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CUTTING THE GORDIAN KNOT: THE EFFECT OF KNOWLEDGE COMPLEXITY ON EMPLOYEE MOBILITY AND ENTREPRENEURSHIP

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Employee entrepreneurship and employee moves to rival firms (employee mobility) have both been recognized as critical drivers of the transfer of knowledge. Drawing on a unique database of intra-industry inventor entrepreneurship and mobility events in the U.S. semiconductor industry, I examine the effect of the complexity of inventors' prior patenting activities on their decisions to join a rival firm or found a start-up. The findings show that even though complexity inhibits knowledge diffusion to rival firms through employee mobility, complex knowledge may be underexploited within existing organizations and may still flow to startups through employee entrepreneurship. This study sheds new light on how technology shapes patterns of employee entrepreneurship and mobility, with implications for knowledge flows and competitive dynamics.

INTRODUCTION

Employee entrepreneurship—the intra-industry founding of a new venture by an individual who previously worked for an incumbent firm—has been heralded as a hallmark of innovation (Freeman, 1986; Klepper and Sleeper, 2005), a critical source of new firm capabilities and heterogeneity in performance (Agarwal *et al*., 2004; Phillips, 2002), and an impetus to the creation and growth of industries and regional clusters of firms (Klepper, 2007; Sorenson and Audia, 2000). Through employee entrepreneurship, a new venture inherits industry-specific knowledge and strategies that are based on the founders' prior work experience (Agarwal *et al*., 2004; Chatterji, 2009; Klepper and Thompson, 2010). Similarly, scholars have long recognized intra-industry employee mobility (i.e., individual moves to another firm in the same industry) as a powerful engine of knowledge diffusion between firms, established and start-ups alike (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003; Singh and Agrawal, 2011).

At the heart of these issues is a question that relates to the underlying drivers of employee entrepreneurship and mobility. Scholars have noted that profitable opportunities frequently arise as a result of information asymmetries while emphasizing the role of individuals' prior knowledge (Helfat and Lieberman, 2002; Shane, 2000). For instance, Federico Faggin, Intel employee and inventor of the original Intel 4004 microprocessor, founded Zilog in 1975 after discovering that significant improvements to the Intel 8080 architecture were possible. His decision led to the famous Z80 microprocessor, improving the Intel 8080 in terms of both speed and costs (National Inventors Hall of Fame Foundation, Inc; Pitta, 1997). T. J. Rodgers founded Cypress Semiconductor in 1982 to exploit his experience with MOS designs acquired while

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working at AMD and American Microsystems (Cypress Semiconductor). Similarly, John Birkner and H. T. Chua founded QuickLogic in 1988 as a way of exploiting their invention of programmable array logic, which they invented while working at Monolithic Memories (Computer History Museum; QuickLogic). These anecdotes illustrate that employees working at existing organizations have preferential access to knowledge related to technologies, markets, and environmental drivers (Agarwal *et al*., 2004; Freeman, 1986; Sørensen, 2007). Such work experience may also help the individuals to acquire critical networks and bolster confidence in their success (Sorenson and Audia, 2000). Employee entrepreneurship and mobility thus represent key mechanisms for exploitation of valuable resources and opportunities outside the boundaries of parent firms. Indeed, extant studies suggest that technologically more advanced firms generate more entrepreneurs (Brittain and Freeman, 1980; Franco and Filson, 2006) and that underexploited technological opportunities often lead to employee entrepreneurship (Agarwal *et al*., 2004; Freeman, 1986; Garvin, 1983; Klepper and Thompson, 2010).

While the drivers of employee entrepreneurship and mobility have been extensively studied, they are largely examined in isolation of each other, some exceptions notwithstanding (e.g. Campbell *et al*., 2012). To the extent that some characteristics of knowledge may affect employee entrepreneurship and mobility differently, we can gain unique insights by examining the antecedents of employee entrepreneurship and mobility jointly. In this study, I focus on an area that has received relatively little attention, namely the micro-level variation in the nature of knowledge gained while solving technological problems. Specifically, I examine the effect of technological complexity on employees' choices about mobility and entrepreneurship. In other words, how does the complexity of the technological problems impact inventors' decisions to move to another firm or start up a new venture, either individually or in teams?

I develop a theory connecting knowledge complexity with employee entrepreneurship and mobility, based on the conceptualization of knowledge as a recipe, and inventors as carriers of the recipes that they acquire while solving technological problems (Dosi and Grazzi, 2010; Nelson and Winter, 1982; Sorenson, Rivkin, and Fleming, 2006). I define complex knowledge as a recipe that has many interdependencies between its ingredients. Two ingredients are considered interdependent if a change in one ingredient affects performance of another ingredient.

The empirical context of the study is the U.S. semiconductor industry from 1973 to 2003, a canonical example of an industry driven by technological intensity, knowledge spillovers, and employee mobility and entrepreneurship (Agarwal *et al*., 2009; Freeman, 1986; Macher, Mowery, and Hodges, 1998). To operationalize the complexity of knowledge held by individuals, I examine the patent-level complexity of inventors' prior activities in the incumbent firm. The complexity of prior patents thus serves as a proxy for the complexity of recipes that the inventor has acquired. I measure the complexity using NK methodology (Fleming and Sorenson, 2001; Kauffman, 1993; Sorenson *et al*., 2006), which I also validate for my empirical context with the help of industry experts. To isolate the effect of knowledge complexity on employee mobility and entrepreneurship from existing explanations, I employ a stringent empirical approach. I focus only on large public firms as sources of employee moves and utilize firm-year fixed effects. The resulting estimation is based on comparing individuals within the same focal firm in the same year. This approach also simplifies the estimation since all time-varying firm level controls are subsumed in the fixed effects.[1]

To briefly foreshadow the results, I theorize and find that inventors whose patents reflect higher complexity are less likely to join rival firms, but are more likely to become entrepreneurs. Further, I find that knowledge complexity increases the likelihood of both team mobility (moving to rival firms together with co-inventors) and team employee entrepreneurship (starting a new firm together with co-inventors). I also find that the impact of complexity is significantly stronger in its effect on team employee entrepreneurship relative to its effect on team mobility.

Understanding how differences in knowledge complexity affect mobility and entrepreneurship

[1] The controls only need to capture the individual level differences within the 'firm-year'. I also employ a multitude of robustness tests including an alternative measure of knowledge complexity and patent class-year fixed effects (which means comparing inventors who patent in the same technological class in the focal year).

outcomes has multiple practical and theoretical implications. From the practical perspective, the awareness of which technological areas spawn most employee entrepreneurs may help incumbent firm managers recognize underexploited opportunities. Further, such an understanding can directly inform managerial practices with respect to individual employees. To harness the employees' innovative talent, these practices may need to vary with the complexity of the technological problems. In cases when the employee exit occurs without the approval of the incumbent firm, the firms need to mitigate potential misappropriation threats. Incumbent firm managers could employ different strategies depending on the complexity of the employees' tasks. Similarly, incumbent firm employees may better understand why and when their ideas would face hurdles within the existing organizations while realizing that disagreements may have structural underpinnings and are not personal in nature. A better understanding could help the employees in their negotiations with employers or facilitate their transition to other firms or to entrepreneurship.

