THE EFFECT OF TECHNOLOGICAL COMPLEXITY ON INNOVATION PERFORMANCE, EMPLOYEE ENTREPRENEURSHIP AND MOBILITY: THREE ESSAYS

BY

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DISSERTATION

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ABSTRACT

Technological innovation, knowledge diffusion and employee entrepreneurship and mobility are closely related phenomena. Multiple literature streams in strategy, entrepreneurship and technology management focus on explaining them. However, relatively little is known about the micro-level variation in technological tasks as their driver. To improve our understanding of the role technology plays in these phenomena, I examine how the complexity of the technological problems that employees solve affects innovation performance and employees' choices about entrepreneurship and mobility. In essay 1 I examine whether modeling the innovative process as an iterative and adaptive search of boundedly rational agents is a valid approach. I develop a novel measure of technological complexity and empirically analyze how technological complexity affects innovation performance. In essay 2 I develop a model connecting attributes of technological tasks with the probability of idea rejection within incumbent firms. I show that rejection of profitable ideas within incumbent firms may occur without asymmetric information, incomplete contracts or resource constraints. In essay 3 I look at how technological complexity affects decisions to engage in employee entrepreneurship and mobility within the context of the U.S. semiconductor industry. The dissertation highlights a new driver of innovation patterns, knowledge flows and employee entrepreneurship and mobility with implications for firm performance and competitive dynamics.

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CHAPTER 1

INTRODUCTION

Technological innovation, knowledge diffusion and employee entrepreneurship and mobility are closely related phenomena. Multiple literature streams in innovation management, strategy and entrepreneurship focus on explaining them.

Understanding what drives successful innovations became a central concern of an eclectic body of research. Many scholars, dating back at least to Schumpeter (1934), propose to conceptualize innovations as novel combinations of existing resources (Schumpeter, 1934; Penrose, 1959; Nelson and Winter, 1982; Mahoney, 1995) or knowledge (Henderson and Clark, 1990; Galunic and Rodan, 1998). The more recent work on complex adaptive systems (Frenken, 2000, 2001a, 2001b; Fleming and Sorenson, 2001, 2004; Ethiraj and Levinthal, 2004; Murmann and Frenken, 2006; Sorenson, Rivkin and Fleming, 2006; Marengo, Pasquali and Valente, 2007) examines innovation by focusing on the process of searching for novel combinations. By means of analogy to the concepts of mutation and recombination in biology and to the associated NK modeling framework (Kauffman, 1993, 1995), the complexity scholars theorize that innovations emerge from bounded, iterative, trial-and-error searches for novel combinations of existing building blocks over a complex search space. Such a conceptualization of the innovative process is theoretically appealing since it provides an important counterpart to neoclassical economics models that may not capture real life dynamics due to the assumptions of equilibrium and strong rationality (Camerer and Fehr, 2006).

The notion of innovation is closely related to entrepreneurship. For instance, entrepreneurial ideas frequently originate within existing firms. An extensive body of work examines both antecedents and consequences of employee entrepreneurship (e.g Anton and Yao, 1995; Agarwal, Echambadi, Franco and Sarkar, 2004; Hellman, 2007; Klepper and Thompson, 2010).[1] Employee entrepreneurship has been heralded as a driver of innovation (Agarwal, *et al.*, 2004; Klepper, 2005), a critical source of new capabilities and heterogeneity in performance (Rosenkopf and Almeida, 2003; Agarwal, *et al.*, 2004) and an impetus to the creation and growth of industries and regional clusters (e.g. Klepper, 2001). Through employee entrepreneurship, the new venture not only inherits the industry-specific knowledge brought in by its founders (Agarwal *et al.*, 2004; Chatterji, 2009), but its strategies bear the imprinting mark of the founders' prior work experience (Klepper and Thompson, 2010).

Exploiting ideas identified while working within incumbent firms through employee entrepreneurship can be seen as a form of knowledge transfer. Similar to employee entrepreneurship, scholars have long recognized intra-industry employee mobility (i.e. post-exit joining of another firm within the industry) as a powerful engine for knowledge diffusion between established firms as well as between incumbents and startups (Almeida and Kogut, 1997; 1999; Rosenkopf and Almeida, 2003; Agarwal *et al.*, 2004; Agarwal, Ganco and Ziedonis, 2009).

At the heart of the issues above are questions that relate to the underlying drivers. *What factors affect the value of innovation, whether innovations are exploited or not and in which organizational setting*? *Are there any common drivers that affect all these phenomena*? Answering such questions in a coherent framework is important due to the inherent linkages between the creation and exploitation of knowledge that connect multiple levels of analysis. To investigate the possible common drivers of innovation performance, exploitation of ideas within

[1] Employee entrepreneurship is typically defined as the founding of a new venture by an individual who worked for an incumbent firm that operates in the same industry and has no ownership relationship with the new venture (Agarwal, Ganco and Ziedonis, 2009).

incumbent firms, employee entrepreneurship and mobility decisions, as well as the associated knowledge flows, I examine the role of technology.

The nature of innovation and knowledge required to solve technological problems may affect choices individuals make about how they exploit the knowledge. This may have important consequences for patterns of knowledge diffusion and competitive dynamics. The main focus of my dissertation is to contribute to a better understanding of how technology affects innovation patterns and the origins of employee entrepreneurship and mobility. More specifically, I study an area which has received relatively little attention - how the micro-level variation of the technological context affects innovation performance and how it shapes employees' entrepreneurship and mobility decisions. The prior studies suggest that technologically more advanced firms generate more entrepreneurs (Brittain and Freeman, 1980; Franco and Filson, 2006) and that underexploited technological opportunities may lead to employee entrepreneurship (Agarwal, *et al.*, 2004). Additionally, there is abundant anecdotal evidence revealing that employees often quit after their technological ideas are rejected by parent firms. For instance, Klepper and Thompson (2010) trace most of their cases of employee entrepreneurship in the early automobile, semiconductor and laser industries to disagreements about technological strategy. However, whether and how technology matters at a "finer grain" and how it affects employees' decisions to exploit their knowledge is less clear.

The key underlying driver of innovation performance and employee entrepreneurship and mobility decisions that I examine is the technological complexity of inventors' prior patenting activities within the incumbent firm. The technological complexity - being one of the key determinants of innovation performance dynamics - should also affect patterns of employee entrepreneurship and mobility. I model and measure complexity using the methodology of the

NK modeling literature (Kauffman, 1993; Levinthal, 1997; Rivkin, 2000; Fleming and Sorensen, 2001). Complex problems are those that have rugged optimization space due to dense interdependencies between individual component choices (Kauffman, 1993; Rivkin, 2000).

Technological complexity affects characteristics of knowledge at multiple levels. This makes its use as the main *contextual* variable of interest attractive in addition to the modeling tractability provided by the NK model. Technological complexity may not only affect the innovative dynamics within incumbent firms but also influence how such knowledge diffuses across firms. For instance, solving technologically complex problems may lead to breakthroughs (Fleming and Sorenson, 2001) but knowledge necessary to solve such problems is more tacit (Polanyi, 1983; Lowe, 2002; Agrawal, 2006), may require unstructured technical dialogue (Monteverde, 1995) and the solution outcomes are more uncertain (Fleming and Sorenson, 2001). The uncertainty associated with complexity may also lead to greater over-optimism when pursuing entrepreneurial decisions (Shane, 2002; Ziedonis and Lowe, 2006). At the same time, complexity may affect frictions in decision-making (Gavetti and Levinthal, 2000; Gavetti, 2005) and increase the likelihood of idea rejections at the parent firm (Klepper and Thompson, 2010). As a result, technological complexity appears to be a viable driver affecting not only innovations but also employee entrepreneurship and mobility decisions.

To provide an overview of the three essays and describe the overall study, I develop a conceptual framework connecting the individual essays through a common driver of technological complexity (Figure 1.1). Technological complexity is theorized to affect the performance of innovations and how the innovations are exploited. In the first essay, I examine the question of what is the best approximation of innovative process. The traditional approach of neoclassical economics often assumes full rationality and thus provides a polar opposite to the agent-based models that assume very limited rationality. Whether simplifying human behavior towards more rationality as in neoclassical models or less rationality as in agent-based models is more appropriate should be decided on the basis of the predictive powers of the respective models. To contribute to this discussion, I model the innovative process as an iterative experimentation using an agent-based model. The main question that I address is whether such approach is a valid approximation of the technological problem-solving. In particular, I use the NK model for predicting innovation performance.

Importantly, technological complexity matters at multiple levels. It affects whether opportunities are present and the ability of inventors to discover them. As a result, it may also affect how the opportunities are exploited. In the second essay, I rely on the notion that iterative and adaptive search of boundedly rational agents is a valid approximation of technological problem-solving. I use an agent-based model to examine the relationship between technological complexity and idea rejection within parent firms. My main question is what attributes of the underlying technological problems affect idea rejection within parent firms. These are factors that are driven by the technology itself and are separate from agency costs, asymmetric information or resource constraints - factors that have been examined in the prior literature (Anton and Yao, 1995; Cassiman and Ueda, 2006; Hellman, 2007; Klepper and Thompson, 2010). The core objective of developing the agent-based model is to isolate the effects of technological attributes like problem difficulty and technological breadth and show that rejection of profitable ideas may occur even in the absence of factors associated with asymmetric information, contract incompleteness or resource constraints. Could technological tasks that employees solve serve as an independent driver of idea rejection? What attributes of the tasks are relevant and what are their effects on idea rejection? Answering these questions is important since idea rejection is frequently assumed to be a precursor to employee entrepreneurship (Hellman, 2007; Klepper and Thompson, 2010). The empirical evidence suggests that employees frequently leave existing firms to start their own firms after they disclose ideas to their parent firms and these are rejected (Klepper and Thompson, 2010), they implement knowledge they encounter within parent firms (Bhide, 1994), and, more specifically, they have knowledge which is underexploited within these parent firms (Agarwal *et al.*, 2004).

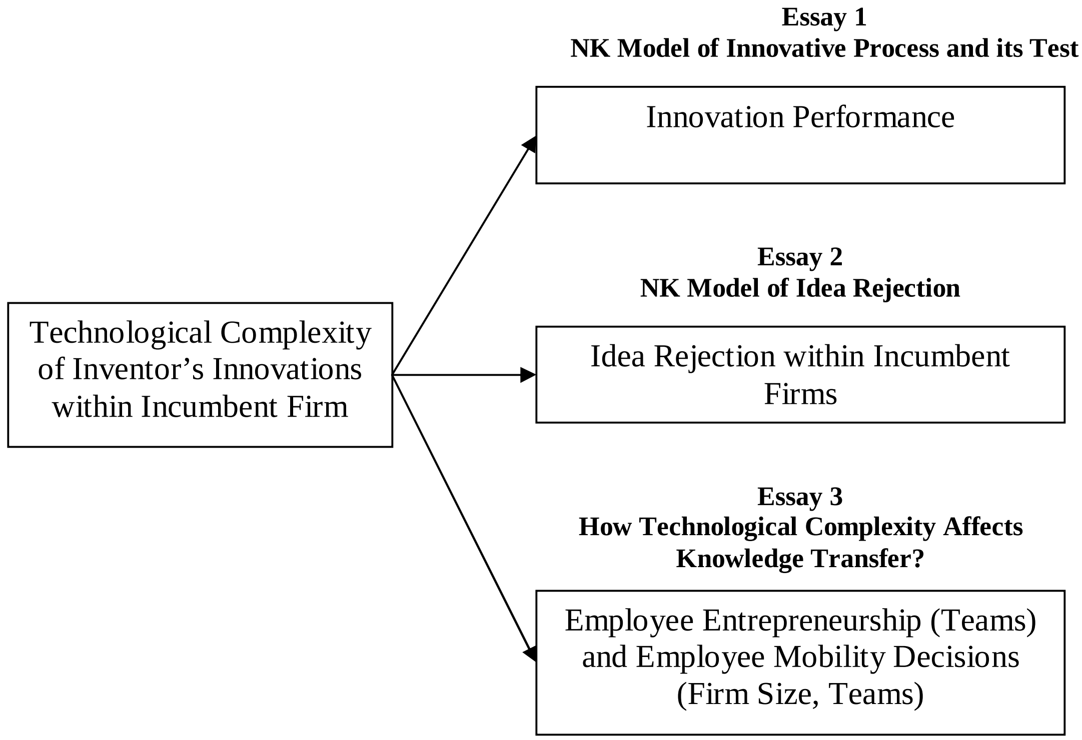
Technological complexity affects performance of innovations and whether these innovations are exploited from within the firms they originate. However, technological complexity also influences the characteristics of knowledge that is required for solving such tasks. Does it have implications for the ability of employees to transfer their knowledge and ideas and implement them outside of the incumbent firm? How important is the organizational setting of the recipient organization? Answering these questions is critically important for determining not only knowledge flows and mobility patterns but also competitive dynamics and industry structure. If more complex knowledge embodies more opportunities then who exploits them? Which firms are best positioned to absorb such knowledge and thus compete with the parent firm?

In the third essay, I address these questions by examining how technological complexity affects the ability of employees to transfer and replicate their knowledge in other organizational settings. I theorize that complexity affects underexploited opportunities that are embodied in knowledge carried by employees and also their ability to transfer such knowledge to other organizational settings. Such dynamics, in turn, affects employee exit choices.

In conclusion, the dissertation examines micro-level technological variation as an antecedent of innovation performance, idea rejection, knowledge flows and employee entrepreneurship and mobility. The phenomena represent multiple levels of analysis – innovation, individual inventor and incumbent firm. I connect these levels of analysis by studying a common driver of technological complexity. Such approach provides a unique opportunity to look at the creation and exploitation of knowledge in a coherent framework with implications for firm performance, knowledge diffusion and industry structure.

FIGURES

Figure 1.1
Technological complexity as a driver of innovation performance, project rejection and employee entrepreneurship and mobility decisions



CHAPTER 2

ESSAY 1: THE INNOVATIVE PROCESS AS A LOCAL SEARCH OVER A COMPLEX LANDSCAPE: EVIDENCE FROM THE DISK DRIVE INDUSTRY

INTRODUCTION

Understanding what drives successful innovations became central to an eclectic body of research. Many scholars, dating back at least to Schumpeter (1934, 1939), propose to conceptualize innovations as novel combinations of existing resources (Schumpeter, 1934, 1939; Penrose, 1959; Nelson and Winter, 1982; Mahoney, 1995) or knowledge (Galunic and Rodan, 1998; Henderson and Clark, 1990). More recent work on complex adaptive systems (Frenken, 2000, 2001a, 2001b; Fleming and Sorenson, 2001, 2004; Ethiraj and Levinthal, 2004; Murmann and Frenken, 2006; Sorenson, Rivkin and Fleming, 2006; Marengo, Pasquali and Valente, 2007) extends this view by focusing on the process of searching for novel combinations. By means of analogy to the concepts of mutation and recombination in biology and to the associated NK modeling framework (Kauffman, 1993, 1995), the complexity scholars theorize that the innovations emerge from bounded, iterative, trial-and-error searches for novel combinations of existing building blocks over a complex search space.

Such a conceptualization of the innovative process is theoretically appealing (Frenken, 2000, 2001a, 2001b; Fleming and Sorenson, 2001, 2004; Ethiraj and Levinthal, 2004; Murmann and Frenken, 2006; Sorenson *et al.*, 2006; Marengo *et al.*, 2007) since it provides an important counterpart to neoclassical economics models that may not capture real life-dynamics due to the assumptions of equilibrium and strong rationality (Camerer and Fehr, 2006). However, perceiving the innovative process as a search by boundedly rational agents and modeling it with the NK model may represent the "opposite extreme" of the neoclassical models – with the hyper-rational agents being replaced by naïve automatons. Such a problem is a valid critique of the agent-based approach and thus trying to ascertain the validity of the model is an important empirical task.

Nevertheless, the empirical tests of the NK framework are limited and provide mixed results. Fleming and Sorenson (2001) empirically test some predictions of the NK model but find only partial support. They report that core predictions of the NK model are inconsistent with the data. The authors conclude that the NK models developed primarily to approximate blind biological evolution have limited applicability to the innovative process – presumably because cognition plays an important role. In support of the argument, Fleming and Sorenson (2004) find that scientific knowledge facilitates the search for innovations as problem complexity increases.

To revisit the issue, I ask the question again: Is modeling the innovative process as a bounded, iterative search over a complex landscape a valid approximation? More specifically, can we predict innovation performance based on the empirical counterparts of the *N* and *K* model parameters? To investigate these questions, I develop a relatively direct test of the NK model using a single industry dataset and a novel patent-level measure of technological complexity.

To foreshadow my main results, I find that the model predictions and the empirical estimates are consistent for the core predictions of the NK model. I also perform supplemental analyses, which reveal that the quality of the correspondence between the model predictions and the empirical estimates depends on how broadly one defines the industry. Including a broader range of patents seems to deteriorate the ability of the measure to capture technological complexity by violating some assumptions necessary for construction of the measure.

The paper provides a contribution to both technology management and complexity literatures (Ethiraj and Levinthal, 2004; Fleming and Sorenson, 2001, 2004; Frenken, 2000, 2001a, 2001b; Marengo, Pasquali and Valente, 2007; Murmann and Frenken, 2006; Sorenson, Rivkin and Fleming, 2006) by showing that the NK model may be a reasonable approximation of the innovative process. In addition to the few recent papers that focused on empirical implementation of the NK model (Fleming and Sorenson, 2001; 2004; Lenox, Rockart and Lewin, 2007), the paper serves an important objective - bringing the rich theoretical NK modeling literature to the data.

THE INNOVATIVE PROCESS AS A LOCAL SEARCH

The application of the NK modeling framework (Kauffman, 1993, 1995; Levinthal, 1997; Frenken, 2000, 2001a, 2001b; Fleming and Sorenson, 2001; Rivkin, 2000, 2001; Ethiraj and Levinthal, 2004) to the innovative process hinges on several assumptions. The problem solved by the agent as well as the agent's search capability are assumed to be exogenous, and its properties are controlled by simulation parameters. More specifically, the size of the solved problem (number of components that need to be combined) and the level of interdependence (number of interactions among components) are controlled by the parameters N and K. The innovative process is typically performed by the trial-and-error local search (one component decision is altered at a time) – which is either a conceptualization of the search for novel combinations of existing knowledge (Fleming and Sorenson, 2001, 2004), the search by imitation (Rivkin, 2000, 2001) or the search for new solutions (e.g. Ethiraj and Levinthal, 2001; Frenken 2001a). Extensions of the basic NK framework allow modeling agents with more powerful search capabilities (Gavetti and Levinthal, 2000; Gavetti, 2005; Ganco, 2009), but even in these implementations agents are always boundedly rational. Full rationality (in the sense of locating the best solution achievable in the search space) within the context of the NK model makes no sense since the focus is on the potential and extent of sub-optimality of discovered solutions.[2]

The core implications of the NK model reside in the relationship between the variables *N* and *K* and the payoff. The payoff is measured as either potentially achievable on the landscape (i.e. the global peak) or achieved by agents on average. Prior research has shown (Kauffman, 1993, 1995; Levinthal, 1997) that higher values of complexity (higher *K/N*) create a more rugged search space with a higher global peak, a higher potential performance, but also lead to a premature lock-in called the complexity catastrophe (Kauffman, 1993). As the value of opportunities increases with *K* for a given *N* the landscape consists of many "peaks and valleys", and better opportunities become on average harder to find through a local search. The size of the system determined by *N* or, more precisely, the ratio between *K* and *N* determines problem complexity (Fleming and Sorenson, 2001).[3] With increasing *N* the peaks are more spread out throughout the search space which increases maxima since conflicting tradeoffs are less likely (a component affecting performance of more than one other component). Consequently, an increase in *N* attenuates the likelihood of complexity catastrophe and increases the average as well as the global peak. Since the space is easier to search, the reward for the best, relative to the mean performance, also decreases.[4] Due to potentially different effects on the average versus the best

[2] Also note that the application of the NK model does not necessarily require that inventors recombine existing and stable functional "building blocks" of knowledge. However, the measure of technological complexity does. I discuss this issue more extensively below.
[3] There exists a special case of the interaction pattern when *N* is irrelevant for ordering of payoffs (it only affects the variance of the overall payoff distribution). In this case, only *K/2* neighbor components on each side are linked, the space wraps around as a torus and *K* is low relative to *N*.
[4] The majority of the existing literature within the domains of strategy and technology management assumes that the size of the solved problem *N* is fixed. Aside from some discussion in Kauffman (1993, 1995) the information on how *N* and *K* exactly interact is not readily available. Consequently, the purpose of the section that follows is not only to establish baseline results for the comparison with the empirical model but also disentangle the driving force behind both the performance mean and its variance.

agents, the NK model has implications not only for the mean performance but also for its variance, which necessitates an analysis that looks at both.

The above imagery as well as the NK modeling apparatus has spurred many studies and led to important insights. For instance, Ethiraj and Levinthal (2004) study how underlying technological complexity and its modularization interact and affect performance. Murmann and Frenken (2006) theorize how innovations and dominant designs emerge over time and Frenken (2001a) suggests how complexity changes with the industry life-cycle. Further studies look at the link between organizational attributes and technological problem solving (e.g. Marengo *et al.*, 2007; Rivkin and Siggelkow, 2007).

The more fundamental question is whether the NK model is a valid approximation of the innovative process. The only study to date that tackles this issue explicitly is by Fleming and Sorenson (2001) who laid an important groundwork for resolving it. The authors hypothesize and test some of the predictions of the NK model. Importantly, Fleming and Sorenson (2001) found no support for the core prediction that the performance in rugged landscapes is driven by the interaction between the N and K attributes – i.e. technological complexity does not matter.

To revisit the issue of how the NK model approximates the innovative process, I take the following approach: first, I simulate the basic NK model and use regression analysis to obtain predicted values of performance as a function of the N and K parameters. I then carry out a similar analysis empirically by developing measures of N and K and performing regression on a single-industry dataset. I then conclude by comparing the two sets of predicted values.

NK MODEL OF LOCAL SEARCH FOR INNOVATIONS

I use the basic NK model to generate theoretical predictions. First, I generate n values of N_i with integers uniformly drawn from the interval $U[1,10]$. Second, I generate n values of K

again with integers uniformly drawn from the interval $U[0,N_i\text{-}1]$.[5] Each observation consists of a pair $\{N_i,K_i\}$. The sample consists of n such pairs. Third, using the simulation of the NK model (Kauffman, 1993), I generate an NK landscape using each pair $\{N_i,K_i\}$ as an input and simulate an agent that searches this landscape. For each observation, I then record the discovered converged value for each NK run.[6] I measure the actual absolute payoff achieved on the landscape.[7] The sample now consists of n triples $\{\Pi_i,N_i,K_i\}$ where Π_i is the converged performance achieved by an agent through a local search after 50 periods on a random landscape given by the input pair $\{N_i,K_i\}$.[8] Instead of using the standard approach in the literature to tabulate the results for different values of K and N, I apply a regression analysis to the simulated data. The estimated "pseudo-empirical" predicted values from such an exercise then serve as the basis for comparison with the empirically estimated predictions. The NK model is seen as "mimicking" the empirical data generating process.

Since the NK model predicts not only the effect of N and K on the mean but also on the variance, I need to find an approach that allows estimation of the effect of the independent variables not only on the mean but also on the residuals. The empirical studies using the NK model (Fleming and Sorenson, 2001, 2004) typically utilize a negative binomial model with variance decomposition for the estimation from the empirical sample. Since the negative binomial models rely on count data as the dependent variable, its use is not feasible for the data

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[5] K can be at most $N\text{-}1$. See the appendix for more details and for a formal definition of the model.

[6] An alternative would be to record the distribution of the actual peaks rather than the discovered peaks. However, that would assume that the nature of the search is irrelevant and that the distribution of discovered peaks is identical to the distribution of the actual peaks. I thank Dan Levinthal for valuable discussion on this point.

[7] An alternative would be to measure the relative payoff in the form *Relative payoff* = *Actual payoff* / *Global max*. However, by using relative payoffs I would implicitly assume that the inventors compete only with patents that have the same attributes of the search space as defined by K and N. In other words, achieving a global max on a smooth landscape – by solving a simple problem - would be as valuable as achieving a global max on a very rugged landscape by solving a very complicated problem, and both should receive the same number of citations. Subsequent testing also showed that the model with the relative payoff as the dependent variable fits the data poorly.

[8] In the period 50, for the given range of the values N and K almost all agents find a local peak. Period 50 approximates for performance in the limit. Extending the last period to more periods does not alter any of the results.

generated through the NK simulation. To maintain as much consistency as possible and allow for joint estimation of the mean and variance, I utilize the classic model of multiplicative heteroscedasticity (Harvey, 1976; Green, 1996). This model extends the standard MLE OLS framework by allowing joint estimation of the conditional variance with the conditional mean. The estimated equations have the form (Harvey, 1976):

[1] $$y_i = x'_i \beta + u_i \qquad (i = 1 \ldots n)$$

[2] $$\sigma_i^2 = \exp(z'_i \alpha) \qquad (i = 1 \ldots n)$$

where z_i is the vector of observations on a set of variables that are possibly but not necessarily related to the regressors in [1]. Since I am interested in the impact of *K* and *N* on the mean and variance, in my case, $z_i = x_i$ for all i. Harvey's estimator requires that the disturbance terms u_i are independently and normally distributed with zero means. The first element in z_i is a constant term. All the elements in z_i must be bounded from below for all $i=1..n$. All of these conditions are naturally satisfied in the simulated NK model. The independence is satisfied by the simulation design (draws of the pairs $\{N_i,K_i\}$ are independent) and the normality of the payoffs follows from the fact that I use normal distribution for the generation of the individual component payoffs.

The effects of the inputs *N* and *K* may be non-linear so I estimate a higher order polynomial of *N* and *K*. To ensure that the interactions are products of the independent variables and to be consistent with prior empirical studies (Fleming and Sorenson, 2001, 2004, Sorenson *et al.*, 2006) I estimate the effect of *1/N* instead of *N*. The results of this estimation where integers *N* are drawn from *U[1,10]* and *K* from *U[0,N-1]* are reported in Table 2.1. The models differ by the degree of polynomial. I have estimated the model up to the fifth degree polynomial though only the first three are reported.[9] The estimation is implemented as *reghv* procedure in Stata. The regression results are shown in Table 2.1.

Clearly, the effects of *N* and *K* on the payoffs are highly non-linear. Although almost all of the coefficients are statistically significant, it is evident that the coefficients on the interaction terms are important in determining the payoffs. This holds even as I take into account different magnitudes of the underlying variables (i.e. *K* is between 0 and 9 and *K/N* between 0 and 0.9). For instance, at *N* equals *3* and change in *K* from 0 to 1, the impact of the interaction terms on the payoff is 3.93 times larger than the effect of the coefficients on *K* and K^2. It implies that the payoffs in the NK model are driven by a delicate interplay between the *N* – size of the problem being solved - and *K* – the number of linkages among the problem components. In other words, problem complexity is the key determinant of performance dynamics in the model.

Complementing the regression results in Table 2.1, predicted values for the mean and the variance as a function of *N* and *K* are shown in Figures 2.1-2.6. Figure 2.3 shows an increase in *N* for fixed *K*. With increasing problem size the peaks spread out over a larger space and conflicting tradeoffs are less likely, which improves mean performance. However, this occurs at a decreasing rate since as *N* gets large relative to *K* it is increasingly unlikely that a single component affects performance of more than one other component.

A higher value of *K* implies higher global maxima but also a more rugged landscape and increased potential for lock-in. More dense linkages between the components lead to better opportunities but also create difficulties in their exploitation. Nevertheless, the *K* value itself has smaller direct impact on the actual discovered payoffs than the interplay between the *K* and *N*. An increase in *N* mitigates the impact of a rugged landscape. For low values of *K/N*, as *K/N*

[9] I have also tried to include cross products of all terms. Despite some of the coefficients - especially for the variance portion of the model - being significant their magnitude is very small and they do not seem to change the nature of the predicted effects. I omit them for the sake of simplicity and estimation power.

increases (Figure 2.1), the agent is able to exploit the increasing payoff of local peaks. High relative *N* allows better fine-tuning of the solution due to lower likelihood of conflicting trade-offs. However, this occurs at a decreasing rate since increasing *K* for fixed *N* increases the number of linkages and the likelihood that they will be conflicting (a single component choice affecting multiple other components for a given *K* and *N*), which rapidly increases the chances of lock-in and eventually leads to a decline in the payoffs as *K/N* goes to 1.

The case with *K/N* fixed and changing both *N* and *K* shows similar non-linearity (Figure 2.5). In this case, the pattern is driven by the coefficients on the terms 1/*N* and *K*. As *N* and *K* increase, the performance again increases though at a decreasing rate as is the case with the fixed *K*. The marginal benefit of having larger space outweighs the costs of increases in *K* since the coefficients on *K* are small.[10]

Although the interpretation of the variance portion of the estimated model is less straightforward, the results show that the variance is non-linear and driven by all components - *N*, *K*, the interaction terms *K/N* and their higher order terms (Table 2.1). It is also notable that the variance decreases for all cases and at a decreasing rate (Figure 2.2, 2.4, 2.6). The intuition behind this result is that increases in *K/N* make differences across landscapes less random (Figure 2.2). The average payoff achieved on a more rugged landscape will be similar across landscapes since all will exhibit similar lock-in problems. Within a landscape the differences may very well increase with *K/N* as a higher *K* makes distribution of payoffs within a landscape more dispersed. The increasing within-landscape differences contribute to the decreasing rate at which across-landscape differences decrease. However, the across-landscape effect dominates.[11]

[10] For instance, with $K = 1$ and $N = 2$ the probability that the focal component does not affect any other component beyond itself is 0. For $K = 2$ and $N = 4$, this probability increases to 1/27. Even for a fixed *K/N* the likelihood of conflicting tradeoffs increases.

