period from 1993 to 2012. Intel
is a highly innovative and leading semiconductor company. In semiconductors, recombining knowledge components is essential and patents offer a valid mechanism to appropriate returns from R&D (Arora et al., 2008) and a reliable indicator of employee’s collaborations (Nerkar and Paruchuri, 2005). Focusing on a single company also facilitates the collection of reliable data on employee mobility and entrepreneurship as well as effectively controls for and eliminates unobserved firm heterogeneity effects that may have been present in most prior studies.

Identifying employee mobility and entrepreneurship. To determine employee entrepreneurship and mobility events, we followed previous works (Ge et al., 2015) and first identified inventors listed in Intel patents from 1993 to 2012 at the United States Patent and Trademark Office (USPTO) and recorded their patent-based career histories. We then identified and selected from LinkedIn all individuals reporting Intel as one of the employers during her working career and matched this list, using first and last name, with the set of inventors reporting Intel as assignee of one or more of her patents, using first and last name\(^1\). The final sample of exact matched inventor-LinkedIn profiles includes 4,382 engineers and scientists who were employed and filed patents for Intel during the time window of this study. We consolidated patent records and LinkedIn data to an annual basis.

**Measures**

**Dependent variables.** Our main dependent variable refers to the outward mobility of inventors. To this purpose, we proceeded as follows. From the curriculum vitae of each matched inventor, we recorded a) the year in which they were firstly employed at Intel; b) the last year in which they were employed at Intel.

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\(^1\) Please note that this methodology also allows to correct for a problem that has plagued previous research on inventors’ mobility, namely the possibility that an individual may show on a firm’s patents not due to formal employment but because they were employed at a partner firm (Hagedoorn 2003).
For those inventors whose last employment at Intel was before 2012, we coded the mode of exit from Intel. More specifically, we identified two types of mobility event: employee entrepreneurship and firm mobility.

As far as employee entrepreneurship is concerned, this captures employees’ departure from Intel to found a new venture. If the LinkedIn profile of an inventor shows (1) two consecutive jobs with Intel and a different employer (where the time gap is no more than one year) and (2) a job title of founder at the new employer, we supposed that the inventor left Intel to found the new employer firm in the starting year of the record. We coded employee entrepreneurship equal to one at the founding year, and zero otherwise. To ensure data reliability and exclude false positives, we searched for public information on each new venture hereby detected and excluded cases of self-employment and misspecifications in LinkedIn profiles. These yielded to identify 116 employee entrepreneurship events.

We adopted a similar approach to measure inventors’ mobility from Intel to other firms. If the LinkedIn profile of an inventor shows two consecutive jobs with Intel and a different employer, we supposed that the inventor left Intel to join the new employer. We coded firm mobility equal to one at the inventor’s starting year at the new employer, and zero otherwise. These yielded to identify 1,389 employee mobility events.

For those inventors who did not experience exit before 2012, we right-censored observations. In other words, employee entrepreneurship and firm mobility are set equal to zero for the remaining inventors 2,993 inventors who did not experience an exit event during the time window of this study.

Having information on inventors’ mode of exit, we adopted a discrete time-to-event modelling and for each inventor we selected the time window when she remained at risk of an exit event.
(i.e., either entrepreneurship, mobility to other incumbents, or retirement) during their employment at Intel. The inventor observations are split annually and balanced to update covariates. Our final dataset includes 35,242 inventor-year observations.

**Explanatory variables.** To compute inventor’s knowledge interdependence with the firms’ knowledge stock, we rely upon patent data. More precisely, we follow previous studies (Fleming and Sorenson, 2001; Yayavaram and Ahuja, 2008) by assuming that the technology classes assigned to patents are the basic elements in the firm’s and, by extension, in the inventor’s knowledge base and that the frequency with which two elements are combined by a firm is an indicator that the two elements are highly interdependent (or coupled) in that firm’s knowledge base. Building upon this idea, our measure of an inventor’s knowledge interdependence was derived from the following three step procedure. First, from each patent filed by Intel in a five year rolling window \([t - 4, t]\) we extracted the 3-digit technology classes to which the patent has been assigned. We then counted the number of times two technology classes \(j\) and \(k\) co-occur in patents. Formally:

\[
\begin{align*}
  n_{jk} &= \sum_p \delta_j^p \delta_k^p \\
  &\text{represents the total number of co-occurrences of technology classes } j \text{ and } k \text{ in the firm’s patents, where the index } p \text{ runs over all patents in the time period } [t - 4, t], \delta_j^p \text{ is equal to 1 if class } j \text{ is included in patent } p, \text{ and 0 otherwise, and } \delta_k^p \text{ is equal to 1 if class } k \text{ is included in patent } p, \text{ and 0 otherwise.}
\end{align*}
\]