Theoretically, the paper adds a contingency to the traditional view that complexity is a barrier to knowledge diffusion (Fleming and Sorenson, 2004; Sorenson, Rivkin, and Fleming, 2006; Williams, 2007). Even though complexity may prevent spillovers to rivals through mobility, I show that complex knowledge can still flow to new firms. Such a finding is important given that employee entrepreneurship has a detrimental effect on parent firm performance (Campbell *et al*., 2012; Phillips, 2002; Wezel *et al*., 2006). The results also imply that the assignment of a technological task can facilitate or inhibit the transition to entrepreneurship. The study thus provides a step towards a 'contextual' theory of entrepreneurship (Aldrich and Fiol, 1994; Elfenbein, Hamilton, and Zenger, 2010; Shane, 2000; Sørensen, 2007; Sorenson and Audia, 2000; Stuart and Sorenson, 2003). Such a 'contextual' approach to entrepreneurship suggests that entrepreneurial outcomes may be driven by knowledge or organizational context as opposed to entrepreneurial traits (Busenitz and Barney, 1997; Sarasvathy, Simon, and Lave, 1998). This focus on the context as a driver of entrepreneurship extends and complements the dominant theories of entrepreneurship (Kirzner, 1997; Sarasvathy, 2001; Shane and Venkataraman, 2000).

THEORETICAL FRAMEWORK AND HYPOTHESES

Knowledge has been identified as one of the most strategically important resources of a firm (Grant, 1996; Kogut and Zander, 1996; Nickerson and Zenger, 2004). According to this view, knowledge is generated and held by individuals and applied to the production of goods and services through the coordination facilitated by the firm. Similarly, I assume that while solving technological problems, inventors acquire knowledge. I conceptualize their knowledge as a set of recipes (Dosi and Grazzi, 2010; Nelson and Winter, 1982; Sorenson *et al.,* 2006). These recipes include the 'list of potential ingredients [that] encompasses both physical components and processes' and 'details [about] how to combine these ingredients' (Sorenson *et al.,* 2006: 997) or a 'set of actions that need to be taken to achieve the desired outcome' (Dosi and Grazzi, 2010: 173). In my context, for instance, an inventor may have acquired knowledge of how to design a semiconductor device with certain specifications. It is possible that the codified part of the recipe is complemented by an important tacit knowledge (Agrawal, 2006; Lowe, 2002; Polanyi, 1983) that cannot be codified but is embodied in the practice of the individual (Nelson and Winter, 1982).

Employees not only acquire and hold knowledge but also carry it across organizational boundaries. Employee entrepreneurship and mobility have both been recognized as critical drivers that mitigate the difficulties associated with the transfer of knowledge. The literature on employee entrepreneurship emphasizes that founders with prior work experience in the focal industry bring with them highly relevant industry-specific knowledge (Agarwal *et al*., 2004; Freeman, 1986; Klepper and Sleeper, 2005; Phillips, 2002). Similarly, the literature on mobility shows that mobility is a key driver of knowledge diffusion across existing organizations (Marx, Strumsky, and Fleming, 2009; Rosenkopf and Almeida, 2003). Importantly, the recipient firms 'learn by hiring'—the knowledge brought in by mobile inventors diffuses throughout hiring firms (Singh and Agrawal, 2011). The robust implication of the employee entrepreneurship and mobility literatures is that employees carry knowledge that is valuable across organizations.

Transfer of complex knowledge

Building on the notion that knowledge is a key resource, the prior literature has conceptualized the creation of knowledge as a search for new recipes over a space of possible combinations of ingredients (Nelson and Winter, 1982) or as a search over a problem landscape (Nickerson and Zenger, 2004; Sorenson *et al*., 2006). Consistent with this approach, the knowledge brought into the recipient organization may need to be adapted (Williams, 2007). The received recipe, combined with the existing recipes of the hiring organization, provides a starting point for subsequent searching.

Perceiving knowledge as a recipe, Sorenson *et al*. (2006) develop a logic connecting complexity with the knowledge diffusion across actors and organizational boundaries. According to this view, the innovative search for new recipes takes place in a rugged landscape, with ruggedness being analogous to complexity (Kauffman, 1993; Levinthal, 1997). The rugged landscape is a 'problem space' searched by agents, who are, in the context of the current research, individual inventors solving a given technological problem. The agents are assumed to be bounded in their ability to search this space and, thus, have to search for the solutions by iterative experimentation—that is, by a local search. As the ruggedness of the space increases, the problem becomes more difficult to solve (Rivkin, 2000). The boundedness of the agents' search behavior may lead to 'lock-in,' or a cessation of searching before the best recipe is found. Kauffman (1993) showed that the ruggedness (complexity) of a problem space increases with the density of interdependencies between individual components—i.e., between the ingredients of the recipe.

The transfer of complex knowledge is also prone to difficulties. Rivkin (2000) showed theoretically that, because of interdependencies, even small errors in the transfer process can lead to large performance penalties. To be functional, complex recipes either have to be kept intact or a coordinated change in multiple ingredients needs to be performed to improve the existing recipe (Rivkin and Siggelkow, 2002). Transferring complex knowledge thus imposes greater coordinative challenges (Grant, 1996; Nickerson and Zenger, 2004). Because complex recipes may embody knowledge of many interacting ingredients, a higher proportion of such knowledge may be tacit, which further complicates the knowledge coordination and transfer. Additionally, the number of local optima and the variance of their performance increase with complexity (Fleming and Sorenson, 2001; Levinthal, 1997), which could make the *ex-ante* evaluation of outcomes associated with subsequent searches more uncertain (Gavetti and Levinthal, 2000).

Consequently, the transfer of a complex recipe and, in particular, the transfer between its carrier and other parties, may be ineffective. Consistent with such a view, studies have reported that the complexity of knowledge inhibits its transfer to other contexts (Sorenson *et al*., 2006; Williams, 2007). However, it is possible that complexity also affects the coordination, transfer, and exploitation of knowledge within existing firms. This may lead to differences between the mechanisms of knowledge transfer as they operate through employee entrepreneurship and mobility. Knowledge complexity may affect not only which knowledge is absorbed by other actors but also the knowledge that is exploited within original firms. To examine these differences, I combine the logic connecting complexity and knowledge diffusion (Sorenson *et al*., 2006) with the notions of employee mobility and entrepreneurship, occurring individually and in teams.

Knowledge complexity and the use of knowledge within existing firms

The mechanisms operating within the source firm will determine the set of recipes that individuals acquire and potentially transfer to other organizational settings. Importantly, these mechanisms may also determine which recipes are *used* by the existing organizations. In an early work, Freeman (1986) argued that individuals working for incumbent firms have the opportunity to learn about badly served markets. Their parent organizations fail to exploit these opportunities because they lack speed or are unable to allocate resources efficiently. The more recent modeling literature suggests that employees may prefer not to disclose certain inventions (Anton and Yao, 1995) or they may discover new ideas through exploratory searching, which will remain unrewarded by the incumbent firm (Hellman, 2007). Further, the presence of opportunities (i.e., unused recipes) has been attributed to intrafirm frictions in knowledge transfer (Franco and Filson, 2006),

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underexploitation of knowledge (Agarwal *et al*., 2004), or information asymmetries (Klepper and Thompson, 2010). The overarching implication of this literature is that profitable, unexploited opportunities exist in organizations. I proceed to explore how knowledge complexity affects the likelihood that a new recipe discovered by an inventor is not utilized by the original firm.

When solving a complex problem, inventors search a landscape that is rugged—has many peaks and valleys (Kauffman, 1993). In such a case, the implementation of a newly discovered complex recipe requires a coordinated change in multiple ingredients relative to the currently used solution. When the problem is simple, the peaks are clustered together—discovered recipes differ from each other only by a few ingredients (Kauffman, 1993; Rivkin and Siggelkow, 2002). When the problem is complex and the ingredients have dense interactions, then peaks are distributed across the search space—searching inventors may discover recipes that are more distant from the currently used one. Even though the newly discovered recipe may represent improvement over the recipe currently used by the incumbent firm, the firm may be unwilling to make the transition. The coordinated change of many ingredients may interfere with complementarities across projects (Cassiman and Ueda, 2006), and the firm may view the new recipe as inconsistent with its long-term strategic direction (Gavetti and Levinthal, 2000). Prior theoretical work (Cassiman and Ueda, 2006) showed that, even when the new project itself is viable, it is not necessarily optimal for the firm as a whole. Due to a lack of complementarities with other existing projects, the firm may willingly let the new project be exploited by others. The challenge to make the coordinated changes may be even more pronounced when the inventor has a specialized knowledge and discovers a new but only partial complex recipe (Dosi and Grazzi, 2010). The complementary parts of the existing recipe residing within the firm may be inadequate for the newly discovered recipe due to the interdependencies. The firm needs to perform further searches to find the new complementary pieces of the recipe, imposing additional burdens and increasing the likelihood that the recipe will not be used.