[11] If we would measure the relative payoffs instead of the actual payoffs the variance would increase with *K/N*.

Increasing *N* (Figure 2.4) lowers variance by allowing an easier search through smoother space and decreasing both the within- and across-landscape variation. This is again at a decreasing rate since a higher *N* slows down a search and imposes time constraints on the agent. For high *N*, some agents might be cut-off before settling on a local peak, which leads to increasing within-landscape variance.

To summarize, the above analysis suggests that the payoffs in the NK model are determined by the interplay between the attributes of the innovation that lead to an increase in available innovation opportunities (*K*) and attributes that simplify their discovery (*N*). If the NK model is a good representation of a particular innovative process the empirical data should exhibit similar patterns. Inventors must strike a delicate balance when selecting the innovation design to capitalize on the trade-offs between the number of components and the linkages between them:

Proposition: The performance of innovations will be driven by the interplay between the N (number of innovation components) and K (number of linkages among the components) in a way consistent with the simulated NK model.

DATA AND ANALYSIS

To test the conjecture that the NK model is a good approximation of the innovative process I focus on a single industry - the disk drive industry - as characterized by the US Patent Class 360. I analyze inventions (patents), seeing them as precursors of innovations and marking a successful solution of a technological problem. The US Patent classification associates function of the invention and of its parts with classes and subclasses, which allows construction of the measures of *N* and *K*.

I focus on this particular industry for several reasons. Analogous to prior research (Fleming and Sorenson, 2001, 2004; Sorenson *et al.,* 2006), the measure of interdependence proposed here requires a good correspondence between the subclasses and physical components of an invention. As previously suggested (Fleming and Sorenson, 2004; Sorenson *et al.*, 2006) such correspondence tends to be good for electronics patents. As the example below indicates, the correspondence between components and subclasses is likely to be exceptionally good in disk drive patents. Similarly, the disk industry experienced waves of innovations with varying degrees of technological complexity (Chesbrough and Kusunoki, 2001). Innovations in the industry typically progressed from more architectural in the early stages to component innovations when new architectural innovation reignited the search again (Chesbrough and Kusunoki, 2001). Most of the innovations in the industry were component innovations with some of them having a dramatic impact on the subsequent technological evolution of the industry – like those that marked the transitions from air bearing ferrite core heads to thin film magneto resistive heads or spindle motors with ball bearings to thin film bearings (Coughlin, Waid and Porter, 2005).

The measure also requires stability across observations (the functional nature of components classified in a particular subclass needs to be relatively stable) which necessitates a single and, as I explain below, relatively narrow industry focus. The Class 360 covers only magnetic storage (Dynamic Magnetic Information Storage or Retrieval), which provides a narrow and well-defined industry definition. The industry, as defined by this class, is also in its very mature stage. It implies that most of the important inventions have been undertaken and exhaustive ex-post analysis with “self-contained” data can be performed. It is also convenient that the patents classified in a single patent class well represent the disk drive-related patents introduced by firms operating within the industry (Hoetker and Agarwal, 2007).

My main interdependence measure is based on analyzing 30,861 patents classified in Class 360 between 1972 and 2004 and 18,185 prior to 1999. The year 1972 is given by the establishment of class 360 and the first patents issued with this classification. Establishment of a separate patent class marks the transition from magnetic drum storage and suggests that the knowledge base related to the disk drives was not only different from prior categories but also sufficiently stable that the creation of a new patent class was possible. The patents issued in the last 5 years of the sample are excluded from the estimation to consistently measure citations over a 5-year period following the patent issue. To empirically test the NK model, I start with the empirical framework from prior studies (Fleming and Sorenson, 2001, 2004) and then extend it by developing additional controls and verifying its robustness to alternative model specifications.

Dependent Variable

I measure patent performance by the number of citations a patent receives in the first 5 years post patent issuing date - i.e. the citing patent application date must be no later than 5 years after the cited patent issue date. As a result, patents in the last 5 years of the industry data are not used in the estimation as independent variables.[12] Since the main objective of the citation counts is to obtain a proxy for the general patent usefulness or performance (Trajtenberg, 1990; Hall *et al.*, 2000; Fleming and Sorenson, 2001), I use citations from all patents and not just from the ones classified in the class 360. Restricting the citations only to within industry citations would bias the measure toward the patents with narrow applicability and reduce variability in the dependent variable. Nevertheless, I have confirmed that restricting citations only to the within-industry citations has no effect on the shape of the predicted values of the model.[13]

[12] The results are robust to different specifications of this time window (4 vs. 6 years).
[13] The correlation between the two citation counts (all citations and those from patents classified in the Class 360) is 0.8. Using only within industry citations leads to more precise estimates of the variance equation and less precise

Independent Variables

N: Number of Components

Consistent with prior studies (Fleming and Sorenson, 2001, 2004; Sorenson *et al.*, 2006), I operationalize the number of components by the number of subclasses. The estimation and testing of the NK model requires good correspondence between the physical components (or "chunks of knowledge," Sorenson *et al.*, 2006) and patent subclasses. The focus on the disk drive industry was partly motivated by expectation of a good correspondence. I include the number of components in the form $1/N$ to reflect the fact that the interaction should be a product of two independent variables.

K: Level of Interdependence

One of the contributions of the current paper is to construct and test a new measure of technological interdependence *K*. My measure of interdependence is based on a representation of the interaction matrix from Kauffman's NK theory (1993, 1995). The interaction matrix in the NK model specifies the interdependencies between the individual components of a complex system and typically has the form:

$$L = \begin{array}{c|cccc} & 1 & 2 & 3 & 4 \\ \hline 1 & x & & x & x \\ 2 & x & x & & x \\ 3 & x & & x & x \\ 4 & & x & x & x \end{array}$$

The numbers represent components of the system and *x* stands for the existing interaction between the corresponding components. The interaction between components is present when change in the input value (component *A* vs. *B* being chosen) of the j^{th} component leads to the

estimates of the mean equation relative to all citations and some loss of overall estimation power. 33% of the sample for the dependent variable when created using only the citations from within the Class 360 is either zero or one citation as opposed to only 17% when created using all citations. Only results with all citations are reported.

change in the payoff of the i^{th} component. The model assumes that the underlying functional structure of the system is exogenous and agents optimize it by selecting (or designing) appropriate functional components. An *x* along the diagonal indicates that payoff of each component depends on its own design or choice. Then, typically, rows are influenced by columns so an *x* in the first row and third column indicates that the payoff contribution of the first component is affected by the design or choice of the third component.[14] The matrix above is a case with $N = 4$ and $K = 2$.[15]

As opposed to the binary interactions in the NK model, I estimate the amount of interaction in each "cell" of the interaction matrix. For each component, I estimate the amount of interaction it has with all other components. The *K* associated with the component *i*, K_i is the sum of interactions the focal component has with all other components. Interdependence *K* of an invention is then an average of the individual component K_i*'s*.

Note that every patent represents a solution of a different technological problem. Every invention can be thus represented by an independent NK landscape. However, I am inferring *K* (which is a property of the landscape) from the final position of the inventor on the landscape by assuming that the solution will be composed of components that serve a certain function - i.e. functional blocks - and that these blocks were also used in other inventions. I am deriving the *K* of the focal landscape (which is given by the relationships between its functional blocks) by analyzing the pattern in which the functional blocks are utilized across all inventions within the industry. Such an inference implicitly assumes that a given component will serve the same function on all inventions and thus the relationships between the functional blocks are stable within the sample. For instance, to solve the friction problem of the disk drive head inventors

[14] The overall system payoff in the NK model is determined by the mean of the payoff contributions of the individual components. See the technical appendix for more details.
[15] The *K* does not include the interaction with itself.

may coat the head surface with a thin metal film. Inventors may optimize this function by selecting different metals. My inference implies that the component "thin metal film" will always serve the function of mitigating surface friction. This assumption necessitates my core assumption of a single industry. The interdependence of the "thin metal film" with other components may be very high within the disk drive patents but not necessarily outside of this set. Whenever this subclass appears on a disk drive patent it is more likely to appear with subclasses representing "recording head" or "disk surface." However, within a broader context such an inference of interdependence may be incorrect as the function may be industry-specific. The subclass "thin metal film" may recombine with a wide variety of subclasses when one looks across industries. The necessity of a stable functional context requires focus on a single industry and a self-contained patent data set.

More specifically, the key idea behind the measure is that when two functional blocks (represented by patent subclasses) are coupled we are more likely to observe components belonging to these subclasses in a single invention. If there is a high coupling between the functions A and B and the component a is classified in patent subclass A, $a \in A$ and b is in B, $b \in \mathrm{B}$ (USPTO classifies patents into subclasses by their functions), then we are more likely to encounter components a and b appearing on a patent together. In other words, high interdependence between A and B implies that whenever an inventor solves a problem related to one of these functions she needs to redesign or include the coupled function as well, and we are likely to observe the components optimizing these functions together in a patent (e.g. head surface and recording head). Similarly, if the patent improves architecture of multiple functions we are likely to observe all components that correspond to these functions coupled to the architecture. On the other hand, if *A* and *B* are independent with respect to each other, we are likely to observe *A* combined with other subclasses without *B* being present.

Technically, the measure of interdependence *K* is computed in several steps. First, I compute the interdependence K_i for each focal component (subclass) of patent *l*:

$$\text{Interdependence of subclass i} \equiv K_i = \sum_{j \in l_{-i}} \frac{\text{count of patents in subclasses } i \text{ and } j}{\text{count of patents in subclass } i} \qquad [1]$$

where *j* belongs to all subclasses except *i*. The focal patent *l* is excluded from the calculation of these counts.[16] The measure K for the patent *l* is then calculated as follows:

$$\text{Interdependence of patent } l \equiv K_l = \frac{1}{\text{count of subclasses of patent } l} \sum_{i \in l} K_i \qquad [2]$$

For instance, when calculating the interdependence of the first subclass (first subclass is focal "*i*") the interdependence between the first and the third subclasses is the number of patents where the first and third subclasses appear together, divided by the number of patents where only the first subclass appears.

Using the focal industry dataset to derive the measure assumes stability in the nature of interdependencies between the individual functional components over time within the given industry.[17] The variable K_i thus captures the interdependence between subclasses *A* and *B* that is not patent-specific. The invention is assumed to consist of building blocks that have certain level of interdependence associated with each pair of its components. If subclasses *A* and *B* appear on two patents, one in the beginning of our observation period and another at the end, the interdependence between them would be identical. The assumption of the stability of

[16] I also exclude patents that include subclasses that are very rare and appear only on the focal patent. If I would include these patents I might bias the measure of *K*. Rare subclasses would appear as highly interdependent which may not be the case. I also exclude patents with only one subclass. In the model, $N = 1$ implies $K = 0$. However, in the data, the interdependencies may be hidden at a finer grain, which may create heterogeneity that I am unable to capture. These procedures eliminate about 7% of the patents from the estimation sub-sample.
[17] As I discuss below, I subject this assumption to a multitude of robustness checks.

interdependencies between the subclasses ("building blocks") is not entirely realistic, but assuming stability at least within a certain time frame is a necessary simplification. The measure of K is also in the interval [0, N-1] and, thus, has the correct scaling consistent with the NK model.

It is also important to note that I use the current subclass classification as published by the USPTO at the end of my sample time frame.[18] The subclasses assigned to patents at the time of issue (called the original classification or "ocl") are sometimes abolished as irrelevant, and new classes are created (24% of the patents in my sample have at least one subclass that is subject to reclassification) and patents are reclassified. I believe that the current classification is more precise since it is more likely to represent the same functional components in different patents by the same subclass. However, as I show below, I have verified that the results are fully robust whether I use the original or the current classification.[19]

To highlight the mechanics of the measure, it may be instrumental to discuss an example (Table 2.2). The patent #5,949,612 "*Low friction sliding hard disk drive system*" was classified into the following subclasses (the subclasses are listed with the calculated values of K_i).[20] Figure 2.7 provides the description of a patent from the first page of the patent document.

I note that the most interdependent classes in the above patent are the "stock material" subclasses 428. Within the context of the main class 360, the "material" subclasses typically represent the surface of the rotating disk or material of the reading head. The functional context of these subclasses tends to be the same across many patents. Whenever the "stock material"

[18] I utilize the NUS-MBS patent database maintained by Kwanghui Lim. The source of the subclass classification is the field "ccl-2004-12" which originates from the USPTO CASSIS DVD 2004-12.
[19] I thank Mu-Yen Hsu for a valuable discussion on this issue.
[20] The patent has received 24 citations.

subclass appears on the patent, it is more likely that the subclass representing the disk or the head appears as well, suggesting interdependence.

It is also illustrative to look at how the measure orders the patents within the industry. If I order the patents according to complexity, K/N, the patents range from $K/N = 0$ to $K/N = 0.704$ with the mean of 0.077 and the median of 0.062. The patents with higher values of K/N are typically those that solve specific design and method issues with the disk's mounting, disk surface, head design or application specific issues of the tape handling mechanism - loading, reeling, etc. Around the mean value tend to be inventions addressing more systemic issues like data processing, mounting structures, cartridge design issues, etc. Among the least complex inventions are those that deal with methods of data processing, memory design issues, wiring and grounding of the systems, controllers, signal filters, etc. As an interesting extreme example, one of the patents with a very low complexity, K/N is an IBM patent 5,953,180 describing different markings of the disk assembly mechanism.

Control Variables

When inventors file patent applications they do so in anticipation of economic returns – supposedly in a technological area where they expect such returns to be the greatest. Consequently, the distribution of patents across subclasses is not random, which creates an endogeneity problem that needs to be addressed. The approach that I adopt is to include a set of proxy variables that should control for unobserved differences potentially driving the results as well as employ a host of robustness checks using alternative measures and model specifications.

Technology Controls

From the perspective of the above endogeneity problem, the main concern with the proposed measure is that it relies on relative frequency counts for the inference of interdependence. Inventors are more likely to patent in attractive technological areas so attractiveness (unrelated to interdependence) in a certain domain may affect both the frequency ratios used to measure K as well as the number of citations. The objective of some of the controls is thus to proxy for the general attractiveness of a given technological area.

Prior studies have tackled this issue by introducing the technology mean and variance controls (Fleming and Sorenson, 2001, 2004). I utilize a similar approach but I add several additional controls complementing those used in prior research. The technology mean control has the form:

$$\text{Average Citations in Class } i \equiv \mu_i = \frac{\sum_{j \in i} \text{citations}_j}{\text{count of patents } j \text{ in class } i}$$
$$\text{Technology mean control for patent } l \equiv M_l = \sum_i p_{il}\mu_i \qquad [3]$$

The weight p_{il} is the number of subclasses categorized in the main class i on patent l. For instance, if a patent has 5 subclasses classified in the main class 360 the p_{360} = 5/9 and μ_{360} would be the count of citations per patent that patents classified in the class 360 received. I again use the entire industry for this computation. Note that patents classified in class 360 may be also classified in other main classes. Similarly, the variance measure is defined as:

$$\text{Citation variance in Class } i \equiv \sigma_i^2 = \frac{\sum_{j \in i} (\text{citations}_j - \mu_i)^2}{\text{count of patents } j \text{ in class } i}$$
$$\text{Technology variance control for patent } l \equiv V_l = \sum_i p_{il}\sigma_i^2 \qquad [4]$$

Note that the means μ_i and σ_i are at the main class level (and then are weighted by the number of subclasses in a given class i) but the measure K_i is at the subclass level. To control for the possibility that the citations matter at a finer-grain than at the main class level I add measures of technological mean and variance at the subclass level. These measures have the form:

$$\text{Average Citations in Subclass } i \equiv \eta_i = \frac{\sum_{j \in i} \text{citations}_j}{\text{count of patents } j \text{ in subclass } i}$$

$$\text{Technology mean control for patent } l = \frac{1}{\text{number of subclasses of patent } l} \sum_i \eta_i \qquad [5]$$

$$\text{Citation variance in Subclass } i \equiv \vartheta_i^2 = \frac{\sum_{j \in i} (\text{citations}_j - \eta_i)^2}{\text{count of patents } j \text{ in subclass } i}$$

$$\text{Technology variance control for patent } l \equiv \frac{1}{\text{number of subclasses of patent } l} \sum_i \eta_i \qquad [6]$$

These measures are, in fact, "quality" measures reflecting weighted citations per patent in a technological domain of a given patent. To control for the possibility that it is the density of patents in a given technological area that is the proxy for attractiveness I add a simple patent density measure that has the form:

$$\text{Patent density control for patent } l = \frac{1}{\text{number of subclasses of } l} \sum_i \text{count of patents in subclass } i \qquad [7]$$

Prior Art Citations

The prior art citations - in the form of the number of references made by the focal patent - control for the localness of search and propensity to patent (Fleming and Sorenson, 2001). Building more on the existing patents suggests that the inventor searches in the neighborhood of the existing knowledge (Podolny and Stuart, 1995) as opposed to looking for truly novel knowledge. The propensity to be cited correlates with the number of citations a patent makes on average, and, thus, the number of citations a focal patent makes may capture "idiosyncratic differences in patenting activity that [the] class controls miss" (Fleming and Sorenson, 2001).

Number of Main Classes

Consistent with the logic described in prior studies (Fleming and Sorenson, 2001, 2004), a higher number of main classes may mean broader applicability and relevance of the patent for subsequent innovations. The patents with more classes may also be more at risk for subsequent citations simply because they happen to be in the same class as the subsequent patent.

Number of Trials

The number of prior trials measures the number of times a particular combination of subclasses has been used before (Fleming and Sorenson, 2001, 2004). It serves to capture the number of peaks that have been already found and search limitations associated with the exhaustion of combinatorial possibilities. Using this control should capture the pre-emption or crowding out - factors that likely affect citation patterns.

Time Dummies and Inventor Fixed Effects

I add time dummies to all regressions as a way of capturing changes over time. Using the matching algorithm described in Agarwal *et al.* (2009) I also match inventor names to create unique inventor identifiers. To control for unobserved heterogeneity at the individual inventor level, I run the models using the inventor fixed-effects. On average, each patent lists multiple inventors so using inventor fixed-effects changes the sample structure. Instead of an observation being a patent it becomes an inventor-patent with an increase in the sample size. For this reason, I report the fixed-effects models as a robustness check.

The descriptive statistics of the sample are provided in Table 2.3.

Regression Models

I adopt the estimation technique from prior studies (Fleming and Sorenson, 2001, 2004), but I test its robustness using alternative specifications. Since it is necessary to estimate both the conditional variance and the conditional mean (ideally jointly) of a data with a count dependent variable, the choice of an estimation method is relatively limited. Ideally, I would like to use a method that is fully equivalent to the multiplicative heteroscedasticity model used in the estimation of the theoretical model. Since the dependent variable in the NK model is normally distributed and I use non-normally distributed citation counts as the dependent variable in the empirical model, clean use of the same model specification on both sets of data is not possible. Using the multiplicative heteroscedasticity model on count data violates the normality assumption necessary for consistent estimates using maximum likelihood.

For the joint estimation of the variance and mean of the citation count data I use the Negbin II specification (Cameron and Trivedi, 1986) of the negative binomial regression as the main model. This specification allows joint maximum likelihood estimation of the mean and the dispersion parameter α conditional on the exogenous regressors (STATA implements this routine as *gnbreg*). The Negbin II model has the form:

$$P(Y_i = y_i) = \frac{\Gamma(y_i + v_i)}{\Gamma(y_i + 1)\Gamma(v_i)} \left(\frac{v_i}{v_i + \phi_i} \right)^{v_i} \left(\frac{\phi_i}{v_i + \phi_i} \right)^{y_i}$$

where $\phi_i = \exp(X_i \beta)$

$$v_i = \frac{1}{\alpha}$$

where α is the dispersion parameter specified as: $\alpha = \exp(Z_i \delta)$

Then: $E[Y_i] = \exp(X_i \beta)$

$$Var(Y_i) = (1 + \alpha \exp(X_i \beta)) \exp(X_i \beta)$$

The above formulation implies that the variance-mean ratio is $(1+exp(Z_i\delta)exp(X_i\beta))$ where Z_i is the vector of exogenous regressors affecting the dispersion parameter and the over-dispersion is linear in the mean.

Since OLS is a consistent estimator even with count data, I use a simple two-step procedure as an alternative model. In the first step, I regress citations on all variables predicting the mean. In the second step, I regress squared residuals from the first step on the variables predicting the variance. I also run the multiplicative heteroscedasticity model on the empirical sample as a robustness check. I run all models with robust standard errors.

Despite the theoretical section suggesting that the best fit is provided by the model with the third degree polynomial, such a model is difficult to estimate empirically. The terms in the higher order polynomial are highly correlated and the standard errors increase rapidly. Consequently, I use the model with the second degree polynomial as the basis for comparisons.

RESULTS

Table 2.5 shows the estimated main models. Model 1 includes only the control variables. Model 2 is a full Negbin II model with the NK and control variables. Model 3 is the second degree polynomial model from the simulated data (Model 2 from Table 2.1).

Since in the Negbin models the predicted values are a non-linear function of the variables, I cannot compare the coefficients directly. However, I can compare the signs and the relative effect in the mean portion of the model since *exp(.)* is a monotonic transformation. The correspondence between the coefficients as well as the predicted values (Figures 2.8, 2.10, 2.12) of the mean portion between the empirical and the theoretical model is strong.[21] The empirical

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[21] The figures are created as follows: the value which is fixed is at the 50th percentile in the empirical sample and the *x* axis starts and ends at the 5th and 95th percentiles, respectively. For instance, in Figure 8, the N is fixed at 3 which is the median of the sample and the *x* axis starts at $K = 0$ (5th percentile) and ends at $K = 1$ (95th percentile).

estimation also correctly captures the smaller direct effect of the interdependence K and its square term K^2 and the stronger and significant effect of its interactions with N. For instance, at $N = 3$ and a change from $K = 0$ to $K = 1$ the effect of interaction term coefficients on citations is twice as large as that of the coefficients on K and K^2. Empirical analysis thus supports the prediction of the model that even as the level of interdependence determines the nature of the landscape what matters for performance is the interplay between the interdependence and the number of components. The effects of the interdependence and the number of components cannot be analyzed in isolation – i.e. technological complexity does matter.

Overall, the effects of K and N and their interaction terms are relatively large. For example, for $N = 3$, deviating from the mean level of K/N by one standard deviation increases the citations on average by about 0.5. As the inverted U-shaped relationship in Figure 2.8 and the concave and increasing relationship in Figure 2.10 suggest, I find a strong support for the complexity catastrophe (Kauffman, 1993, 1995). The complexity catastrophe implies that the penalty for interdependence will be strongest when K is close to N for small N. Further, I find that at fixed K, increasing N improves performance but at a decreasing rate - consistent with the NK model. Overall, the mean estimation of the empirical model captures the attributes of the simulated NK model well.

On the other hand, the results of the variance portion of the model are statistically weaker (Figure 2.9, 2.11, 2.13) and tend to be inconsistent with the NK model. The most notable difference is that the estimated variance tends to closely scale with the mean. This could happen for several reasons. First, the precision of the measure of interdependence K may decrease with K. Since patent interdependence negatively correlates with the frequency of its subclasses in the sample and positively with the number of subclasses *N*, it is possible that *K* of patents with higher interdependence will be based on fewer data points and estimated with more noise.

Second, the noise in the citation counts as a measure of economic value may increase with its magnitude. The count models typically assume independence between events, which is potentially violated in the case of citation counts due to preferential attachment (Barabasi and Albert, 1999; Powell *et al*., 2005). In other words, a patent with many citations is more likely to receive additional citation because it is well known (it has already received many citations) and not necessarily because it has exceptional economic value. The patent citations are not only a noisy estimate of the economic value but also the noise may increase with the number of citations. In such a case, the conditional variance will positively correlate with the conditional mean, which may yield the observed predicted patterns and overwhelm the dynamics predicted by the model.

A third possible explanation is related to a more fundamental issue of the NK model. In the simulations, I measure absolute payoffs. The absolute payoffs are affected by the attributes of the problem space as well as by the ability of agents to search it. I suggested that it is reasonable to expect a similar pattern in the sample of patent data since innovations with different natures of the search spaces (different *N* and *K*) compete for citations with each other. An alternative approach would be to measure relative performance (conditional on how well an agent *can* perform on a landscape given by *N* and *K*). The focus on relative performance in the model would imply increasing variance with the level of complexity. However, the mean estimates based on the NK model measuring relative payoffs does not seem to fit the empirical estimates which provides evidence against this specification of the model. At the same time, focusing on relative performance would imply a decreasing relationship in Figure 2.9 rather than an inverted-

U. In general, the estimation of the variance relationship is considerably less robust than the mean estimation and appears to be very sensitive to possible biases in the measures.

Alternatively, it could be the case that the NK model fails to predict the variance pattern of the real-life dynamics while capturing the mean performance relatively well. It could also be the case that the assumptions of the NK model that have been hypothesized to be violated in real life – like the effects of cognition (Fleming and Sorenson, 2001) manifest themselves strongly in the variance portion of the model. On average, inventors may behave like local searching automatons. However, cognitive differences allow some inventors to capture opportunities present in highly complex technological domains, which has a positive effect on variance of the observed performance.

The coefficients on controls have generally expected signs and are consistent with prior studies (Fleming and Sorenson, 2001, 2004). However, a count of main classes has a negative effect on citation counts after controlling for interdependence, which suggests that more generalist patents are less valuable within the industry. I also find that Number of Prior Trials and Prior Art Citations - factors commonly characterizing a local search (March and Simon, 1958; Nelson and Winter, 1982; Stuart and Podolny, 1995; Fleming and Sorenson, 2001) - are positive and significant in their effects on citations. The positive effect on the Number of trials suggests that the positive spillovers outweigh the crowding out effects and slightly increase citations. I also find that within a single industry context the technology mean control is considerably more important at the subclass rather than at the main class level.

Table 2.6 provides a comparison of the results with the ones based on the prior measure of interdependence (Fleming and Sorenson, 2001). Model 3 shows the results based on the prior measure applied to the disk-drive industry. Model 4 reproduces the results reported in a prior study (Fleming and Sorenson, 2001). The mean estimates are similar in both models (Model 3 and 4), which suggests that the measure developed by Fleming and Sorenson (2001) is not sensitive to the single industry assumption. However, the measure developed in this paper (Model 2) not only improves the fit of the model but also captures dynamics that more closely correspond to the NK model.

ROBUSTNESS CHECKS AND LIMITATIONS

Even though the empirical model (or at least its mean portion) seems to perform relatively well, the results need to be taken with caution for several reasons. Beyond the standard concerns arising from the use of patent data, I will mention the most pertinent ones that remain. The robustness checks are reported in Table 2.7.[22]

The first possible issue relates to the construction of the measurement sample. I constructed the measure of interdependence based on the tabulation of subclass frequencies and co-occurrences in the entire industry. To test the robustness of this assumption I constructed the measure on several different sub-samples. In Model 5, I show results of the estimation where I split the sample into two equal-sized sub-samples by randomly assigning each observation either into a measurement sub-sample or a regression sub-sample. The values of K of the patents in the regression sample were calculated based on tabulations of subclasses in the measure construction sub-sample.[23] The coefficient estimates of this exercise are highly consistent with the main model. The predicted values were very similar to the ones reported for the main model. The results are also robust to the use of the classification system. In Model 4, I show results using

[22] Note that I do not use the citations to measure knowledge flows but rather to infer their economic importance, so the criticism by Alcacer and Gittelman (2006) does not apply to my estimation framework.

[23] I have also used additional rules for creating the sub-sample for the measure inference like using only the first 10 years, last 10 years or moving, 10-year and 5-year windows. All yielded qualitatively identical results.

original classification as opposed to the reclassified patents as of the end of the estimation time frame.

The second issue relates to truncation. One may argue that patents represent only the best inventions that in expectation exceed a certain threshold value. Thus, the empirical results can be seen as based on truncated data. Similar to prior studies (Fleming and Sorenson, 2001), I estimated the simulated NK model on truncated data for various percentiles of truncation. The estimated coefficients appear qualitatively robust to truncation though the usual attenuation results (Greene, 1996). From this perspective, our empirical results could be seen as conservative and biased downwards.

Third, to test the robustness of the model specification I analyzed the data using a simple 2-step OLS procedure, a multiplicative heteroscedasticity model and a model with inventor fixed-effects combined with the 2-step OLS. The pattern of the predicted values of all models is consistent with the main negative binomial model. The magnitude of the coefficients of the mean portion of the multiplicative heteroscedasticity model is substantially smaller than in the OLS models, likely resulting from the bias (due to the violation of the distributional assumption).

Fourth, I have tested the robustness of the results to the choice of the industry sample. This exercise has confirmed the conjecture that the measure is sensitive to the single-industry assumption and stability in the "knowledge blocks." I have tried to calculate the measure of *K* based on an expanded sample including Data Processing classes 700-714 (memory, input/output, arithmetic processing, data and file management, artificial intelligence, etc.) and the estimation lost a significant amount of power. Importantly, as opposed to class 360, which has patenting activity spread out relatively evenly over most of our sample period and declines towards the end, almost all patenting activity in classes 700-714 occurs between 1995 and 2004. This suggests that the technologies patented in classes 700-714 represent a different stage of the technology life-cycle which violates the assumptions underlying the measure. Nevertheless, I have also estimated the model on a well-defined sample of 30,000 semiconductor design patents with almost identical results. It implies that though the model is applicable across domains, the self-containment of the sample is critical.

