Who Exits and Who Stays? The Impact of Core Experience on chances of Inventor Exit

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Abstract

We reconcile seemingly contradictory findings in extant research that firms learn-by-hiring 'distant' inventor but inventors with unique skills (distant) seldom join rival firms. We also provide clarity on seemingly ambiguous impact of quantum of inventor’s core experience on her chances of exiting current employer. We argue that a clearer picture of transfer of core or unique knowledge across firms emerges if we classify inventor-exit into hiring by rival firms and hiring by non-rival firms. We find that inventors with high core experience move to non-rivals because non-rivals learn by exploiting core technologies; whereas inventors with high experience in core move to rival firms only if they possess unique knowledge as well so that rivals learn from inventor’s ability to explore with core technologies. Our findings extend our understanding of core knowledge being spilled over to rival firms within an industry and non rival firms to other industries because of inventor mobility.
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Abstract
We reconcile seemingly contradictory findings in extant research that firms learn-by-hiring ‘distant’ inventor but inventors with unique skills (distant) seldom join rival firms. We also provide clarity on seemingly ambiguous impact of quantum of inventor’s core experience on her chances of exiting current employer. We argue that a clearer picture of transfer of core or unique knowledge across firms emerges if we classify inventor-exit into hiring by rival firms and hiring by non-rival firms. We find that inventors with high core experience move to non-rivals because non-rivals learn by exploiting core technologies; whereas inventors with high experience in core move to rival firms only if they possess unique knowledge as well so that rivals learn from inventor’s ability to explore with core technologies. Our findings extend our understanding of core knowledge being spilled over to rival firms within an industry and non rival firms to other industries because of inventor mobility.

Introduction and Theoretical Contribution
Why do inventors exit an organization (Fernández-Zubieta, Geuna, & Lawson, 2015)? What type of inventors exit an organization (Ganco, Ziedonis, & Agarwal, 2015)? These are some important research questions as answers to these have implications for practitioners because retaining valuable human assets is a management dilemma (Coff, 1997). Understanding inventor exit should help practitioners design better contracts to retain knowledge workers (Campbell, Ganco, Franco, & Agarwal, 2012). Policymakers should also have a better picture of what type of workers move, and in what direction (e.g. from large to small firms) do certain type of workers move. Ultimately, policies aimed at enhancing (or suppressing) certain type of labor mobility can be better devised (Ganco et al., 2015).

Answers to these questions also contribute to the management and labor economics literature. We identify two research gaps. Recent scholarly works on inventor-turnover and inter-firm knowledge flows suggest that inventors with new knowledge (or complex knowledge) are less likely to exit current employer and join a rival firm (Ganco, 2013; Palomeras & Melero, 2010), while learning by hiring literature says that firms learn about rival firms’ knowledge by hiring ‘distant’ inventor (i.e. inventor possessing new knowledge) (Rosenkopf & Almeida, 2003; Tzabbar, 2009). Further, prior research does not hold consensus on the effect of the worker’s experience in core activities on her chances of exiting current employer (Palomeras & Melero, 2010). Hence the research puzzle- how does core or new knowledge flow across firms because of worker mobility?

Second, the learning by hiring literature has highlighted the benefits of hiring inventors (Jain, 2016; Rosenkopf & Almeida, 2003; Tzabbar, 2009), but does not provide implications for a firm losing inventors. For example, it is known that the hiring firm benefits from more knowledge inflows when the new hire works in non-core areas of the hiring firm (Song, Almeida, & Wu, 2003). However, the picture from the losing firm’s perspective is not clear. What type of inventors exit a firm and join non-core research activities in a rival firm? Or, does inventor mobility occur systematically more often for those inventors who work in non-core areas of the firm in an industry?