There are additional mechanisms that may amplify the relationship between the knowledge complexity and the potential for employees to acquire unused recipes. The actual use of the discovered recipe by the incumbent firm requires a transfer of knowledge from the inventor to other individuals within the firm. Attributes of complex knowledge, including its sensitivity to small errors, tacitness, and uncertainty may increase the likelihood that the parent firm will be unable to evaluate and adapt the knowledge effectively. The transfer ineffectiveness may be further amplified by the fact that the newly discovered complex recipe is likely to be distant from the currently used one.

The arguments above suggest that, in the repertoire of acquired recipes, an inventor solving complex problems is more likely to have a recipe that will not be used by her employer. Importantly, the acquired knowledge—consisting of both used and unused recipes—can be valuable in other contexts. The recipes can provide the seed for subsequent searches within another firm.

Knowledge complexity and employee mobility

From the recipient organization's perspective, the purpose of hiring a new individual from another firm is the potential gain from knowledge diffusion (Singh and Agrawal, 2011). Such knowledge could consist of the recipes that were both used and unused by the original firm. However, key to the value creation potential of the employee to the recipient firm is whether such recipes can be gainfully exploited within its own organizational boundaries.

For established firms, one barrier to exploiting these recipes is based on the fact that the situations in the original and the potential recipient firm are analogous. The existing organization has an ongoing operation that relies on coordination of its existing knowledge. The incoming recipes may need to be adapted for solving new problems, or they need to be integrated with existing recipes (Sorenson *et al*., 2006; Williams, 2007). The adaptation and integration process leads to a new search. The coordinated changes necessary to improve or implement successfully the complex recipes brought in by the mobile inventor may be problematic given the constraints imposed by the existing activities of the hiring firm or the pursuit of complementarities. The ability to perform the search also requires a transfer of knowledge between the newly hired individual and other parties within the hiring firm. Because of the sensitivity to small changes of the ingredients, the

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tacit nature of the knowledge, and the uncertainty associated with subsequent outcomes, the complexity of the knowledge may render such a transfer difficult. As a result, the existing organizations are likely to experience difficulties when adapting complex knowledge originating outside their organizational context for their own use (Hoetker and Agarwal, 2007; Williams, 2007). Further, the ability of the organization to learn from the newly hired individual may be negatively affected by the knowledge complexity. Singh and Agrawal (2011) show only limited diffusion of the hired inventor's knowledge within the recipient organization. The attributes of complex knowledge likely further inhibit such 'learning-by-hiring' and decrease the ability of an organization to diffuse efficiently the knowledge within its structures.

Consequently, implementing complex recipes into existing organizations is difficult. Even though inventors solving complex problems may acquire recipes that are not used by their original employers, the recipient organizations may be unable to take advantage of them either. The ability of existing organizations to absorb any kind of complex knowledge—used or unused by the original firm—is constrained. The efficiency with which the potential recipient firms can exploit the knowledge carried by the inventors in turn affects the mobility choices that the inventors face. As shown by the modeling literature (e.g., Anton and Yao, 1995), the viability of outside alternatives affects exit and mobility decisions. Consistent with the logic of these models, the complexity of recipes that inventors carry is likely a barrier limiting the number and scope of job alternatives that would-be mobile inventors have. In other words, the complexity of the entire knowledge held by the inventors may be a more important determinant of their mobility options than the fact that they hold some potential entrepreneurial ideas. Such a mechanism leads to the following prediction:

Hypothesis 1. An employee is less likely to move to a rival firm as the complexity of the employee's knowledge increases.

Transfer of complex knowledge and team mobility

Multiple studies have shown that technological problem solving and innovation is increasingly a team phenomenon (Singh and Fleming, 2010; Wuchty, Jones, and Uzzi, 2007). The trend is consistent with the view that production requires both knowledge specialization (Grant, 1996; Kogut and Zander, 1996) and the technological recipes to be distributed among multiple parties (Dosi and Grazzi, 2010). However, keeping the distributed nature of knowledge constant, there may be higher or lower levels of interdependencies between the knowledge ingredients held by different individuals. For distributed but less complex recipes, i.e., when the interdependencies are low, inventors may still be able to move individually and to transfer recipes effectively.

When the recipe is not only distributed among multiple individuals but there are also interdependencies between its components, then transfer of a partial recipe carried by a single individual may be ineffective.[2] The recipient organization needs not only to adapt the incoming knowledge for its own use but also to provide complementary parts of the recipe for its basic functionality. When only a partial complex recipe is transferred, the need for a tight coordination between the ingredients held by the hired individual, and existing knowledge within the hiring organization may substantially complicate the use of this knowledge. The coordinative challenge (Grant, 1996; Nickerson and Zenger, 2004) associated with the use of complex knowledge is more pronounced when the incoming recipe is partial. The transfer of knowledge between the newly hired individual and the organization has to occur. The ability of the recipient organization to match the partial recipe carried by the inventor with complementary knowledge will be hindered by the attributes of complex knowledge—its tacit nature and outcome uncertainty.

The solution to this problem could be movement of a larger proportion of the recipe as embodied in the joint mobility of a collaborating team. When the knowledge is complex, the recipient organizations may look to hire teams of innovators rather than individuals. Team mobility provides parallel channels for knowledge transfer—minimizing the impact of tacitness and transfer errors. Team

[2] The argument implies that knowledge complexity and the distributed nature of knowledge are separate drivers of team mobility. Also note that Hypothesis 1 implies that complexity inhibits mobility directly and not only through its effect on team size. Empirically, I control for the size of inventor teams. I thank an anonymous reviewer for these insights.

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movement allows groups of collaborators to remain intact, maintaining communication routines and social interaction developed while working at the parent firm and retaining the coordination that is critical for implementing and improving complex recipes. In other words, team mobility allows the retention of team-specific private knowledge that emerges due to interdependencies and that would be lost if inventors moved individually or if the team dissolved (Fortune and Mitchell, 2012; Hoetker and Agarwal, 2007).

Consequently, team mobility mitigates the detrimental effect of complexity on knowledge transfer. The inventor teams may be incentivized by recipient organizations to move together, and the likelihood of observing team mobility should increase with knowledge complexity:

Hypothesis 2. An employee is more likely to move to a rival firm with coworkers relative to individually as the complexity of the employee's knowledge increases.

Knowledge complexity and employee entrepreneurship

Scholars have explained employee entrepreneurship as driven by parent-firm frictions that lead to unexploited, profitable opportunities (Franco and Filson, 2006; Freeman, 1986; Hellman, 2007; Klepper and Thompson, 2010). As I propose above, knowledge complexity can serve as an additional friction, increasing the likelihood that an inventor acquires a recipe that is not used by her employer. The unused recipe could provide the seed for a subsequent search within a new firm.

Consider the case of Garmin—a manufacturer of consumer-oriented global positioning systems (GPS). While working on aerospace navigation, AlliedSignal employees Gary Burrell and Min Kao realized that it is possible to design a GPS system targeted at the consumer market. AlliedSignal liked the idea but felt that it did not fit with the company's identity as an aerospace products manufacturer, leading to the founding of Garmin, Inc. (Corporate History). Similarly, Federico Faggin identified that significant improvements to the Intel 8080 architecture were possible. However, he left Intel and founded Zilog because "Intel, still in 74, was a memory company. Microprocessors always were taking second . . . second best . . . and I felt not appreciated, frankly, at Intel."[3] Both of these examples illustrate that, even though the inventors discovered viable solutions to complex problems, their employers did not want to change their current activities and fully commit to the proposed ideas.

