Make hay while the sun shines or be more loyal than the king? The impact of external labor markets on the technological search process within firms.

by

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Dedicated to all my teachers.

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ABSTRACT

Past research on technological search has extensively studied the consequences of searching in different loci and in different manners. Less attention in given to the antecedents of the search process: why do researchers search in the way that they do? This dissertation attends to the career concerns of the researchers and investigates how the state of external labor market influences the way in which researchers conduct their technological search, i.e. where they look for technological ideas for innovations: inside the firm or outside; in familiar or new technological domains. I argue that when external job opportunities for researchers decline, they pay greater attention to knowledge flows inside their firms and build on ideas from inside the firm. Further, they expand their search into new technological domains to broaden their skills. On the other hand, when external opportunities increase, contributing to firms' existing research trajectories becomes less important and returns to specialization increase. I also examine the moderating influence of two individual specific factors – the specialization and the relative position of researchers, and two firm specific factors – the division of labor in the firm and the technological prominence of the firm. Using a comprehensive dataset of patents filed by the public electronic firms from 1992 to 2002, I construct an individual inventor specific measure of external job opportunities based on the R&D investments of all external firms in the technological domains that the inventor has worked on during the previous three years and relate it to her technological search. The tests show that greater growth in job opportunities is associated with reduced technological breadth of search. This effect is reduced by

a researcher's relative position in the firm and increased when the firm's researchers are more specialized. Contrary to expectation this effect is increased with a firm's technological prominence. The tests provide mixed support for the prediction that greater growth in opportunities is associated with increased organizational breadth of search. I find strong support for the predictions that this effect is increased when the firm's researchers are more specialized and with the technological prominence of the firm.

Chapter 1

Introduction

1.1. The Research Questions

Scholars of learning (March, 1991), technological evolution (Nelson and Winter, 1982; Levinthal and March, 1993) and technology strategy (Nerkar, 2003; Katila, 2002; Rosenkopf and Nerkar, 2001) have demonstrated that firms differ in the way they search for innovations. Further, they have shown that how and where this search occurs has important consequences for the firm's technological performance (Henderson and Cockburn, 1994), ability to acquire future capabilities (Cohen and Levinthal, 1990) and even survival (Tushman and Anderson, 1986), especially in technologically intensive industries. Yet, we do not completely understand why firms search in the way that they do: why do they sometimes restrict their search to familiar domains while at other times they cross into new domains in search for ideas? This is partly because past research on a firm's search behavior assigns a rather passive role to the researchers within the firm who actually conduct the technological search and therefore ignores the impact of incentives affecting the researchers (Cohen and Sauermann, 2007).

Given the information asymmetry and uncertainty associated with technological search, researchers within firms retain autonomy in technological decisions (Cohen and Sauermann, 2007; Siemsen, 2008; Bailyn, 1985; Burgelman, 1983b). Further, researchers need inherent motivation and a feeling that they own the research process to gain creative insights essential for successful technological search (Damanpour, 1991; Cohen and Sauermann, 2007). This is difficult to achieve if top managers direct the researcher's efforts too strictly. These considerations provide added reasons for firms to give autonomy to researchers. Thus understanding the technological search behavior of firms should also include examining the concerns of the researchers within the firms and how those concerns influence the technological choices that the researchers make.

The state of the external labor market for technological skills is an important concern for researchers in technology-intensive industries (Brown et al., 2006; Costlow, 2000; Campbell and Brown, 2001). These industries are characterized by a fast changing technological landscape where current technologies are constantly threatened by new ones (Tushman and Anderson, 1986). In such circumstances, researchers are constantly threatened by obsolescence since the returns to experience with older technologies are uncertain and short-lived (Brown and Campbell, 2001; Campbell and Brown, 2001). Further, firms in such industries frequently hire new researchers with latest skills and relegate the existing workforce to legacy projects which are typically less interesting and promise less career advancement (Campbell and Brown, 2001). As a result, concerns about future employability, job mobility and relative position within the firm are of great importance to researchers within firms. These concerns make tracking job opportunities in the environment and responding to fluctuations in external labor market conditions necessary for the researchers.

The fluctuations in external labor market conditions impact how researchers conduct technological search within firms through many related mechanisms. The state of the labor market alters the relative importance a researcher attaches to external job opportunities in comparison to a firm's internal labor market (March and Simon, 1958; Halaby, 1988). This relative importance influences the technological skills that she wants to develop, the kind of social networks she chooses to participate in, the kind of technological developments and problems that she pays attention to, and the extent to which she tries to increase her influence within the firm. These choices impact the composition of the set of technological problems she is aware of and chooses to tackle as well as the set of technologies she brings to bear to solve them. The state of the labor market also alters the bargaining power and the risk-propensity of researchers. For instance, a good labor market allows them to take more risks and venture into unfamiliar and latest technologies. Although working on such technologies is more risky for researchers, the challenge associated with the technologies gives them more excitement while allowing them to update their skill sets (Campbell and Brown, 2001). These arguments strongly suggest that the labor market conditions facing the researchers influence their behavior and consequently the nature of technological search within the firm.