As in Yayavaram and Ahuja (2008), we standardized this raw measure, by computing the so-called Jaccard coefficient, i.e.:

\[
C_{jk} = \frac{n_{jk}}{n_{jk} + n_{j(-k)} + n_{(-j)k}}
\]

where \(n_{j(-k)}\) is the number of patents assigned to class \(j\), but not class \(k\), and \(n_{(-j)k}\) is the number of patents assigned to class \(k\), but not class \(j\). The \(C_{jk}\) index captures the intensity with
which the knowledge elements represented by technology classes are combined or, using a
different terminology, the degree of coupling among them. Iterating the same procedure for all
pairs of technology classes, one obtains the matrix $\mathbf{C}$ where the cells consists of the $C_{jk}$ index for
all possible pairs of knowledge elements. This matrix represents the structure of the firm’s
knowledge base at a given point in time. The information contained in the $\mathbf{C}$ matrix can be
visually represented as a graph, where the nodes are the knowledge elements (i.e. technology
classes) and the ties connect pairs of knowledge elements combined in the firm’s patents, with
weights given by the coupling index $C_{jk}$. Figure 1 illustrates the structure of Intel’s knowledge

[Insert Figure 1 here]

In the second step of our procedure, for each inventor at Intel we counted the number of
times two technology classes $j$ and $k$ co-occur in her patents. Formally:

$$n_{jk}^i = \sum_p \delta_{j}^{p,i} \delta_{k}^{p,i}$$  \hspace{1cm} (3)

represents the total number of co-occurrences of technology classes $j$ and $k$ in the inventor $i$’s
patents, where the index $p$ runs over all patents made by inventor $i$ before time $t + 1$, $\delta_{j}^{p,i}$ is
equal to 1 if class $j$ is included in patent $p$ made by inventor $i$, and 0 otherwise, and $\delta_{k}^{p,i}$ is equal
to 1 if class $k$ is included in patent $p$ made by inventor $i$, and 0 otherwise. Then, for each
combination of technology classes, we simply computed the share on all the combinations made
in inventor $i$’s patents, i.e.:

$$w_{jk}^i = \frac{n_{jk}^i}{\sum_n n_{jk}^i}$$  \hspace{1cm} (4)

As an illustration, Figure 2 maps the combinations made by two Intel inventors,
respectively, John Palmer and Alan C. Folmsbee, on the overall knowledge structure of the firm
in the period 1978-1982. The red-colored nodes indicate the technology classes where the two inventors have been active, the red-colored, dashed lines indicate the combinations of technology classes that were realized in their patents, while the weight on the dashed line represent the share of that combination on all combinations made by the inventor. Thus, for example, John Palmer has been active before 1983 in three technology classes, i.e. 708 (Electrical computers: arithmetic processing and calculating), 712 (Electrical computers and digital processing systems: processing architectures and instruction processing) and 714 (Error detection/correction and fault detection/recovery). He realized three combinations of knowledge elements, i.e. 708-712, 708-714 and 712-714, and each combination accounted for 1/3 of all combinations made in his patents\(^2\).