But just as transferring complex knowledge to another existing firm is problematic, exploiting complex knowledge through entrepreneurship raises potential difficulties. The question is whether the factors that prevent the exploitation of complex recipes by existing organizations are potentially mitigated in cases of employee entrepreneurship.

When the complex recipe does not need to be integrated into an existing structure, there are no trade-offs driven by the complementarities with existing activities. Coordinated changes necessary to improve or implement the recipe do not interfere with current strategies, and the complex recipe can serve as the foundation of a new organization. The knowledge coordination that is associated with the use of complex knowledge is, thus, less challenging in a new organization. Entrepreneurs also create and optimize their new organization to exploit the knowledge they bring in, assembling complementary assets that match the opportunity they pursue (Freeman, 1986; Wezel *et al*., 2006).[4]

Further, the carrier of knowledge controls the firm so there is no need to convince other managers about proposed changes or the viability of ideas. That being said, the start-up founders still face a bottleneck in the form of external funding. There is again evidence, however, that existing firms' managers evaluate ideas differently than do venture capitalists (VCs) (Dushnitsky and Shapira, 2010), and VCs fund many projects that incumbent firms have rejected (Kenney and Florida, 2002). In particular, the projects that are rejected by existing firms because they do not fit with their current activities may be very attractive targets for VC funding. Managers of existing firms evaluate ideas

[3] Interview with Federico Faggin, Stanford University, March 3, 1995. http://silicongenesis.stanford.edu/transcripts/faggin.htm [June 18, 2009].

[4] This argument assumes that such complementary assets are available, being either transferred from an incumbent firm (e.g., human assets) or bought on the market. If the necessary complementary assets are not available, employee entrepreneurship is very difficult. For instance, Mitchell's (1991) study of the diagnostic imaging industry showed a persistent advantage for incumbents due to their dominance of distribution channels.

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by considering trade-offs with existing activities while such considerations are less likely to be present in an evaluation by an independent VC. Further, VC funding decisions are based on a broad range of characteristics, going beyond the evaluation of a specific idea and including recommendations, the backgrounds of founders, market conditions, and general attractiveness of the technological domain (Kenney and Florida, 2002). Consequently, VCs may fund the exploitation of a complex recipe even though they may be unable to perfectly evaluate the prospects of the recipe itself.

Although the ability to transfer complex recipes to other organizations decreases with complexity, the challenges are mitigated when a new organization is established to exploit the complex recipe. Further, in the repertoire of acquired recipes, individuals solving complex problems are more likely to hold recipes that are not used in their existing organizations. Both of these factors favor exploitation of complex recipes by establishing a new firm relative to moving to a rival firm:

Hypothesis 3. An employee is more likely to start a new venture relative to move to a rival firm as the complexity of the employee's prior knowledge increases.

Transfer of complex knowledge and team entrepreneurship

In light of the fact that the relevant knowledge is likely distributed among collaborating individuals (Singh and Fleming, 2010; Wuchty *et al*., 2007), the interdependence between the ingredients held by different individuals creates similar challenges for the transfer of knowledge to a new organization as it does for the transfer to an existing one. The founder, who may be the carrier of a partial recipe, needs to assemble a team of individuals holding complementary pieces of knowledge while achieving the tight coordination necessary for implementing the complex recipe. Analogous to the situation of when the recipient is an existing firm, the attributes of complex knowledge may render the founder's search for complementary ingredients problematic. The solution, again, may be to found the firm together with individuals who helped to co-develop the complex recipe within the incumbent firm.

The critical difference between team mobility and team entrepreneurship, however, is that in cases of entrepreneurship the organization is assembled afresh. The founding team members not only serve as important complementary assets for determining the survival of the new venture (Eisenhardt and Schoonhoven, 1990), but they also allow the coordination developed while collaborating within the parent organization to continue. In cases of team mobility to an existing organization, the recipient firm needs to integrate the entire team while facing a dual challenge—maintaining the coordination within the team and adapting their knowledge to match the existing activities. Importantly, the adaptation of the incoming complex recipe may change the optimal configuration of the existing team and render some individuals unnecessary. The recipient organization may also already own the complementary pieces of knowledge and may be unwilling to duplicate them by hiring individuals with similar knowledge.

The characteristics of complex knowledge, including its tacitness, difficulties in evaluation, and uncertainty may further inhibit the ability of the recipient organization to absorb a larger team. The recipient organization may have difficulties understanding when it is necessary to hire the complementary parts of the knowledge embodied in different individuals.

Extending the examples above, Federico Faggin started Zilog in 1974 with Ralph Ungerman, who worked as a manager for him while at Intel.[6] If Mr. Faggin had decided to pursue his ideas within another organization, the exit of Mr. Ungerman may not have occurred. Integration of Mr. Faggin's knowledge with the knowledge of a recipient organization may have rendered the team move unnecessary. The recipient organization could have provided similar resources, and the team move based purely on the fact that they had worked together before would have been harder to justify.

Consequently, (1) the knowledge complexity increases the likelihood of team entrepreneurship, and (2) the effect of complexity on team entrepreneurship is likely more pronounced relative to its effect on the mobility of teams across existing organizations:

Hypothesis 4a. An employee is more likely to found a firm with coworkers relative to individually as the complexity of the employee's knowledge increases.

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Hypothesis 4b. The effect of the employee's knowledge complexity on team founding relative to individual founding is greater than its effect on team mobility to rival firms relative to individual mobility.

METHODS

Industry context and data description

The context of the study is the U.S. semiconductor industry. This industry exhibits a high degree of employee entrepreneurship and mobility; and prior studies have documented that such mobility facilitates interfirm transfers of knowledge (Almeida and Kogut, 1999; Singh and Agrawal, 2011). Firms in this industry have a high propensity to file patents (Hall and Ziedonis, 2001), a characteristic that allows construction of a patent-based measure of complexity (Fleming and Sorenson, 2001, 2004). The semiconductor industry is also ideal for these research purposes because of its focus on complex technological innovation (Macher *et al*., 1998). Following the shift of the U.S. semiconductor industry post-1990 to 'fabless' firms that design semiconductors and outsource manufacturing, entry became relatively easy, which further fostered innovation (Macher *et al*., 1998).[5] The critical complementary assets required in new design firms were highly mobile human assets (Campbell *et al*., 2012; Teece, 2003). When critical complementary assets are not locked into incumbent firms, the entrepreneurial ideas can be more easily transferred to other organizations. Such characteristics highlight the importance of knowledge as a determinant of entrepreneurship and mobility patterns and provide an ideal setting for this study.

Empirically, I trace the innovative activities of 649 U.S. semiconductor firms over a three-decade period, 1973–2003. The construction of the sample is analogous to that in prior studies on mobility (Agarwal *et al*., 2009; Rosenkopf and Almeida, 2003) in that firms that were potential *sources* of inventive talent were distinguished from firms in the industry that were potential *recipients* (rival incumbents and start-ups). The source firm sample consists of large publicly traded U.S. firms that (1) competed primarily in semiconductor product markets and (2) were founded prior to 1995. Restricting attention to firms that were public by the mid 1990s ($n = 136$) allowed a sufficiently long window through which to view possible mobility and employee entrepreneurship events. Focusing on large public firms as potential sources of employee mobility and entrepreneurship events was necessary to allow for firm-year fixed effects. Only firms that have inventors with different observable outcomes (staying vs. mobility, mobility vs. entrepreneurship) in the same year can be used in the estimation. This restrictive empirical design allowed me to isolate the effects at the individual inventor level and control for existing explanations of employee entrepreneurship and mobility that operate at the firm or regional level (Agarwal *et al*., 2004; Almeida and Kogut, 1999; Klepper, 2007). To assemble a larger pool of potential recipients of inventive talent in the industry and to maximize the likelihood of observing employee entrepreneurship and mobility events within the industry, the recipient firm sample includes all firms from the source firm sample and the following: (1) using the Venture One database, I added semiconductor firms that were founded between 1980 and 2003 ($n = 454$), and (2) using Compustat, I added firms in the industry (SIC 3674) that went public between 1995 and 2003 ($n = 59$).