DISCUSSION AND CONCLUSION

The main objective of my study was to test the conjecture that the iterative trial-and-error local search represented by an NK model is a good approximation of the innovation process. Using an empirical analysis that is based on a novel measure of technological complexity I find relatively strong support for the NK model when predicting the conditional mean of observed citation patterns. More specifically, I find that the technological complexity (i.e. *K/N*) is a key predictor of these dynamics. The paper not only provides evidence in support of the NK model but also shows an empirical operationalization of the model measures and their boundary conditions. This opens multiple avenues for future research.

Prior studies (Fleming and Sorenson, 2001, 2004; Sorenson *et al.,* 2006) found a relatively weak effect of technological complexity, *K/N,* on the patent performance and conclude that the payoffs are driven by the single parameter *K*. Fleming and Sorenson (2001) suggest that "*'the complexity catastrophe' operates almost entirely as a function of the degree of interdependence among the system components. Since this diverges from the predictions of the NK model, these findings suggest a need to consider seriously how evolution in social systems differs from biological evolution*." My analysis provides a refinement of this conclusion. On average, inventors behave in a way that is not dissimilar to the predictions of the NK model and perhaps analogous to biological evolution. The key attributes of the adaptive search in the NK landscape are its boundedness and experimentation. The process is driven by incremental improvements resulting from the trial-and-error steps guided by path dependency. As the performance of a biological genome results from the interplay between its length and linkages between the individual genes, the performance of innovations appears to arise from the interplay between the number of components and the interdependence between them. Analogous to species climbing the "hills" of biological fitness, inventors face complexity catastrophe when solving very complex problems. However, my findings also highlight possible differences. In the biological systems, the selection operates at the level of population or species. In the technological systems, it also operates at the level of individual inventors through cognition (Gavetti and Levinthal, 2000). Cognition is typically assumed to accelerate the search process by allowing "offline," directed and distant "jumps" over the search space (Kauffman, 1993, Gavetti and Levinthal, 2000; Gavetti, 2005). It relaxes the constraints of myopia and allows for skipping the small trial-and-error steps by traversing large sections of the search space. In contrast to the predictions of the NK model, my results suggest that variance of the performance increases with complexity. Even though on average inventors face lock-in problems associated with complexity, thanks to cognitive differences and vast heterogeneity in search abilities some inventors may be able to discover opportunities that are present in complex technological spaces. My analysis suggests that solving complex problems provides opportunities, and cognitive diversity perhaps allows one to exploit them.

The study produces several important questions. The natural question that arises is the one related to optimality. If inventors have full discretion over the choice of components should we not be more likely to observe optimal performance? The analysis suggests that this is not the case. The peak of citations is at the 87^{th} percentile of the distribution of *K/N* in the sample. Most of the inventions in the sample have very low complexity. The question is why? One possible explanation may relate to the problem of unobservable costs. In expectation of high costs in terms of time, effort and financial resources inventors may decide not to work on complicated problems. On the other hand, even though solving simple problems may lead to lower expected returns it may be cheap and can be done quickly.

At a more fundamental level the question is what drives the distributions of N and K in the data. To what extent are attributes like N and K exogenous? How much discretion do inventors have over these attributes? The innovations are rarely standalone - it is reasonable to see them as embedded in an intricate web of relationships to other innovations within the systems in which they function. The disk drive inventions are embedded within the architecture of the personal computer. The inventors may have some discretion over the number of components and linkages but such discretion may be limited due to the interdependencies with the overall system. The functionality within the environment may pre-determine the invention structure. The question is when and how this matters. What is the role of the individual in this process? How do inventor attributes affect the innovation performance and what factors interact with the complexity? Disentangling these underlying mechanisms is an important venue for further research.

This study contributes to multiple literature streams. I show that the innovation process can be successfully modeled using the NK model. This not only shows an empirical operationalization of the model but also connects the innovation and complexity literatures (Henderson and Clark, 1990; Mahoney, 1995; Galunic and Rodan, 1998; Frenken, 2000, 2001a, 2001b; Fleming and Sorenson, 2001, 2004; Ethiraj and Levinthal, 2004; Murmann and Frenken, 2006; Sorenson, Rivkin and Fleming, 2006; Marengo, Pasquali and Valente, 2007). In a broader sense, the study implies that agent-based models could be a viable counterpart of neoclassical economic models when used carefully while being aware of their limitations.

In conclusion, I theorized and found evidence that the NK model provides a reasonable approximation of the innovation process. In the course of my investigation, I have found important contingencies in the proposed operationalization of the model. Furthermore, the analysis revealed intriguing patterns in the nature of technological complexity which opens interesting questions and promising possibilities for continued research.

TABLES AND FIGURES

Table 2.1 Multiplicative heteroscedastic regression on NK simulated data

Payoff	**Model 1** (Linear)	**Model 2** (2^{nd} degree)	**Model 3** (3^{rd} degree)
MEAN			
1/N	-0.18***	-0.69***	-0.58**
$1/N^2$		0.547***	0.59*
$1/N^3$			-.084
K	-.019***	-0.037***	0.0017
K^2		0.0009*	-0.0056*
K^3			0.00036*
K/N	0.0016	0.5927***	0.731***
$(K/N)^2$		-0.498***	-1.078***
$(K/N)^3$			0.4576***
Cons.	0.745***	0.715***	0.648***
VARIANCE			
1/N	2.44***	5.67***	6.835***
$1/N^2$		-2.93***	-11.16***
$1/N^3$			7.184***
K	-0.21***	-0.091*	-0.59***
K^2		0.000076	0.084***
K^3			-0.0046***
K/N	0.895***	-0.419	3.65***
$(K/N)^2$		0.448*	-4.775***
$(K/N)^3$			2.2825***
Cons.	-2.78***	-3.13***	-3.238***
Pseudo R2	0.4116	0.4198	0.4219
n	200,000	200,000	200,000
Log Likelihood	-60935.183	-60085.581	-59865.773

Significance levels: † 10%, * 5%, **1%, *** 0.1%, double-sided test

Table 2.2 Example of *K* calculation: patent #5,949,612 "*Low friction sliding hard disk drive system*"

Subclass (as of 12/2004)	**Description**	**K_i**
360/97.01	Record transport with head stationary during transducing, Disk record	0.14
360/122	Head, Head surface structure	0.07
360/135	Record medium, Disk	0.6
360/246.1	Head mounting, Disk record, Full contact suspension	0.15
428/654	All metal or with adjacent metals, Composite: i.e., plural, adjacent, spatially distinct metal components (e.g., layers, joint, etc.), Al-base component, Next to Al-base component	2.3
428/694tr	Composite (nonstructural laminate), Of inorganic material, Metal-compound-containing layer, Defined magnetic layer, Dynamic recording medium, Metal thin film magnetic layer, Specified surface feature or roughness.	1.45
428/694tf	Composite (nonstructural laminate), Of inorganic material, Metal-compound-containing layer, Defined magnetic layer, Dynamic recording medium, Metal thin film magnetic layer, Topcoat, or protective overlayer, Fluorocarbon or organosilicon layer.	1.95
428/900	Magnetic feature.	0.67
	$K_{\#5,949,612}$ =	0.92

Table 2.3 Descriptive statistics

Variable	Mean	St. Dev.	Min.	Max.
1) Citations	7.42	9.09	0	180
2) Mean technology control (main class level)	7.99	1.06	2.67	18.96
3) Variance technology control (main class level)	85.30	34.36	17.27	412.70
4) Mean technology control (subclass level)	7.98	2.80	1.58	55.36
5) Variance technology control (subclass level)	66.40	63.16	1.27	1849.16
6) Patenting density in focal technology	370.58	243.44	2.50	1239
7) Number of prior art citations	6.94	6.78	0	145
8) Number of main classes	1.88	0.95	1	8
9) Number of repeated trials	3.92	15.40	0	309
10) 1/N	0.34	0.14	0.034	1
11) K	0.36	0.62	0	13.47
12) K/N	0.08	0.08	0	0.70

Observations: 18,185

Table 2.4 Correlation table

Correlations	1)	2)	3)	4)	5)	6)	7)	8)	9)	10)	11)
1) Citations	1										
2) Mean technology control (main class level)	0.232	1									
3) Variance technology control (main class level)	0.165	0.769	1								
4) Mean technology control (subclass level)	0.508	0.574	0.404	1							
5) Variance technology control (subclass level)	0.380	0.436	0.495	0.739	1						
6) Patenting density in focal technology	0.055	-0.170	-0.077	0.055	0.103	1					
7) Number of prior art citations	0.149	0.098	0.056	0.158	0.083	-0.031	1				
8) Number of main classes	0.097	0.301	0.169	0.195	0.096	-0.469	0.088	1			
9) Number of repeated trials	0.040	-0.076	-0.034	0.023	0.056	0.356	0.002	-0.154	1		
10) 1/N	-0.146	-0.156	-0.055	-0.151	-0.079	0.251	-0.068	-0.431	0.183	1	
11) K	0.081	0.118	-0.031	0.101	0.009	-0.123	0.053	0.410	-0.026	-0.437	1
12) K/N	0.055	0.027	-0.060	0.014	-0.052	-0.039	0.043	0.265	0.130	-0.203	0.707

Table 2.5 Negative binomial models of citation counts, patent class 360

Variable	**Model 1** **Controls only**	**Model 2** **Full model**	**Model 3** **NK simulation** (from Table 2.1)
MEAN EQUATION**:**			
1/N		**-2.418*****	**-0.69*****
$1/N^2$		**1.696*****	**0.547*****
K		**-0.353****	**-0.037*****
K^2		**0.048*****	**0.0009***
K/N		**3.183*****	**0.5927*****
$(K/N)^2$		**-5.277*****	**-0.498*****
Mean technology control (main class)	-0.058***	-0.050***	
Mean technology control (subclass)	0.197***	0.194***	
Patenting density in focal technology	0.000***	0.000***	
Number of prior art citations	0.013***	0.012***	
Number of main classes	0.010	-0.044***	
Number of repeated trials	0.002***	0.001**	
Constant	0.555***	1.111***	0.715***
Year dummies	Yes	Yes	
VARIANCE EQUATION (ln(alpha))			
1/N		**1.241***	**5.67*****
$1/N^2$		**-1.491****	**-2.93*****
K		**0.123†**	**-0.091***
K^2		**0.011**	**0.000076**
K/N		**-1.896*****	**-0.419**
$(K/N)^2$		**1.912**	**0.448***
Variance technology control (main class)	0.001†	0.001*	
Variance technology control (subclass)	0.003***	0.003***	
Patenting density in focal technology	0.000***	0.000***	
Number of prior art citations	-0.001	0.000	
Number of main classes	-0.197***	-0.179***	
Number of repeated trials	-0.002***	-0.002*	
Constant	-0.935***	-1.118***	-3.13***
Year dummies	Yes	Yes	
Wald χ^2	6288	6169	
Pseudo R^2	0.0584	0.0643	0.4198
Observations	21,711	18,185	200,000
Log likelihood	-61540.623	-51539.739	-60085.581

Significance levels: † 10%, * 5%, **1%, *** 0.1%, double-sided test

Table 2.6 Negative binomial models of citation counts, comparison with prior measures

Variable	Model 1 NK simulation (Table 2.1)	Model 2 Full model	Model 3 Fleming and Sorenson (2001) measure, Disk-drive sample	Model 4 (from Fleming and Sorenson, 2001)
MEAN EQUATION:				
1/N	**-0.69*** **	**-2.418*** **	**-2.813*** **	**-1.5823*** **
$1/N^2$	**0.547*** **	**1.696*** **	**2.48*** **	**0.8778†**
K	**-0.037*** **	**-0.353** **	**0.472*** **	**0.2893*** **
K^2	**0.0009***	**0.048*** **	**-0.124*** **	**-0.1225*** **
K/N	**0.5927*** **	**3.183*** **	**0.103**	**0.2571***
$(K/N)^2$	**-0.498*** **	**-5.277*** **	**0.01**	**-**
Mean technology control (main cl.)		-0.050***	-0.08***	0.9019***
Mean technology control (subclass)		0.194***	0.111***	
Patenting density in focal technology		0.000***	0.000***	
Number of prior art citations		0.012***	0.018***	0.017***
Number of main classes		-0.044***	0.029*	0.0432***
Number of repeated trials		0.001**	0.003***	-0.0009
Single class[24]		-	-0.751**	-0.1135
Constant	0.715***	1.111***	0.258*	0.1933**
Year dummies		Yes	Yes	Yes
VARIANCE EQUATION (ln(alpha))				
1/N	**5.67*** **	**1.241***	**-2.493*** **	**0.4942**
$1/N^2$	**-2.93*** **	**-1.491** **	**2.625***	**0.7613**
K	**-0.091***	**0.123†**	**-0.016**	**-0.6098*** **
K^2	**0.000076**	**0.011**	**-0.056†**	**0.2544*** **
K/N	**-0.419**	**-1.896*** **	**0.547***	**-0.3984†**
$(K/N)^2$	**0.448***	**1.912**	**-0.07**	**-**
Variance technology control (main class)		0.001*	0.003***	-0.0203***
Variance technology control (subclass)		0.003***		
Patenting density in focal technology		0.000***	0.000***	
Number of prior art citations		0.000	0.007***	-0.0001
Number of main classes		-0.179***	-0.065**	-0.03
Number of repeated trials		-0.002*	0.001	-0.0036†
Single class		-	-1.104*	-0.5465
Constant	-3.13***	-1.118***	-0.687***	0.0616
Year dummies		Yes	Yes	Yes
Wald χ^2		6169	2639	
Pseudo R^2	0.4198	0.0643	0.0272	
Observations	200,000	18,185	20,157	17,264
Log likelihood	-60085.581	-51539.739	-59927.666	-41,024.85

Significance levels: † 10%, * 5%, **1%, *** 0.1%, double-sided test

[24] Patents with a single class were dropped from my estimation. The measure as developed here does not allow calculation of complexity for single class patents.

Table 2.7 Robustness checks

Variable	Model 1 NK simulation (from Table 2.1)	Model 2 2-step OLS	Model 3 2-step OLS and Inventor Fixed-Effects	Model 3 Multiplicative hetero-scedasticity model	Model 4 Neg. bin. (original classification)	Model 5 Neg. bin. (regression and measure estimation sub-samples)
MEAN EQUATION:						
1/N	**-0.69*** **	**-19.716*** **	**-21.305*** **	**-10.79*** **	**-1.732*** **	**-1.836*** **
$1/N^2$	**0.547*** **	**16.185*** **	**16.314*** **	**8.503*** **	**1.202*** **	**1.336*** **
K	**-0.037*** **	**-1.641*** **	**-1.676** **	**-1.57*** **	**-0.19***	**-0.175**
K^2	**0.0009***	**0.132*** **	**0.285** **	**0.123*** **	**0.025**	**0.021**
K/N	**0.5927*** **	**18.421*** **	**20.314*** **	**13.623*** **	**2.25*** **	**2.314*** **
$(K/N)^2$	**-0.498*** **	**-28.429*** **	**-46.297*** **	**-14.737** **	**-3.868*** **	**-4.394*** **
Mean technology control (main class)		-0.679***	-0.29*	-0.226***	-0.059***	-0.054***
Mean technology control (subclass)		1.733***	1.453***	1.331***	0.194***	0.193***
Patenting density in focal technology		0.001**	0.001**	0	0***	0***
Number of prior art citations		0.108***	0.031*	0.087***	0.013***	0.014***
Number of main classes		-0.269***	-0.191	-0.031	-0.035***	-0.027*
Number of repeated trials		0.019**	0.017**	0.008*	0.002**	0.003**
Constant	0.715***	2.628***	3.462**	0.33	1.009***	1.044***
Year dummies		Yes	Yes	Yes	Yes	Yes
Inventor dummies			Yes			
R^2		0.2986	0.1622			
VARIANCE EQUATION						
ln(alpha) or squared residuals						
1/N	**5.67*** **	**-291.026*** **	**-169.994‡**	**-3.608*** **	**1.389***	**0.456**
$1/N^2$	**-2.93*** **	**259.888*** **	**117.096‡**	**2.306*** **	**-1.984** **	**-0.84**
K	**-0.091***	**-23.278†**	**-25.278‡**	**-0.046**	**0.119**	**0.014**
K^2	**0.000076**	**2.274***	**8.317†‡**	**0.023***	**0.001**	**0.006**
K/N	**-0.419**	**326.095** **	**145.371‡**	**2.822*** **	**-1.838** **	**-1.122**
$(K/N)^2$	**0.448***	**-406.746**	**-435.125‡**	**-8.004*** **	**3.748***	**3.59†**
Variance technology control (main class)		-0.05	-0.13	-0.002*	0.001	0.001
Variance technology control (subclass)		1.562***	0.668***	0.014***	0.003***	0.003***
Patenting density in focal technology		0.03†	-0.002	0.001***	0***	0*
Number of prior art citations		1.88*	-0.025	0.026***	-0.001	-0.001
Number of main classes		-10.291**	-2.241	-0.154***	-0.199***	-0.209***
Number of repeated trials		0.309	-0.001	-0.001	0.001	-0.002
Constant	-3.13***	19.272	44.32	2.92***	-1.103***	-1.041***
Year dummies		Yes	Yes	Yes	Yes	Yes
Inventor dummies			Yes			
Wald χ^2					6159.87	3072.52
Pseudo R^2 (NB) or R^2 (OLS)	0.4198	0.08	0.0256	0.1322	0.06	0.0612
Observations	200,000	18,185	40,444	18,185	18,611	9,327
Log likelihood	-60085.581			-57198.951	-52797.893	-26401.639

Significance levels: † 10%, * 5%, **1%, *** 0.1%, ‡ jointly significant at 5%, double-sided test

Figure 2.1 Mean as a function of *K* (*N* is fixed at 10)[25]

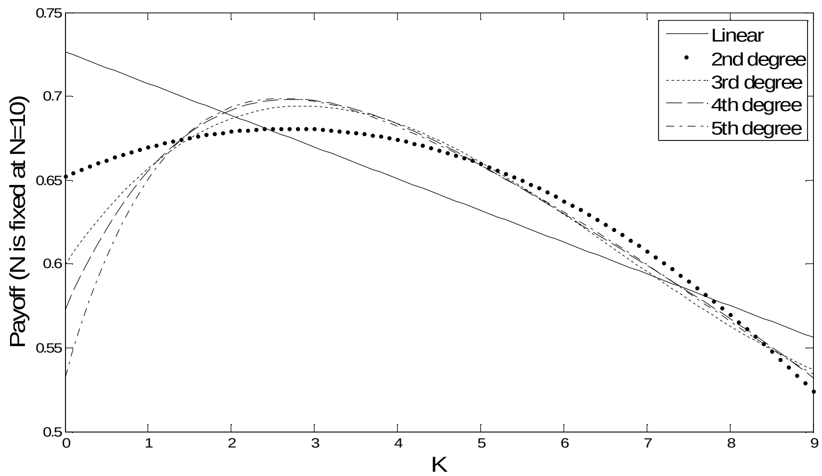
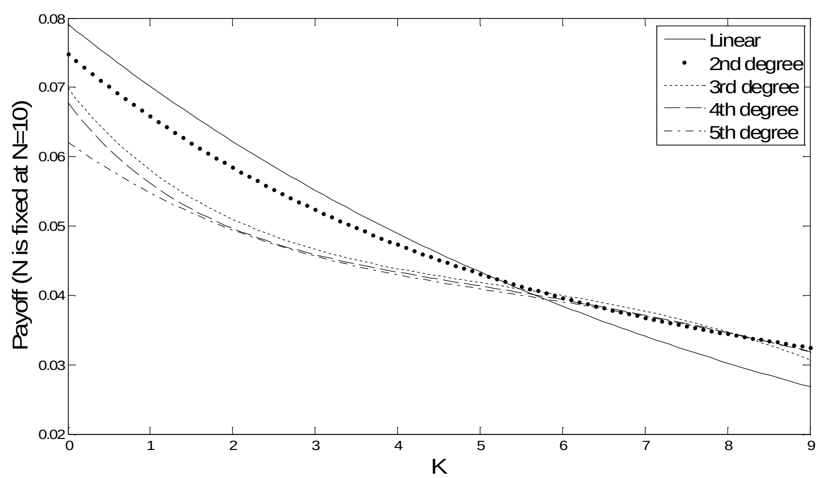


Figure 2.2 Variance as a function of *K* (*N* is fixed at 10)



[25] In the conditional heteroscedastic model the mean predicted value has the linear form Xβ and the variance value the form exp(Xβ).

Figure 2.3 Mean as a function of *N* (*K* is fixed at 2)

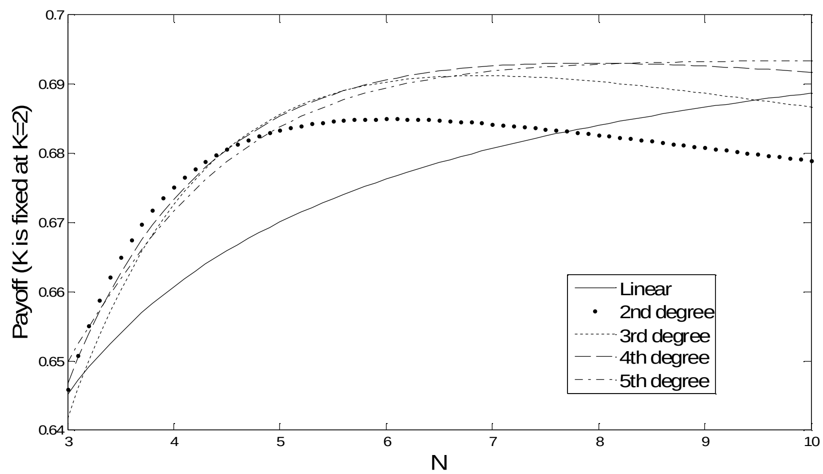


Figure 2.4 Variance as a function of *N* (*K* is fixed at 2)

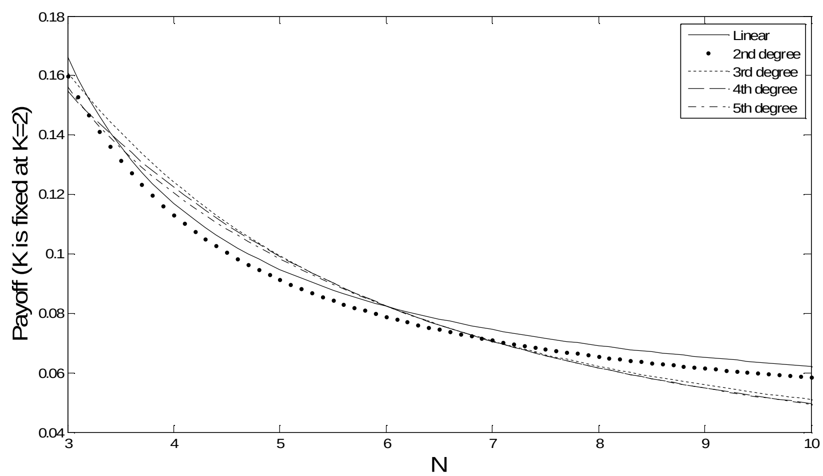


Figure 2.5 Mean as a function of *N* (*K/N* is fixed at 0.2)

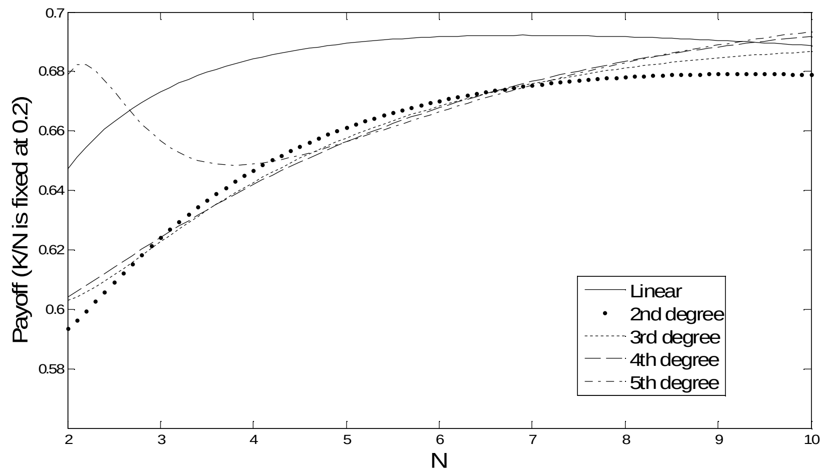


Figure 2.6 Variance as a function of *N* (*K/N* is fixed at 0.2)

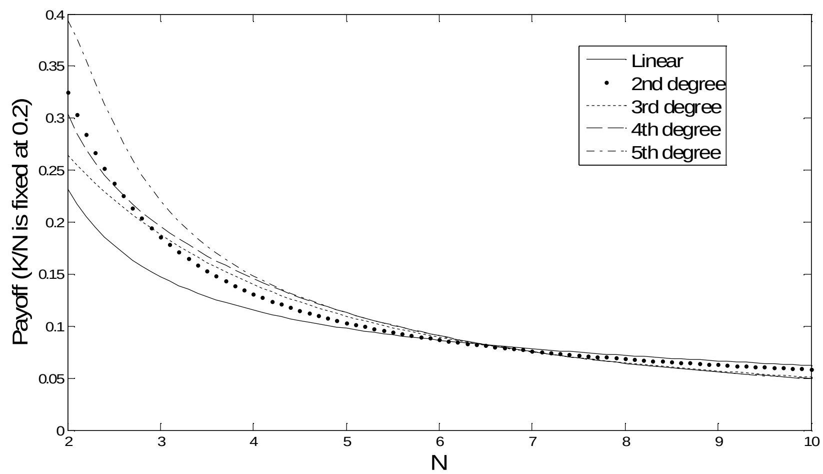


Figure 2.7 Example description: patent #5,949,612 “*Low friction sliding hard disk drive system*”

US005949612A

United States Patent [19]
Gudeman et al.

[11] **Patent Number:** **5,949,612**
[45] **Date of Patent:** **Sep. 7, 1999**

[54] **LOW FRICTION SLIDING HARD DISK DRIVE SYSTEM**

[75] Inventors: **Christopher S. Gudeman**, Los Gatos; **Michael H. Azarian**; **Michael A. Baldwinson**, both of Cupertino; **Keith R. Berding**, San Jose; **Kaynam Chun**, San Francisco; **Garrett A. Garrettson**, Los Altos Hills; **Harold J. Hamilton**, Santa Clara; **Robert D. Hempstead**, Los Gatos; **Dimitre A. Latev**, San Jose; **Mark A. Lauer**, Pleasanton, all of Calif.

[73] Assignee: **Censtor Corp.**, San Jose, Calif.

[21] Appl. No.: **08/515,140**

[22] Filed: **Aug. 15, 1995**

Related U.S. Application Data

[63] Continuation-in-part of application No. 08/408,036, Mar. 21, 1995.

[51] **Int. Cl.**[6] **G11B 05/12**
[52] **U.S. Cl.** .... **360/97.01**; 360/102; 360/103; 360/122; 360/135; 428/694 TF; 428/694 TR; 428/65.4; 428/900
[58] **Field of Search** .... 428/65.3, 65.4, 428/65.5, 141, 156, 694 TP, 694 TR, 694 TS, 900, 694 SG, 694 TF; 360/135, 97.01, 102, 103, 122

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4,926,274	5/1990	Saitoh et al.	360/102
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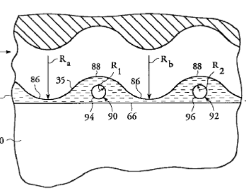
Primary Examiner—Stevan A. Resan
Attorney, Agent, or Firm—Mark Lauer

[57] **ABSTRACT**

A operationally contacting hard disk drive system has reduced friction due to lower capillary adhesion between the disk surface and a transducer in a substantially continuous sliding relationship with the surface. The disk surface has an adhesion-reducing texture that includes a microscopic RMS roughness in a range between about 1.5 and 5.5 nanometers, or a number of asperities having a mean plane to peak height in a range between about 6 and 50 nanometers. The roughness may increase in a radially graded fashion to compensate for the increased linear velocity and concomitant frictional power loss near the outer diameter of the disk. It is important that the uppermost reaches of the textured surface are smooth but not flat in order to obtain lasting low friction operation, which is accomplished by constructing the surface with a highest approximately one percent having an average radius of curvature in a range between 2 microns and 100 microns. An area of the slider in apparent contact with the disk surface is preferably less than 1000 square microns, and a ratio between this nominal area and the mean to peak height is less than 0.3 meters. The slider may also include a substantial thickness of partially wetting material in contact with the disk, or may alternatively be textured with deep grooves or materials having differing wear rates, in order to provide reduced frictional adhesion despite wear of the slider.