The third and final step of our procedure consisted of computing the degree of knowledge interdependence of each inventor. To this purpose, we proceeded as follows. For each pair of knowledge elements in the firm’s knowledge structure (see point 1. above and Figure 1), we computed the so-called edge betweenness centrality (Freeman, 1977; Girvan and Newman, 2002), using the degree of coupling as weight. The betweenness of an edge is defined as the number of shortest paths among all pairs of nodes in a graph that pass through the given edge. The concept of edge betweenness is particularly relevant in our context as it is directly related to the idea of modularity and to the graph decomposition into modules (Girvan and Newman, 2002; Newman, 2006). An edge with a high betweenness value is vital to connect different modules (i.e. clusters of nodes) in a graph, whereas an edge with a low betweenness value connect pairs of nodes in the same module. In our case, an edge with a high betweenness value corresponds to a pair of knowledge elements that are crucial to connect distinct areas (or modules) of a firm’s

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\(^2\) More precisely, John Palmer made two patents while at Intel before 1983, i.e. USPTO Patents 4338675 and 4484259. Both patents were classified into classes 708, 712 and 714. Thus, \(n_{708,712}^{Palmer} = 2\) and \(w_{708,712}^{Palmer} = 2/6\).
knowledge base. On the other hand, an edge with a low betweenness value corresponds to a pair of technology classes that are within the same knowledge area.

To illustrate this idea, let consider, for example, the edge connecting classes 708 and 712. This edge has a low betweenness value as it does not contribute to connecting many pairs of classes. The combination of knowledge elements corresponding to this edge belongs to a rather well defined area, i.e. digital processing systems. On the other hand, the edge connecting classes 257 and 365 has a high value of edge betweenness and it spans different knowledge areas, by connecting knowledge in the field of active solid-state devices (e.g. transistors) and in the field of information storage and retrieval.

Exploiting the insight that higher values of edge betweenness should correspond to less decomposable pieces of knowledge, we computed our measure of an inventor’s knowledge interdependence in the following way. For each inventor, we summed up the edge betweenness of the combinations she realized in her patents, weighting values by the share of each combination on the total number of combinations realized by the inventor. Formally, our measure of knowledge interdependence is defined as follows:

\[ \text{KI}^i = \sum_{jk} w_{jk}^i e_{jk} \]

where the summation runs over all combinations (edges) in the inventor’s patents, \( w_{jk}^i \) is the share of combination \( jk \) on all combinations made in the inventor’s patents, and \( e_{jk} \) is the normalized betweenness value of the edge connecting classes \( j \) and \( k \) in the firm’s knowledge structure.

The intuition behind this measure can be captured with the help of Figure 2. The inventor represented in the upper part of Figure 2 (John Palmer) is engaged in combinations, which are
relatively decomposable from the knowledge structure of the firm. The value of his knowledge interdependence index is rather low (0.05). On the contrary, the inventor represented in the lower part of Figure 2 (Alan C. Folmsbee) is active in fields that span across different knowledge domains and holds a knowledge that looks less decomposable from the knowledge structure of the firm. As a reflection of this, the value of his knowledge interdependence index is rather high (0.33). According to our theoretical predictions, we would expect an inventor such as John Palmer to be more likely to leave the firm than an inventor such as Alan C. Folmsbee.

Our second explanatory variable, social interdependence, is based on patent co-authorship networks. More specifically, from each patent filed by Intel in a rolling five year window \([t - 4, t]\), we extracted the names of the inventors reported in the patent document. Using this information, we built the collaboration graph in which two inventors have a link connecting them if they were reported together on at least one patent. To account for the fact that the number of co-inventors may differ across patents and that the same two inventors may appear together on several patents, we weighted the links on the collaboration graph as follows. For each pair of inventors \(i\) and \(j\), we weighted the link according to the following quantity:

\[
W_{ij} = \sum_p \frac{\delta_i^p \delta_j^p}{n_p - 1}
\]

where measures the strength of the interaction between \(i\) and \(j\), \(\delta_i^p\) is equal to 1 if inventor \(i\) authored patent \(p\), and 0 otherwise, \(\delta_j^p\) is equal to 1 if inventor \(j\) authored patent \(p\), and 0

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3 We note, incidentally, that John Palmer and a group of other Intel’s System Group employees left Intel in 1983 and founded nCUBE, in Beaverton, Oregon. The new venture had the goal of producing MIMD (Multiple Instruction Multiple Data) parallel computers, which, though it was an emerging and promising field, did not capture the attention of Intel that was reluctant to enter this market.