Since I was interested in an inventor-level analysis, but USPTO patent data do not provide a unique individual identifier, I reconstructed individuals' patenting histories via a matching algorithm described in Agarwal *et al*. (2009) that creates inventor patenting and employment histories. This algorithm identifies 28,123 unique names listed in patents awarded to firms, of which 25,339 appear in the source firm sample. Employee mobility was observable only when an inventor patented at both a source and a recipient firm. This restriction eliminated 14 incumbent and 188 start-up firms.[6] The final recipient sample therefore includes 266 private start-ups and 181 incumbent public firms. The matching algorithm yields 1,166 mobility events.

[5] Only 3 percent of the sample are post-1990 entrants that established a foundry. Excluding these firms from the sample does not alter any of the results.

[6] The disproportionate omission of start-ups is not surprising. Many start-ups in the larger sample failed or were acquired at very young ages, which reduced the likelihood of observing patent awards for them.

Searching press releases in Lexis-Nexis, analyzing archived websites of the recipient firms (www.archive.org), and utilizing several online resources (e.g. smithsonianchips.si.edu) enabled the identification of the founders of the recipient firms. Since I was interested in how individuals' past patenting shaped the emergence of new firms, I needed to identify inventor-founders—those whose ideas led to founding start-ups—and not simply early 'board members'. Consequently, I defined founder status stringently, requiring the word 'founder' or 'cofounder' to appear with the person's name on either the archived corporate website (as early as possible after the year of entry) or in early press releases or industry materials. To look at how prior inventive activity affected the decision to start a new firm, I matched the founder names (after verifying and cleaning the matches using Lexis-Nexis and corporate websites to reconstruct precisely founder employment histories) with the source-firm pool of 25,339 inventors. Using this procedure yielded 141 inventor-founders who originated from 49 source firms and founded 114 start-ups. Of these, 10 were started by groups of 3 inventor-founders, 19 by groups of 2 inventor-founders, and the rest by single inventor-founders. It is important to note that the identification procedure did not require a founder to be an inventor at the start-up. He or she only needed to appear as an inventor in the source-firm sample. Further, spin-offs (i.e., incumbent firm divestitures) and start-ups receiving corporate venture capital from a parent firm in the industry, were excluded from the sample. Source-firm observations in which the focal firm exited within the next two years were also excluded. Finally, to avoid possible confounding effects, excluded were all mobility events that appeared to occur between firms linked by a merger or an acquisition event. For the combined set of firms, I integrated financial, founding, and exit year data from Compustat, Hoover's Business Directories, VentureOne, 10-K filings, and Lexis-Nexis with patent data from Delphion and the National University of Singapore.

Estimation strategy

I tested the hypotheses using discrete-time conditional Logit analysis, with the employee entrepreneurship or mobility events as the positive outcome. The models are estimated using pairwise comparisons (staying vs. mobility, mobility vs. entrepreneurship, etc.) that assume that mobility, staying, and entrepreneurship are independent, non-sequential choices.[7] The use of the firm-year fixed effects significantly simplifies estimation since all time-variant firm-level controls are absorbed in the time-variant, firm-fixed effect. To control for individual-level differences, I developed a set of patent-based measures. The sample was constructed as an unbalanced panel with the inventor-year observations. To check for the robustness of the results, I re-estimated the models using an alternative measure of innovation complexity and using the main patent class-time period fixed effects. The class-year fixed effect estimation hinges on comparing individuals who patent in the same patent class in the focal year. Using class-year fixed effects is a very stringent test because the estimation hinges only on the within-class variation of the complexity measure while all across-class differences are subsumed in the fixed effects. However, it addresses the concern that systematic differences across technological areas drive the results.

Variables

Dependent variables

The dependent variable for tests of Hypothesis 1 was *mobility*, a binary indicator set to 1 if an employment spell in a source firm in a focal year was followed by a move to a different firm in the recipient sample and 0 if the spell was followed by a further employment at the source firm. The variable *team mobility* (Hypothesis 2) was coded as 1 if the inventor patented together with the same co-inventor within the parent firm and the recipient firm and 0 otherwise (sub-sample with employee mobility = 1). For Hypothesis 3, the dependent variable was *employee entrepreneurship*. This binary variable was set to 1 if founding a start-up followed an employment spell in a focal year and 0 if joining a rival firm *or* further employment with the same firm followed (depending on the comparison group). The variable *team*

[7] The multinomial Logit could be an alternative method of estimation. However, pairwise estimation using conditional Logit is superior because it allows conditioning on firm year. The estimation passes the Hausman test of the IIA assumption with χ^2 of 0.039 suggesting that nested Logit is not an appropriate model.

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entrepreneurship (Hypothesis 4a) was coded as 1 if the inventor patented together with another inventor within the parent firm and both were listed as start-up cofounders and 0 otherwise (subsample with employee entrepreneurship = 1).

Main explanatory variable: knowledge complexity

Because a patent is essentially a codified recipe, the complexity of the patent can stand as a proxy for the complexity of the recipes the inventor acquired while working on the innovation. The density of interdependencies between functional components of a patent thus represents the density of interdependencies between recipe ingredients that the inventor holds. In keeping with prior work (Fleming and Sorenson, 2001, 2004; Sorenson *et al*., 2006), I measured knowledge complexity by relying on classification of patents into subclasses. The NK literature (Kauffman, 1993) shows that the ratio between K (the number of interdependencies per component) and N (the number of components) is the main driver of performance when solving complex problems.

In this research context, the measure of interdependence K is a single-industry measure analogous to the cross-sectional one used in prior studies (Fleming and Sorenson, 2001, 2004; Sorenson *et al*., 2006). It is based on the interaction matrix from Kauffman's NK model (1993). The key idea behind the measure is that when two underlying functions (represented by patent subclasses) are coupled, components belonging to these classes are more likely to occur in a single invention. If the functions A and B are highly coupled, if component a is classified in patent subclass A, $a \in A$, and if component b is in subclass B, $b \in B$, then one is more likely to see subclasses a and b in a single invention. In other words, high interdependence between A and B implies that whenever an inventor solves a problem related to one of these functions, she/he needs to redesign or include the coupled function as well, and the components optimizing these functions are likely to be observed together in a patent. Similarly, if the patent improves the architecture of multiple functions, all components that correspond to these functions are likely to be coupled to the architecture. On the other hand, if A and B are independent with respect to each other, A is likely to be combined with other subclasses without B being present.

The measure of interdependence K was computed in several steps. In the first step, I tabulated co-occurrence frequencies for all subclass combinations and also created a table of occurrence frequency for each subclass. Then, by selecting entries from the tables, I computed the interdependence K_i for each focal component (subclass) of patent l:

$$\text{Interdependence of subclass i} \equiv K_i = \sum_{j \in l_{-i}} \frac{\text{count of patents in subclasses } i \text{ and } j}{\text{count of patents in subclass } i} \quad (1)$$

where j belongs to all subclasses except i. The measure K for patent l is calculated as:

$$\text{Interdependence of patent } l \equiv K_l = \frac{1}{\text{count of subclasses of patent } l} \sum_{i \in l} K_i \quad (2)$$

E.g., when calculating the interdependence of the first subclass (a focal i), the interdependence between the first and the third subclasses is the number of patents in which the first and third subclasses appear together, divided by the number of patents in which only the first subclass appears.