19 Claims, 6 Drawing Sheets



U.S. Patent Sep. 7, 1999 Sheet 1 of 6 **5,949,612**

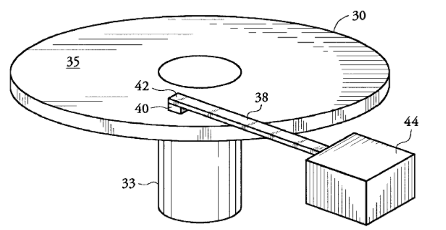


FIG. 1

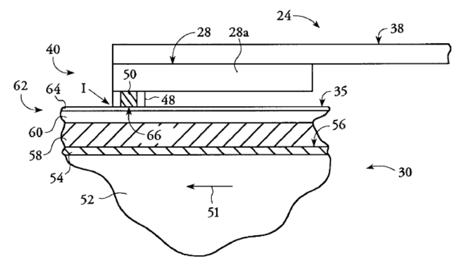


FIG. 2

Figure 2.8 Estimated mean citations as a function of K (N is fixed at 3)[26]

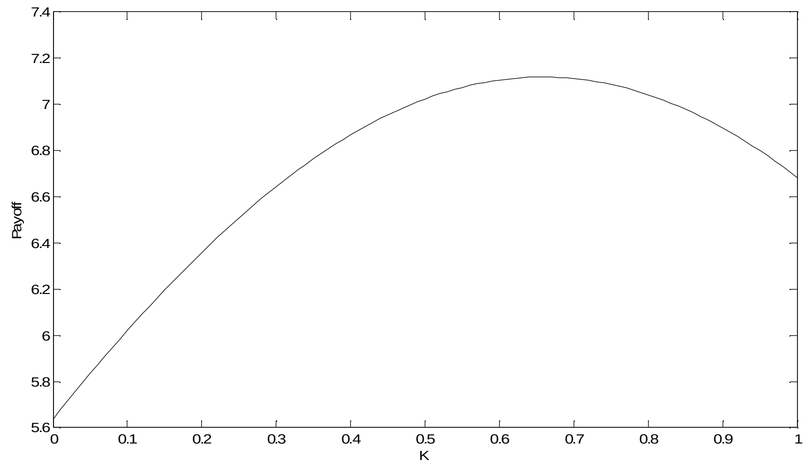
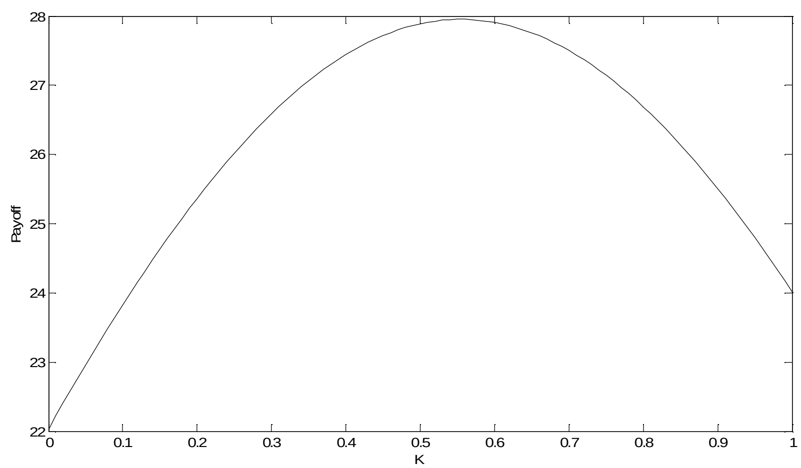


Figure 2.9 Estimated variance of citations as a function of K (N is fixed at 3)



[26] In the Negbin II specification of the negative binomial model, the predicted values have the form exp(Xβ) for the mean portion and (1+ exp(Zβ)exp(Xβ))exp(Xβ) for the variance portion.

Figure 2.10 Estimated mean citations as a function of N (K is fixed at 0.2)

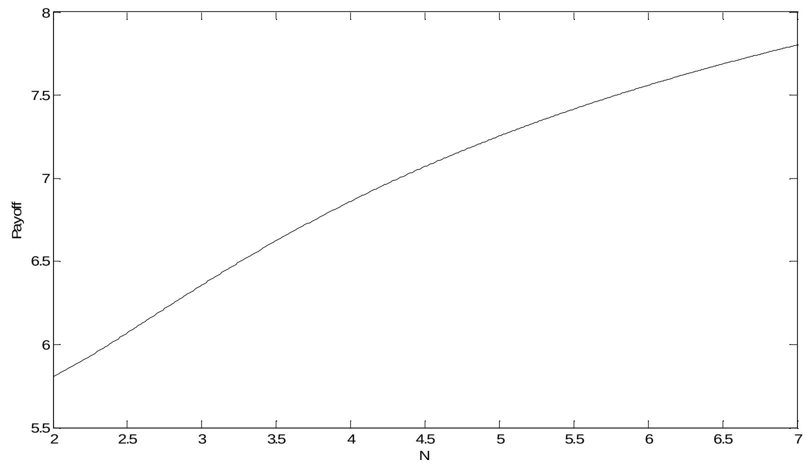


Figure 2.11 Estimated variance of citations as a function of N (K is fixed at 0.2)

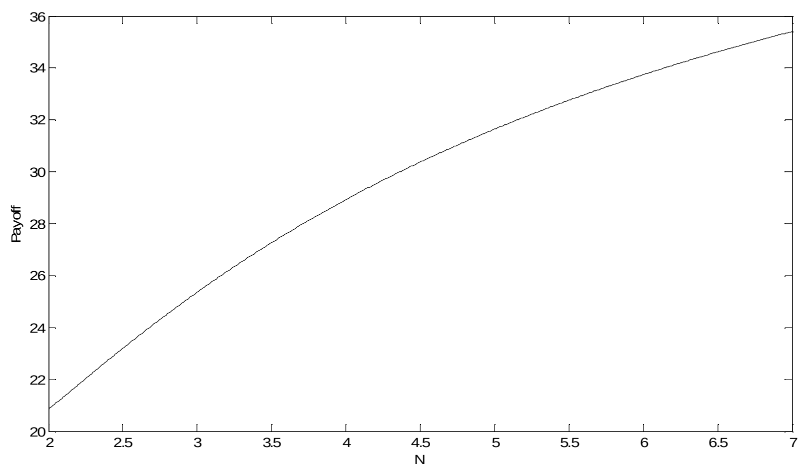


Figure 2.12 Estimated mean citations as a function of *N* (*K/N* is fixed at 0.06)

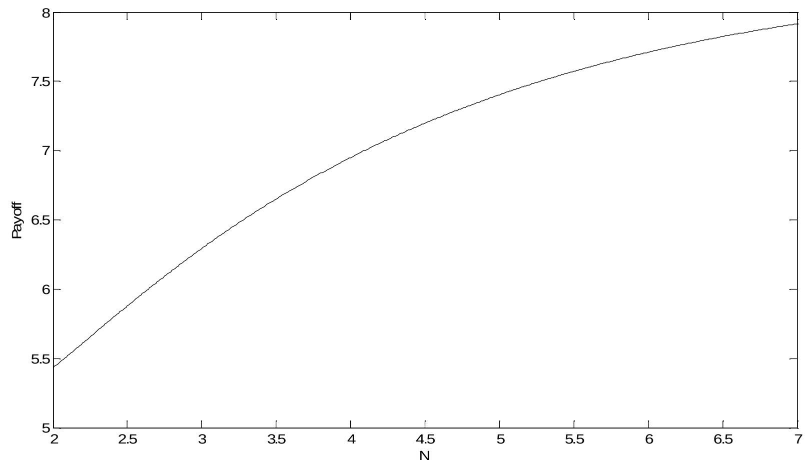
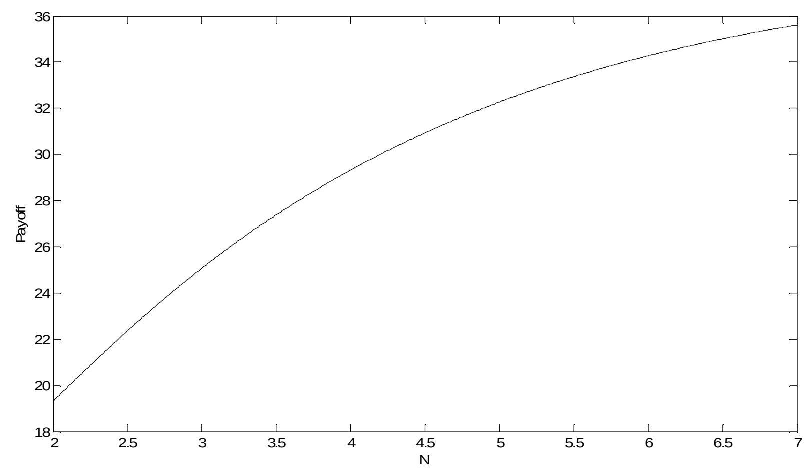


Figure 2.13 Estimated variance of citations as a function of *N* (*K/N* is fixed at 0.06)



CHAPTER 3

ESSAY 2: WHAT IS THE ROLE OF TECHNOLOGY IN EMPLOYEE ENTREPRENEURSHIP?

INTRODUCTION

Entrepreneurial ideas frequently originate within existing firms. An extensive body of work has examined both antecedents and consequences of employee entrepreneurship (Anton and Yao, 1995; Agarwal, Echambadi, Franco and Sarkar, 2004; Casiman and Ueda, 2004; Dahl, Østergaard and Dalum, 2005; Klepper, 2005; Dahl and Reichstein, 2006; Agarwal, Audretsch and Sarkar, 2007; Hellman, 2007; Chatterji, 2009; Klepper and Thompson, 2009; Elfenbein, Hamilton and Zenger, 2010; Ioannou, 2010; Mostafa and Klepper, 2010).[27] Employee entrepreneurship has been heralded as a driver of innovation (Agarwal *et al.*, 2004; Klepper, 2005), a critical source of new capabilities and heterogeneity in performance (Rosenkopf and Almeida, 2003; Agarwal *et al.*, 2004; Dahl and Reichstein, 2006) and an impetus to the creation and growth of industries and regional clusters (Klepper, 2001; Dahl *et al.*, 2005; Agarwal *et al.*, 2007; Mostafa and Klepper, 2010). Consequently, understanding mechanisms leading to employee entrepreneurship is of utmost importance for both academic researchers and practitioners. These mechanisms are non-trivial. From the perspective of the employees, employee entrepreneurship implies the choice to pursue ideas outside of the parent firms. Employees may opt for risky and costly exits, giving up the security and support of being with the parent. From the perspective of the incumbent organization that has invested the critical resources necessary for the knowledge creation, it implies internal imperfections and lost opportunities. When explaining employee entrepreneurship, the existing literature has relied on

[27] Employee entrepreneurship is typically defined as the founding of a new venture by an individual who worked for an incumbent firm that operates in the same industry and has no ownership relationship with the new venture (Agarwal, Ganco and Ziedonis, 2009).

agency costs and incomplete contracts (Pakes and Nitzan, 1983; Anton and Yao, 1995; Kim and Marschke, 2005; Hellman, 2007), information asymmetries (Agarwal *et al.*, 2004; Franco and Filson, 2007; Klepper and Thompson, 2009) or resource constraints (Cassiman and Ueda, 2006). A related literature has examined intra-firm decision-making and learning processes through the agent-based approach (Gavetti and Levinthal, 2000; Rivkin and Siggelkow, 2003; Ethiraj and Levinthal, 2004; Sommer and Loch, 2004; Miller, Zhao, and Calantone, 2006; Barr and Saraceno, 2009; Kavadias and Sommer, 2009; Miller and Lin, 2009; Banerjee and Cole, 2010; Grahovac and Butler, 2010; Miller and Martignoni, 2010).

By connecting these theoretical approaches, I highlight a novel mechanism potentially leading to employee entrepreneurship. I show that employee entrepreneurship may emerge due to a mechanism that does not necessitate agency costs, asymmetric information, resource constraints or heterogeneity in agent quality. I assume bounded rationality and a need for collaboration when agents solve complicated problems. Modeling employee entrepreneurship with the agent-based approach (Levinthal, 1997; Gavetti and Levinthal, 2000) allows greater focus on drivers that were not previously studied. In particular, questions related to technology seem well suited to such an analysis. The problems solved by employees are closely linked to the underlying technology. Looking back at the literature, the question of how the micro-level variation in technology affects employee entrepreneurship is uncharted territory. The prior studies suggest that technologically more advanced firms generate more entrepreneurs (Brittain and Freeman, 1986; Franco and Filson, 2007) and that underexploited technological opportunities may lead to employee entrepreneurship (Agarwal *et al.*, 2004). Additionally, there is abundant anecdotal evidence of employees quitting after their technological ideas are rejected by the parent firms. Klepper and Thompson (2009) trace most of their cases of employee entrepreneurship in the early automobile, semiconductor and laser industries to disagreements about technological strategy. Even the most well-known examples of employee entrepreneurship were cases when technological ideas were rejected by the parent firm. For instance, Fairchild Semiconductor formed when the “traitorous eight” - employees of Shockley Semiconductor Laboratories who included Robert Noyce and Gordon Moore - disagreed with Shockley about the prospects of Shockley’s four layer germanium diode technology in comparison to silicon transistors (Holbrook, Hounshell, Klepper and Cohen, 2000; Shurkin, 2006). History repeated itself later at Fairchild when Robert Noyce and Gordon Moore left to form Intel after Sherman Fairchild - who funded the venture - disagreed with Noyce about the prospects of his strategy and refused to promote him as a new CEO (Berlin, 2001; Shurkin, 2006). The anecdotal evidence also suggests that some industries and some periods within the industry life-cycle experienced booms of employee entrepreneurship (Agarwal *et al.*, 2004; Klepper and Thompson, 2009). In the semiconductor industry, Fairchild Semiconductor generated many *Fairchildren* and at the time proudly proclaimed that “*We Started It All!*” (Moore, 1998). Overall, technology seems to matter for employee entrepreneurship at a very fine grain and its importance possibly increases with technological intensity of the problems that employees solve. How exactly it affects entrepreneurship is unclear. This study tries to take a first step towards filling this gap.

To briefly foreshadow my main results, the model predicts that the likelihood of project rejection will increase as the technological problems become more difficult and the technological landscape more volatile. The effect of technological shocks on project rejection rises faster for more simple problems. For very complex problems, even a small technological shock can dramatically increase project rejection but additional volatility has little effect. The model also suggests that solving problems with intermediate technological breadth leads to a higher likelihood of project rejection relative to general or specialized problems.

EXTANT LITERATURE EXPLAINING ANTECEDENTS OF EMPLOYEE ENTREPRENEURSHIP

The existing theoretical explanations of employee entrepreneurship fall into several broad categories based on the type of imperfection researchers employ. In a frictionless equilibrium environment, employee entrepreneurship would not emerge – all profitable new projects would be developed within existing firms. Scholars explaining employee entrepreneurship thus assume frictions, including agency costs and incomplete contracts (Pakes and Nitzan, 1983; Anton and Yao, 1995; Kim and Marschke, 2005; Hellman, 2007), asymmetric information (Franco and Filson, 2007; Klepper and Thompson, 2009) or resource constraints (Cassiman and Ueda, 2006).

For instance, Anton and Yao (1995) focus on designing an employment relationship that would mitigate incomplete contracts for intellectual property rights. They assume that employees personally discover innovations in an environment with non-enforceable property rights. To avoid expropriation or ex-post competition with the incumbent firm, an employee may decide not to disclose the innovation to the employer and instead exits to commercialize it. Similarly, Hellman (2007) assumes an inability to contract for private benefits and predicts employee entrepreneurship as arising from an employer policy of discouraging exploration by its employees. He assumes that employees faced with the choice of either working on an assigned task or developing their own ideas derive higher private (non-contractible) benefits from working on their own ideas. This may lead to excessive exploration (time spent on own ideas as opposed to the ones assigned by the employer). The employer may curb such over-exploration by rejecting some profitable ideas.

Cassiman and Ueda (2006) assume that the incumbent firm can only implement a limited number of projects over its lifetime. They assume a perfect market for innovations and assume that each proposal has three attributes - potential for complementarities (value generated if projects are developed internally), cannibalization, and an intrinsic value. If a project offers low complementarities the focal firm may reject it to wait for better future projects. However, a startup may find this project profitable, leading to employee entrepreneurship. Franco and Filson (2007) assume asymmetric information. In their model, each employee receives a wage and has a fixed probability of imitating its employer's knowledge (the agent's productivity does not depend on whether the employee managed to imitate the knowledge or not). The employee thus "pays" for the probability of imitating the employer's knowledge through lower wages. Conditional on imitating the knowledge, however, it becomes optimal to exit since the employer is unwilling to compensate for the increase in the employee's stock of knowledge. The model by Klepper and Thompson (2009) hinges on the temporary imperfections arising from the information asymmetries in the decision-making process. Each firm consists of Bayesian agents that in each period draw a noisy signal of the optimal strategy. The authors assume that there exists a subset of agents that have lower variance of their signal draws. However, the rest of the agents do not know that some agents have more precise estimates of the strategy. Then, even though the prior estimates of the optimal strategy are identical and the posteriors converge in the limit, there is a temporary divergence in the estimates between the two types of agents, which leads to idea rejection and employee entrepreneurship.

The type of imperfections built into the models and the exact mechanism driving employee entrepreneurship vary, but all models highlight two salient features: 1) not all viable entrepreneurial ideas are exploited within incumbent firms, and 2) imperfections within the parent firm environment result in some form of conflict, which potentially leads to exit and exploitation of entrepreneurial ideas outside of the parent firm boundaries.

The model I propose utilizes the same basic notions – imperfections in the parent firm processes lead to the possibility of rejection of viable entrepreneurial opportunities. I assume that problems tackled by the agents are complicated and, due to their bounded rationality, solving them requires a combination of rational optimization and trial-and-error experimentation. I also assume that problem-solving is a collaborative effort necessitating diverse expertise. Such framing of the discovery process allows greater focusing on my main question - what is the role of technology in the rejection of viable entrepreneurial ideas?

MODEL PRELIMINARIES AND MAPPING OF THE PARAMETERS TO THE CONTEXT OF EMPLOYEE ENTREPRENEURSHIP

The key component of the model is the NK landscape (Figure 3.1; Kauffman, 1993, 1995). The use of the NK model is well established within the strategy literature as a way to analyze situations where boundedly rational agents face complicated environments (Levinthal, 1997; Rivkin, 2000; Ethiraj and Levinthal, 2004).[28] Analogous to prior literature (Ethiraj and Levinthal, 2004; Rivkin, 2000), I assume that binary bits of the decision vector represent choices about the technological strategy of the firm. The value of each bit – either zero or one – represents a decision about these elements (e.g. decision *A* vs. decision *B* is chosen). In each period, a firm thus makes *N* choices about various components of its technological strategy.

Consistent with prior literature (Kollman, Miller and Page, 2000; Sommer and Loch, 2004; Gavetti, 2005), I assume that agents within the firm search an identical NK landscape. It implies that the incumbent firm employees collaborate on solving a joint problem. The key component of the NK model is the *K* parameter controlling the degree of interdependence

[28] Interested readers should consult Levinthal (1997) or Kauffman (1993, Ch. 6) for an introduction to the NK model.

between the decision elements (i.e. controlling the ruggedness of the space). The performance contribution of each element of the decision vector x_i, $i = 1 \ldots N$, is affected by K other elements x_j, where j is not equal to i. A high value for K implies a rugged landscape and a very complicated problem to be solved (i.e. it is NP-hard, Rivkin, 2000). The NK landscape is generated using the standard procedure (Kauffman, 1993; Levinthal, 1997; Rivkin 2000).

Mapping of the *K* parameter to our Context

The ruggedness of the landscape, controlled by the parameter *K*, typically proxies for the difficulty of the problem that is being solved (Rivkin, 2000; Kollman *et al.*, 2000). As *K* and the density of interdependencies between the problem components increase, the problems are getting more difficult. The problems with high *K* can also be thought of as "non-decomposable" (Simon, 1969). It is conceivable that settings with higher technological intensity – like the semiconductor, laser, and auto industries in my examples above - will present more complex problems. The literature also suggests that the need for vertical integration may increase problem coupling due to the linkages between upstream and downstream activities (Sorenson, 1997). *K* may also proxy for differences in the product design matrix (Rivkin and Siggelkow, 2007) when it captures the density of interactions between design components (i.e. the components A and B are interdependent if a change in component *A* affects the performance of component *B*).

An alternative way of thinking about the mapping between the parameter *K* and problem difficulty is to think of it as a proxy for problem modularization (Baldwin and Clark, 2000; McCormack, Rusnak and Baldwin, 2006; Ethiraj and Levinthal, 2004). As a way of tackling underlying problem complexity, problems may be modularized by delineating modules and standardizing the interfaces between the modules (Baldwin and Clark, 2000; McCormack, *et al.*, 2006). Standardization of interfaces limits the degree of freedom for the designers but also limits cross-module interactions. This, in turn, makes problems simpler to solve, and the compartmentalization into modules allows a parallel and decentralized search. Such mapping is consistent with the existing literature. Christensen (1997), in his study of thin film heads in the disk drive industry, describes that "*…modularity narrows degrees of freedom in design.*" Similarly, Fleming and Sorenson (2001) suggest that the "*…onset of complete modularity severely limits opportunity*." Consequently, a landscape with high *K* may proxy for an environment before the onset of modularization and the emergence of dominant design (Abernathy and Utterback, 1978; Anderson and Tushman, 1990; Suarez and Utterback, 1995) when designers are faced with complex problems with dense interactions.

Mapping of the *N* parameter to our Context

The parameter *N* controls whether the problem is narrow and specialized (low *N*) or broad and cutting across multiple domains (high *N*). I assume that the problem breadth always exceeds the expertise of an individual agent. To solve a problem, a firm needs to make choices about *N* individual decision elements, but the individual agents have "expertise" only for a subset of these elements. When different agents have expertise over different elements, some form of collaboration is highly beneficial. Consequently, problem breadth determines the need for collaboration.

These assumptions are consistent with the notion that modern technological knowledge requires specialization and "depth" of knowledge rather than breadth (Jones, Uzzi, and Wuchty, 2007; Jones, 2009). The new knowledge does not simply replace the old but rather builds upon it, which increases the need for both specialization and collaboration (Jones, 2009). The empirical evidence supports the argument that the importance of collaborative innovation and technological problem-solving increased dramatically over the last few decades (Jones, Uzzi, and Wuchty, 2007; Jones, 2009; Singh and Fleming, 2010).

Modeling Need for Collaboration, Cognitive Search and Experimentation

I model the technological expertise of agents using the notion of a cognitive search. Analogous to the NK models of cognition (Gavetti and Levinthal, 2000; Gavetti, 2005), I assume that agents create a cognitive representation of reality. Based on past experiences, education and skill endowments, agents can create a simplified version of the actual rugged landscape – which then guides them in subsequent experimentation (Gavetti and Levinthal, 2000; Gavetti, 2005). The combination of cognitive search and trial-and-error experimentation provides significantly more powerful search capabilities relative to experimentation alone (Gavetti and Levinthal, 2000). I assume that agents are able to search in their domain of expertise.

More specifically, I define expertise as those decision elements (i.e. dimensions of the problem space) that can be changed by the agent to perform the search. For example, let's assume that first, second and fifth are the "expertise" dimensions of the agent *A* with *N* equals 5. I will use the following notation to describe such a situation: _ _ **_. The stars denote dimensions outside of the area of expertise of this agent and the underscores represent the ones it can search. It is important to note that the payoff depends on the entire vector of the length *N* (i.e. all individual decisions need to be made) and not only on the contribution of the "expertise" dimensions. Decisions along the dimensions outside of the expertise of the agent *A* directly and indirectly (through interdependencies) affect the agent's payoff. The problem is the same for all agents - though the limited expertise allows the agents to search only portions of the space. This necessitates cooperation. The remaining dimensions must be searched by other agents or left unsearched and remain as gaps in the problem space. The agents can search dimensions within their domain of expertise either through cognitive search or experimentation (i.e. local search).

The above setup embodies several additional assumptions. First, it implies that there are no private benefits. A given decision implies equal payoffs for the firm as well as for the individual employee. Such an approach also abstracts from property rights and agency costs. I assume that agents can perfectly evaluate each other's proposals (i.e. no asymmetric information). Similarly, there are no frictions related to managerial diseconomies (Penrose, 1959) and no noise in the communication or transfer of knowledge (Agarwal *et al.*, 2004; Franco and Filson, 2007).

The agent experiments by an alteration of a single random decision element of the decision vector. If a change implies a higher payoff, the agent moves toward it. For instance, if N equals 5 and if the agent's possible move from 00101 to 00100 (the expertise is again _ _ **_) results in the increased payoff, the agent will make the move. Otherwise, it will stay at the original position.[29]

The cognitive search is significantly more powerful. The agent is assumed to "understand" the linkages and their impact on the expertise dimensions of the problem space. Consequently, it can consider a large number of changes or fully optimize over this subset. For instance, from the solution 00101, the 00**1 can be a solution based on cognitive search. The solution _ _ 10_ is outside of the expertise of the agent. I assume that the agent cannot change these elements even though they affect the agent's payoff. In general, the difference between experimental and cognitive search is in the distance and the number of solutions the agent can consider in one step. For the experimental search, the agent can evaluate only one local change, for instance 00101 → 00100. However, using the cognitive search it can consider significantly more distant solutions. Following prior studies (Gavetti and Levinthal, 2000; Gavetti, 2005), I

[29] Gavetti and Levinthal (2000) term such search *experiential* search.

assume that every agent can fully optimize over its expertise dimensions. In one step, the agent considers all strings (ordered samples with replacement) of zeros and ones and selects the best string in the places of the cognitive dimensions. In our case, the agent can select from eight choices in the position of underscores (00**0, 00**1, 01**0, 10**0, 01**1, 11**1, 11**0, 10**1) and select the best one. However, to obtain the problem payoff, the agent needs to evaluate the entire decision vector. In other words, the impact of the other decisions on the overall payoff needs to be determined (since the problem is larger than the individual expertise covers). Prior literature (Gavetti and Levinthal, 2000; Gavetti, 2005) has modeled this aspect by assuming that the agent creates unbiased expectation over all possible solutions in the outside dimensions that are consistent with the given proposal. For instance, we can assume that the agent needs to evaluate payoff of the decision 01**0. This proposal is consistent with four decision vectors (replace stars by the strings of zeros and ones): 01000, 01010, 01100, and 01110. Let's assume the following payoff structure:

Decision	Payoff
01000	0.54
01010	0.21
01100	0.01
01110	0.78

Following the algorithm of Gavetti and Levinthal (2000), the payoff of the cognitive solution 01**0 is 0.385 (which is the mean value of the four decisions consistent with 01**0).

Figure 3.1 can provide an illustration of the nature of cognitive search.[30] Imagine that N equals 6 and that the agent performs cognitive search over the first three dimensions of the space (let's define this as the x axis). The agent first generates expectation over the second three dimensions (y axis) which can be seen as a cut through the space parallel to the y axis with height

[30] The visualization of the space is developed following the method discussed in Rivkin and Siggelkow (2007)

equal to the mean of values along the *y* axis for each of the points on the *x* axis. The outcome of the cognitive search is the highest point on this “mean slice” of the space along the *x* axis.

The cognitive search provides only guidance – it is inherently imprecise and fuzzy. Nevertheless, the cognitive solution positions the agent in the correct “mountainous” region of the space.[31] I model the agent as capable of selecting the best cognitive solution from all possible strings along the cognitive dimensions in one step. The solution based on the cognitive search is thus independent of the current state of the “non-expertise” dimensions. The cognitive search leads the agent to the same solution regardless of the state of the world along the outside dimensions. The cognitive search provides guidance in the subsequent experimentation but also “blinds” the agent from considering the current state of the world.[32]

The cognitive search is thus powerful but imprecise. The experimental search adjusts the solution to a fine grain but is slow and prone to lock-ins. The value of the experimental search is especially useful when the agent is already located in the attractive region of the space and a high payoff is close. I follow prior studies (Gavetti and Levinthal, 2000; Gavetti, 2005) and assume that agents perform cognitive search only once at the beginning of the simulation and then proceed through experimental search by adjusting the decision elements within their expertise.

[31] Gavetti and Levinthal (2000) find that such positioning is especially beneficial for spaces with a low to moderate degree of *K* when the peaks are spatially correlated. Once the value of *K* is high, the space becomes uncorrelated and the global peak can be anywhere (Kauffman, 1993; Gavetti and Levinthal, 2000).

[32] A slightly different approach has been used by Sommer and Loch (2004), who assume, that the agent does not create expectation over all possible strings consistent with the given proposal but instead considers the outside dimensions as given. I adopt the specification of Gavetti and Levinthal (2000) - it better captures the idea that expertise provides guidance for subsequent experimentation. The main predictions of the model are robust to either version of the cognitive search.

Modeling Problem Breadth and Collaboration

For simplicity, I assume that the firm size is constant at two agents.[33] To reflect the observation that technological knowledge requires depth, specialization and collaboration (Jones, Uzzi and Wuchty, 2007; Jones, 2009; Singh and Fleming, 2010), I assume that the breadth of expertise is fixed and vary the problem breadth, *N*. If the firm needs to solve a more general problem it may need to assemble experts who cover all relevant technological domains. For instance, a structure of the firm solving a technologically specialized problem with *N* equals 5 and *E* equals 4 (the parameter *E* controls the width of expertise of a single agent) may look as follows:

N	**1**	**2**	**3**	**4**	**5**
Agent 1	_	_	_	*	_
Agent 2	_	*	_	_	_

The agents overlap in three of the five dimensions. *Agent 1* has exclusive expertise over the second and *Agent 2* over the fourth dimension. An example of a firm solving a general problem with *N* equals 7 and *E* equals 4 may look like:

N	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Agent 1	_	_	_	*	*	*	_
Agent 2	*	*	*	_	_	_	_

Performing baseline simulations, as described below, shows that it is never optimal to leave some dimensions of the problem space unsearched by the agents.[34] For instance, the following situation is never optimal:

[33] I do not model any explicit coordination or communication costs associated with adding agents. The model would thus imply that the firm size should be infinite. Since the coordination and communication costs are not essential for the mechanism, I abstract from these issues and focus on two agents for the sake of parsimony.