Hence, we explore how inventor mobility contributes to transfer of core or unique knowledge across firms. We argue that a clearer picture of transfer of knowledge across firms emerges if we classify instances of inventor exits into hiring by rival firms and hiring by non-rival firms. We argue and find that both rival firms and non rival firms may value inventors with high experience in core technologies, however for different reasons. An inventor with high experience in core technologies may move to a non rival firm so that the hiring non rival firm can learn about core technologies. On the other hand, an inventor with high experience in core technologies may move to rival firms if the inventor possesses unique knowledge as well so that the hiring rival firm learns by the inventor’s ability to combine new knowledge with core technologies. In other words, inventors with tendency to exploit core technologies are more likely to exit and join a non-rival firm, whereas inventors with tendency to explore core technologies are more likely to exit and join a rival firm.

This work-in-progress project answers the research question by focusing on inter-firm inventor mobility (Hoisl, 2007; Rosenkopf & Almeida, 2003). Specifically, we focus on inventor mobility from the point of view of the firm subject to exit (Ganco, 2013; Palomeras & Melero, 2010).

Hypotheses
The core of a firm can be thought of as ‘a set of differentiated skills, assets or routines that provide the firm a basis for its competitive capacities and sustainable advantage in a particular business’ (Leonard-
Barton, 1992; Teece, Pisano, & Shuen, 1997). For a knowledge intensive firm, the core comprises technological areas typically associated with the firm’s comparative advantage (Leonard-Barton, 1992). Thus, the innovative activity is especially intensive in these areas, to which the firm devotes many of its human and technical resources (Palomeras & Melero, 2010).

Labor market should value inventors with moderate experience in core technologies more than inventors with less experience in core technologies. As an inventor’s experience in core technologies increases, she is more likely to possess knowledge valuable in the market (Leonard-Barton, 1992) because she learns by solving many technical problems (related to firm specific techniques as well as related to scientific understanding). Such learning is valuable for the current employer and other firms. Because other firms can learn by hiring (or by exploiting prior inventions of new hires) (Agrawal & Singh, 2011; Rosenkopf & Almeida, 2003) such inventors are more likely to receive opportunities for making a switch.

Further, inventors with moderate experience in core technologies are more valuable than inventors with high experience in core technologies. As an inventor’s experience in core technologies increases, she is consistently solving firm specific problems. The more she is occupied with core of the firm, the more likely is she to be dependent on the focal firm’s resources (Huckman & Pisano, 2006), and hence, the more will be the costs of switching employers. Knowledge workers who rely heavily on firm specific skills experience dip in productivity after move (Groysberg, Lee, & Nanda, 2008; Groysberg, Nanda, & Nohria, 2004; Groysberg, Sant, & Abrahams, 2008) or when working in other organization (Huckman & Pisano, 2006). From the above lines of reasoning, we predict an inverted U-shaped relationship of an inventor’s experience in core technologies and her chances of exiting the focal firm.

H1. An inventor’s experience in core technologies of a firm has inverted U-shaped relationship with her chance of exiting the firm (at low and high levels she is less likely to exit and at intermediary level she is more likely to exit).

A Deeper look into the Core of a Firm

According to Leonard-Barton (1992), employee knowledge and skills (firm-specific techniques and scientific understanding) constitute as one of the key dimensions of a firm’s core capability. Within the knowledge/skills dimension are two important microdimensions: ‘Excellence in the dominant discipline’ and ‘Pervasive technical literacy.’ The first microdimension suggests that a firm needs ‘excellence in the technical and professional skills and knowledge base underlying’ core capabilities (Leonard-Barton, 1992). Engineers dealing in core technologies achieve such excellence by solving seemingly intractable technical problems. The second microdimension suggests that (apart from highly qualified people working in dominant discipline) a firm needs ‘a reservoir or complementary skills and interests’ outside the dominant discipline. This consists of technically skilled people who provide skilled criticism and insights and help shape new products (Leonard-Barton, 1992).

Putting together the two microdimensions, it follows that the core of a knowledge intensive firm consists of two types of inventors: type1 are those who have excellence in core technologies and type2 are those who have unique skills but provide insights to shape new products in core technologies. This is in line with the dynamic capabilities view of the firm’s resources i.e. a firm needs not only excellence in its core technologies for competitive advantage but also an ability to reconfigure its core competencies to address changes in the environment. We borrow this school of thought to make predictions.