Using a focal industry dataset to derive this measure relies on assuming stability in the nature of the interdependencies between the functional components of an innovation over time in the industry. The variable K_i thus captures the interdependence between functions A and B in general and not interdependence that is 'patent-specific'. In other words, the inventions are assumed to consist of components that have a certain level of interdependence associated with each pair of functions represented by observable components. If functions A and B appear on two patents, one in the beginning of the sample (in terms of calendar time) and another at the end, the interdependence between them would be the same. The assumption of the stability of interdependencies between the subclasses ('building blocks') is not entirely realistic, but assuming stability within an industry and a certain time frame is a necessary simplification. The measure of K is scaled consistently with the NK model since it is in the interval [0, $N - 1$].

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As has been done in prior studies (Fleming and Sorenson, 2001, 2004; Sorenson *et al*., 2006), I operationalized the total number of components N by the number of patent subclasses. Following the cited studies, I obtained the complexity measure by dividing the number of interdependencies K by the number of components N.[8] To obtain the final measure of knowledge complexity for a given inventor in a given year, I averaged the K/N for all patents awarded to the inventor in that year.

To verify the validity of the measure, I interviewed two industry experts. One is a professor of electrical engineering and a leading authority in semiconductor design at a top research institution, and the other is a senior designer holding a doctoral degree and multiple semiconductor patents. The experts were asked the following question:

> How would you describe the typical invention in a given patent class in terms of its complexity? I define inventions with low complexity as those that are composed of standardized components that are selected to optimize a given problem. There are few interdependencies (choice of one component affects performance of few other components) between components of these problems. I define inventions with high complexity as those that are composed of unique components that are selected or designed to optimize a given problem. There are many interdependencies (design of one component affects performance of many other components) between components of these problems.

The respondents answered 'high,' 'medium,' or 'low' for each of a series of patent classes that I identified. Then I aggregated the patents in my data into main classes and calculated average complexity based on the measure described above. Table 1 shows the correspondence between the measure and the expert opinions. This validation (a crude one, owing to the aggregation into main class domains) shows that the correspondence is relatively good, with a correlation of 0.63.[9] Both experts agreed with the general idea behind the measure, while mentioning that with complex problems, '*everything talks to everything on the chip*' and '*you need a close collaboration between the team members*.' Problems are simpler when '*things are standardized*' and '*you can draw boundaries around things*.'

To check the robustness of the results further, I developed an alternative specification of the measure. A possible concern was that the averaging produced biases in the measure. To address this concern, in Equation 1, I replaced the summation with Max(*count of patents in subclasses* i *and* j/*count of patents in* i) and then, in Equation 2, I replaced 1/(*number of subclasses*) with Max(.), yielding the most frequently co-occurring subclass pair over all subclasses and patents for the focal inventor in a focal year as a proxy for innovation complexity.

Control variables

Beyond the firm-year or patent class-year fixed effects, all models included a set of control variables. To control for individual heterogeneity, I introduced variables capturing inventor quality or other differences that might affect an individual's propensity to engage in mobility or employee entrepreneurship and correlate with knowledge complexity. I calculated an inventor's *patenting productivity* as the log of the number of patents the focal inventor applied for at the source firm divided by the tenure at the source firm and *patenting quality* as the number of citations the focal inventor received within the next five years divided by the number of patents at the source firm. To supplement the individual quality controls and to capture gender and race differences in propensity to exit focal firms (Kim and Marschke, 2005), I created the variable *female*, which is coded as 1 if the first name on the patent application sounds female and 0 otherwise, and the variable *nonwhite*, which is set to 1 if the first and last names on the patent application do not sound of Anglo-Saxon origin, and 0 otherwise. To control for whether the inventor works in

[8] Alternatively, one could specify the model using N, K, K/N and their squared terms (Fleming and Sorenson, 2001). However, using only K/N parsimoniously captures the effect of the full set of variables, and the robustness checks showed that a fully specified model yielded identical results.

[9] The crudeness of the aggregation into main classes does not allow using the expert ranking in the estimation.

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Table 1. Knowledge complexity: measure versus questionnaire

#	Patents aggregated by main class (domain)	Complexity measure (mean)	Questionnaire (average over two respondents, complexity is low: 1, medium: 2, high: 3)
365	Static information storage	0.084	1.5
711	Memory	0.092	1
323	Power supply	0.109	1.5
371	Error detection (circuits and process)	0.112	1
327	Non-linear circuits	0.114	2
713	Digital processing support	0.122	1.5
712	Processors	0.124	1
326	Digital logic	0.124	2
438	Semiconductor device manufacturing process	0.127	2.5
257	Active solid state device	0.129	1
710	Input/output data processing design	0.131	2
330	Amplifiers	0.131	3
395	Processing system organization	0.133	2
345	Graphics processing	0.158	1
331	Oscillators	0.176	3
375	Pulse and digital communication	0.179	2.5
324	Measure and testing circuits	0.180	2
360	Magnetic storage circuits	0.182	3
348	TV circuits	0.218	2
702	Data processing calibration systems	0.237	3
250	Radiant energy (photocells)	0.238	2.5
379	Telephonic communication circuits	0.287	3
	Correlation = 0.63		
	(Both experts assigned the same score to 15 out of 22 categories)		

the core versus niche technological area within the firm, I included the variable *proximity to firm core*. It is calculated as the angular distance (Jaffe, 1989) between the 'technology' vectors of the focal inventor and all other inventors in the parent firm in the focal year. Each dimension of the vectors is calculated as the proportion of the patenting in a focal main class over the focal year. Further, I included the variable *co-inventors* by calculating the log of the average number of patent co-inventors at the source firm in a given year for the inventor and *patenting breadth* by calculating the log of the average number of patent main classes for the inventor in the focal year to capture an inventor's specialization. The variable *tenure*, measured as the log of the difference between the focal year minus the application year of the first patent within the given parent firm plus one, proxies for the intra-firm experience of the inventor. It is also possible that differences in the opportunity space, both for mobility and employee entrepreneurship, vary with knowledge complexity. Employees may exit to pursue general opportunities in a given area rather than to exploit their own complex knowledge. To control for these differences, I introduced variables that rely on the firm entry and exit rates into a particular complexity segment. First, the complexity variable was split into ten equal-sized bins. The variable *domain attractiveness* was calculated as the firm entry rate within the same bin as the focal inventor and year. It is a ratio between the number of new firms entering with patents for which the complexity is on average in the same bin as the focal inventor's patents in the focal year and the total number of firms with patents applied for in the focal year in the same bin. Similarly, the variable *domain default risk* was calculated as the firm exit rate within the same bin as the focal inventor in the focal year. Only actual bankruptcies are considered as exits. It is a ratio between the number of firms failing with patents for which the complexity is on average in the same bin as the focal inventor's patents in the focal year and the total number of firms with patents applied for in the focal year in the same bin. Table 2 provides descriptive statistics, including correlations.