4 The adoption of a time window has become quite standard in the literature using patent and scientific publication data to examine professional collaboration networks. The idea is that, unless continuously nurtured and renewed, social links have the tendency to decay. In the absence of objective measures of such a decay rate, most analysts just assume that the influence of a person’s social ties disappears after a given number of years.
otherwise, and \( n_p \) is the total number of co-inventors of patent \( p \). The interaction between two inventors is thus stronger if they collaborated on many patents and/or they collaborated on patents with a small number of other inventors. Using the weighted collaboration graph described above, our measure of social interdependence is the so-called Burt constraint index (Burt, 1992). Formally, this is defined as:

\[
C_i = \sum_j \left( p_{ij} + \sum_{q \neq i \neq j} p_{iq} p_{qj} \right)^2
\]

where \( C_i \) is the network constraint of inventor \( i \), \( p_{ij} \) is the proportion of time and energy devoted by inventor \( i \) to her interaction with inventor \( j \), and \( p_{iq} \) and \( p_{qj} \) are defined in a similar way. In our context, the proportion \( p_{ij} \) is given by:

\[
p_{ij} = \frac{w_{ij}}{\sum_q w_{iq}}
\]

Higher values of the constraint index \( C_i \) indicate that inventor \( i \) is embedded in a highly cohesive network of relations, i.e. either her links are concentrated on few other actors or her strongest relations are with partners that are strongly tied to her other partners. Following Lee (2010), we set the index equal to 2 for inventors without collaborators.

**Control variables.** We control for several variables that might influence the risk of exit. Prior literature suggest that inventors with high experience and patenting performance may be better able to benefit from job mobility (Hoisl, 2007) or perceive better entrepreneurship opportunities (Gambardella et al., 2014), thus they are exposed to a higher risk of exit. We therefore control for several covariates, such as inventor’s tenure at the beginning of her risk set (i.e., the number of years elapsed between her recruitment at Intel and her first patent application during her tenure at Intel), her prior patents (inventor’s patenting experience) and her impact (yearly mean forward citations received on her prior patents).
Founding a new venture can be a risky career choice. Following prior research (Cirillo et al., 2014), we account for inventor’s risk neutrality in face of a career change to entrepreneurship by controlling for inventor’s prior geographical mobility (number of prior residence changes across US States), prior firm mobility (number of prior employer changes) and prior entrepreneurship (number of prior new ventures founded), taking full account of the LinkedIn data, we also coded and controlled for inventor’s managerial job title in Intel (Manager) and education degree (MBA and PhD). Finally, we acknowledged that many exit events concern Indian and Chinese inventors in our dataset. Thus, we used the IBM InfoSphere Global Name Management© database to account for inventor’s fixed effects, such as gender and ethnicity (Indian and Chinese).

Table 1 contains a description of our main variables and measures.

[Insert Table 1 here]

**Statistical approach**

We developed two econometric models to evaluate the determinants of inventor’s exit. Given that inventors are faced with three competing options (move to rival firm, start a new venture, or stay with existing employer), we used a competing risk discrete time duration model with a Weibull hazard function. We followed the approach proposed by Prentice and Gloeckler (1978) and adopted two discrete time duration models with a Weibull hazard function to derive the predicted hazard of inventor’s exit by entrepreneurship and mobility to incumbents. The hazard rate function for inventor i at time t takes the proportional hazard form $\lambda_i(t) = \theta_0(t) \cdot X_i^\beta$, where $\theta_0(t)$ is the baseline hazard function and $X_i$ is a series of time-varying covariates summarizing observed differences across inventors. The discrete time formulation of the hazard of
entrepreneurship (or mobility) for inventor i in year t is then given by the complementary log logistic function

\[
h_t(X_{it}) = 1 - \exp\{-\exp(X'_{it}\beta + \theta(t))\}
\] (1)

where \(\theta(t)\) is the baseline hazard function relating the hazard rate \(h_t(X_{it})\) of entrepreneurship (or mobility) at year t with the spell year duration (Jenkins, 1995).

Furthermore, we relaxed the assumption of homogeneous exit by accounting for the mode of exit—i.e. either entrepreneurship or mobility to incumbents—and we used a multinomial logit competing risks model (Jenkins, 2004). The two exit modes are treated as independent and competing, and the competing risk framework treats exit events as right censored. Thus we estimated a complementary log logistic model with function

\[
h_t(X_{it}) = 1 - \exp\{-\exp(X'_{it}\beta + \theta_j(t))\}
\] (2)

where j equals 1 for exit to entrepreneurship, and 2 for exit to mobility.