Unique Knowledge

The dynamic capabilities view suggests that in order to outdo rivals and earn above normal returns, a firm needs to have an ability to continuously reconfigure its human assets (or resources) to address changes in environment. Accordingly, the firm needs to alter its core competence to address changes in the environment. A firm that fails to do so should lose its competitive advantage. Although research suggests that firms learn by hiring, we still do not have a clear picture of how do a firm alter its core competencies, particularly because of hiring. Does the firm hire inventors who have excellence in core technologies or inventors who have unique knowledge?

H1 does not distinguish between an inventor exiting and joining a rival firm and an inventor exiting and joining a non rival firm. We expect H1 to hold true for both the cases, however for different reasons. We argue that rival firms value inventors of type2, i.e. those who have unique knowledge along with
understanding of core technologies compared to those who have only excellence in core technologies (type1) or those who have only unique knowledge. Whereas non rival firms value inventors of type2 i.e. inventors with only excellence in core technologies over inventors of type1. Let us consider why is so the case.

By virtue or rivalry, rival firms (as opposed to non rivals) are those that deal in businesses or technologies similar to those of focal firm. This suggests that rival firms (compared to non rival firms) should have knowledge and resources similar to those of the focal firm. Type1 inventors, those who have excellence in core technologies of the focal firm, are more likely to possess knowledge that provides less marginal benefits to rival firms. This is because of three reasons. First, inventors who spend most of their time working in core technologies are less likely to possess new knowledge because they spend less time on non-core research projects. Second, such inventors are more likely to possess focal firm specific problem solving skills. Third, rivals firms are likely to already possess similar knowledge repertoire of core technologies (Ganco, 2013). Because learning by hiring takes place when the mobile inventor possesses ‘distant’ knowledge (Tzabbar, 2009), type1 inventors are less likely to be hired away by rival firms.

On the other hand, inventors of type2, those who have unique knowledge along with knowledge of core technologies are more likely to explore and combine new knowledge with core technologies. Research suggests that new knowledge is important because it opens up avenue for future knowledge combinations and thereby help a firm to enhance its competitive advantage (Cohen, 2010; Fleming & Sorenson, 2004). In other words, the ability of an inventor to combine new knowledge with core technologies (and not the experience in core technologies alone) provides more marginal benefit to the rival firms. An inventor with displayed ability to produce scientific output by combining unique knowledge with core technologies should be valued by rival firms because such inventors can produce inventions that can be more readily commercialized and provide a firm competitive advantage. Because rival firms would monitor research trends related to core technologies, they should be able to identify and assimilate inventors who have experience in core technologies and at the same time experience in other new technology(ies). Hence, rival firms value such inventors more than their counterparts.

H2. The more unique knowledge and experience in core technologies an inventor has, the more likely she is to exit the focal firm and join a rival firm.

Next, we exploit another inventor characteristic, inventor’s tenure at the focal firm. As an employee gains experience in a firm, she develops firm specific skills (Huckman & Pisano, 2006). Also, because inventors exploit their prior inventions, as inventors gain experience in the focal firm, they are less likely to possess new knowledge (Audia & Goncalo, 2007). Therefore, inventors with high tenure in core technologies may not possess sufficiently new knowledge that can be combined with core technologies. Rival firms will not benefit from hiring them because they are less likely to possess new knowledge and they may experience dip in productivity after making a move. Non rival firms may hire inventors with high tenure in core to benefit from transfer of core knowledge.

On the other hand, inventors with low tenure in core technologies are more likely to move to rival firms because they are more likely to possess knowledge of new inventions that can be combined with core technologies, thereby relevant exploration. Because rival firms would monitor research trends related to core technologies, they should be able to identify and assimilate inventors who have low tenure in core technologies.

H3. The more tenure and core knowledge an inventor has, the less likely she is to exit the focal firm and join a rival firm.