[34] The agent's behavior is optimal if the agent achieves the best performance it can, given the constraints of the model. Optimal performance is the maximum over the alternatives available to the agent. Note that the optimal performance does not refer to the global maximum on the NK landscape.

N	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Agent 1	_	_	_	*	_	*	*
Agent 2	_	*	_	_	_	*	*

The result holds across all *K* and all types of search behavior as described below. It is always optimal to cover the entire space of the problem by agents' expertise. Note that the degree of overlap between the domains of expertise of the agents is a function of *N* (i.e. it equals 2*E*-*N*). For all of the subsequent simulations, I assume that agents jointly cover all dimensions of the problem and do not leave any dimension unsearched. The structure also implies that any individual agent will have a more accurate cognitive representation of the problem space and will be more accurate in making its initial guess when solving a more specialized problem.

Modeling the Decision-Making Process

I model the decision-making process within the firm using a common and relatively simple algorithm (e.g. Kollman *et al.*, 2000; Sommer and Loch, 2004).[35] I assume that agents start searching the space independently, starting from the solution based on cognitive search and continuing with experimentation. The agents try to fine-tune their solution to find the best possible payoff. In each period, agents evaluate a change in one individual decision element from their expertise dimensions and propose the new solution only if they observe an increase in performance. For instance, in our case above, the agents in period 1 may evaluate:

Period 0: Cognitive search

N	**1**	**2**	**3**	**4**	**5**	**6**
Agent 1	1	0	1	*	1	*
Agent 2	*	*	1	0	1	1

↓

Joint solution implemented: 101011

[35] The qualitative results are not sensitive to different specifications of the decision-making rule. Different rules would affect the absolute performance but not the qualitative predictions of the model.

Period 1: Experimental search begins[36]

N	**1**	**2**	**3**	**4**	**5**	**6**
Agent 1	***0***	**0**	**1**	0	**1**	1
Agent 2	1	0	**1**	***1***	**1**	**1**

Proposals considered: Agent 1: 001011
Agent 2: 101111

The agents can propose changes only within their domain of expertise. Further, I assume that agents perform search independently for *k* periods (Kollman *et al.*, 2000). Agents do not consult on the proposals with each other but continue to fine-tune the implemented solution. Every k^{th} period agents "meet," compare the payoffs of the two proposals and select the better one. The selected proposal is implemented by the firm and the agents search for another *k* periods independently, starting from the new implemented solution. The parameter *k* represents the trade-off between the time the agents search in parallel and the implementation delay. A short period between meetings (small *k*) allows rapid increases in firm performance due to frequent implementation but it does not provide agents with sufficient time to perform local search. Long intervals (large *k*) between meetings give sufficient room for experimentation but create delay in project implementation and lead to a slow increase in performance of the firm. Since I do not explicitly model these trade-offs, I assume fixed *k* equals 5. The robustness of the qualitative predictions has been tested for a wide range of *k*.[37]

Consistent with prior literature, I run the models with specific values for *N*, *K*, *E* and *k*. Due to the computational burden, I selected low values of *N* and *K* that lead to a reasonably fast convergence. The simulations were implemented in MATLAB and model parameters and assumptions are summarized in Table 3.1.

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[36] Decisions that are within the expertise of each agent are in bold and the proposed changes are in bold and italics.
[37] If there is no penalty for the delay in implementing proposals it is best to have a large *k*.

BASELINE PREDICTIONS: SHARED EXPERTISE AND INCUMBENT FIRM STRUCTURE

Before I can analyze the dynamics of project rejection, I need to develop another preliminary of the model – incumbent firm structure. Let's assume that agents start solving a given problem by performing the cognitive search, which leads to the following proposals by the two agents:

N	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Agent 1	**1**	**0**	**1**	*	*	*	**1**
Agent 2	*	*	*	**0**	**1**	**1**	**0**

In the place of underscores are zeros or ones - representing the proposed solutions based on the cognitive search of both agents (the non-cognitive dimensions do not affect the proposals and are omitted). Note that along the seventh dimension there is a conflict in how the agents perceive the solution of the seventh decision. The question is whether it is optimal to create the firm in the presence of such differences. The presence of a conflict along the overlapping dimension suggests that the agents perceive the solution differently, and they may be guided to different portions of the space in their subsequent experimentation for the best payoff. Intuitively, one could expect that such cooperation is inefficient.

Table 3.2 shows baseline simulations that confirm this conjecture. For all *K* and *N* combinations and regardless of whether agents subsequently experiment with the shared dimensions or not, having a firm that started with conflict in cognitive representations along the shared dimensions is not optimal. Note that the shared solution may be imperfect – it may not necessarily point to the best solution in the space. However, it is crucial that both agents "agree" on it. This leads to the baseline implication:

Implication 1: It is not optimal for the firm to operate when there are solution differences in the shared portion of agents' cognitive searches.

For the remainder of the paper, I assume that the incumbent firm starts with alignment. Table 3.2 reveals additional intuitive patterns. The benefit of the initial alignment between the agents' cognitive searches decreases with *N* and increases with *K*. For highly specialized problems (low *N*), the likelihood that the agents search for the same solution (if aligned) is high and consequently the coordination is very valuable. Misalignment is, thus, very costly. Similarly, the value of coordination increases with *K*. If the agents are misaligned, it is very unlikely that they are searching for the same solution if the *K* is high.

I also assume that conditional on incumbent firm formation, the agents implement a joint solution and use it as a starting point for the subsequent experimentation. For instance, if the cognitive searches of the agents lead to the following proposals,

N	**1**	**2**	**3**	**4**	**5**	**6**
Agent 1	**1**	**0**	**1**	*****	**1**	*****
Agent 2	*****	*****	**1**	**0**	**1**	**1**

the incumbent firm would implement solution 101011 at time zero of the simulation. This simplifying assumption is not crucial qualitatively and is more efficient than the alternative.[38, 39]

BASELINE PREDICTIONS: SHARED EXPERTISE AND EXPERIMENTATION

The results in this section are extensions of a prediction reported by Gavetti and Levinthal (2000) and are analogous to classical thoughts in Strategy emphasizing the role of direction in coordinating an individual's actions (Weick, 1987). Gavetti and Levinthal (2000) find that in a model where one agent searches the entire space (*N* equals 10) and the agent's cognitive dimensions constitute a subset of the space (*N1* equals 3) it is not optimal to search the

[38] The alternative would be to assume that each agent starts searching from its own solution. In such a case, the joint solution would emerge as the firm's solution after the first meeting (as described below).

[39] Additional baseline simulations also confirm the optimality of the existence of an incumbent firm. The firm outperforms the same number of individuals searching independently, and it outperforms the arrangement where one agent searches the entire problem space. The combination of the cognitive search followed by the local search is superior to searching through either cognitive or local search separately.

cognitive dimensions *N1*. It is optimal to keep the initial solution based on the cognitive search intact even though it provides only an imprecise representation of the actual problem.[40] In other words, the agent locally searching only the remaining *N-N1* dimensions outperforms the agent that locally searches the entire *N* vector. Within my model, the agents have searching ability which is narrower than the entire space but can complement each other through collaboration.[41]

Table 3.2 shows additional patterns when comparing different types of searches. In Figure 3.2, I highlight some of them and show three sets of simulation runs for different problem breadth *N*. The first model (solid line) represents the case where agents search experimentally their entire cognitive domains. In the second (dotted line), they keep the shared, overlapping dimensions intact and in the third (dashed line) they only search the shared dimensions.

Consistent with Implication 1, Table 3.2 and Figure 3.2 show that agents that do not experiment with the shared solution outperform agents that experiment with the entire vector, and dramatically those that search only the overlap. The result holds for small as well as for large *N*. Again, the shared cognitive solution represents a set of core technological ideas around which is the search is organized. It is an implicit agreement on which subsection of the space is jointly searched and coordinates subsequent agents' search efforts. Even though the shared solution is imperfect, it is better when it is left intact. It leads to another baseline implication:

Implication 2: It is not optimal for the firm to deviate by experimental search from the alignment in the shared portion of the technological solution.

[40] In Figure 1, it implies that it is optimal to keep the position on the *x* axis, which is determined by the cognitive search, intact and perform experimentation only along the *y* axis.

[41] As I discuss above, the objective of my assumption to narrow the search only to the cognitive dimensions is to create an additional constraint that would necessitate collaboration. Alternatively, the assumption implies that if an agent proposes a change outside of its domain of expertise it will be always overridden by another agent's idea based on its expertise.

The simulations highlight additional patterns. The benefit of not deviating from the shared solution decreases with the elapsed simulation time. The value of cognitive guidance is high only when agents are uncertain about the solution. When they start converging on a solution, the value provided by local search increases and the cognitive solution becomes relatively less important (Gavetti, 2005). Thus, the advantage associated with following the direction delineated by the cognitive search is temporary.

MODELING DYNAMICS: THE ROLE OF TECHNOLOGICAL SHOCKS

In the model, the agents are uncertain about the best solution for a complex technological problem, they need to combine cognitive and experimental searches and they need to collaborate to maximize performance. However, the problem they are solving is static - the shape of the NK landscape does not change. Without the presence of asymmetric information, agency costs, or differences in rationality or quality, it is optimal for both of the agents to behave according to Implications 1 and 2 – maintain alignment and change only those decisions that fall outside of the shared expertise. In such an environment, there are no rational reasons for rejection of better technological ideas. However, the assumption of a static technological landscape may not be entirely realistic, and changes in the nature of problems may provide an important impetus that systematically affects project rejection.

In particular, high-technology and early industry settings may be prone to frequent and more pronounced shocks and turbulence (Abernathy and Utterback, 1978; Ganco and Agarwal, 2009; Vaaler and McNamara, 2010). Turbulent or high velocity settings typically embody nonlinear and unpredictable change, short product cycles, and rapidly shifting competitive landscapes (Brown and Eisenhardt, 1997; Eisenhardt and Martin, 2000).

To model the dynamic aspect of the technological landscape, I introduce exogenous shocks. Consistent with prior studies (e.g. Gavetti and Levinthal, 2000; Siggelkow and Levinthal, 2003), at a given period the landscape is altered by redrawing the performance contributions of a subset *s* of individual decision components.[42] The parameter *s* thus controls the size of the technological shock. A small *s* loosely represents technological changes at a component level. A large *s* loosely corresponds to more systemic changes – as in the replacement of germanium by silicon in the case of the early semiconductor industry (e.g. Holbrook *et al.*, 2000). Note that component changes (small *s*) can still lead to large changes in technological landscape if problems are complex and interdependencies are dense.

EMERGENCE OF EMPLOYEE ENTREPRENEURSHIP

Implications 1 and 2 show that it is sub-optimal to operate a firm that has misalignment in the portion of solution that is shared across the two agents. Even though some of the proposed ideas may improve short-term performance, the misalignment is not optimal in the long-run - the agents lose the guidance and coordination provided by the commonalities in their cognitive representations. The firm loses the direction around which it organizes the search (Gavetti and Levinthal, 2000; Weick, 1987).

When the technological landscape shifts, it is reasonable to expect that it may affect how the agents perceive the solution – i.e. shift their cognitive representations. Even though the agents were aligned prior to the shock, they may have a conflict in the shared solution after it. If that occurs, both agents can improve their performance by stopping the collaboration and "renegotiating the truce" (Nelson and Winter, 1982) – replacing the conflicting agent with an aligned one. Note that right after the shock, no agent is better at judging the solution. The agents

[42] Since cognitive representations do not depend on the current state of the world, the period at which I shock the landscape is arbitrary.

may simply see the solutions differently even though they were on the same page before the shock. To examine how changes of N, K and s affect the likelihood of such conflicts, I assume that agents are fully aware of the technological shock. Following the shock, they perform new cognitive searches. I also assume that when the new cognitive searches by the agents lead to misalignment in the shared portion of the solution, because of Implications 1 and 2, one of the agents exits the firm, and I record such an event as project rejection.

Figure 3.3 shows how increases in K affect the probability of conflict in the shared portion of the solution for various levels of N. The results confirm the conjecture that the likelihood of project rejection will increase with increases in problem difficulty or complexity. As the landscape becomes more rugged, the likelihood that after the shock the collaborating agents select different regions of the space as a starting point for their subsequent experimentation increases. Problem complexity increases the likelihood that the agents will perceive the new technological environment differently. This leads to the third implication of the model:

Implication 3: The likelihood of project rejection increases with the complexity of problems solved by the incumbent firm.

Figure 3.4 shows the impact of problem breadth N on the likelihood of conflict in the shared portion of the solution for various levels of K.[43] The relationship shows a non-monotonic relationship between problem breadth, N, and the likelihood of project rejection.[44] The relationship hinges on the extent of overlap in agents' expertise – which is driven by problem

[43] Note that, by construction, the project rejection likelihood at N=E=5 is zero.

[44] Ideally, we would like to hold problem difficulty constant when manipulating the overlap between the agents' expertise. The prior studies showed (Kauffman, 1993; Altenberg, 1996) that increasing N makes problems simpler for fixed K. As a result, the ratio K/N may be a better proxy for problem difficulty. However, even when comparing Prob(project rejection) while holding K/N fixed and varying N, I obtain an inverted-U relationship. Consequently, the results are robust to either specification of the parameters.

breadth. When the problem is general (high N), agents tend to perceive the best solution after the shock very differently. The agents have narrow expertise relative to problem breadth, their cognitive searches are crude and they are very different in their domains of expertise. However, the likelihood of conflict on a few overlapping decision components is still relatively small. When the technological problem is highly specialized (low N), agents' cognitive searches are very powerful and precise. Even though the overlap is large (and the "potential" for conflict could be large), the agents perceive the best solution similarly. Consequently, the likelihood of conflict is relatively smaller. At the intermediate degree of problem breadth, the cognitive searches are less precise and there is also a potential for conflict due to the overlap. I can formulate this model prediction as follows:

Implication 4: The likelihood of project rejection has an inverted U-shaped relationship with the technological breadth of the problems solved by the incumbent firm.

Finally, Figure 3.5 shows the impact of shock size on the likelihood of project rejection for various levels of K.[45] Larger shocks perturb the problem landscape more (i.e. affect more decision components) and, thus, increase the likelihood that the alignment in the shared solution prior to the shock will be no longer valid. The marginal effect of shock size is largest for more simple problems. For complex problems, even a small shock can spread through the system through the interdependencies and significantly alter the technological landscape of the problem. It then leads to misalignment of the shared solution and conflict. However, the additional effect of increasing the shock size is relatively minor. This observation leads to the last implication of the model:

Implication 5: The likelihood of project rejection increases with the size of technological shocks with a negative interaction between shock size and problem complexity.

[45] The problem breadth is fixed at $N = 9$. Fixing N at different level shows identical patterns.

DISCUSSION

The objective of my model was to develop a new theory linking characteristics of technological problems with employee entrepreneurship. I set out to highlight a novel mechanism that may underlie some of the observed regularities. Even though my primary objective was not to develop a model that would replicate all empirical patterns, it may be useful to examine how its predictions map onto existing findings.

First, the mechanics of the model are, by construction, consistent with the empirical accounts maintaining that conflicts occur over the core strategies of incumbent firms (Christensen, 1997; Klepper and Sleeper, 2005; Klepper and Thompson, 2009). The ventures founded by former employees typically implement solutions that are closely related but not identical to solutions pursued by their parent firms (Klepper and Sleeper, 2005; Klepper and Thompson, 2009). This is consistent with my model. Differences in the shared solution cause conflict, but the two solutions are very similar. Both agents try to solve identical problems and only perceive the best solution differently.

Second, the model structure is consistent with the accounts (Bhide, 1994; Lindholm and Dahlstrand, 2001; Klepper, 2002; Klepper and Sleeper, 2005; Klepper and Thompson, 2009) maintaining that the majority of employee entrepreneurs emerge due to idea rejection within incumbent firms. These scholars argue that employees try to convince their employers about the viability of their ideas and exit only when rejected. Similarly, in a survey of 100 fast-growing private companies, Bhide (1994) found that 71% of the entrepreneurial founders commercialized ideas they had encountered or discovered while working at other companies.

Note that some of the existing explanations of employee entrepreneurship do not necessitate inherent conflict with the parent firm. For instance, in Cassiman and Ueda (2006) firm innovative efforts create more knowledge that the firm utilizes and projects that lack complementarities with existing products may be rejected. However, the firm may still support exploitation of such ideas outside of its boundaries by licensing or other involvement. The model that I develop applies to disagreements about the orientation of the firm rather than to product portfolio decisions. The mechanism in my model, thus, more closely corresponds to the anecdotal evidence mentioned above. It remains an empirical question which mechanism is more pervasive and important in reality.

Third, the empirical literature shows that the likelihood of employee entrepreneurship exhibits an inverted U-shaped relationship with industry age in automobiles (Klepper, 2002) and lasers (Klepper and Sleeper, 2005) but a decreasing rate in disk drives (Agarwal *et al.*, 2004) and in a sample of venture capital-funded startups (Gompers *et al.*, 2006).[46] However, all of these studies are consistent in suggesting that employee entrepreneurship is more prevalent in the growth stages of an industry and declines as an industry matures. I do not model the evolution over the industry life-cycle since the technological shocks are assumed to be exogenous in the model. However, the model naturally implies (both Implications 3 and 5) a decline in idea rejection as an industry matures. Such a pattern simply emerges if we assume that growth phases exhibit technological volatility and lack of standardization, which resolve with industry age. The model is, by construction, consistent with the empirical evidence showing that shocks like IPOs or acquisitions (Brittain and Freeman, 1980; Romanelli and Schoonhoven, 2001; Stuart and Sorenson, 2003) create conditions that lead to more employee entrepreneurship originating from incumbent firms.

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[46] By definition, some incumbents need to be present to generate employee entrepreneurs so the rate has to be increasing initially. However, some industries may experience a period of sharp increase when most of the early incumbents generate many employee entrepreneurs. Differences in the shape of the inverted U may contribute to the reported differences across studies.

Fourth, there is evidence that more technologically advanced firms (Brittain and Freeman, 1980; Franco and Filson, 2006; Klepper and Sleeper, 2005) generate more employee entrepreneurs. If we expect that firms at the cutting edge of technological knowledge solve more complex and less standardized problems – this finding is consistent with Implication 3. In support of this argument, anecdotal evidence suggests that some settings like the early semiconductor industry had exceptional rates of entrepreneurial spawning (Moore, 1998). More empirical research is, however, needed to see how the technological complexity affects project rejection and employee entrepreneurship.

Fifth, the model suggests that even small technological shocks can lead to a dramatic increase in conflict if the underlying technology is sufficiently complex. Even though none of the existing studies looked at the technological aspect, some studies provide indications in support for this argument. Hannan, Polos and Carroll (2003a, 2003b) develop a concept of organizational intricacy (loosely analogous to the notion of interdependence) and cascading organizational change and argue that even small changes can lead to significant organization turmoil if the linkages are sufficiently dense. Such a mechanism appears also consistent with case study evidence showing that interactions can amplify small changes, leading to dramatic organizational transformation (Plowman, Baker, Beck, Kulkarni, Solansky and Travis, 2007).

Sixth, there is very limited literature that would indicate how problem specialization affects project rejection and entrepreneurship. Firms that produce a wider variety of products were found to generate more employee entrepreneurs in semiconductors (Brittain and Freeman, 1980) and lasers (Klepper and Sleeper, 2005). However, firms with a single industry focus were reported to generate more employee entrepreneurs than firms operating in multiple industries in a sample of venture capital-backed startups (Gompers *et al.*, 2005). Since the studies measured different constructs (product categories, SIC codes) and found conflicting results, one cannot easily map them onto our construct of technological problem breadth. Clearly more research is needed, but the mechanism that I propose may prove useful in disentangling the underlying drivers.

The predictions of the model may, to some extent, also map on to the extensive literature on team diversity (e.g. Pelled, Eisenhardt, and Xin, 1999; Harrison and Klein, 2007; Joshi and Roh, 2009). Within the model, solving more general problems directly implies collaboration of more diverse experts. For instance, Jehn, Northcraft and Neale (1999) found that functional diversity increases the likelihood of task conflict. However, this stream of studies typically looks at performance as the outcome variable, the findings depend on the operationalization of diversity (Bunderson and Sutcliffe, 2002; Harrison and Kleine, 2007) and overall predictions are mixed (Van Knippenberg and Schippers, 2007). At the same time, these studies do not examine technology as the underlying driver and project rejection as the operationalization of conflict. Consequently, the relevance of the findings for the model proposed in this paper is limited and clearly more empirical work is needed to examine these important relationships.

Further, it may be useful to compare the model with theoretical explanations of employee entrepreneurship. For instance, sociological approaches to entrepreneurship maintain that employee entrepreneurship is driven by environmental context (Brittain and Freeman, 1980; Freeman, 1986; Thornton, 1999; Romanelli and Schoonhoven, 2001; Stuart and Sorenson, 2003; Audia and Rider, 2005; Dobrev and Barnett, 2005; Sørensen, 2007). Sørensen (2007) argues that the *"fundamental premise of sociological approaches to entrepreneurship [is that] the social context shapes the likelihood of entrepreneurial activity, above and beyond any effects of individual characteristics."* Since the *context* may correspond to the nature of technological problems that employees solve, this approach is fully consistent with the specification of my model.

The logic behind the model is also consistent with the explanations of employee entrepreneurship relying on the existence of underexploited opportunities (Agarwal *et al.*, 2004; Cassiman and Ueda, 2006; Franco and Filson, 2007; Klepper and Thompson, 2009). Following the change in the technological landscape, both agents propose viable ideas, but they are unable to decide which one is better (each agent prefers its own idea due to its cognitive constraints) and the firm cannot implement both.

The model predictions and its mechanics have also subtle managerial and policy implications. They highlight the fact that technology has broader implications for performance, competitive patterns and knowledge spillovers. In a normative sense, managers need to be aware that solving difficult problems in uncertain technological environment carries a risk of employee entrepreneurship that can have a detrimental effect on the parent firm (Wezel, Cattani and Pennings, 2006; Campbell, Ganco, Franco and Agarwal, 2010; Aim *et al.*, 2010). The predictions also have implications for knowledge spillovers. The extant literature (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003; Agarwal, Ganco and Ziedonis, 2009) suggests that employee mobility is the key conduit for knowledge transfer. Since idea rejection increases with problem complexity, the model implies that it will be the more complex (and potentially more valuable) knowledge that exits the firm. The model highlights that the likelihood and impact of exit events does not depend only on the legal environment and geographical distance (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003; Marx *et al.*, 2007; Agarwal *et al.*, 2009) but crucially depends on intricate mechanisms operating within incumbent firms.

LIMITATIONS, CONTRIBUTION AND CONCLUSION

To make the model tractable, I assumed away several attributes that potentially influence decision-making processes within incumbent firms.

First, I do not model firm size. Project rejection may depend on size as larger firms have well-defined administrative structures, communication channels and authority. In the model, the firm size is determined exogenously and I do not model any explicit communication, coordination costs or differences in authority. The model has to be seen as an abstract representation of reality, focusing on mechanisms that may take place irrespective of size. However, firm size may interact with our variables of interest. To determine exactly how remains a task for future work.

I also do not explore how different patterns of interdependence (Rivkin and Siggelkow, 2007) affect project rejection. I assume that interdependencies randomly link decision components. It is possible that there are non-trivial interactions between interdependence distributions and project rejection – especially when agents' expertise does not map precisely onto modules and the structure is either over- or under-modularized (Ethiraj and Levinthal, 2004). Exploring these fine-grained interactions again goes beyond my immediate objective of highlighting a new mechanism leading to project rejection and remains for future research.

I model the decision-making mechanism without assuming communication frictions, managerial diseconomies (Penrose, 1959) or additional imperfections like the Type I and Type II error in project evaluation (Sah and Stiglitz, 1988). It is reasonable to expect that communication costs, evaluation errors and managerial diseconomies positively correlate with problem complexity, amplifying Implication 3 of the model. At the same time, these costs may increase with the technological breadth, leading to conflict even when solving very general problems. If such effects are sufficiently strong they could potentially change the shape of the relationship between problem breadth and project rejection toward a concave curve. Disentangling these interactions remains an important empirical task.

Analogous to prior theoretical models discussed above, I do not examine whether rejected ideas lead directly to startups or some of them are exploited within existing rival firms. The implicit assumption of these approaches is that the same or similar imperfections exist at other incumbent firms. As a result, a large proportion of the rejected ideas may not be implemented in other established firms and will be exploited within startups. The likelihood of a startup founding will, thus, positively correlate with the likelihood of project rejection. Again, various contingencies may apply. A few recent empirical studies started to examine the factors that affect whether employees exit to join startups or rival firms (Campbell *et al.*, 2010; Ganco, 2010).

This study contributes to multiple literature streams. Within the context of employee entrepreneurship literature (Agarwal *et al.*, 2004; Cassiman and Ueda, 2006; Franco and Filson, 2007; Hellman, 2007; Klepper and Thompson, 2009; Ioannou, 2010; Chatterji, 2009) the model provides the needed focus on factors that condition emergence of employee entrepreneurship.[47] By highlighting a new mechanism, the paper connects employee entrepreneurship literature with the technology management literature (Baldwin and Clark, 2000; Suarez and Utterback, 1995; Fleming and Sorenson, 2001). It shows that the nature of technological problems has implications for how and who exploits emergent opportunities. The model also connects entrepreneurship and complexity literatures (Levinthal, 1997; Rivkin, 2000; Gavetti, 2005; Rivkin and Siggelkow, 2007). Connecting these two streams of research is particularly promising since agent-based modeling seems to be an excellent tool for modeling disequilibrium phenomena. By extending the framework proposed by Gavetti and Levinthal (2000), I contribute

[47] Klepper, S (2008). Keynote speech, DRUID International Conference, Copenhagen, Denmark.

to the complexity literature by developing an NK model with cognitive search and multiple cooperating agents. By modeling collaborating agents with bounded rationality iteratively solving complex problems, the study also contributes to the literature modeling intra-firm decision processes and learning (Sommer and Loch, 2004; Miller and Lin, 2009, Banerjee and Cole, 2010; Miller *et al.*, 2006; Siggelkow and Rivkin, 2002; Ethiraj and Levinthal, 2004; Miller and Martignoni, 2010; Kavadias and Sommer, 2009).

The purpose of my study is to extend the current theoretical understanding of employee entrepreneurship by introducing technology as an important driver. Both anecdotal and empirical evidence shows the importance of technological strategy in determining project rejection and employee entrepreneurship. To open the black box of this relationship, I rely on a novel modeling approach. The study sheds new light on one of the important contingencies affecting entrepreneurship and reveals promising pathways for continued research.