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Table 2. Descriptive statistics

	Mean	S.D.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Employee entrepreneurship	0.008	0.086	1.000													
(2) Mobility	0.025	0.158		1.000												
(3) Team entrepreneurship (emp. ent = 1)	0.49	0.506			1.000											
(4) Team mobility (mobility = 1)	0.129	0.336				1.000										
(5) Knowledge complexity	0.092	0.084	0.007	−0.017	0.010	0.090	1.000									
(6) Patenting productivity	0.107	0.634	0.010	−0.008	0.001	−0.003	0.010	1.000								
(7) Patenting quality	8.08	8.28	0.005	0.004	0.007	0.007	0.053	0.044	1.000							
(8) Female	0.027	0.162	−0.004	−0.014	0.002	0.008	0.005	−0.017	0.002	1.000						
(9) Nonwhite	0.262	0.439	0.013	0.026	0.014	−0.060	−0.001	0.047	−0.010	−0.059	1.000					
(10) Proximity to firm core	0.338	0.258	0.007	−0.002	0.004	−0.004	−0.039	0.234	0.118	0.007	0.061	1.000				
(11) Co-inventors (inventor team size)	0.949	0.561	−0.007	−0.045	−0.004	0.162	0.046	0.089	0.115	0.044	0.040	0.131	1.000			
(12) Patenting breadth	0.932	0.260	−0.007	−0.008	−0.009	−0.009	−0.083	−0.048	0.014	0.004	−0.058	−0.015	−0.032	1.000		
(13) Tenure	1.17	0.61	0.012	0.004	0.009	0.038	0.049	−0.020	0.069	−0.044	−0.049	0.094	0.012	−0.029	1.000	
(14) Domain attractiveness	0.172	0.146	−0.006	0.000	−0.002	−0.037	−0.066	−0.072	−0.057	0.003	−0.042	−0.073	−0.031	0.028	−0.055	1.000
(15) Domain default risk	0.013	0.056	−0.007	−0.009	−0.004	−0.029	−0.047	−0.018	−0.033	0.000	0.007	0.001	0.010	0.005	0.005	−0.121

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RESULTS

In Table 3, models 1–4 show the results of the analysis testing Hypotheses 1 and 2. The significant coefficients on the controls indicate that more productive employees and nonwhites are more likely to move to a rival firm, and female inventors are less likely to do so. The coefficients on the number of coinventors and patenting breadth are negative and significant in the mobility regression, suggesting that inventors embedded in collaborative networks and generalists are less likely to move. Further, tenure strongly predicts mobility. The variable ‘nonwhite’ is negatively associated with team mobility while the variable ‘co-inventors’ is positively associated with team mobility.

Supporting Hypothesis 1, in model 1 the coefficient on complexity is negative and significant. Interpreting the coefficient indicates that a one standard deviation increase in knowledge complexity causes the likelihood of employee mobility relative to staying to decrease by 13 percent. Consistent with Hypothesis 2, complexity significantly increases the likelihood of team mobility (models 2–4) relative to individual moves. An increase of complexity by one standard deviation increases the likelihood of team mobility as opposed to individual mobility by about 40 percent.

In model 5, tenure predicts employee entrepreneurship while the domain default risk is a negative and significant predictor. The variables ‘nonwhite’ and ‘female’ are positively associated with team entrepreneurship (models 7–8). In keeping with Hypothesis 3, the coefficient on knowledge complexity is positive and significant in model 5. One standard deviation increase in innovation complexity predicts a 28 percent increase in the likelihood of employee entrepreneurship rather than employee mobility. Model 6 provides an additional test of Hypothesis 3 by comparing employee entrepreneurship with staying at the existing firm and also shows a positive and significant relationship.[10] One standard deviation increase in knowledge complexity predicts a 17 percent increase in the likelihood of employee entrepreneurship relative to staying.

Consistent with Hypothesis 4a, knowledge complexity significantly increases the likelihood of team entrepreneurship (models 7–8) relative to individual entrepreneurship. An increase of complexity by one standard deviation increases the likelihood of team founding by about 55 percent. Using a direct t-test and the coefficient ratio test (Hoetker, 2007) to compare the coefficients of the conditional Logit models (model 2 was tested against model 7, and model 3 was tested against model 8) reveals that the coefficients on complexity for team entrepreneurship and team mobility are significantly different at the 5 percent level, supporting Hypothesis 4b.[11,12]

Tables S1 and S2 in the on-line appendix show the results of the robustness tests. I re-estimated all models using an alternative measure of knowledge complexity as described above and the main patent class-year fixed effect. The findings remain robust (Table S1 in the on-line appendix), at least at the 10 percent significance level. The coefficients and the coefficient ratios of the respective models comparing employee entrepreneurship and employee mobility in Table S2 in the on-line appendix remain statistically different at the 5 percent level.

DISCUSSION

Employee mobility is a vibrant channel for knowledge transfer. Similarly, employee entrepreneurship is widely heralded as an important driver of innovation, firm formation, and industry growth. Far less is known about how the knowledge context affects an employee’s propensity to engage either in employee entrepreneurship or mobility. I investigated how knowledge complexity affects the relative likelihoods of these outcomes and examined the additional factor of team movements. In

[10] We would need additional theoretical assumptions to predict this alternative test. The unconditional version of Hypothesis 3 can only hold if the benefits associated with exploitation of complex recipes through entrepreneurship outweigh the transfer difficulties as argued in Hypothesis 1. I thank an anonymous reviewer for this insight.

[11] Comparing coefficient magnitudes across groups in Logit assumes equal unobserved variance (Hoetker, 2007). Explicit tests of the equality of the unobserved variances is not available with non-nested samples or conditional Logit. A coefficient ratio test (Hoetker, 2007) between innovation complexity and more precisely estimated controls (nonwhite, co-inventors) was used and showed consistent results.

[12] Some compromises were necessary in the conditional Logit models of team entrepreneurship and mobility. To mitigate a substantial loss of observations some models include firm-period instead of the firm-year fixed effect. I.e. each combination of a firm and 5-year period was modeled with a fixed effect.

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Table 3. Individual and team mobility and individual and team employee entrepreneurship

Conditional FE Logit	Mobility (H1)	Team mobility (conditional on mobility) (H2)			Employee entrepreneurship (conditional on exit) (H3)	Employee entrepreneur-ship (unconditional)	Team employee entrepreneurship (conditional on entrepreneurship) (H4a)	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Dependent variable Positive outcome	Mobility	Same co-inventor(s) at source and recipient firms			Employee entrepreneurship		Firm founded with co-inventors	
Zero outcome	Staying	Different co-inventors at source and recipient firms			Mobility	Staying	Individual inventor founder	
Knowledge complexity	−1.809***	3.9468**	9.331**	10.463**	5.603**	2.617**	25.836**	24.28***
Patenting productivity	0.1503**	−0.008	−0.483	−0.408	0.491	0.344*	−0.606	−0.911
Patenting quality	0.003	−0.013	−0.041	−0.106	0.03	0.016	0.048*	0.007
Female	−0.841**	1.115	0.12	−0.864	−0.744	−0.49	11.208***	11.425***
Nonwhite	0.387***	−0.959	−1.224*	−1.761**	−0.164	0.28	2.007**	2.245*
Proximity to firm core	−0.249	0.05	0.569	0.36	0.244	0.172	2.82	2.999
Co-inventors	−0.359***	1.555***	1.652***	1.918**	0.186	−0.224	1.051	1.172
Patenting breadth	−0.338**	0.772	1.447	1.273	0.006	−0.485	−0.14	0.05
Tenure	0.23**	0.031	0.046	−0.110	0.972**	0.702***	−1.258	−1.144
Domain attractiveness	0.006	−0.381	−0.093	2.283	1.193	−0.522	1.876	2.493
Domain default risk	−0.161	−7.549	−2.156	5.472	−15.71*	−10.58**	−37.98	−38.05
Fixed effect level	Firm-year	Firm and period	Firm-period	Firm-year	Firm-year	Firm-year	Firm and period	Firm-period
Pseudo R-square	0.015	0.137	0.208	0.296	0.149	0.045	0.506	0.402
Log likelihood	−2811	−94.791	−64.178	−34.869	−85.36	−3940	−13.895	−11.501
N	32,731	544	301	153	296	13,088	63	42

*p < 0.1, **p < 0.05, ***p < 0.01, double-sided tests, errors clustered at the same level as the fixed effects. Five-year periods are used in Models 2, 3, 7, and 8. Knowledge complexity coefficients and coefficient ratios (with nonwhite and co-inventors) in model 2 vs. model 7 and model 3 vs. model 8 are significantly different at 5% (H4b).