Learning by hiring depends on knowledge diffusion from incoming inventor to others (Agrawal & Singh, 2011). However, diffusion may be limited (Agrawal & Singh, 2011) depending on how recruiting firm exploits incoming knowledge. Ganco (2013) suggests that diffusion or learning by hiring is limited if the incoming inventor possesses complex knowledge1. This is because the recruiting rival firm may not have relevant resources to appreciate the complexity of incoming knowledge. In this vein,

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1 Complex knowledge can be defined as one which is difficult to be diffused (for quick summary, see Ganco (2013) For detailed elaboration on complexity and knowledge diffusion across actors, see (Sorenson, Rivkin, & Fleming, 2006)).
Ganco (2013) finds that an inventor with more complex knowledge is less likely to move to rival firm. In this vein, rival firms will not value inventors who possess complex core knowledge because the rival firm may not learn by hiring.

H4. The more complex and core knowledge an inventor has, the less likely she is to exit the focal firm and join a rival firm.

**Research Design**

**Sample**

A micro-level data is needed to study mobility of knowledge workers and measure characteristics of knowledge possessed by them. Patent data, which serves this purpose, has been frequently used by researchers for studying inventor mobility (Agrawal & Singh, 2011; Rosenkopf & Almeida, 2003). We examine our hypotheses using U.S. Patent and Trademark Office (USPTO) patent data, which is available on the National Bureau of Economic Research website (Hall, Jaffe, Trajtenberg, & National Bureau of Economic, 2001). Patent data is helpful because of many reasons (Singh & Fleming, 2010).

First, the data helps us identify mobility of employees (inventors) by systematically tracking the firm they are working with. Second, the data helps us create measure of attributes of knowledge possessed by inventors. Finally, the data is a panel data, which helps us control for unobserved heterogeneity and control for path dependency and related factors.

We restrict the analysis to inventors working in IBM because of several reasons. First, the context is very suited for our research because of non firing policy in IBM. As mentioned elsewhere, IBM did not have a firing policy until 1992 (i.e. IBM had a lifetime employment policy); post 1992, IBM started offering attractive severence packages to motivate employees to exit (Palomeras & Melero, 2010). However, there is little evidence that inventors moved out of IBM involuntarily (Carroll 2003 Audio book). Second, IBM operated in technological domains that are characterised by standardized patenting process, such as semiconductors, computers, etc (Stuart, 2000). This is desirable for our research as more standardized patenting process means less measurement errors in computing our variables. Third, since IBM operates in multiple technologies, it offers a research setting in which we can distinguish between some of our key variables (for example distinguish knowledge of non-core technologies from uniqueness of knowledge). Finally, research suggests that different employers have different likelihood for their employees to exit (Ganco et al., 2015); therefore we control for firm related heterogeneity by sticking to inventors in a single firm.

In order to identify instances of mobility, we have identified unique inventors. We have utilized inventor level information available in the U.S. Patent and Trademark Office (USPTO) patent data. However, this raw inventor level data is fraught with problems primarily because there is no unique identifier to identify inventor in the patent data. Therefore two main identification problems come up: a) there may be cases in which same inventor is named differently (perhaps because of spell error, or omission/inclusion of mid name, etc.) and b) there may be cases in which two same names refer to different inventors. To tackle the problem, we have made use of a name-matching algorithm used by Jain (2016). Trajtenberg, Shiff, and Melamed (2006) originally proposed this algorithm. In its original form, the algorithm tries to match names based on a matching score. This score is calculated using a number of parameters such as sound (names sounding similar are scored more), frequency (less occurring names are more likely to be different inventors, and hence low score is awarded to them), technology class (scores are assigned on the basis of technology class and technology class size of the names), city (higher scores are awarded to names belonging to same city, especially to cities where less number of patents are developed), assignee (firm name and firm size are utilized to score) and self-citation (higher score is awarded if an inventor name cites the name of inventor it is being matched to). Jain (2016) added an additional constraint on name matching: only the names differing in either the first names or the last names by only one character were allowed for score matching. This whole process of name matching results into much refined inventor identification, generating a unique inventor ID for each of the unique inventor.