### RESULTS

Table 2 provides descriptive and correlation statistics. The variance inflation factors (VIFs) are lower than 10 and the mean VIF is 1.09, indicating that multicollinearity is not present in the data set.

[Insert Table 2 here]

Table 3 shows results of two discrete time duration models with a Weibull hazard function. We test the effect of knowledge interdependence, social interdependence and controls on the hazard rate of employee entrepreneurship (Column 1) and on that of mobility (Column 2). Knowledge interdependence significantly decreases the likelihood of an inventor to move to a rival firm and to start a new venture supporting Hypotheses 1a-b, respectively. Comparison between the two hazard coefficients further suggests that the negative effect of interdependence...
is stronger on the likelihood of highly interdependent engineer to start her own venture relative to moving to a rival firm (p < 0.001; two-sided Wald test, not shown here). Similarly, while social interdependence did not have a significant effect on mobile inventor mobility to rival firms it has a significant negative effect on inventor likelihood to start a new venture, supporting H2b.

To account for heterogeneity of exit we also run additional analysis by estimating a multinomial logit competing risk model. Result shown in Table 4 confirm our prior findings.

[Insert Table 3 and 4 here]

In Table 5, we report the predicted probability of each mode of exit. First, we computed the predicted probability of each event holding the values of all other covariates at their median values. Overall, for an inventor with median values of all covariates the risk of exit to mobility is 2.79%, the rate of exit to entrepreneurship is 0.41% and the probability of survival is 96.8%.

[Insert Table 5 here]

Second, to better assess the economic significance of our results we derived the percentage of change in the likelihood of exit to mobility and entrepreneurship by computing marginal effects as discrete changes in knowledge and social interdependence. Our results show that a variation in inventor’s knowledge interdependence of one standard deviation around its mean is associated with a decrease in the probability of entrepreneurship by 47.82% and a decrease in the probability of mobility by 9.86%. Then, a variation in inventor’s social interdependence of one standard deviation around its mean is associated with a decrease in the probability of entrepreneurship by 49.06%, yet it increases the probability of mobility by 6.22%.

**DISCUSSION AND CONCLUSION**

Using a competing risk hazard rate model, our results indicate high knowledge and social capital decrease the likelihood of all type of mobility and that this effect is significantly higher in
preventing inventors from starting a new venture relative to mobility to another firm. Consequently, we conclude that high degree of inventor knowledge and social interdependencies serve as a defense against inventor outward mobility and with that prevent critical knowledge spillover.

Our arguments and findings contributes to several streams of research. First, consistent with knowledge-based view arguments, the causal ambiguity in knowledge building efforts and the aggregation of individual knowledge to firm knowledge, associated with knowledge and social interdependencies indeed serve as a mean to reduce inventor ability to expropriate knowledge developed while employed to external sources (Tzabbar et al., 2015; Reagans and McEvily, 2003). As such, our theory and results challenge existing conventions associated with the ability of skilled inventors to ‘leave at will’. Identifying knowledge and social interdependence as a mechanism against knowledge leakage is critical because other mechanisms that can employed, such as litigation, can be costly and inherently require the firm to surrender the very knowledge that they aim to protect (Agarwal et al., 2009).

Second, our theory and results also provide fresh insights into the theory of the firm by providing novel insights on the push and pull forces that drive individual inventors’ decisions to remain with their current employers, move to a rival firm, or start a new venture. The opportunities and incentives that these individuals face within and outside the firm could provide novel insights on firm boundary outcomes. This is particularly the case for inventors in high-tech firms who have considerable choice of continuing their invention activities within the firm or take them outside by founding new ventures.