TABLES AND FIGURES

Table 3.1 Model parameters and summary of assumptions

Parameter	Description	Value used in text	Underlying assumptions	Robustness Tested	Possible empirical proxies
N	Problem breadth (number of decision elements)	6 - 9	Proxy for specialized versus general problems	6 - 9	Patent based measures (Fleming and Sorenson, 2001), product design matrix (Rivkin and Siggelkow, 2007)
K	Number of linkages between problem components (for each row of the interaction matrix), Randomly distributed within interaction matrix	1 - 5	Proxy for problem difficulty, complexity, modularization	1 - 5	Patent based measures (Fleming and Sorenson, 2001), product design matrix (Rivkin and Siggelkow, 2007), vertical integration (Sorenson, 1997)
E	Breadth of expertise	5	Assume that E < N, Expertise does not cover all problem components	4 - 6	Patent based measures (Fleming and Sorenson, 2001)
Agents	Number of agents	2	Fixed team size	2	Number of team members
k	Number of periods between meetings (baseline models)	5	Agents interact periodically	1-100 (alternative meeting rules tested)	
s	Shock size	1-4	Change in NK landscape proxies for technological change	1-4	Technological or environmental uncertainty
Number of periods	Observe payoff patterns (baseline models)	20-50		3-100	

Table 3.2 Convergent performance for different types of search and initial alignment

Baseline models, periods = 20, runs=3,000

A) Experiment with all decisions within expertise

Misalignment allowed?	Yes	No	Diff.	Yes	No	Diff.	Yes	No	Diff.	Yes	No	Diff.	Yes	No	Diff.
	K=1			K=2			K=3			K=4			K=5		
N=6	0.565	0.686	21%	0.562	0.757	35%	0.524	0.775	48%	0.484	0.746	54%	0.446	0.698	56%
N=7	0.567	0.662	17%	0.552	0.718	30%	0.541	0.711	31%	0.496	0.703	42%	0.461	0.657	43%
N=8	0.607	0.675	11%	0.624	0.718	15%	0.594	0.730	23%	0.581	0.705	21%	0.556	0.656	18%
N=9	0.645	0.671	4%	0.694	0.739	7%	0.702	0.748	6%	0.684	0.735	8%	0.664	0.714	8%

B) Experiment only with decisions within expertise that are not shared - core is intact

Misalignment allowed?	Yes	No	Diff.	Yes	No	Diff.	Yes	No	Diff.	Yes	No	Diff.	Yes	No	Diff.
	K=1			K=2			K=3			K=4			K=5		
N=6	0.600	0.750	25%	0.616	0.857	39%	0.599	0.918	53%	0.595	0.926	56%	0.574	0.906	58%
N=7	0.625	0.726	16%	0.656	0.831	27%	0.661	0.864	31%	0.662	0.860	30%	0.629	0.820	30%
N=8	0.661	0.716	8%	0.710	0.811	14%	0.715	0.832	16%	0.694	0.812	17%	0.679	0.782	15%
N=9	0.675	0.694	3%	0.733	0.777	6%	0.746	0.791	6%	0.731	0.775	6%	0.708	0.752	6%

C) Percentage difference (i.e. C = (B-A) / A)

	K=1		K=2		K=3		K=4		K=5	
N=6	6%	9%	10%	13%	14%	18%	23%	24%	29%	30%
N=7	10%	10%	19%	16%	22%	21%	33%	22%	37%	25%
N=8	9%	6%	14%	13%	20%	14%	19%	15%	22%	19%
N=9	5%	4%	6%	5%	6%	6%	7%	5%	6%	5%

Figure 3.1 Visualization of a complex technological problem

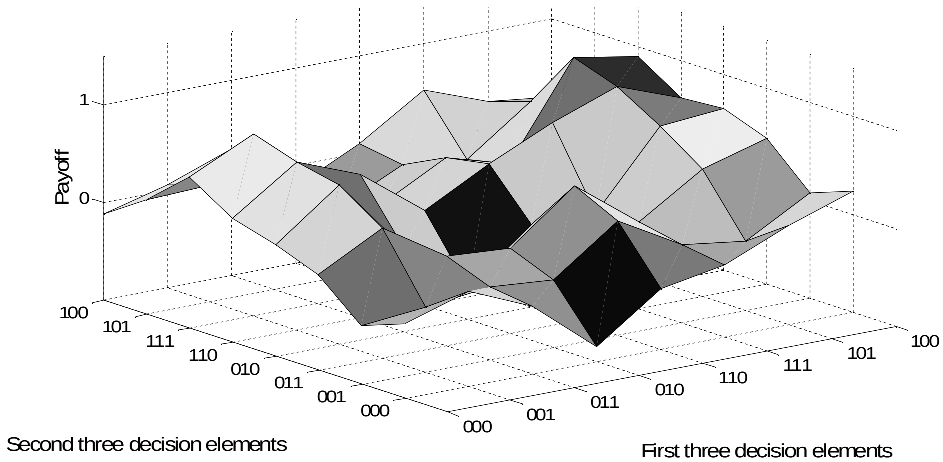


Figure 3.2 Converged performances for different values of *K* and *N*

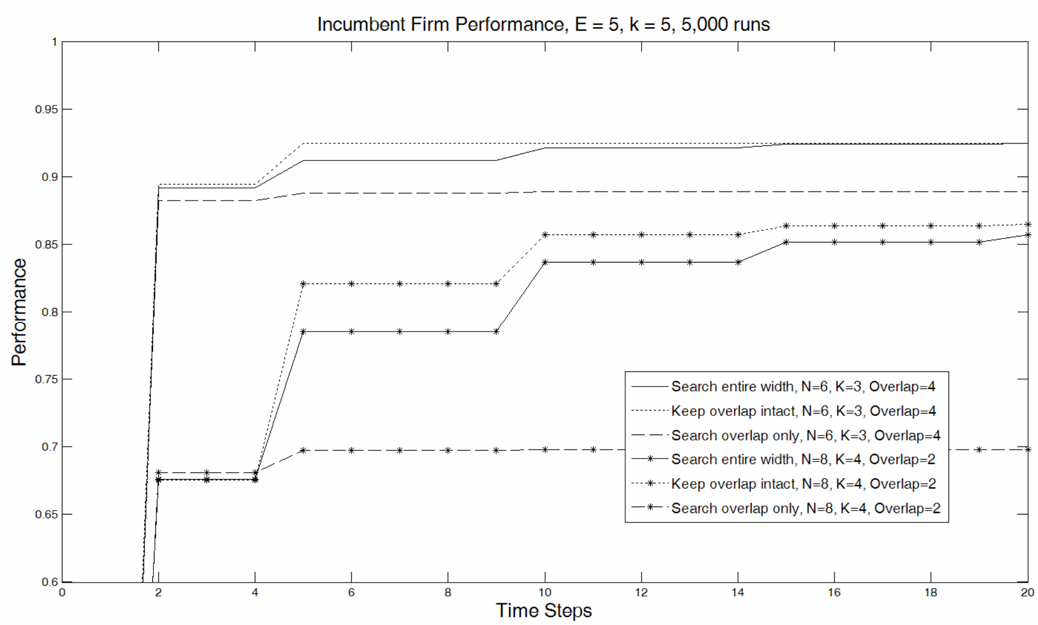


Figure 3.3 Likelihood of project rejection as a function of *K*

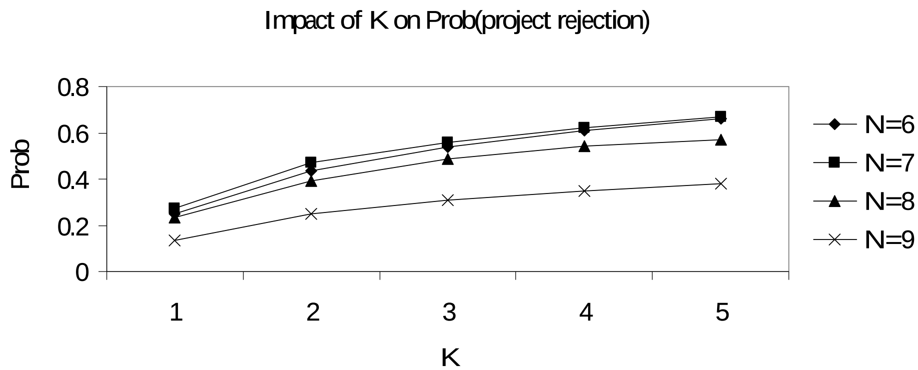


Figure 3.4 Likelihood of project rejection as a function of *N*

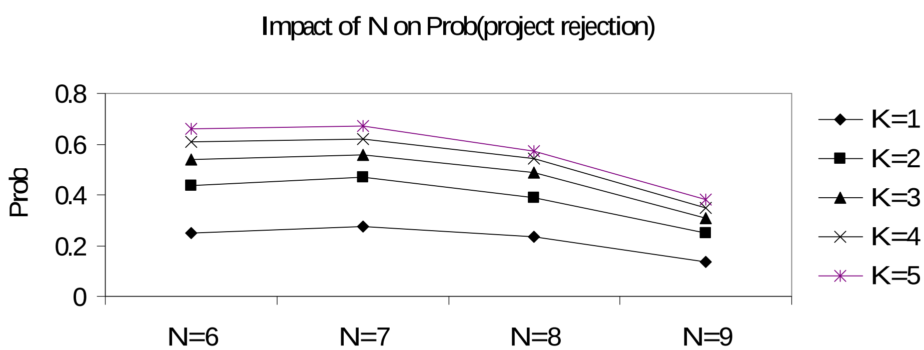
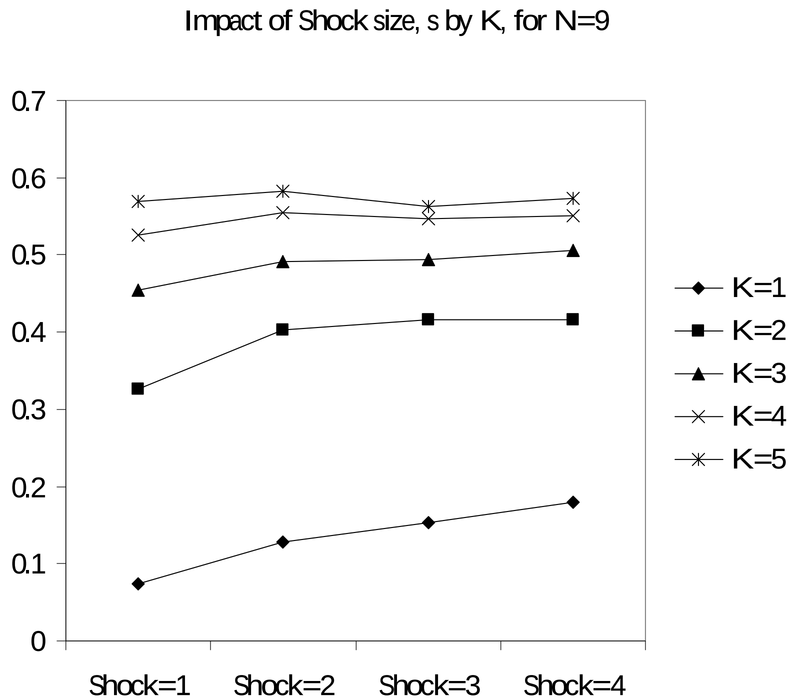


Figure 3.5 Likelihood of project rejection as a function of shock size



CHAPTER 4

ESSAY 3: EMPLOYEE ENTREPRENEURSHIP VERSUS MOBILITY: THE EFFECT OF TECHNOLOGICAL COMPLEXITY

INTRODUCTION

The intra-industry activities of employees post-exit from incumbent firms have received increasing scholarly attention within a wide range of disciplines. This is not surprising, given that a significant portion of a firm's knowledge – a core source of competitive advantage – is embedded in the human capital of employees who are free to quit at will. Employee entrepreneurship – the post-exit founding of a new venture by an individual who worked for an incumbent firm – has been heralded as a hallmark of innovation (Klepper, 2005; Klepper and Thompson, 2008), a critical source of new firm capability development and heterogeneity in performance (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003; Agarwal, Echambadi, Franco and Sarkar, 2004; Dahl and Reichstein, 2006) and an impetus to the creation and growth of industries and regional clusters (Klepper, 2001; Dahl, Østergaard and Dalum, 2005; Agarwal, Audretsch and Sarkar, 2007; Mostafa and Klepper, 2010). Through employee entrepreneurship, the new venture not only inherits the industry-specific knowledge brought in by its founders (Agarwal *et al*., 2004; Chatterji, 2009), but its strategies bear the imprinting mark of the founders' prior work experience (Klepper and Thompson, 2009). Similarly, scholars have long recognized intra-industry employee mobility (i.e. post-exit joining of another firm within the industry) as a powerful engine of knowledge diffusion between established firms as well as between incumbents and startups (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003; Agarwal *et al.*, 2004; Agarwal, Ganco and Ziedonis, 2009).

At the heart of the issues raised above is a question that relates to the underlying drivers of employee entrepreneurship and mobility and their impact on the transfer of resources, capabilities and knowledge. Entrepreneurship scholars have noted that opportunities frequently arise due to information asymmetries and access to “knowledge corridors” (Venkataraman, 1997). Individuals working at existing organizations have preferential access to knowledge related to technological developments, markets, and environmental or regulatory drivers (Agarwal *et al.*, 2004; Chatterji, 2009; Sørensen, 2007). Employee entrepreneurship and mobility represent key mechanisms for exploitation of these valuable resources and opportunities outside of the boundaries of parent firms. Furthermore, both employee entrepreneurship and mobility have been found to impact the performance of parent firms (Wezel, Catani and Pennings, 2006; Campbell, Ganco, Franco and Agarwal, 2010; Ioannou, 2010). A central question, however, relates to why and when the employee entrepreneurship and mobility occur.

The main focus of this paper is to contribute to a better understanding of origins of employee entrepreneurship and mobility events. In particular, I study an area which seems an uncharted territory – how the nature of technological problems that employees work on while employed within incumbent firms affects their entrepreneurship and mobility decisions.

There is abundant anecdotal evidence suggesting that technology plays a prominent role in the employees’ decisions to exploit the knowledge and opportunities outside of parent firm boundaries. For instance, Federico Faggin, Intel employee and inventor of the original Intel 4004 microprocessor, founded startup Zilog in 1975 after discovering that significant improvements to the Intel 8080 architecture are possible. His decision led to the famous Z80 microprocessor, improving the Intel 8080 both in terms of speed and costs.[48] T. J. Rodgers founded Cypress Semiconductor in 1982 to exploit his experience with high-speed MOS designs acquired while working at AMD, American Microsystems and during his graduate education.[49] Similarly, John

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[48] Forbes.com, National Inventors Hall of Fame Foundation, Inc
[49] Cypress Semiconductor website, www.cypress.com

Birkner and H. T. Chua founded Quicklogic in 1988 as a way of exploiting their invention of Programmable Array Logic (later leading to field programmable gate arrays – FPGAs) that they invented while working on programmable logic in Monolithic Memories.[50] In support of these examples, Klepper and Thompson (2009) trace most of their cases of employee entrepreneurship in the early automobile, semiconductor and laser industries to disagreements about technological strategy. The evidence thus invites the question of whether and how the technology affects the employee entrepreneurship and mobility decisions. Would these employees decide to use their knowledge outside of their parent firms if they happened to work on different technological problems? What characteristics of prior technologies matter in their decisions? We know very little about these questions. The current study is a first step towards answering them.

The key variable that I investigate is the technological complexity of inventors' prior patenting activities within an incumbent firm. I define and measure complexity using the methodology of the NK modeling literature (Kauffman, 1993; Levinthal, 1997; Rivkin, 2000; Fleming and Sorensen, 2001). Complex problems are those that have rugged optimization space due to dense interdependencies between individual component choices (Kauffman, 1993; Rivkin, 2000).

Using complexity as the main *contextual* variable of interest is attractive at multiple levels. Solving technologically complex problems may lead to breakthroughs (Fleming and Sorenson, 2001). However, the knowledge necessary to solve a complex problem is more tacit (Polanyi, 1983; Lowe, 2002; Agrawal, 2006), may require unstructured technical dialogue (Monteverde, 1995) and the solution outcomes are more uncertain (Fleming and Sorenson, 2001). The uncertainty associated with complexity may also lead to greater over-optimism when pursuing entrepreneurial decisions (Shane, 2002; Ziedonis and Lowe, 2006). At the same time,

[50] Computer History Museum, www.computerhistory.org, Quicklogic Website, www.quicklogic.com

complexity may affect frictions and the likelihood of idea rejection at the parent firm leading to disagreements (Klepper and Thompson, 2010; Ganco, 2010). As a result, the technological complexity variable appears to be a viable driver affecting both employee entrepreneurship and mobility decisions.

Combining multiple theoretical approaches, I develop propositions connecting technological complexity with employee entrepreneurship and mobility. I hypothesize that technological complexity affects the ability of employees to replicate knowledge in other contexts. I test these propositions within the context of the U.S. semiconductor industry providing a canonical example of an industry driven by technological intensity, knowledge spillovers, employee mobility and entrepreneurship (Freeman, 1986; Macher and Mowery, 1998; 2007; Agarwal *et al.*, 2008). I base the analysis on a unique hand-collected dataset of 465 dedicated semiconductor firms operating between 1973 and 2003. To briefly foreshadow the main results, I find that incumbent firm inventors patenting inventions with higher technological complexity are less likely to join rival firms, but, if they do exit, they are more likely to become entrepreneurs relative to joining rival firms. I also find that technological complexity increases the likelihood of team founding relative to individual founding.

The paper contributes to multiple literature streams. Within the context of employee entrepreneurship literature (Agarwal *et al*, 2004; Klepper, 2005; Klepper and Sleeper, 2005) the study provides the needed focus on factors that condition the emergence of employee entrepreneurship (Klepper, 2008).[51] I also contribute to the literature on employee mobility and knowledge spillovers (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003; Agarwal, Echambadi, Franco and Sarkar, 2004; Agarwal, Ganco and Ziedonis, 2008) by suggesting that,

[51] Klepper, S (June 2008). Keynote speech presented at the 25th DRUID Celebration Conference 2008. Copenhagen, Denmark.

consistent with the simulation studies (Rivkin, 2000), technological complexity is an important contingency affecting knowledge flows through employee mobility. I contribute to the complexity literature (Levinthal, 1997; Rivkin, 2000; Fleming and Sorenson, 2001) by showing a practical empirical application of theoretical models and constructs developed within the complexity theory.

LITERATURE ON EMPLOYEE ENTREPRENEURSHIP AND MOBILITY

Employee entrepreneurship and mobility literatures developed as separate lines of inquiry, but the questions related to the exploitation of parent firm knowledge, resources and opportunities outside of their boundaries connect them together.

First, scholars within economics and strategy have focused on explaining employee entrepreneurship through imperfections within parent firms. At the individual level of analysis, researchers have typically attributed entrepreneurial opportunities to the decision-making imperfections within a parent firm (Anton and Yao, 1995; Cassiman and Ueda, 2004; Franco and Filson, 2006; Hellman, 2007; Klepper and Thompson, 2009). More specifically, studies suggest that employee entrepreneurship events occur due to the agency problems and contractual hazards arising from employees having an option to not disclose their inventions (Anton and Yao, 1995) or employees deriving private benefits from exploratory search (Hellman, 2007). At the firm level of analysis, studies typically attribute the presence of idle opportunities to frictions in knowledge transfer (Franco and Filson, 2006), managerial diseconomies of scale and under-exploited knowledge (Agarwal *et al.*, 2004) or intra-firm information asymmetries (Klepper and Thompson, 2009).

Similarly, sociological approaches to entrepreneurship maintain that employee entrepreneurship is driven by environmental context (Brittain and Freeman, 1980; Freeman, 1986; Eisenhardt and Schoonhoven, 1990; Thornton, 1999; Romanelli and Schoonhoven, 2001; Stuart and Sorenson, 2003; Audia and Rider, 2005; Dobrev and Barnett, 2005; Sørensen, 2007). Sørensen (2007) argues that the *"fundamental premise of sociological approaches to entrepreneurship [is that] the social context shapes the likelihood of entrepreneurial activity, above and beyond any effects of individual characteristics*".

Even though the underlying mechanisms differ, the studies underscore that the existence of profitable opportunities within parent firms that are left unexploited leads to employee entrepreneurship events. Supporting empirical evidence has been found in a variety of industry contexts, including disk drives, automobiles and lasers (Agarwal *et al.*, 2004; Klepper, 2005; Klepper and Sleeper, 2005; Franco and Filson, 2006). Similarly, in a survey of 100 fast-growing private companies, Bhide (1994) found that 71% of the entrepreneurial founders commercialized ideas they had encountered or discovered while working at other companies.

The literature on employee mobility (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003; Agarwal *et al.*, 2004, 2008; Marx *et al.*, 2009, 2010) typically focuses on implications of employee mobility on knowledge flows. This literature shows that employee mobility is a key driver of knowledge diffusion. The knowledge flows tend to be geographically localized (Almeida and Kogut, 1999), but mobility is also a strong conduit facilitating the knowledge flow over large geographical and technological distances (Rosenkopf and Almeida, 2003). The knowledge brought in by mobile inventors tends to diffuse within hiring firms (Tzabbar, Silverman and Aharonson, 2005), is especially beneficial for small hiring firms (Almeida, Dokko and Rosenkopf, 2003) and has been hypothesized to be a driving force behind successful industrial clusters like Silicon-Valley (Saxenian, 1994; Gilson, 1999; Fallick, Fleischman and Rebitzer, 2005). On the other hand, parent firms try to reduce knowledge outflows through employee mobility by increasing patenting efforts (Kim and Marschke, 1999) or building reputations for litigiousness (Agarwal *et al.*, 2008).

While the bulk of the literature related to employee entrepreneurship and mobility has employed an economics or strategy lens, the related literature in organizational behavior on voluntary turnover (Lee and Mitchell, 1994; Lee *et al.*, 1999; Holton *et al.*, 2005) is also relevant to the issue of why employees exit incumbent firms. The theories related to voluntary turnover focus on the process-related antecedents of voluntary exit and provide a window into micro-level decision-making. The core idea is that the decision to exit is a result of a multi-stage process that unfolds when several possibly sequential conditions are met. The process of decision "unfolding" is assumed to be triggered by a shock, and the ultimate decision to exit depends on the nature and number of outside options (Lee and Mitchell, 1994). While the literature does not pay much attention to whether the exits lead to mobility to existing firms or to new firm formation, it emphasizes that the decisions to exit depend on the interaction between the intra-firm processes and attractiveness of outside options.

Despite the focus of the literature on employee entrepreneurship and mobility, little is known about their relationship with technology. The results in the extant literature have been limited to the finding that more technologically advanced firms generate more employee entrepreneurship events (Brittain and Freeman, 1986; Franco and Filson, 2006) and that employee entrepreneurship may be driven by underexploited technological opportunities within the parent firms (Agarwal *et al.*, 2004; Klepper and Thompson, 2009). From the perspective of the contextual approaches to entrepreneurship in economics and strategy, it is unclear if and how the technological context, as it varies across and within firms, affects employee entrepreneurship and mobility.

CONCEPTUAL FRAMEWORK AND HYPOTHESES

The centerpiece of imagery of complex systems research and related NK modeling literature is the notion of a rugged landscape. The rugged landscape (Kauffman, 1993, 1995; Levinthal, 1997; Rivkin, 2000) represents the problem space searched by the agents (i.e. in our context individual inventors solving a given technological problem). The agents are assumed to be bounded in their ability to optimize over the decision elements of this space and thus have to search for the optima by iterative experimentation – i.e. local search (Kauffman, 1993). As the ruggedness of the space increases (the space has more "peaks" and "valleys"), the global maximum increases but the problem is more difficult to solve. The boundedness of the agents' search behavior potentially creates lock-in problems. Kauffman (1993) showed that ruggedness of the problem space increases with the density of linkages between individual decision components. For instance, if an inventor makes decisions on N components and all component decisions are independent (in the sense that changing the decision about the component N_i does not affect the performance contribution of any other component N_j) then the space is perfectly smooth and the inventor is able to locate the global optimum (see Figure 4.1). However, when there are interdependencies, the decision about the component N_i affects the performance of not only itself but also of all components N_j that are linked to (depend on) the component N_i. Consequently, small changes – e.g. a change in one decision component N_i – can lead to dramatic changes in overall performance of the system (defined as the average of the performance contributions of the individual components). What follows is that when the space is searched by a boundedly rational agent that can evaluate only options in the local neighborhood of the current decision (e.g. those decisions that differ by one decision component), the lock-in problems emerge and agents are unable to improve on the suboptimal local peak. To get to the higher peaks the agents would have to traverse valleys. However, they may be unable to evaluate distant points and choose the direction of higher optima due to the myopia of their local search. Figure 4.1 illustrates the search process for a complex versus simple problem. The conceptualization of problem complexity using the NK lens is analogous to the notion of problem difficulty (Kollman *et al.*, 2000) since high *K* problems were shown to be NP-hard (Rivkin, 2000).

TECHNOLOGICAL COMPLEXITY AND EMPLOYEE MOBILITY

Knowledge complexity likely affects how embedded individuals are within the firm and what outside options they face. First, to create value individuals solving complex problems may need strong internal ties with other employees within the firm (Krackhardt and Porter, 1986; Jackson *et al.*, 1991; Dess and Shaw, 2001; Lee *et al.*, 2004). Similarly, new knowledge often builds on existing knowledge rather than replaces it (Jones, 2009). This increases knowledge depth and specialization and necessitates collaboration (Jones, Uzzi and Wuchty, 2007; Jones, 2009). It is conceivable that such effects will be stronger for more complex knowledge. Due to the strong complementarities with other individuals, and knowledge external to the focal inventor (Hoetker and Agarwal, 2007), it may be very difficult to individually exploit complex knowledge outside of the parent firm boundaries.

Second, the exit and mobility decisions are affected by the viability of outside alternatives (Lee and Mitchell, 1994). The ability of employees to transfer knowledge through mobility to rival firms and create value there likely varies with its complexity. Due to the inherent difficulty in communicating dense interdependencies, complex knowledge may be more tacit (Polanyi, 1983; Lowe, 2002; Agrawal, 2006), may require unstructured technical dialogue (Monteverde, 1995) and the recipient organizations may have difficulty diffusing and utilizing such knowledge (Tzabbar *et al.*, 2002). Solution outcomes based on solving complex problems tend to be more varied (Fleming and Sorenson, 2001) and uncertain (Knight, 1921), which can make their evaluation by other organizations problematic. The uncertainty can also amplify the expropriation hazards faced by the inventors during their negotiation with potential hiring organizations (Anton and Yao, 1995). Prior research has shown that more complex knowledge is less robust to errors in the transfer process (Rivkin, 2000). Small errors in the replication of complex knowledge can have a dramatic negative impact on the ability of individuals to successfully solve complex problems (Rivkin, 2000).

Further, the complementary assets and knowledge in the parent firm may be optimized to solve given complex technological problems. Pre-existing structures of other firms may have been designed to solve different problems. The hiring organizations may be more interested in general knowledge that complements their capabilities rather than in integrating complex knowledge from other organizations. Consequently, technological complexity may be a burden limiting the number and scope of job alternatives that mobile inventors have.[52]

Individuals solving complex problems are more embedded within parent firms and may be less able to transfer their knowledge to other recipient organizations - which likely affects their mobility decisions:

H1: The probability of mobility to a rival firm decreases with the technological complexity of an employee's prior innovations.

However, existing recipient organizations potentially vary in their ability to integrate complex technological knowledge. For instance, larger organizations relative to smaller ones may have greater financial, managerial, and related technological or marketing resources and

[52] Note that the argument developed here assumes away how the value of employee's knowledge within the parent firm affects mobility decisions (e.g. Campbell *et al.*, 2010) and focuses on the effect of complexity on an employee's ability to extract the knowledge and transfer it to another setting. Empirically, I control for the value of knowledge that inventors hold.

capabilities to successfully integrate complex knowledge. If the knowledge brought in by the mobile scientist is incompatible with the existing capabilities, the larger firms can create a separate unit that would exploit the knowledge. Such an approach is fully consistent with the real-options perspective (Dixit and Pindyck, 1994; Trigeorgis, 1996; Lander and Pinches, 1998). In search for breakthroughs that are more likely with more complex knowledge (Fleming and Sorenson, 2001), larger firms may exploit complex knowledge from various sources.[53] Smaller firms are typically more specialized and focused on solving only one or a few technological problems at a time. Integrating outside complex technological knowledge may re-direct the technological strategy of a small firm and it may be risky. Similarly, small firms may lack complementary assets (Teece, 1987) and support structures that are necessary to successfully integrate outside complex knowledge. Larger firms may also have greater absorptive capacity (Cohen and Levinthal, 1990; Zahra and George, 2002) due to more extensive experience in activities related to the hired scientist's knowledge. This reasoning leads to the following prediction:

H2: Conditional on mobility, the probability of moving to a larger rival firm relative to a smaller one increases with the technological complexity of an employee's prior innovations.

TECHNOLOGICAL COMPLEXITY AND EMPLOYEE ENTREPRENEURSHIP

Solving technologically complex problems may potentially lead to breakthroughs (Fleming and Sorenson, 2001). However, complex technological knowledge may be valuable for exiting employees because it also embodies entrepreneurial opportunities not exploited by the

[53] The NK models show that the average performance has an inverted U-shaped relationship with complexity (Kauffman, 1993; Altenberg, 1994; Fleming & Sorenson, 2001). Solving very simple problems has a low potential payoff and solving very complex problems has a high potential payoff but a low likelihood of actually succeeding. However, the variance of performance increases with complexity – individuals who happen to find solutions for complex problems enjoy significant payoffs. In other words, breakthroughs are more likely based on solving difficult problems (Fleming & Sorenson, 2001).

parent firms. The economics and strategy literatures (Agarwal *et al.*, 2004, Klepper and Sleeper, 2005; Klepper and Thompson, 2009) suggest that the existing firms are prone to leave some opportunities idle. Consequently, the value that the knowledge has within the incumbent firms does not capture underexploited opportunities.

Employees frequently try to convince their superiors about the viability of their ideas and may leave when they are rejected (Klepper and Thompson, 2009). Working in complex technological domains may be prone to a higher likelihood of such rejection of viable opportunities. For instance, within the context of Penrose (1959) one could perceive the boundary of the firm (and the extent to which projects outside of this boundary are rejected) as determined by scarce managerial talent and path dependency. Penrose argues that the bundle of current resources determines the services the firm is capable of rendering (Penrose, 1959, p. 5; Kor and Mahoney, 2004). Due to the managerial diseconomies of scale or scope, the manager may even become a bottleneck in the efficient growth of the firm (Penrose, 1959, p. 237; Kor and Mahoney, 2004). It is reasonable to expect that these diseconomies will increase with the complexity of technological problems. The likelihood that a manager rejects viable technological ideas (i.e. a manager makes a Type II error, Sah and Stiglitz, 1968) thus increases with their technological complexity. Rejection of viable ideas can also increase due to the miscommunication between managers and inventors. This can be driven by the tacitness of complex knowledge (Polanyi, 1983; Lowe, 2002; Agrawal, 2006) and its inherent uncertainty (Knight, 1921). The parent firm may also be unable or unwilling to implement proposed ideas due to agency considerations. Agency theorists (Anton and Yao, 1995; Hellman, 2007) model profitable project rejections as emerging from various incomplete contract settings. Both the private benefits of search on inventors' personal projects as opposed to assigned tasks (Hellman,

2007) and benefits of not disclosing some projects to the management (Anton and Yao, 1995) increase with the expectation of breakthrough inventions. The rejection of viable entrepreneurial ideas may also be driven by their inconsistency with the strategic vision of the firm (Gavetti and Levinthal, 2000; Ganco, 2010). Ganco (2010) shows that the likelihood of such inconsistency increases with the complexity of the technological problems that are being solved.