We select all the inventors who appear in at least one patent assigned to IBM between 1971-1999. This sample consists of 23751 inventor IDs. In this sample, we validate the algorithm-generated inventor IDs. First, we look for inventors having same name (first, last and middle) but having different IDs. We require coincidence in either location of assignee to match the IDs (Palomeras & Melero, 2010). Finally, we have a sample of 19250 unique inventors. Then, we check for inventors having same IDs
but different names; after taking into account minor spell errors, we are left with 19458 unique inventors. These inventors account for 24585 patents in IBM from 1971-99. Next, since we only want serious inventors (who are professional rather than who have sporadic inventions or co-authoring opportunity) because we do not want our results to be biased by observing those who are authors to some inventions but are not actual inventors, we restricted to only those who have at least 3 years of experience (i.e. the difference between application years of the earliest and latest patent must be separated by at least 2). This process provided us with a sample of 8054 unique and ‘serious’ inventors from 1971 to 1999; these inventors account for a 22121 patents from 1971-99. On an average, an inventor produces 6.2 patents in this period.

Analysis

We adopt our empirical approach from two prior studies (Ganco, 2013; Palomeras & Melero, 2010). Specifically, we use duration analysis to estimate the hazard rates of an inventor exiting the focal firm (IBM) and joining a rival firm and of an inventor exiting IBM and joining a non-rival firm. The hazard rate gives the rate at which inventors exit the focal firm by t given that the inventors had stayed until t (Box-Steffensmeier & Jones, 2004: 14) where t represents the given year of observation. An inventor is observed for every year from the time she files her first patent in IBM till the time she files her last patent with IBM if she exits IBM or till the survival time is censored because of the end of the period of the study if she does not exit IBM. The instance of exit is identified when there is a systematic change in the assignee name for patents of the inventor.

Duration analysis (or event history analysis) is ideal here primarily because when we predict the probability of an inventor exit, essentially we are predicting the duration of the inventor’s stay at the focal firm. Further, it is preferable to probistic or Poisson because it takes into consideration right-censored observations that occur because the sample ends at a certain point in time (Audia & Goncalo, 2007: 9; Blossfeld & Rohwer, 2002). Because our sample ends at 1999, some variables that are based on patenting histories of inventors might be biased because inventors may have applied patents before 1999 but may be granted after 1999. To further mitigate the bias because of right censoring, we restrict the analysis to 1997, such that we are more sure of patenting histories of the inventors working in IBM till 1997.

Hence, our sample consists of longitudinal data of inventors in IBM; and we predict hazard rates for an exit to rival firms and an exit to non-rival firms separately. The hazard rates take the following form and are estimated by maximum likelihood.

$$h(t|X) = \exp(-\beta'X)$$

where, X represents a matrix for covariates and β represents the vector for coefficients including the constant term. Note that all the covariates are computed till t-1. The above specification means that we use a parametric model, specifically exponential model, to estimate the hazard rate. This implies that the risk of a hazard happening, conditional on covariates, is same for all time points (Box-Steffensmeier & Jones, 2004: 22). This is desirable because it allows the hazard rate to be independent of tenure of an inventor, which is one of our key predictors. It also means that the duration times of inventors follow exponential distribution (Box-Steffensmeier & Jones, 2004: 22), which should be a fair assumption to make. (To test the robustness of econometric specification, we estimate hazard rate with other parametric specifications such as gamma distribution, weibull distribution and log-logistic distribution and find consistent results. To further test the robustness of findings, we use panel random effect logit and probit models to predict the probability of an inventor exiting, separately for joining a rival and joining a non-rival. The findings still hold.) Robust standard errors clustered at the inventor level are used to allow for non-independence of observations belonging to the same inventor (Audia & Goncalo, 2007: 9).