Third, we advance understanding of the spinout, or employee entrepreneurship, by delving deeper into how employee human and social capital influence their ability and
motivation to start a new technology venture. Although extant research highlights the importance of industry experience in establishing a new technology venture (e.g., Agarwal et al., 2004), arguing that only insiders of that industry can recognize entrepreneurial opportunities and possess the necessary human and social capital to found and grow new ventures (Colombo and Grilli, 2005; Shane, 2000), our theory and results show that not all industry insiders are likely to possess similar likelihood to found and succeed in entrepreneurial firms (Elfenbein et al., 2010). Our analyses using knowledge relatedness and co-inventor networks provide fine grain details on precise mechanisms that capture our theoretical constructs of knowledge and social interdependencies affecting spin-out behavior. Our theory provides a more nuanced and pinpointed view on the kind of experience, as reflected at the knowledge and social level, which facilitates or hinders employee spinout. Recognizing knowledge and social interdependencies as critical mechanism to spin outs is an important topic to study in technology entrepreneurship and can have important policy implications for selecting and nurturing entrepreneurs and entrepreneurial ventures.

**Limitations and directions for future research**

Our study provides several avenues for possible future studies. First, although we were able to control for firm heterogeneity using a single firm as our context to study employee mobility, a study based on a single firm has inherent limitations to its generalizability. Future research could unpack whether the mechanisms described in this study could be generalized for other firms in different industry and geographical contexts.

Second, our study has used patent classes and co-inventing network data to measure knowledge and social interdependencies. Although filing for patents is an important activity to protect intellectual property in technology-based industries, it is more applicable for explicit
knowledge domains. It would be interesting for future studies to examine whether our mechanisms work in a similar fashion to protect more tacit know-how, such as managerial capability or artistic endeavor. It is possible that social interdependences plays a larger role in such instances as knowledge transfer is likely to become an even more of a social process, but future research could confirm our speculation.

**Conclusion**

Our study examining how knowledge and social interdependencies constrain employees from moving to a rival firm or starting a new business provides more nuanced insights in employee mobility and employee entrepreneurship. These insights could help firms to better protect their valuable human capital. At the same time, we hope that our findings could help us better understand the most efficient allocation of human capital across firm boundaries and allocate human and other resources that lead to better innovation outcomes that can benefit the society.
REFERENCES


<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entrepreneurship</td>
<td>Inventor funds a start-up</td>
<td>1{inventor leaves Intel to fund a startup in year t}; 0 otherwise.</td>
</tr>
<tr>
<td>Mobility</td>
<td>Inventor’s mobility to other incumbents</td>
<td>1{inventor leaves Intel to join another incumbent in year t};</td>
</tr>
<tr>
<td>Knowledge interdependence</td>
<td>Inventor’s knowledge decomposability from Intel’s knowledge stock</td>
<td>Edge betweenness centrality of inventor’s patents USPC classes with respect to Intel’s patents USPC classes in ([t-5, t-1]).</td>
</tr>
<tr>
<td>Social interdependence</td>
<td>Inventor’s embeddedness in Intel’s co-patenting network</td>
<td>Inventor’s Burt constraint index computed on her co-patenting network in ([t-5, t-1]).</td>
</tr>
<tr>
<td>Time (Log)</td>
<td>Inventor’s risk set clock</td>
<td>at year t, # years since inventor applied her first patent with</td>
</tr>
<tr>
<td>Tenure</td>
<td>Inventor’s tenure clock in Intel</td>
<td>at year t, # years since inventor joined Intel</td>
</tr>
<tr>
<td>Patents</td>
<td>Inventor’s patenting experience</td>
<td># patents applied by inventor at USPTO prior year t</td>
</tr>
<tr>
<td>Impact</td>
<td>Inventor’s patents impact in a technological field</td>
<td>Weighted sum of forward citations received by inventor’s patents prior year t</td>
</tr>
<tr>
<td>Prior geographical mobility</td>
<td>Inventor’s prior residence changes</td>
<td># times inventor changed state of residence prior year t</td>
</tr>
<tr>
<td>Prior firm mobility</td>
<td>Inventor’s mobility experience</td>
<td># times inventor changed employer prior joining Intel</td>
</tr>
<tr>
<td>Prior entrepreneurship</td>
<td>Inventor’s entrepreneurship experience</td>
<td># times inventor funded a startup prior joining Intel</td>
</tr>
<tr>
<td>Manager</td>
<td>Inventor’s job title in Intel</td>
<td>1{inventor has a managerial position in Intel in year t}; 0 otherwise.</td>
</tr>
<tr>
<td>Degree(MBA)</td>
<td>Inventor’s degree</td>
<td>1{inventor has a MBA degree}; 0 otherwise.</td>
</tr>
<tr>
<td>Degree(PhD)</td>
<td>Inventor’s degree</td>
<td>1{inventor has a PhD degree}; 0 otherwise.</td>
</tr>
<tr>
<td>Gender(Female)</td>
<td>Inventor’s gender</td>
<td>1{female inventor}; 0{male inventor}</td>
</tr>
<tr>
<td>Ethnicity(Indian)</td>
<td>Inventor’s ethnicity</td>
<td>1{inventor has an Indian name}; 0 otherwise.</td>
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<tr>
<td>Ethnicity(Chinese)</td>
<td>Inventor’s ethnicity</td>
<td>1{inventor has a Chinese name}; 0 otherwise.</td>
</tr>
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<td></td>
<td>Descriptive statistics and correlations</td>
<td>Mean</td>
</tr>
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<tr>
<td>1</td>
<td>Entrepreneurship</td>
<td>0.003</td>
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<td>Social interdependence</td>
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<td>5</td>
<td>Time (Log)</td>
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</tr>
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<td>Patents</td>
<td>6.064</td>
</tr>
<tr>
<td>8</td>
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</tr>
<tr>
<td>9</td>
<td>Prior geographical mobility</td>
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</tr>
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<td>10</td>
<td>Prior firm mobility</td>
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<td>11</td>
<td>Prior entrepreneurship</td>
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<td>12</td>
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<td>13</td>
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<td>0.065</td>
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<tr>
<td>14</td>
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<tr>
<td>15</td>
<td>Gender(Female)</td>
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<td>16</td>
<td>Ethnicity(Indian)</td>
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</tr>
<tr>
<td>17</td>
<td>Ethnicity(Chinese)</td>
<td>0.060</td>
</tr>
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</table>