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doing so, I shed new light on a theoretical mechanism that has received little attention, even though limited evidence and a significant body of modeling literature suggest its importance. The study highlights that the knowledge context may have wider implications for knowledge flows and industry structure.

Drawing on a uniquely rich database of employee entrepreneurship and mobility events and firm patenting in the U.S. semiconductor industry over three decades, I found that inventors' moves to rival firms decrease with the complexity of the work they have done (supporting Hypothesis 1). The finding is consistent with prior modeling and empirical literature suggesting that complexity inhibits knowledge diffusion (Rivkin, 2000; Sorenson *et al*., 2006; Williams, 2007). In keeping with Hypothesis 3, however, I found that the complexity of an inventor's prior patents positively affects the inventor's propensity to engage in employee entrepreneurship relative to both mobility to another firm and staying at the original firm. On one hand, transferring complex knowledge across organizational boundaries through employee mobility is problematic. On the other hand, exploitation of complex knowledge is more likely to occur within the context of a newly established firm. Transferring such knowledge to a new firm is easier and the individuals with complex knowledge may carry ideas that were not implemented in their prior organizations. Complexity also dramatically increases the likelihood that employees leave as a team, with this effect being stronger for employee entrepreneurship (Hypotheses 2 and 4a, b). Consequently, the departure of entire teams solving complex technological problems presents a serious misappropriation and competitive threat for incumbent firms (Campbell *et al*., 2012; Wezel *et al*., 2006). The employee retention strategies that incumbent firms employ against possible competitive entry of their employees are then particularly relevant when teams solve complex technological problems.

Further, the results of the study may partly explain the 'start-up phenomenon'—that in some settings, start-ups are more innovative, better performers than established firms (Agarwal *et al*., 2004; Ganco and Agarwal, 2009; Khessina and Carroll, 2008). At the same time, the findings suggest a new explanation for why inventors exiting to start their own firms are likely to have a more negative impact on source firm performance than inventors exiting to join rival firms (Campbell *et al*., 2012).

Limitations and alternative explanations

Both the limitations and the findings of the study present avenues for future research. Although the semiconductor industry represents a canonical context for examining my research questions, the single-industry focus may limit the generalizability of findings. In theory, I would expect knowledge complexity to be an important driver of employee entrepreneurship and mobility patterns in sectors characterized by high technological intensity and high innovation rates. Following this logic, the findings should generalize to other knowledge-intensive sectors. However, the results could be less generalizable to settings where the complementary assets are not easily transferrable across organizations (Campbell *et al*., 2012; Mitchell, 1991).

Since my empirical analysis hinges on the use of patent data to identify employee moves, the observations are necessarily restricted to instances in which an inventor was identified on a patent assigned to a source firm and identified as founder (employee entrepreneurship) or appeared as an inventor both in a source and a recipient firm (mobility). Missing from the sample, thus, are instances in which an individual may have had involvement with or general awareness of a developing technology, but no patent. Similarly, technologies that were in the initial stages of development but not patented prior to an employee's departure are not captured in the study. However, *a priori*, there is no reason to expect that knowledge complexity would differentially affect the behavior of inventors who are involved in technology development without being documented in patents.

The validity of the results hinges on the ability to rule out alternative explanations. The stringent empirical approach, control variables, and a multitude of robustness checks were used to isolate the effect of knowledge complexity from potential confounding factors like individual inventor quality or the heterogeneity in the opportunity space. For instance, higher-quality inventors may be more likely to solve more complex problems. To address this concern, I included multiple individual-level controls capturing inventor quality and characteristics. Prior research has shown that inter-firm mobility

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increases with the inventor's quality (Hoisl, 2007), which is consistent with my estimates on the patenting productivity. The fact that knowledge complexity is negatively associated with mobility should further alleviate the concern that complexity is a simple proxy for inventor's quality. One could also argue that future entrepreneurs self-select into complex domains in anticipation of entrepreneurial opportunities. Although I cannot completely rule out this conjecture, it implies significant foresight by the future entrepreneurs. They self-select into technological domains with more frictions and fewer outside mobility options. Existing studies (Garvin, 1983; Klepper and Thompson, 2010) have argued that inventors tend to disclose ideas to their employers and leave only when they are rejected. Such findings provide further evidence against the claim that future entrepreneurs self-select into complex domains because they anticipate entrepreneurship.[13]

CONTRIBUTIONS AND CONCLUSION

These limitations notwithstanding, the study makes several contributions. In the context of research on employee entrepreneurship (Agarwal *et al*., 2004; Klepper, 2007; Klepper and Sleeper, 2005), I develop a theoretical mechanism connecting complexity with the under-exploitation of knowledge by existing firms and the subsequent transition to entrepreneurship. The mechanism not only highlights an additional friction operating within existing firms but also helps to illuminate a key question in the study of entrepreneurship: 'why, when, and how some people and not others discover and exploit [entrepreneurial] opportunities' (Shane and Venkataraman, 2000: 218). Since entrepreneurial opportunities are more likely to reside in complex knowledge domains, employees working with such knowledge are better positioned to discover the opportunities. By focusing on the type of knowledge that inventors acquire while solving technological problems, I contribute to building a theory of entrepreneurship emphasizing that entrepreneurial decisions may be driven by knowledge or by organizational context (Agarwal *et al*., 2004; Aldrich and Fiol, 1994; Elfenbein *et al*., 2010; Sørensen, 2007; Sorenson and Audia, 2000). Such a theory implies that entrepreneurial propensities could be actively influenced by the assignment of tasks and the management of knowledge acquisition.

The study contributes to the literature on knowledge spillovers (Rosenkopf and Almeida, 2003; Singh and Agrawal, 2011; Sorenson *et al*., 2006). I show that, even though complex knowledge may not be readily imitated by other firms, it may still flow to startups through entrepreneurship. The study thus implies that the transfer of complex knowledge that is inhibited by the mechanisms operating within existing recipient firms can be overcome in appropriate organizational settings.

Further, I contribute to the recent literature on innovative teams (Singh and Fleming, 2010; Wuchty *et al*., 2007) by showing that retaining collaborative teams allows the transfer of acquired complex knowledge across organizational boundaries. It constitutes a step toward a theory in which collaborative work is an integral part in the discovery, exploitation, and transfer of knowledge.

Unique to this study is the combination of employee entrepreneurship, employee mobility, and complexity. Employee entrepreneurship and mobility are phenomena that have been typically studied in isolation. Examining them jointly as both driven by knowledge complexity allows for the gaining of insights about the mechanisms of knowledge exploitation and transfer. Extending the recent work that empirically tested the insights gained in agent-based models (Lenox, Rockart, and Lewin, 2010; Sorenson *et al*., 2006), I also contribute to the complexity literature by showing an empirical application of the modeling insights within a new context of entrepreneurship.

The study also has implications for the knowledge-based view of the firm (Grant, 1996; Kogut and Zander, 1996; Nickerson and Zenger, 2004). It highlights that mechanisms associated with knowledge coordination and transfer within original firms may lead to the generation of knowledge that falls outside of the boundaries of the firm when the problems are complex.

[13] I do not disentangle employee entrepreneurship that occurs with the approval of a parent firm from that which occurs without it. The arguments developed here should apply in both cases. Knowledge complexity increases the likelihood that individuals may discover recipes that will not be used by their parent firms—whether they leave with or without the firm's approval. One way of examining the two possibilities is to look at the variation as driven by the non-compete regimes (e.g. Marx *et al*., 2009), which I leave for future work. I thank an anonymous reviewer for this suggestion.

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In summary, I theorized and found evidence that the complexity of knowledge acquired while solving technological problems is an important driver of mobility and entrepreneurship decisions. The study sheds new light on an important contingency while revealing promising pathways for continued research.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

TABLE S1. Robustness Tests: Individual and Team Mobility.
TABLE S2. Robustness Tests: Individual and Team Employee Entrepreneurship.

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