Similar to mobility to rival firms, employee entrepreneurs who try to exploit complex knowledge outside of the parent firm boundaries face potential difficulties. I suggest above that the ability to transfer knowledge decreases with its complexity and that large recipient organization are relatively better at integrating complex knowledge than small ones. Additionally, the ability to transfer complex knowledge may dramatically improve when it does not need to be integrated into an existing structure. In the case of employee entrepreneurship, the new organization is created and optimized to exploit knowledge and ideas brought in by its founders. The startup founders assemble complementary assets that match the opportunity they pursue.[54] In support of this argument, the extant literature found that parent firm routines can be successfully transferred when firm structures are created afresh (Wezel *et al.*, 2007). The fact that it is the inventor (i.e. the owner of the idea) who controls the startup, potentially mitigates agency and communication problems. In other words, there is no need to convince other managers about the viability of ideas. Instead, the bottleneck that startup founders face is in the venture funding. However, there is again evidence that existing firms and venture capitalists evaluate ideas differently (Dushnitsky and Shapira, 2009) and many projects that are rejected by incumbent

[54] The argument implicitly assumes that such complementary assets are available – either transferred from the parent firm (e.g. human complementary assets, Campbell *et al.*, 2010) or bought on the market. If the necessary complementary assets are unique and locked in within incumbents then employee entrepreneurship is very difficult. For instance, Mitchell (1991), in his study of the diagnostic imaging industry found a persistent incumbent advantage due to their dominance in distribution channels. I will revisit this issue when discussing empirical context below.

firms are funded by VCs (Kenney and Florida, 2002). In fact, Kenney and Florida (2002) describe that venture capitalists decide about funding based on a broad range of characteristics including recommendations, backgrounds of founders, market conditions and technology.

The employees may also prefer to pursue underexploited opportunities they identified while working on complex technological problems through employee entrepreneurship relative to exploiting them within rival firms because they may be able to appropriate a greater share of rents (Campbell *et al.*, 2010). The expropriation hazards that may prevent the inventor from disclosing the idea to the parent firm may also prevent him from revealing it to other firms (Anton and Yao, 1995). Further, the uncertainty associated with complex technological domains (Fleming and Sorenson, 2001) may lead employees to overestimate the value of their entrepreneurial ideas (Shane, 2002; Lowe and Ziedonis, 2006).

Overall, knowledge based on solving complex technological problems may embody underexploited opportunities. When employees exit to exploit such knowledge, it is more likely that they exploit it by founding a new firm relative to joining a rival:[55]

H3: Conditional on exit, the probability of starting a new venture relative to joining an existing rival firm increases with the technological complexity of an employee's prior innovations.

TEAMS AS FACILITATORS OF KNOWLEDGE TRANSFER

It is in the best interest of recipient organizations to mitigate the problems associated with the transfer of complex knowledge. Team transfer may serve as such a mitigating factor. The co-inventors working together at the parent firm – whether moved together and then allowed to collaborate within the hiring organization or within the context of the startup they jointly

[55] Empirically, I also test the unconditional hypothesis that the technological complexity of prior innovations increases the likelihood of employee entrepreneurship relative to staying. I discuss the findings and their implications below.

establish – may facilitate the transfer of complex knowledge. Co-inventors may also serve as an important complementary asset (Campbell *et al.*, 2010) necessary for implementation of complex knowledge. Teams can lower transfer costs by providing parallel channels for knowledge transfer – minimizing the impact of tacitness (Polanyi, 1983; Lowe, 2002; Agrawal, 2006) and transfer errors (Rivkin, 2000). Crucial for solving complex problems is collaboration and coordination (Rivkin and Siggelkow, 2003; Barr and Hanaki, 2008). The team entrepreneurship and team mobility allow keeping the team of collaborators intact, maintaining the coordination capabilities, communication routines and social interaction developed while working at the parent firm.

The teams should facilitate transfer of complex knowledge whether they are hired by an existing firm or found a startup:

H4: The probability of team founding of a new venture relative to individual founding increases with the technological complexity of an employee's prior innovations.

H5: The probability of mobility to an existing rival firm with a team relative to individually increases with the technological complexity of an employee's prior innovations.

DATA AND METHODOLOGY

Industry Context and Data Description

The context of the study is the U.S. semiconductor industry. The industry exhibits a high degree of employee entrepreneurship and mobility and prior studies document that such mobility facilitates inter-firm transfers of technological knowledge (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003). Firms in this industry also have a high propensity to file patents (Hall and Ziedonis, 2001) which allows construction of a patent-based measure of technological complexity (Fleming and Sorenson, 2001, 2004; Ganco, 2010). The semiconductor industry is also ideal because of its focus on complex technological innovation (Macher, Mowery and Hodges, 1998) like the "system-on-a-chip" and ASICs (Linden and Somaya, 2002). Macher *et al.* (1998) document the shift of the US semiconductor industry since the early 1990's toward the emergence of "fabless" firms and the focus on semiconductor design with the outsourcing of manufacturing capability. In fact, approximately 90% of new entrants in our recipient firm sample are pure design "fabless" firms.[56] The separation of design and manufacturing made entry relatively easy, which further fostered innovation (Macher *el al.*, 1998). The critical complementary assets required within new design firms were highly mobile human assets (Coff, 1997; Teece, 2003; Campbell *et al.*, 2010). Such characteristics highlight the importance of knowledge as a determinant of entrepreneurship and mobility patterns and provide an ideal setting for our study. Macher, Mowery and Di Minin (2007) also report that the innovation in the semiconductor industry remains largely US-based, which justifies focus on the domestic market and allows for abstracting away from the international variation in the knowledge transfer.

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 prior studies on mobility (Rosenkopf and Almeida, 2003; Agarwal *et al.*, 2008) by distinguishing between firms that are potential *sources* of inventive talent and other firms in the industry that are potential *recipients* (rivals or startups).

The source firm sample is drawn from a comprehensive list of publicly-traded U.S. firms that a) compete primarily in semiconductor product markets and b) were founded prior to 1995. Restricting attention to firms that are public by the mid-1990s (n=136) allows a sufficiently long window through which to view possible mobility and employee entrepreneurship events. In 2000, these firms collectively generated over $88 billion in annual revenues and spent $12 billion in

[56] Only 3% of the sample are entrants that entered post-1990 and established a foundry.

R&D. To assemble a larger pool of potential recipients of inventive talent within the industry, I add to source firms (a) 454 additional venture-backed semiconductor firms that were founded between 1980 and 2001, and (b) 59 additional firms in the industry (SIC3674) that went public post-1995. Recent public entrants are identified from Compustat. The additional venture capital-backed startups are identified using data provided by VentureOne.

Since I am interested in an inventor-level analysis and the USPTO patent data does not provide a person's identifier, I match inventor names to reconstruct individuals' patenting histories. I implement the matching algorithm described in prior literature (Agarwal *et al.*, 2009) that creates inventor patenting and employment histories at focal firms within the sample. This algorithm identifies 28,123 unique names listed in patents awarded to sample firms of which 25,339 appear within the source firm sample. I also require that the source firms receive at least one patent which eliminates 7 source firms. The final source firm sample includes 129 firms.

The only method to identify mobility is if inventors patent at both source and recipient firms. Consequently, I require that recipient firms receive at least one U.S. patent. This restriction eliminates 14 public and 188 startup firms.[57] The final recipient sample therefore includes 266 private startups and 181 public firms. The matching algorithm yields 1,166 mobility events. Of these, 52 individuals moved within teams (with average team size of 2.24) identified using the procedure described below.[58]

By searching press releases in LexisNexis, analyzing archived websites of the recipient firms (www.archive.org) and utilizing several online resources (e.g. smithsonianchips.si.edu) I identify founders of the recipient firms. Since I am interested in how past employment histories shape the emergence of new firms, I need to identify inventors whose ideas lead to the

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[57] The disproportionate omission of startups is not surprising. Many startups in the larger sample fail or are acquired at very young ages, thus reducing the likelihood of observing patent awards for these firms.
[58] Cf. Agarwal *et al.* (2008) for a comparison of how this algorithm performs to the ones used in the prior literature.

emergence of startups and not simply early "board members." Consequently, I employ a relatively stringent requirement to define a person as a founder – the word "founder" or "co-founder" needs to appear with the person's name on either the archived corporate website (as early as possible after the year of entry), early press releases or industry materials. To look at how prior inventive activity affects the decision to start a new firm I match the founder names (I verify and clean the matches using LexisNexis and corporate websites to precisely reconstruct the founder employment histories) with the source firm inventor pool of 25,339 inventors. Using this procedure yields 141 inventor-founders who originated from 49 source firms and founded 114 startups. Of these, 10 were started by 3 inventor-founders, 19 by 2 inventor founders and the rest by single inventor-founders.[59] It is important to note that the identification procedure does not require the founder to be an inventor within the startup firm. He or she only needs to appear as an inventor within the source firm population. The parent firm spin-offs or startups receiving corporate venture capital from the parent firm were excluded from the sample.

For the combined set of firms, I integrate financial, founding and exit year data from Compustat, Hoover's Business Directories, VentureOne,10-k filings and LexisNexis, patent data from Delphion and the National University of Singapore.

Estimation Strategy

I test H1 and H3-5 using discrete time conditional logit as well as OLS (linear probability models) with the employee entrepreneurship or mobility events as the positive outcome. I estimate H2 using the OLS with the recipient firm size as the dependent variable. Due to likely unobserved heterogeneity across firms and over time, I utilize a relatively stringent empirical approach by using the "source firm-year" combinations as the fixed-effect. Consequently, the

[59] Results for H3 remain unchanged when estimated on the sample of firms started by a single inventor-founder.

results are based on the within firm-year. Such an approach significantly simplifies estimation since all time-variant firm-level controls are absorbed in the time-variant firm fixed-effect. Beyond individual level differences proxied by patenting patterns, I also control for traditional variables used in the labor literature that I can infer from the patent documents – gender and race. To address individual selection concerns (i.e. higher quality individuals may solve more complex problems), I employ a two-stage approach. First, I regress the raw measure of technological complexity on all controls discussed below, including individual inventor fixed effects. Then, I use the residuals of the first stage in all subsequent regressions. The sample is constructed as an unbalanced panel with the inventor-year observations.

Variable Definition

Dependent Variables

For H1, the dependent variable *mobility* is a binary indicator set to 1 if the given employment spell in the focal year is followed by a mobility event to a firm in the recipient sample different than the source firm and 0 if the employee stays with the parent. For H2, the dependent variable is the *number of employees* of the recipient firm in the first year when the inventor patents at this firm. I test H3 using the dependent variable *employee entrepreneurship*. This binary variable is set to 1 if the event of employee entrepreneurship follows the given employment spell in the focal year and 0 if the employee stays employed with the parent or joins a rival firm (depending on the comparison group).[60]

H4 is tested on a sub-sample of employee mobility events. The dependent variable *team mobility* is set to 1 if a given inventor moves to an existing firm within an inventor team and 0 if he or she moves individually. Team mobility is an event when co-inventors collaborating in the

[60] The employee entrepreneurship and mobility events within the sample are strongly correlated over time.

last year pre-exit from the parent are also listed as co-inventors in the first year at the recipient firm. H5 is tested on a sub-sample of employee entrepreneurship events. The dependent variable *team entrepreneurship* is set to 1 if a given inventor starts a firm within an inventor team and 0 if there is only one inventor founder on the team. Team entrepreneurship is an event when co-inventors collaborating within the parent firm are listed as co-founders of the startup.

Main explanatory variable: Technological Complexity

Consistent with prior work (Fleming and Sorenson, 2001, 2004; Ganco, 2010; Sorenson *et al.*, 2006), I measure technological complexity utilizing the patent classification into subclasses. The NK literature shows (Kauffman, 1993, 1995; Ganco, 2009) that the performance when solving complex problems is mainly driven by the ratio between the K – the number of interdependencies per component (or the number of component choices that the performance of a focal component depends on) – and N – the total number of components.

The measure of interdependence K is adopted from a prior study (Ganco, 2010), which is a single-industry measure analogous to the cross-sectional measure developed by Fleming and Sorenson (2001, 2004). The measure is based on the interaction matrix from Kauffman's NK model (1993, 1995). The key idea behind the measure is that when two underlying functions (represented by patent sub-classes) are coupled we are more likely to observe components belonging to these classes in a single invention. If there is a high coupling between the functions A and B and the component a is classified in patent subclass A, $a \in A$ and b is in B, $b \in B$ (USPTO classifies patents into subclasses by their functions), then we are more likely to encounter subclasses a and b appearing on a patent together. In other words, high interdependence between A and B implies that whenever an inventor solves a problem related to one of these functions she needs to redesign or include the coupled function as well, and we are likely to observe the components optimizing these functions together in a patent. Similarly, if the patent improves the architecture of multiple functions we are likely to observe all components that correspond to these functions coupled to the architecture. On the other hand, if *A* and *B* are independent with respect to each other, we are likely to observe *A* combined with other subclasses without *B* being present.

The measure of interdependence *K* is computed in several steps. In the first step, I tabulate co-occurrence frequencies for all subclass combinations and also create a table of occurrence frequency for each subclass. Then, by selecting entries from the tables, I compute 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 the patent *l* is calculated as follows:

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

For instance, when calculating the interdependence of the first subclass (first subclass is focal "*i*") the interdependence between the first and the third subclasses is the number of patents where the first and third subclasses appear together divided by the number of patents where only the first subclass appears.

Using the focal industry dataset to derive this measure assumes stability in the nature of interdependencies between the functional components of an innovation over time within a given 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 building blocks that have a certain level of interdependence associated with each pair of its functions represented by observable components. If functions *A* and *B* appear on two patents, one in the beginning of the sample (along the time dimension of the sample) 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 at least within a certain time frame is a necessary simplification. The measure of K has the correct scaling consistent with the NK model since it is in the interval [0, *N*-1].[61]

Similar to prior studies (Fleming and Sorenson, 2001, 2004; Sorenson, Rivkin and Fleming, 2006), I operationalize the total number of components *N* by the number of patent sub-classes. Consistent with this literature, I obtain the raw technological complexity measure by dividing the number of interdependencies *K* with the number of components *N*.[62] To obtain the final raw measure of technological complexity for a given inventor within a given year, I average the *K/N* for all patents awarded to the inventor in the given year.

Finally to calculate the measure of technological complexity, I develop a panel with patents as individual observations. Then I regress (using OLS) the raw measure on all control variables described below, including individual inventor fixed effects. The residuals from this regression are used as the final measure of technological complexity.

To triangulate and further validate the measure, I interviewed an expert who is a professor of electrical engineering and a leading authority in semiconductor design at a Top 10 research institution in the field. The expert was asked the 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*

[61] Ganco (2010) highlights the mechanics of the measure and further tests its validity.
[62] Alternatively, one could specify the model using N, K, K/N and their squared terms (Fleming & Sorenson, 2001; Ganco, 2008). However, using only K/N parsimoniously captures the effect of the full set of variables and the robustness checks showed that having a fully specified model yields qualitatively identical results.

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 are 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 respondent answered High, Medium or Low. Then, I aggregated the patents in my data into main classes and calculated average complexity based on the measure described above. Table 4.1 shows the correspondence between the measure and the expert opinion. This crude validation (due to the aggregation into main-class domains) shows that the correspondence is relatively good with the correlation of 0.54.

Control Variables

Beyond the firm-year fixed effects all models include a set of control variables. To control for individual heterogeneity, I introduce variables capturing inventor quality or other differences that may affect the propensity to engage in mobility or employee entrepreneurship at an individual inventor level. These variables include: *Log Number of Patents, Log Number of Citations, Female, Nonwhite, Technological Proximity, Log Number of Co-inventors, Log Number of Main Classes* and *Log Years Patenting within Parent*.

Even after controlling for individual heterogeneity, it is possible that differences in the opportunity space, both for mobility and employee entrepreneurship, vary with technological complexity. Employees may exit to pursue general opportunities in a given area rather than to exploit complex technological knowledge they have. To control for these differences, I introduce variables that rely on the firm entry and exit rates into a particular technological complexity "segment": *Entry Rate of Firms with Similar Tech. Complexity* and *Exit Rate of Firms with*

Similar Tech. Complexity. Table 4.2, provides more detail on the variable construction. Table 4.3 provides bivariate correlations.

RESULTS

Table 4.4 shows the results of the regression analysis. The significant coefficients on the controls indicate that female inventors are less likely to move to a rival firm and dramatically less likely to found a startup (relative to mobility or staying). Nonwhites in the industry are more likely to join a rival firm. The coefficient on the number of co-inventors is negative and significant in the mobility regression, suggesting that inventors embedded in collaborative networks are less likely to move. After controlling for technological complexity, the number of main classes negatively predicts employee entrepreneurship (relative to staying), suggesting that specialists are more likely to found firms. Number of years inventors patent with the parent firm is associated with higher likelihood of both mobility and employee entrepreneurship and makes joining a large firm less likely. The coefficient on the entry rate of firms with similar technological complexity weakly negatively predicts employee entrepreneurship relative to staying. The exit rate of firms with similar technological interdependence is negative and significant for both employee entrepreneurship and mobility, implying that if a given technological domain is in decline employees opt for the safety of their present employment.

Consistent with H1, in Model 1, the coefficient on technological complexity is negative and significant (employee mobility as the dependent variable). Weakly supporting H2 ($p=0.077$), technological complexity positively predicts joining a larger firm. Consistent with H3, the coefficient on technological complexity is positive and significant in Model 3 (employee entrepreneurship as the dependent variable). Interpreting these coefficients, one standard deviation increase in technological complexity causes the likelihood of employee mobility to decrease by 13%, increases the size of the recipient organization by 1500 employees and predicts the employee entrepreneurship relative to mobility to increase by 28%. Even though not hypothesized, Model 4 predicts the likelihood of employee entrepreneurship relative to staying (unconditional) and also shows a positive and significant relationship. One standard deviation increase in technological complexity increases the likelihood of employee entrepreneurship relative to staying by 17%.[63]

A test of the Hypotheses 4 and 5 is provided in Table 4.5 using both conditional logit and a fixed-effect linear probability model. The coefficient on technological complexity for team mobility has the correct sign but is not significant (Models 1-2), suggesting that technological complexity does not increase the likelihood of team mobility. Hypothesis 4 is thus not supported. The results (Models 3-5) provide support for Hypothesis 5 suggesting that technological complexity makes team founding more likely. Increase of technological complexity by one standard deviation increases the likelihood of team founding as opposed to individual founding by 60%. Using a *t*-test to compare the coefficients of the linear probability models reveals that the coefficients on technological complexity for team entrepreneurship and team mobility are significantly different at the 5% level (even as the coefficient on team mobility is not significant).[64]

DISCUSSION

Employee mobility is considered to be a vibrant channel for knowledge transfer. Similarly, employee entrepreneurship is widely heralded as an important driver of innovation,

[63] Note that in Model 2, I had to revert to Firm & Year fixed effects instead of Firm-Year due to many missing observations for the recipient firm size.

[64] It is important to note that some compromises were necessary in the conditional logit model of team entrepreneurship. Model 3 includes only Firm and Year fixed effects (as opposed to Firm-Year elsewhere) but retains a substantial portion of the observations. Model 4 uses a full fixed effect structure, but the number of observations drops substantially. At the same time, the firm entry and exit rate controls had to be dropped from Model 4 to prevent even further loss of observations.

firm formation and growth. However, far less is known about how the nature of technological problems solved by employees affects their propensity to engage either in employee entrepreneurship or mobility. I investigate how technological complexity affects the propensity of inventors to engage in employee entrepreneurship and mobility and examine additional factors like mobility to large firms or team transfer. In doing so, I shed new light on a contingency that has received little empirical attention despite the fact that it relates to anecdotal evidence and a significant body of theoretical literature. Importantly, the study highlights that the nature of technological problems may have wider implications for knowledge flows and competitive patterns.

Drawing on a uniquely rich database of employee entrepreneurship and mobility events and firm patenting in the U.S. semiconductor industry during a three-decade period, I find that the mobility of inventors to rival firms decreases with technological complexity (consistent with H1). This finding is consistent with the view that technological complexity is locking inventors within parent firms, inhibiting transfer of knowledge to rival firms. Even though the number of underexploited opportunities increases with the technological complexity, not all mobile inventors may be able to exploit them, and the nature of such knowledge inhibits its applicability within rival firms. As the complexity of inventors' prior technological experience increases, the potential hiring firms face difficulties in deploying the knowledge within their existing structures which translates into limited job alternatives (Lee *et al.*, 1994) and lower probability of actual mobility. The results also suggest that larger firms may be able to better mitigate the problems associated with the transfer of complex knowledge (H2). The complex knowledge is more likely to stay locked in within the structures of parent firms, but if it does diffuse it is more likely to flow to larger firms.

Consistent with H3, I find that the technological complexity of an inventor's prior patents positively affects the inventor's propensity to engage in employee entrepreneurship. Such a finding is consistent with the view that the prevalence of underexploited opportunities increases with the technological complexity. The inventors directly working with potentially underexploited technologies are in the best position to recognize these opportunities due to being in the appropriate "knowledge corridor" (Venkatamaran, 1997) or work context (Eisenhardt and Schoonhoven, 1990; Schoonhoven and Romanelli, 2001; Sørensen, 2007). However, note that the technological complexity increases the likelihood of employee entrepreneurship both conditional on exit (as hypothesized in H3) and unconditionally (relative to staying). The unconditional relationship highlights the fact that within the context of semiconductor startups (that are mostly design firms) the transfer costs are sufficiently mitigated when inventors start their own firms. As the results on team entrepreneurship reveal, the complementary assets are mostly human, and they are transferable from the parent firms (Campbell *et al.*, 2010). The employee entrepreneurship thus allows exploitation of opportunities arising from complex parent firm technologies while mitigating transfer costs.

Further, I find that teams facilitate knowledge transfer to startups with technological complexity, substantially increasing likelihood of team founding. However, I do not find support for the hypothesis that complexity increases the likelihood of team mobility. In fact, team mobility is a rare event – only less than 4.5% of inventors moved in teams (as opposed to 48% of inventors who co-founded firms together). It shows that existing organizations face difficulties in absorbing entire teams of inventors and perhaps are more interested in generic transferable knowledge that readily recombines with their existing structures rather than integrating complex technological knowledge.

The findings of the study have important implications. First, the results imply that it is the more simple knowledge that flows easily through the channel of inventor mobility to rival firms. This finding is consistent with prior studies that find that less complex knowledge diffuses more easily (Fleming and Sorenson, 2004; Sorenson *et al.*, 2006). Nevertheless, the findings in this study suggest that the most easily assimilated knowledge within the structures of the hiring firms may not always be optimal. Hiring firms may want to accommodate inventors working on more technologically complex problems, and more so within the context of teams, to exploit potential underexploited opportunities brought in by these inventors.

Second, the analysis suggests that the underexploited knowledge tends to flow to startups through employee entrepreneurship. This implication may partly explain the "startup phenomenon" – startups rather than the established firms are more innovative and better performers in some settings (Christensen, 1997; Khessina, 2002, 2003; Agarwal *et al.*, 2004; Carrol and Khessina, 2005; Ganco and Agarwal, 2009). At the same time, the findings suggest a new mechanism for why inventors exiting to start their own firms are likely to have a more negative impact on parent firm performance than inventors exiting to join rival firms (Campbell *et al.*, 2010; Wezel *et al.*, 2006). Inventors leaving to startups are fundamentally different that inventors who leave to rival firms in terms of knowledge they carry and exploit. Parent firms may need to use strategic levers to protect their intellectual property (Agarwal *et al.*, 2008) from its exploitation by new firms even though such knowledge may be less prone to imitation by rival firms (Rivkin, 2000).

Limitations and Alternative Explanations

Both the limitations and the findings of the study present avenues for future research. First, while the semiconductor industry represents a canonical context for examining the research questions, the findings may be limited in generalizability given this single-industry focus. In theory, I should expect the technological complexity as an important driver of employee entrepreneurship patterns in sectors characterized by high technological intensity, innovation rates and difficult technological problems that need to be solved by the firms. Following this logic, the findings should generalize to other hi-tech regimes and to other knowledge-intensive sectors, such as biotechnology or medical devices.

Second, since my empirical analysis hinges on the use of patent data to identify the employee entrepreneurship and mobility events across firms, the observations are necessarily restricted to instances where the inventor was identified on patents assigned to parent firms and was identified as a founder (employee entrepreneurship) or appeared as an inventor both within the parent and recipient firm within my focal sample (mobility). Missing from the sample, thus, are instances where the employee entrepreneurs or mobile employees may have had minor involvements or had general awareness of the technology while it was being developed (but no patent). Similarly, technologies that were in the initial stages of development but not patented prior to the employee departure are not captured in the study. However, a priori, there is no reason to expect that the technological complexity would differentially affect the behavior of inventors who are involved in the technology development without being documented through patents.

The validity of the results also hinges on the ability to rule out alternative explanations. For instance, the findings may be driven by the variation in the general attractiveness of opportunities if they correlate with technological complexity. To address this issue in the estimation, I include the control *Entry rate of firms with similar technological complexity*. I have also experimented with similar controls – including *Weighted number of patents (and citations)* *in the same main classes (and complexity bins) as the focal inventor* – all yielding identical results.[65] To further rule out the endogeneity, I performed additional analysis that shows that, while there are significantly more firms present (higher firm density) in low complexity categories, the entry and exit rates within years do not seem to vary significantly with technological complexity. Similarly, when one tracks the patenting histories of founders who patent post-departure from the parent firm, the observed technological complexity tends to exhibit a trend downward toward lower complexity. Such a pattern is consistent with the industry-wide trend toward higher modularity and possibly relates to the findings reported in the literature (Linden and Somaya, 2000) that startups tend to address complex problems (in our case, identified while working within parent firms) through modular solutions.[66] Such a comparison hinges on the assumption that innovations composed of modular components are simpler to solve. The prior literature has indeed suggested that to tackle underlying problem complexity, problems may be modularized by delineating modules and standardizing interfaces between the modules (Baldwin and Clark, 2000; Ethiraj and Levinthal, 2004; McCormack *et al.*, 2006). Standardization of interfaces limits degrees of freedom for the designers (and thus may lower the ability to find breakthrough innovations) but also limits cross-module interactions. This, in turn, makes problems simpler. Consequently, the conjecture that generally attractive technologically complex technologies are driving the results does not seem to be the case. Solving more complex technological problems may present more underexploited opportunities and may lead to

[65] Available from the author.
[66] Linden and Somaya (2000) discuss how integrated designs (i.e. "system-on-a-chip" solutions) typically pursued by large integrated incumbent firms were challenged by more specialized startups pursuing modular solutions and their trading with similar firms.

breakthroughs, but complex technological domains are not, in general, more attractive. Such a finding is fully consistent with the complexity theory (Kauffman, 1993; Altenberg, 1997).[67]

Similarly, selection bias is a valid concern. Higher quality inventors may more likely be solving more complex technological problems. To alleviate this issue, I implemented a two-step approach – I regress the raw complexity measure on controls and individual inventor fixed effects and then utilize a set of controls in the final regression. A further look at the observable differences comparing employee entrepreneurs with mobile inventors and inventors without observable event in the sample (Table 4.6) reveals that there no observable quality differences between employee entrepreneurs and inventors joining rivals (e.g. in terms of number of patents, citations, etc.). Even though such interpretation needs to be taken with caution, it may suggest that unobservable quality differences do not differentiate employee entrepreneurship and mobile inventors. However, one could also argue that future entrepreneurs self-select into technological areas that make future entrepreneurship more likely due to the discovering of underexploited opportunities (i.e. more complex domains). 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.

It may also be valuable to look at technological complexity from a different perspective. Murmann and Frenken (2006) suggest that technological complexity of a given component with other components is a proxy of how core this component is to the technology. They develop a theory relating the core versus periphery nature of components to the emergence of dominant design and the technology cycles. Such a view is not only fully consistent with my theorizing

[67] In support of this argument, examining technological distance between patents filed by firms founded by employee entrepreneurs and parent firms shows that employee entrepreneurs working in more complex technological domains tend to stay technologically closer to their parent firms. This is consistent with the finding that simple knowledge diffuses more easily. It should also alleviate the concern that more complex technologies give rise to entrepreneurial ideas that the parent firms are not interested in.

above but looking at the empirical phenomena through the new lens potentially offers additional insights. For instance, the findings in this paper suggest that most employee entrepreneurs emerge from core technological domains as opposed to the mobile inventors who originate at the periphery. Murmann and Frenken (2006) propose that core components are typically decided early within the technology life cycle (defining dominant design) and are difficult to change successfully afterwards. The theory in this paper suggests what may underlie these frictions and how it can lead to employee entrepreneurship – exploitation of ideas outside of the constraints of the parent firms.

Examining the patent documents of employee entrepreneurs and mobile inventors in my sample provides consistent patterns and reveals differences between employee entrepreneurs and mobile inventors. For instance, employee entrepreneurs originating in Intel in 1997 seemed to be mostly solving problems that involved components that were part of the core of the microprocessor technology – speed path, timing, parallel processing, etc. – and ended up applying their knowledge within their startups but in a different context – network processors, network switches, wireless chips, and so on. The inventors who merely moved across existing firms worked on important (highly cited) problems but nevertheless contained more peripheral components – cache memory, processor bus, slot design, etc – and typically patented in the same domain post-mobility. Looking at other examples in the sample reveals similar patterns – inventors working on problems composed of more densely connected components are more likely to become entrepreneurs.

Overall, the patterns discussed above offer intriguing opportunities for further research. The current paper is only the first step. What exactly happens post-exit with the inventors and what are the performance implications? How does technological complexity change over time and across firms? How does it relate to performance? What roles do inventor founders and mobile inventors play in the technological evolution of the industry?

Finally, the study opens up interesting avenues for research on the impact of the technological environment on employee entrepreneurship, knowledge flows and competitive patterns with the potential to look at a number of important contingencies. How do individual inventor characteristics interact with technological complexity in their impact on employee entrepreneurship? How does the stage of the industry life cycle affect the dynamics? I hope that the study will trigger additional research that examines many of these questions.