Unlike in Palomeras and Melero (2010) which analyses data at inventor patent level, in this study we follow Ganco’s (2013) approach to construct our sample at inventor year level. This is more relevant as we treat inventor to be at risk of exiting IBM for all the years she is in IBM. Further, unlike in Palomeras and Melero (2010) who observe an inventor only for years in which she files a patent, in our analysis we observe all the inventor year combinations because we allow several variables to change with time (and not necessarily with application of a patent). Further, it reduces multicollinearity issue by observing an inventor only once ever year (rather than observing an inventor the number of times she files patent in a year).
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In our sample, there are 742 cases of inventor exits out of which 326 cases are for exits to rival firms and the remaining are for exits to non rival firms. To classify the recruiting firm into a rival firm or non rival firm, we follow a series of steps. First, we identify technological subcategories in which IBM is a dominant player (Palomeras & Melero, 2010). We note that IBM dominates in four out of thirty six technological subcategories occupying a share of at least 5% in terms of patents granted in a twenty year window 1975-94. Consistent with intuition, the four technological subcategories in which IBM is a dominant player are Computer Hardware & Software (6.7%), Computer Peripherals (6.5%), Information Storage (6.2%), and Semiconductor Devices (5.6%). The next best technological subcategory holds for only 1.3%. Second, we observe the total number of research outputs of all the recruiting firms across technological subcategories in the same period. Any recruiting firm that has at least twenty patents in Computer Hardware & Software, Computer Peripherals, or Information Storage, or ten patents in Semiconductor Devices is classified as a potential rival firm. However, to avoid classifying a diversified firm with large research experience as a rival firm, any recruiting firm with majority of patents (more than 95%) in subcategories other than these are re-classified as non rival firm. Next, to identify rival firms with relative less research experience in Computers industry, we check if the recruiting firm is primarily focussed in Computers and not in Communications (note that Computer Hardware & Software, Computer Peripherals, and Information Storage are three of the four subcategories of Computers and Communications). Hence, any recruiting firm for which either of the three subcategories accounts for the majority of research output is classified as a rival firm. Next, to identify rival firms with relative less research experience in Semiconductors industry, we check if the recruiting firm is primarily focussed in Semiconductor Devices and not in Electricals and Electronics (note that Semiconductor Devices is one of seven subcategories under Electricals and Electronics). Hence, those recruiting firms for which patents in Semiconductor Devices account for the majority of their patents in Electrical and Electronics are also classified as rival firms. All the remaining recruiting firms are, therefore, non rival firms.

We perform a series of tests to ensure that the firms we classify as rivals are different from the firms we classify as non rivals. First, a simple unpaired student’s t-test on number of patents (either Computer or Semiconductor Devices) in a period 1975-94 for all the rival hiring firms versus all the non rival hiring firms reveals that the non rivals produce a significant less number of Computer or Semiconductor Devices patents (t-value of 4.4e-9, assuming unequal variances). Second, since the number of patents produced may be biased by firm size or the nature of industry, we perform a similar t-test on the proportion of patents belonging to Computer or Semiconductor Devices (w.r.t total number of patents for the firm) in the same period. T-test reveals that the proportion of patents belonging to Computers and Semiconductor Devices is systematically lower for non rivals than that of rivals (t-value of 2.4e-29). Finally, to do a comparison of distribution of research activities of rivals versus non-rivals, we matched hiring rival firms one-to-one with hiring non-rivals firms based on the research experience (total number of patents assigned to a firm in 1975-94). We were able to match 86 rival-non rival firm pairs. Figure 1 shows the distribution of research activity for rivals versus non rivals. While for non rivals, rarely any firm is dedicated to research in Computers or Semiconductor Devices, for rivals, most of the firms are dedicated to either or both of these technological fields. A paired t-test on number of patents (either Computer or Semiconductor Devices) in a period 1975-94 for matched rival firms versus matched non rival firms still reveals that non rivals produce a significantly less number of such patents (t-value of 2.1e-4).