Notes: N = 35,242. All correlations above |.01| are significant at p < 0.05. For Social interdependence, a value of 2 was assigned to inventors without collaborators (isolates).
Table 3. The Hazards of Employee Entrepreneurship and Mobility at Intel Corporation.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Entrepreneurship vs. survival</th>
<th>Mobility vs. survival</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Standard error</td>
</tr>
<tr>
<td>Knowledge interdependence</td>
<td>- 2.380</td>
<td>(0.774)</td>
</tr>
<tr>
<td>Social interdependence</td>
<td>- 0.627</td>
<td>(0.219)</td>
</tr>
<tr>
<td>Time (Log)</td>
<td>- 0.117</td>
<td>(0.114)</td>
</tr>
<tr>
<td>Tenure</td>
<td>- 0.117</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Patents</td>
<td>0.007</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Impact</td>
<td>0.021</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Prior geographical mobility</td>
<td>- 0.834</td>
<td>(0.377)</td>
</tr>
<tr>
<td>Prior firm mobility</td>
<td>- 0.169</td>
<td>(0.093)</td>
</tr>
<tr>
<td>Prior entrepreneurship</td>
<td>0.506</td>
<td>(0.401)</td>
</tr>
<tr>
<td>Manager</td>
<td>- 0.058</td>
<td>(0.258)</td>
</tr>
<tr>
<td>Degree(MBA)</td>
<td>0.280</td>
<td>(0.365)</td>
</tr>
<tr>
<td>Degree(PhD)</td>
<td>- 0.130</td>
<td>(0.257)</td>
</tr>
<tr>
<td>Gender(Female)</td>
<td>- 0.812</td>
<td>(0.584)</td>
</tr>
<tr>
<td>Ethnicity(Indian)</td>
<td>0.379</td>
<td>(0.237)</td>
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<td>Ethnicity(Chinese)</td>
<td>0.016</td>
<td>(0.375)</td>
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<tr>
<td>Constant</td>
<td>- 4.576</td>
<td>(0.257)</td>
</tr>
</tbody>
</table>