CONTRIBUTIONS AND CONCLUSION

These limitations notwithstanding, the study makes several important contributions. Within the context of employee entrepreneurship literature (Agarwal *et al.*, 2004; Klepper, 2005; Klepper and Sleeper, 2005) the study shows that the nature of technology is an important contingency in the emergence of employee entrepreneurship. By looking at the technology at a finer-grain, the study goes beyond the results in the prior literature that suggested firms with better technology produce more employee entrepreneurs (Freeman, 1987; Franco and Filson, 2006). The study contributes to the literature on employee mobility and knowledge spillovers (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003; Agarwal, Echambadi, Franco and Sarkar, 2004; Agarwal, Ganco and Ziedonis, 2008) by showing that the nature of technology may affect not only how much of the knowledge flows but also what kind and its destination.

In conclusion, my study theorized and found evidence that technological complexity of prior activities negatively affects the likelihood that employee inventors join a rival firm, positively affects the likelihood that they join a larger firm relative to smaller one and engage in employee entrepreneurship relative to join a rival firm. Technological complexity also increases the likelihood of team entrepreneurship relative to individual founding. The study sheds new light on one of the important contingencies affecting entrepreneurship and mobility patterns and reveals promising pathways for continued research.

TABLES AND FIGURES

Table 4.1 Complexity of semiconductor Inventions: measure versus questionnaire

#	Patents aggregated by main class (domain)	Complexity measure (mean)	Questionnaire
323	Power supply	-0.0637	Low
330	Amplifiers	-0.0521	High (Due to noise issues)
371	Error detection I	-0.0476	Low
714	Error detection II	-0.0298	Low
711	Memory	-0.0466	Low
327	Non-linear circuits	-0.0450	Medium
365	Static information storage	-0.0433	Medium
712	Processors	-0.0314	Low
345	Graphics processing	-0.0277	Low
713	Digital processing support	-0.0255	Low
257	Active solid state device	-0.0238	Low
326	Digital logic	-0.0213	Medium
438	Manufacturing process	-0.0160	High
395	Processing system organization	-0.0127	Medium
710	Input/output	-0.0106	Medium
375	Pulse and Digital communication	-0.0025	High
331	Oscillators	0.0030	High
360	Magnetic storage circuits	0.0051	High
324	Measure and Testing	0.0235	Medium
348	TV circuits	0.0280	Medium
250	Radiant energy (photocells)	0.0422	Medium
702	Calibration	0.0613	High
379	Telephonic communication	0.0914	High

Correlation = 0.5378

Table 4.2 Variable Definitions and descriptive statistics

Variable	***Description***	***Mean***	***S.D.***
Employee entrepreneurship (unconditional)	1 if the event of employee entrepreneurship follows the given employment spell and 0 otherwise The event is pegged to the application year of last patent within the source firm. Employee entrepreneurship events that coincide with corporate venture investment or direct parent involvement are excluded.	0.002	0.045
Employee entrepreneurship (conditional)	Sub-sample when exit =1 (employee mobility or entrepreneurship = 1)	0.108	0.311
Mobility (unconditional)	1 if the event of employee mobility to a within-sample firm other than the source follows the given employment spell and 0 otherwise. The event is pegged to the application year of last patent within the source firm. As discussed in the Appendix, the mobility events that correspond to acquisition events are excluded from the sample.	0.017	0.127
Recipient size	Number of employees of the recipient firm (sub-sample with mobility = 1)	5723	11881
Team entrep.	As defined in the text (sub-sample with employee entrepreneurship = 1)	0.32	0.468
Team mobility	As defined in the text (sub-sample with employee mobility = 1)	0.047	0.213
Tech. Complexity	As defined in the text.	0.004	0.127
Log Number of Patents	Capturing inventor "quality." Log number of valid patents the focal inventor applied for in the focal year.	0.621	0.511
Log Number of Citations	Capturing inventor "quality." Log number of citations the focal inventor received within the next 5-years for patents applied for in the focal year.	1.37	1.33
Female	Capturing gender differences in propensity to exit focal firms (e.g. Kim and Marschke, 2005). 1 if the first name on the patent application sounds female, 0 otherwise.	0.024	0.152
Nonwhite	Capturing race differences in propensity to exit focal firms (e.g. Kim and Marschke, 2005). 1 if the first and last names on the patent application sound of non Anglo-Saxon origin, 0 otherwise.	0.242	0.428
Technological Proximity	Capturing how "close" the inventor is to the technological core of the parent firm. Inventors who are closer may possess more valuable knowledge. Calculated as the angular distance (Jaffe, 1989) between the "technology" vectors of 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.	0.358	0.279
Log Number of Co-inventors	Capturing extent of collaboration with others. Log of the average number of patent co-inventors at the parent firm in a given year.	0.701	0.641
Log Number of Main Classes	Captures technological breadth or generalization vs. specialization. Log of the average number of patent main classes for the focal inventor in the focal year.	0.914	0.258
Log Years Patenting within Parent	Captures experience. Calculated as the difference between the focal year minus the application year of the first patent within the given parent firm plus one.	1.29	0.617
Entry Rate of Firms with Similar Tech. Interdependence	Captures activity in the focal domain. The technological complexity variable is split into 10 equal-sized bins. The measure is calculated as the firm entry rate within the same bin as the focal inventor in the focal year. It is a ratio between the number of new firms entering with patents for which technological 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. The technological complexity of a firm's patents is calculated based on the first year post-entry when a given firm applies for a patent.	0.182	0.151

Table 4.2 (Cont.)

Exit Rate of Firms with Similar Tech. Interdependence	Captures default risk of the focal domain. The measure is 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 technological 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. The technological complexity of firm's patents is calculated based on the last year pre-exit when a given firm applies for a patent.	0.015	0.061

Table 4.3 Correlations

	1)	*2)*	*3)*	*4)*	*5)*	*6)*	*7)*	*8)*	*9)*	*10)*	*11)*	*12)*	*13)*	*14)*	*15)*
1) Employee entrepreneurship	1.000														
2) Mobility	-0.003	1.000													
3)Recipient size	-0.072	0.097	1.000												
4) Team Entrepreneurship (Emp. Ent.=1)				1.000											
5) Team Mobility (Mobility=1)					1.000										
6) Technological Complexity (raw)	-0.002	-0.036	0.045	-0.004	0.004	1.000									
7) Log Number of Patents	0.015	0.038	-0.009	0.004	0.011	0.114	1.000								
8) Log Number of Citations	0.016	0.052	0.023	0.020	0.012	-0.051	0.701	1.000							
9) Female	-0.005	-0.011	0.013	0.002	0.000	0.010	0.001	0.003	1.000						
10) Nonwhite	0.014	0.026	-0.017	-0.004	0.012	-0.053	0.050	0.037	-0.053	1.000					
11) Technological Proximity	0.005	0.001	-0.004	0.010	0.003	-0.150	0.307	0.254	0.003	0.058	1.000				
12) Log Average Number of Co-inventors	0.013	0.018	-0.001	0.021	0.010	0.010	0.524	0.485	0.046	0.064	0.125	1.000			
13) Log Average Number of Main Classes	-0.007	-0.006	0.012	-0.008	-0.009	0.181	0.082	0.062	0.005	-0.050	0.012	-0.023	1.000		
14) Log Number of Years Patenting within Parent	0.006	-0.028	-0.094	-0.006	0.003	-0.015	-0.151	-0.166	-0.051	-0.077	0.089	-0.225	-0.023	1.000	
15) Entry Rate for Firms Entering with Similar Tech. Complexity	-0.003	-0.010	-0.007	0.004	0.000	0.042	-0.113	-0.105	0.001	-0.032	-0.073	-0.067	0.005	-0.027	1.000
16) Exit Rate for Firms Entering with Similar Tech. Complexity	-0.005	-0.003	0.014	-0.004	-0.002	0.018	0.047	-0.023	0.003	0.010	0.006	0.062	0.005	-0.017	-0.107

Table 4.4 Conditional fixed-effects logit testing H1, H2 and H3

	Mobility (H1) Model 1 (Logit)	**Recipient size Conditional on Mobility (H2) Model 2 (OLS)**	**Employee Entrepreneurship Conditional on Exit (H3) Model 3 (Logit)**	**Employee Entrepreneurship Unconditional Model 4 (Logit)**
Dependent Variable				
Positive outcome (Logit)	Mobility	Recipient firm size	Employee entrepreneurship	Employee entrepreneurship
Zero outcome (Logit)	Staying	-	Mobility	Staying
Technological Complexity	**-1.003*** **	**11720.37***	**3.482****	**1.937*****
Log Number of Patents	-0.139	-2820.728	-0.284	-0.445
Log Number of Citations	-0.061	328.835	0.212	0.066
Female	-0.444**	-452.401	-14.029***	-13.295***
Nonwhite	0.395***	-9.284	-0.084	0.29
Technological Proximity	0.017	2719.329	0.457	0.651
Log Number of Co-inventors	-0.336***	-563.867	0.218	-0.103
Log Number of Main Classes	-0.065	-1016.376	-0.451	-0.871*
Log Years Patenting within Parent	0.204**	-2280.249***	0.934***	0.849***
Entry Rate of Firms with Similar Tech. Complexity	0.027	-1426.592	0.782	-1.489*
Exit Rate of Firms with Similar Tech. Complexity	-0.714*	3565.83	-21.855**	-21.581**
Fixed Effect	Firm-year	Firm	Firm-year	Firm-year
Pseudo R-square	0.013	0.021	0.127	0.058
χ^2	260	F: 1.45	2168	2942
p-value	0	0.14	0	0
Log Likelihood	-2904		-92	-324
N	30742	802	316	10709

* p<.1, ** p<.05, *** p<.01

Table 4.5 Conditional logit and fixed-effects linear probability model testing H4 and H5

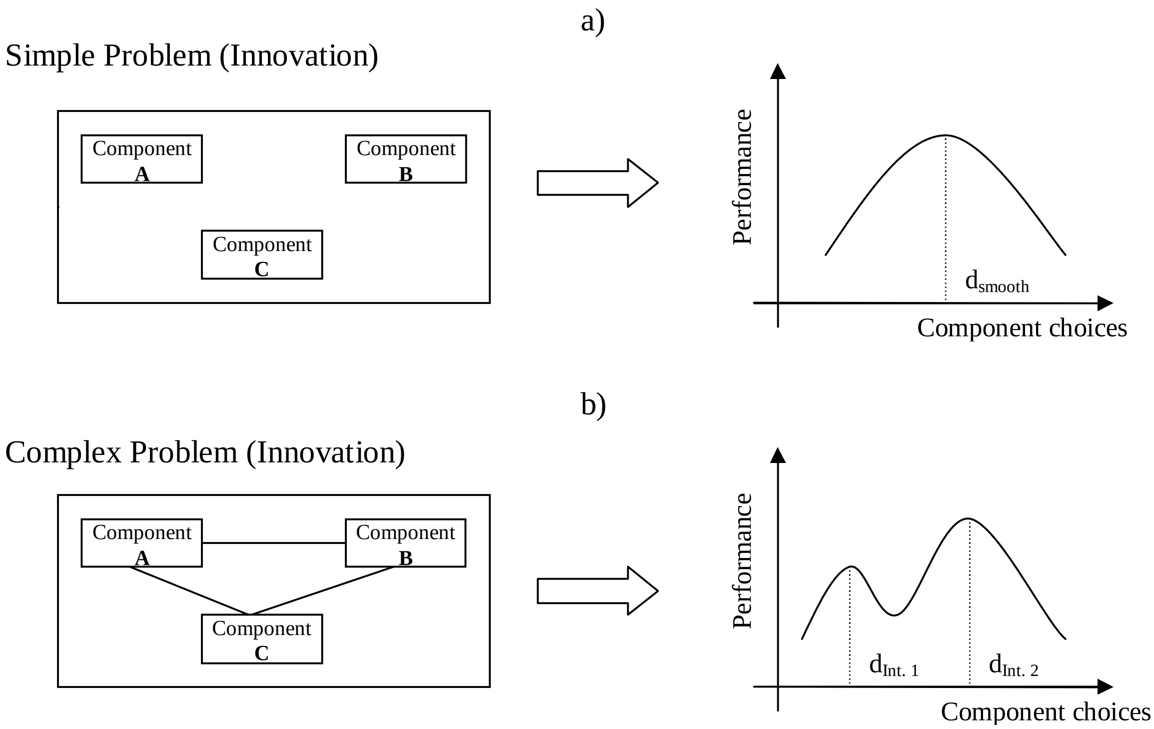
	Cond. Logit	**FE LPM**	**Conditional Logit**		**FE LPM**
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Dependent Variable					
(Positive outcome)	Team mobility		Team entrepreneurship		
(Zero outcome)	Individual mobility		Individual entrepreneurship		
Technological Complexity	**3.93**	**0.019**	**21.51*** **	**37.48*** **	**2.24*** **
Log Number of Patents	-2.22	0.008	0.4	6.64***	0.084**
Log Number of Citations	-0.411	-0.001	-0.25	-0.54	-0.24
Female	14.9***	0.15	15.36***	15.36***	0.72***
Nonwhite	-0.91	-0.008	2.099***	1.64	0.06
Technological Proximity	6.03	0.035	1.65	-0.046	-0.04
Log Number of Co-inventors	2.32***	0.029**	-0.66	-1.36	-0.16
Log Number of Main Classes	-0.665	-0.019	-1.19	1.45	-0.29
Log Years Patenting within Parent	-1.66**	-0.022	-0.7	-1.94*	-0.27**
Entry Rate of Firms with Similar Tech. Complexity	2.09	0.051	1.414	-	2.03**
Exit Rate of Firms with Similar Tech. Complexity	-12.47	-0.027	-60.59***	-	-9.69*
Fixed Effect	Firm-Year	Firm-Year	Firm and Year	Firm-Year	Firm-Year
p-value	0	0.1	0	0	0
N	89	935	72	28	111

* p<.1, ** p<.05, *** p<.01

Table 4.6 Observable differences between employee entrepreneurs, mobile inventors and non-exiting Inventors

Variable	Employee Entrepreneurs (Obs.=119)		Inventors exiting and joining rivals (Obs. = 1038)		Difference, Entrepreneurs vs. Movers	Inventors staying within parents (Obs.=21682)		Difference, Entrepreneurs vs. Stayers
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**(t-stat)**	**Mean**	**Std. Dev.**	**(t-stat)**
Technological Complexity	0.007	0.044	-0.0013	0.039	1.97**	0.0003	0.035	1.65*
Log Number of Patents	0.80	0.38	0.77	0.30	0.80	0.62	0.51	5.34***
Log Number of Citations	1.84	1.18	1.90	1.04	-0.58	1.37	1.33	4.63***
Female	0.01	0.09	0.01	0.10	-0.40	0.02	0.15	-2.14**
Nonwhite	0.38	0.49	0.33	0.47	1.14	0.24	0.43	3.19**
Technological Proximity	0.39	0.28	0.36	0.28	0.91	0.36	0.28	1.08
Log Average Number of Co-inventors	0.89	0.62	0.79	0.55	1.71*	0.70	0.64	3.44**
Log Average Number of Main Classes	0.88	0.22	0.90	0.26	-1.22	0.92	0.26	-1.94*
Log Number of Years Patenting within Parent	1.37	0.58	1.15	0.57	4.02***	1.29	0.62	1.50*

Figure 4.1 Technological complexity and characteristics of search space



CHAPTER 5

CONCLUSION

The objective of my dissertation is to examine micro-level technological variation as a new antecedent of innovation performance, idea rejection, knowledge flows and employee entrepreneurship and mobility decisions in a coherent framework. By studying how a common driver of technological complexity affects these phenomena, I bring together multiple levels of analysis – innovation, individual inventor and incumbent firm. This provides an opportunity not only to address multiple questions proposed in the introduction chapter but also look at the creation and exploitation of knowledge from a broader perspective. I summarize findings and my main questions addressed in each of the essays in Table 5.1.

The findings of the first essay underscore the difference between the search in biological evolution, which is “blind” and driven by mutations, and technological search, which is driven by human cognition and its heterogeneity. Consistent with the notion that technological problem-solving can be approximated with an iterative and adaptive search of boundedly rational agents, I find that, on average, inventors face difficulty when solving complex technological problems and are unable to capture opportunities present in complex technological domains. For an average inventor, performance declines with high problem complexity. However, in contrast with such a view of the innovative process, I find that variance of achieved performance increases with complexity. In a “biological” view of the innovative process represented by the iterative search of boundedly rational agents, all inventors are assumed to have identical search capabilities. In practice, inventors are heterogeneous in their ability to recognize and exploit opportunities. Even though an average inventor faces difficulties when solving complex problems (and iterative experimentation and luck aren’t sufficient to ensure discovery of the best solutions), some inventors may have the required abilities to discover and exploit such opportunities. The findings of the essay thus emphasize that the applicability of the simple agent-based models to human processes may be valuable but must be taken with caution and with attention to boundary conditions.

The essay has important implications for the following two essays. It justifies the use of the iterative and adaptive search of boundedly rational agents as a reasonable approximation of the technological problem-solving process, and it shows that technological complexity has a significant impact on patterns of innovation performance. It also informs the theory in essay 3 by suggesting that innovation outcomes become more varied with highly complex problems even as average performance declines. The opportunities in complex technological domains are more abundant but only some inventors are able to exploit them. Further, the study develops and validates a novel measure of technological complexity that allows the examination of the empirical relationships between complexity and employee entrepreneurship and mobility in essay 3.

In the second essay, I build on the notion that the agent-based models are a valid approximation of the innovative process and develop a model connecting technological complexity with the probability of idea rejection within incumbent firms. I find that rejection of profitable ideas may be driven purely by the attributes of the underlying technology without the presence of agency considerations, asymmetric information or resource constraints (Anton and Yao, 1995; Cassiman and Ueda, 2006; Hellman, 2007; Klepper and Thompson, 2010). The idea rejection in the model is driven by attributes of the task that is being solved (complexity, breadth, volatility of the environment) and their interaction with the bounded search abilities of inventors who solve this task. Even though inventors are assumed to be homogeneous in terms of quality they have different expertise. Further, their expertise is a subset of the dimensions of a given problem, which necessitates collaboration. The model predicts that the likelihood of idea rejection increases with problem complexity and with the size of technological shock; there is a negative interaction between problem complexity and technological shock size; and project rejection has an inverted U-shaped relationship with problem breadth. Assuming that idea rejection is a precursor to the emergence of an employee founded startup, the model suggests that technology can provide an independent driver of employee entrepreneurship.

The mechanics of the model developed in essay 2 informs the theory in essay 3 that connects technological complexity with employee entrepreneurship and mobility decisions. More specifically, the model emphasizes that knowledge originating from more complex technological domains may embody underexploited opportunities – viable ideas which are rejected by the incumbent firms.

In the third essay, I set out to address the question of how does technological complexity affect the ability of employees to transfer and replicate their knowledge outside of the parent firm and how important is the organizational setting of the recipient organization in this transfer. I develop the theory along the tension that more complex knowledge not only contains underexploited ideas but may be also be more embedded within the parent firm structures and be more difficult to transfer to other organizational settings. In particular, I develop a theory connecting the technological complexity of employees' prior innovations with their decisions to engage in employee entrepreneurship and mobility while also examining some of the contingencies like target firm size and team movements. I find that, after controlling for the value of innovations within incumbent firms and the attractiveness of the technological domain, technological complexity affects whether inventors exit and the destinations of their moves. The likelihood of joining a rival firm decreases with technological complexity of inventors' prior work. Conditional on mobility to rivals, complexity increases the likelihood of joining a larger firm. However, conditional on exit, the technological complexity increases the likelihood of founding a startup relative to joining a rival firm. Further, I find that the likelihood of team founding relative to individual founding increases with the technological complexity.

The results show that characteristics of knowledge not only determine whether inventors may transfer such knowledge outside of the incumbent firm but also its destination. Complex knowledge that potentially embodies valuable opportunities is more likely to flow through employee moves to startups relative to established firms. If it does flow to existing rival firms it is transferred to those firms that are sufficiently large to provide necessary slack resources for exploratory activities leading or that have the ability to absorb such knowledge. These findings have important implications. It may explain why employee entrepreneurship is so prevalent in early phases of industry evolution (Klepper and Thompson, 2010) when firms possibly generate more knowledge than they utilize. It may also explain why, in some settings, startups outperform other firms (Christensen, 1997; Khessina, 2002, 2003; Agarwal *et al.*, 2004; Carrol and Khessina, 2005; Ganco and Agarwal, 2009). The results also imply that nature of technology affects industry structure. Complex technological domains favor entrepreneurship and perhaps lead to a more volatile competitive environment in which incumbent firms are frequently displaced by new entrants.

LIMITATIONS AND FUTURE RESEARCH

As I highlight in Table 5.1, the dissertation opens rich venues for future research. A particularly relevant question connecting all three essays relates to the cross-industry differences in how technological complexity affects innovation performance, employee entrepreneurship and mobility patterns. For instance, the cross-industry differences in the nature of complementary assets may affect how technological complexity affects inventors' exit decisions. In the semiconductor industry that I study in essay 3, the entrants were predominantly non-manufacturing firms. This is consistent with the standardization of core designs and transition towards the "fabless" business model (Monteverde *et al.*, 1995). In such a context, the complementary assets are in the knowledge domain and are embedded in the highly mobile human assets (Campbell *et al.*, 2010). However, in some other industries the linkages between the intangible and tangible assets may be tighter, and necessary complementary assets may be embedded within incumbent firms. This may interact with technological complexity and affect inventors' exit choices. The broader related question is how industry context affects creation and exploitation of knowledge. The differences in the nature of complementary assets (Campbell *et al.*, 2010) and characteristics of knowledge may affect studied phenomena through different drivers than the ones explored in this dissertation.

Similarly, characteristics of knowledge may interact with firm strategies in their effect on inventors' incentives and exit choices. For instance, parent firms may design strategies to protect their intellectual property (Kim and Marschke, 2005; Agarwal *et al.*, 2009) or rely on outside legal mechanisms (Saxenian, 1995; Gilson, 1999; Marx *et al.*, 2009, 2010). Such potential interactions underline the necessity to examine these phenomena in a coherent framework.

Consistent with prior research (Anton and Yao, 1995; Cassiman and Ueda, 2006; Klepper and Thompson, 2010), I assume that idea rejection correlates with employee entrepreneurship and a certain proportion of rejected ideas are implemented through employee founded startups. Even though such an assumption may hold in most cases, it may be interesting to examine contingencies and cases when rejected ideas are potentially profitable but do not lead to employee entrepreneurship.

Critical questions that emerge in both essays 2 and 3 (Table 5.1) relate to the post-exit performance of employee entrepreneurs and mobile inventors. Do inventors successfully exploit opportunities embodied in complex knowledge? What are the contingencies? Based on findings of essay 1, it may be the case that average performance is low in very complex technological domains while the variance of performance is high. Founding a startup that exploits a complex technological knowledge may thus represent a high-risk-high-return strategy.

The questions related to post-exit performance also have an international dimension. The existing literature shows the performance premium experienced by startups founded through employee entrepreneurship relative to other startups (Agarwal *et al.*, 2004; Klepper and Thompson, 2010). With the increasing importance of international mobility (Saxenian, 2006), the question is how knowledge characteristics and knowledge transfer affect performance of inventors moving across national borders. Disentangling these contingencies and performance implications is an important project for future research.

The findings in essay 3 suggest that technological complexity affects industry structure by shaping the likelihood of entrepreneurial entry. This has potential implications for overall technological evolution, competitiveness and turbulence of a given industry (Ganco and Agarwal, 2009). How exactly knowledge structure affects industry structure is another important question. Examining the role of technological complexity may provide a meaningful contribution to this discussion.

Another overarching question connecting all three essays (Table 5.1) relates to the drivers of technological complexity, its changes over time and the cross industry differences in its patterns. Does technological complexity increase over time? If yes, in what settings? Why does it change over time and what are the implications? These questions go beyond the scope of my dissertation but are nevertheless important in improving our understanding of drivers of innovation, firm and industry performance. My dissertation provides a first step in the examination of these fascinating phenomena.

CONTRIBUTIONS

The dissertation contributes to technology and innovation management literature, complexity literature and literatures on employee entrepreneurship, employee mobility and knowledge diffusion.

In the first essay, I contribute to innovation and complexity literatures by showing that the innovation process can be successfully modeled as an iterative search of boundedly rational agents. I develop a novel measure of patent-level technological complexity and show that it improves the fit of the NK model over prior studies (Fleming and Sorenson, 2001, 2004) with important theoretical implications.

The second essay contributes to employee entrepreneurship literature by focusing on factors that condition the emergence of employee entrepreneurship. The paper connects employee entrepreneurship literature with the technology management literature by providing a first model that explicitly links technology with employee entrepreneurship. The model also contributes to complexity literature by extending the NK models with cognitive search (Gavetti and Levinthal, 2000) by incorporating team interaction.

The third essay contributes to the employee entrepreneurship literature by empirically documenting that the nature of technology is an important contingency in the emergence of employee entrepreneurship. The study contributes to the literature on employee mobility and knowledge spillovers by showing that the nature of technology may affect the ability of employees to transfer and replicate knowledge in other organizational settings.

In conclusion, the study shows that knowledge creation and exploitation are inherently connected. Common drivers like technological complexity may affect creation and exploitation of knowledge at multiple levels, which underscores the value of examining these phenomena within a joint framework. The study thus provides a unique opportunity to shed new light on an important contingency, opening rich pathways for continued research.

TABLES AND FIGURES

Table 5.1 Dissertation summary: Questions, findings and future research

	Main Question	**Main Finding**	**Questions for Future Research**		
Essay 1	Does the NK model provide a valid approximation of innovative process?	NK model correctly predicts conditional mean of innovation performance. However, inconsistent with model, variance of performance increases with complexity.	Does heterogeneity in human ability account for the inconsistencies?		What determines technological complexity?
Essay 2	How could characteristics of technological tasks affect idea rejection within incumbent firms?	Micro-level variation in technology can serve as an independent driver of idea rejection.	What is the relationship between idea rejection and employee entrepreneurship?		How do the performance patterns vary across industries?
Essay 3	How does technological complexity affect ability of inventors to transfer their knowledge to other organizational setting?	Technological complexity affects inventors' exit choices and destinations of their moves.	How does technological complexity affect industry structure?	What are the performance implications post-exit?	

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APPENDIX

THE NK MODEL

To generate the NK landscape, Chapters 2 and 3 utilize the original NK model specification proposed by Kauffman (1993). The model is characterized by the correspondence mapping of the vector $\boldsymbol{x}$ in the decision space to the outcomes (payoffs). Within the context of technological invention, each component of the vector $\boldsymbol{x_i}$ represents a decision of an agent or a group of agents about a component of the invention. The decisions are modeled as zero or one (component A vs. B is chosen) and the landscape is a mapping from the set $\boldsymbol{X} = \{0,1\}^N$ to R_+ An element $\boldsymbol{x} \in \boldsymbol{X}$ is a vector of binary digits of length N. The mapping assigns to each $\boldsymbol{x} \in \boldsymbol{X}$ a payoff $\pi(x) \in R_+$. The mapping π depends on the parameter K, with $\pi(x, K)$ reflecting the interdependence of the individual components of $\boldsymbol{x}$. The change in the payoff contribution of the i^{th} component is not only influenced by the change in the i^{th} decision x_i, but also by the changes in K other components of $\boldsymbol{x}$. If $K = 0$, there are no interdependencies and the $\pi(.)$ function is additive. The mapping (and the landscape) is generated by assigning a payoff $\pi_i(.)$ which is a random number from a standard normal distribution to each decision x_i, $i = 1,\ldots,N$ and each instance when either x_i changes or some of the K decisions that are associated with x_i change. The mapping for a particular vector $\boldsymbol{x}$ is given by

$$\pi(x,N,K) = \frac{1}{N}\sum_{i=1}^{N}\pi_i(x_i; x^1_{j(i)} \ldots x^K_{j(i)}), i \notin j(i)$$

where for any i we obtain a vector of indexes $j(i)$ mapping from N to N^K. None of the indexes of $j(i)$ is equal to i. The notation $x^k_{j(i)}$ means that the index of x is the k^{th} element of the vector $j(i)$. To create an overall mapping, we randomly generate $2^{K+1}N$ payoff values. The landscape created in this manner is “rugged” for high values of *K*. The structure of the mapping $\pi(.)$ is often depicted as a matrix called the interaction or influence matrix. The rows and columns represent the individual decisions. The matrix has ones in all those entries that affect (or are affected) by a particular decision. For instance, for $K = 0$, the interaction matrix is an $N \times N$ identity matrix and for $K = N - 1$ it is $N \times N$ matrix of ones.

The distance in the space *X* (distance over the landscape) between two decision vectors *x* and *x’* is defined in a standard way by:

$$d(x, x') = \sum_{i=1}^{N} | x_i - x_i' |$$

d(.) is a mapping from *x* to *N*, where *d(.)* is between 0 and *N*. The term “local” region of the landscape denotes the set of vectors that have only one element of the decision vector different. The term “search” on the rugged landscape denotes the process of discovery of a decision vector with a higher payoff. In Chapter 2, I utilize a simple version of a gradient or local search where one decisions of the vector is randomly altered. If the new vector yields a higher payoff than the original vector, the system shifts to the “new location” on the landscape. If the payoff is lower, the new vector is disregarded and the system stays at the original position. In Chapter 3, I use the search algorithm as described in the text.