Variables
Core knowledge (PercentCore): we relied on rationale from prior literature (Song et al., 2003) to identify technologies of IBM that form its core. As in Palomeras and Melero (2010), core classes are the ones that account for at least 2.5% of IBM’s portfolio in a five-year window. To compute quantum of inventor’s core experience, we take a ratio of number of core to total patents.
Unique knowledge (Uniqueness): we observe the quantum of uniqueness of an inventor’s knowledge with respect to IBM. First, we measure angular similarity between a vector of cumulative number of the inventor’s patents across thirty six technological subclasses and a similar vector of cumulative number of IBM’s patents across those subclasses prior to the year of observation. Then, we subtract the above from unity to obtain uniqueness in knowledge possessed by the inventor (Jain, 2016; Tzabbar, 2009).
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Tenure: we proxy tenure of an inventor by calculating the difference between the year of observation and the application year of the very first patent of the inventor at IBM.

Complexity: we compute knowledge complexity of an inventor in a series of steps. First, we make a table for taking note of citation frequencies between patent classes for all the patents between 1975 and 1994. Using this, we get a static measure of interdependence for each focal patent class. Second, for each patent involved in the study, we compute an average of interdependencies of all the patent classes cited by the patent. Third, finally to obtain the measure at the inventor level, we compute an average of interdependencies of all the patents belonging to the inventor prior to the year of observation (Ganco, 2013).

Based on prior literature, we controlled for patenting history of inventors (TotalPatents, Patents in focal year), quality of inventor’s knowledge (AverageTotalCites, CitesDispersion, AverageSelfCites), prior mobility (Hired Inventor), social capital (MeanTeamSize), technological categories, regions, and time (Almeida & Kogut, 1999; Fallick, Fleischman, & Rebitzer, 2006; Hall, Jaffe, Trajtenberg, & National Bureau of Economic, 2001; Hoisl, 2007; Palomeras & Melero, 2010; Topel & Ward, 1992; Zucker, Darby, & Torero, 2002).

Preliminary Results

Table 1 presents the main findings of this paper. Models 1-6 predict hazard rates for inventors exiting IBM and joining a rival firm while models 7-12 (table 2) for inventors joining a non rival firm. The tables show only the variables of interests. Models 2 and 8 test for H1 by adding a second order term for Core. Both the models support H1 as the coefficient of Core is positive and significant while that of (Core)^2 is negative and significant. This represents the curvilinear relationship between the quantum of core experience of an inventor and her chances of exiting.

Model 3 supports H2 as the coefficient of CoreXUniqueness is positive and significant, suggesting that inventors with experience in core technologies and new-to-the firm technologies are valued more by rival firms, and hence are systematically more likely to exit IBM and join a rival firm. We contrast model 3 (exit to rivals) with model 9 (exit to non rivals) because the contrasting findings add to the causality of our argument. In model 9, the interaction term is non significant; suggesting that such inventors may not be hired by non rivals.

Model 4 supports H3. The coefficient of the interaction term CoreXTenure is negative and significant, suggesting that inventors with experience in core technologies and high tenure are less likely to be move to a rival firm. This adds to the causality of our main argument that rival firms learn by hiring inventors if they are able to explore core technologies with new technologies.

Model 5 supports H4. The coefficient of the interaction term CoreXComplexity is positive and significant. This suggest that inventors with complex core knowledge are less likely to move to a rival firm. In contrast, model 11 (exit to non rivals) does not have a significant coefficient for the interaction term.

Figure 2 plots hazard of exiting IBM for the interaction effect of Core and Uniqueness (based on the full models) for exit to rivals (in panel A) and exit to non rivals (in panel B). Inventors with high uniqueness and low core experience are less likely to exit and join a rival firm, whereas inventors with high uniqueness and high core experience are more likely to exit and join a rival firm. In contrast, there is no interaction in panel B. Inventors with high uniqueness and low core experience exit more to join non rival firms.

Similarly, figure 3 displays the interaction effect for the effect of Core and Tenure. Inventors with high core experience may exit to rival firms when they have low tenure. As tenure increases, they are less likely to exit to a rival firm. In contrast, inventors with low tenure and high core experience are less likely to exit to non rival firms.