Link function: C log-log       C log-log
Observations: 35,242            35,242
Number of inventors: 4,382      4,382
Number of positive outcomes: 116 1,389
log likelihood: - 747.8          - 5,722
Chi-square: 80.91               288.64

Notes: Complementary log-log regression. Robust standard errors clustered by inventor.
### Table 4. Multinomial Logit Competing Risks Model

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>entrepreneurship vs. survival</th>
<th>mobility vs. survival</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Standard error</td>
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<td>Knowledge interdependence</td>
<td>-2.401</td>
<td>(0.781)</td>
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<td>Social interdependence</td>
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<td>(0.221)</td>
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<td>Time (Log)</td>
<td>-0.132</td>
<td>(0.115)</td>
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<tr>
<td>Tenure</td>
<td>-0.117</td>
<td>(0.033)</td>
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<tr>
<td>Patents</td>
<td>0.006</td>
<td>(0.003)</td>
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<tr>
<td>Impact</td>
<td>0.021</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Prior geographical mobility</td>
<td>-0.414</td>
<td>(0.260)</td>
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<tr>
<td>Prior firm mobility</td>
<td>-0.172</td>
<td>(0.094)</td>
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<tr>
<td>Prior entrepreneurship</td>
<td>0.511</td>
<td>(0.403)</td>
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<td>Manager</td>
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<td>Degree (MBA)</td>
<td>0.310</td>
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<td>-0.115</td>
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<td>-0.809</td>
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<tr>
<td>Constant</td>
<td>-4.548</td>
<td>(0.259)</td>
</tr>
</tbody>
</table>

Observations: 35,242
Number of inventors: 4,382
log likelihood: -6,467
Chi-square: 362.1

Note: Robust standard errors clustered by inventor.

### Table 5. Marginal effects of Knowledge Interdependence and Social Interdependence on the Mode of Exit

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Survival</th>
<th>Mobility</th>
<th>Entrepreneurship</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted probability</td>
<td>0.9680</td>
<td>0.0279</td>
<td>0.0041</td>
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<tr>
<td>Knowledge interdependence</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Predicted at Mean – 1 SD</td>
<td>0.9670</td>
<td>0.0284</td>
<td>0.0046</td>
</tr>
<tr>
<td>Predicted at Mean + 1 SD</td>
<td>0.9720</td>
<td>0.0256</td>
<td>0.0024</td>
</tr>
<tr>
<td>Absolute difference</td>
<td>0.0050</td>
<td>-0.0028</td>
<td>-0.0022</td>
</tr>
<tr>
<td>Relative difference</td>
<td>+ 0.52%</td>
<td>- 9.86%</td>
<td>- 47.82%</td>
</tr>
<tr>
<td>Social interdependence</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Predicted at Mean – 1 SD</td>
<td>0.9674</td>
<td>0.0273</td>
<td>0.0053</td>
</tr>
<tr>
<td>Predicted at Mean + 1 SD</td>
<td>0.9684</td>
<td>0.0290</td>
<td>0.0027</td>
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<tr>
<td>Absolute difference</td>
<td>+ 0.0010</td>
<td>+ 0.0017</td>
<td>- 0.0026</td>
</tr>
<tr>
<td>Relative difference</td>
<td>+ 0.10%</td>
<td>+ 6.22%</td>
<td>- 49.06%</td>
</tr>
</tbody>
</table>
Figure 1. Knowledge structure of Intel in the period 1978-1982

Note: Nodes in the graph represent technology classes, ties between nodes connect pairs of classes that have been combined in Intel’s patents, while the weights reported on the ties represent the degree of coupling, i.e. $C_{jk}$.

Figure 2. Example of Knowledge Combinations Made by Intel Inventors

Inventor A: John Palmer  
Inventor B: Alan C. Folmsbee

Note: Nodes in the graph represent technology classes. The black solid-line ties between nodes connect pairs of classes that have been combined in Intel’s patents, while the weights reported on the black solid-line ties represent the degree of coupling, i.e. $C_{jk}$ (see equation (2) point 1. above). The red-coloured nodes denote the technology classes in which the focal inventor was active, while the red-dashed lines show the combination of technology classes in the focal inventor’s patents. Finally, the weights on the red-dashed lines represent the share of each combination on all combinations realized by the focal inventor.