Finally, figure 4 plots the same for the interaction effect of Core and Complexity. Inventors with high core experience and low complexity exit to rivals as well as non rival firms. However, we note that inventors with high complexity and high core experience are less likely to exit. The drop is much earlier for non rivals than rival firms because of deeper understanding of core knowledge of rival firms.

Conclusion

Our findings highlight how core knowledge flows across firms in an industry vis-a-vis across industries. We find that inventor mobility contribute to core knowledge flowing across firms. Firms hire from rival
firms for exploration of core technologies. Therefore they systematically hire inventors with core knowledge and unique knowledge more than their counterparts. This explains how a firm learns by hiring a ‘distant’ inventor. On the other hand, core knowledge may simply flow to non rival firms because of inventor mobility because such firms may want to learn by exploiting core knowledge of the incoming inventor.
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Figures

Figure 1  Distribution Plots for Rivals and Non rivals across Proportion of Computers or Semiconductor Patents

A. Rivals

B. Non rivals

Figure 2  Interaction effect for Core and Uniqueness

A. Hazard of Exiting IBM and Joining a Rival: Interaction effect for experience in Core and Unique Knowledge

B. Hazard of Exiting IBM and Joining Non Rival: Interaction effect for experience in Core and Unique Knowledge

Figure 3  Interaction effect for Core and Tenure

A. Hazard of Exiting IBM and Joining a Rival: Interaction effect for Core and Tenure

B. Hazard of Exiting IBM and Joining Non Rival: Interaction effect for Core and Tenure

Figure 4  Interaction effect for Core and Complexity

A. Hazard of Exiting IBM and Joining a Rival: Interaction effect for Core and Complexity

B. Hazard of Exiting IBM and Joining a Non Rival: Interaction effect for Core and Complexity
### Table 1: Hazard of Exiting to a Rival Firm (coefficients)

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<td>5.404***</td>
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<tr>
<td>(PercentCore)2 [H1]</td>
<td>(0.126)</td>
<td>(0.700)</td>
<td>(0.577)</td>
<td>(1.205)</td>
<td>(1.566)</td>
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<tr>
<td>PercentCore X Uniqueness [H2]</td>
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<td>-0.036*</td>
<td>-0.036*</td>
<td>-0.010</td>
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<td>(PercentCore X Tenure [H3])</td>
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<td>(0.015)</td>
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<td>0.583</td>
<td>0.463^</td>
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<td>0.038***</td>
<td>0.038***</td>
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<td>0.038***</td>
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<tr>
<td>(PercentCore X Tenure [H3])</td>
<td>-1.498^</td>
<td>-1.196</td>
<td>-1.246</td>
<td>-1.185</td>
<td>-0.237</td>
<td>-0.051</td>
</tr>
<tr>
<td>PercentCore X Complexity [H4]</td>
<td>-2.961</td>
<td>-3.892*</td>
<td>(0.204)</td>
<td>0.204</td>
<td>0.802</td>
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</tr>
<tr>
<td>Tenure</td>
<td>0.217</td>
<td>0.463^</td>
<td>0.583</td>
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<td>0.669^</td>
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<td>-1.246</td>
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<td>-0.051</td>
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<tr>
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<td>28.775</td>
<td>29.438</td>
<td>29.106</td>
<td>23.952</td>
<td>24.488</td>
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N=61925; Robust standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05, ^ p<0.1

### Table 2: Hazard of Exiting to a Non Rival Firm (coefficients)

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<td>(0.577)</td>
<td>(1.205)</td>
<td>(1.566)</td>
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<tr>
<td>PercentCore X Uniqueness [H2]</td>
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<td>(PercentCore X Tenure [H3])</td>
<td>-1.498^</td>
<td>-1.196</td>
<td>-1.246</td>
<td>-1.185</td>
<td>-0.237</td>
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<tr>
<td>PercentCore X Complexity [H4]</td>
<td>-2.961</td>
<td>-3.892*</td>
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<td>(1.963)</td>
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<td>0.583</td>
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References


“Who Exits and Who Stays? The Impact of Core Experience on chances of Inventor Exit”