The impact of external labor market conditions is however not the same for all researchers or across all firms. Researchers are simultaneously located in two professional environments - external labor market and the internal labor market within the firm (Chevalier and Ellison, 1999; Waldman and Gibbons, 2006; Lazear, 2009). Both their concerns about professional growth and their behaviors are jointly molded by the interactions between the internal and the external environment. Individual level factors such as the researchers' position relative to other researchers within the firm (Paruchuri et al., 2006; Hambrick and Cannella, 1993) influence the degree to which the external labor market conditions present opportunities or pose threats to their careers. Similarly, firm-level factors also condition how the researchers respond to external labor market conditions. For instance, the degree of to which the individual researchers in the firm are specialized influences the learning ability of the researchers (Cohen and Levinthal, 1990) and the extent to which the researchers communicate with and help each other within the firm(Bunderson and Sutcliffe, 2002). These factors, in turn, should condition both the extent to which the researchers are influenced by the external opportunities as well as their best response to the external opportunities. Therefore, analyzing the role of individual and firm-level factors is essential to obtaining a more complete picture of how external labor market conditions influence the nature of technological research conducted by the researchers inside the firm.

In this dissertation, I explore how the external labor market conditions and the characteristics of individuals and that of the firms they work for jointly impact how researchers search for innovations in technology-intensive industries. Building on past search I treat technological search as a multi-dimensional construct. Specifically, I consider two dimensions of search: organizational - the extent to which researchers cross the organizational boundary and draw upon technological ideas outside the firm and technological - the extent to which researchers cross technological domains to search for innovative ideas(Rosenkopf and Nerkar, 2001). These dimensions reflect the broadness of the landscape that researchers search to borrow ideas from (Siggelkow and Rivkin, 2005). I include two individual-level characteristics in my investigation: the relative position of the researcher inside the firm and the level of specialization of the researcher. In addition, I include two firm-level moderators in my study: the technological prominence of the firm and the extent to which the research in the firm is conducted by specialists vs generalists.

To explore the joint impact of the state of the labor market and these firm and individual-level characteristics on technological search, I seek to answer the following two research questions: (a) How does the state of external labor market impact the tendency of researchers within firms to search along each of the two dimensions? (b) How is this tendency influenced by firm and individual-level characteristics?

1.2. Theoretical Perspectives

To answer these questions, I build on and combine ideas from two distinct strands of literature: the literature on technological search (Levinthal and March, 1993; Siggelkow and Rivkin, 2005; Rosenkopf and Nerkar, 2001; Nerkar, 2003; Katila, 2002) and that on career concerns (Gibbons, 2005; Gibbons and Murphy, 1992; Holmstrom, 1999; Chevalier and Ellison, 1999; Siemsen, 2008; Zwiebel, 1995). This combination helps me derive insights into the process of technological search as well as increase our understanding of how career concerns shape behavior inside organizations. The technological search literature has demonstrated that the technological developments researchers attend to (Cyert and March, 1963; Levinthal and March, 1993; Rosenkopf and Nerkar, 2001; Taylor, 2010) and the information networks they participate in (Fleming et al., 2007b) influence the kind of technological combinations they discover (Rosenkopf and Nerkar, 2001; Fleming et al., 2007b; Katila, 2002). This literature however does not explicitly answer why individual researchers would pay attention to certain technologies and networks and not others. This answer is provided by the career concerns literature. The career concerns literature indicates that concerns about future employability, mobility and earning potential should influence the researchers' preferences for certain technologies (Rosen, 1983; Kim, 1989; Lazear, 2009; Siemsen, 2008; Zwiebel, 1995) and information networks (Seibert et al., 2001; Podolny and Baron, 1997; Brown et al., 2006; Joshi et al., 2008) over others. Hence, these literatures together help me build a theoretical framework that relates researchers' career motivations with the nature of technological research that they conduct. Further, this combination advances our understanding of both these literatures.

1.2.1 Contributions to Career Concerns Literature

Many scholars have argued that career concerns create implicit incentives for employees (Holmstrom, 1999; Gibbons, 2005; Waldman and Gibbons, 2006; Siemsen, 2008; Zwiebel, 1995). Since the labor market infers the capability of an employee from the outcomes of her work, she is encouraged to exert greater efforts to achieve better outcomes. Scholars have also recognized that some employees such as technological researchers have enough autonomy to change their task definitions (Siemsen, 2008; Zwiebel, 1995). This recognition has prompted them to build theoretical models that explain how career concerns lead employees to prefer some technological paths over others. These models focus on the signals provided by the outcomes of efforts. They argue that researchers prefer certain technologies because these choices affect the value of signals. For instance, Siemsen (2008) argues that less capable researchers may choose difficult technological designs to obfuscate the unfavorable signals of bad outcomes. In these models however the capabilities of the researchers do not change with their choice of the technological path.

The technological search literature, on the other hand, convincingly argues and demonstrates that searching in a technological domain enables a researcher to enhance her skills in that domain (Nelson and Winter, 1982; Cohen and Levinthal, 1990; Levinthal and March, 1993; Ahuja and Katila, 2001; Phene et al., 2006). Models that connect career concerns to technology choice (Siemsen, 2008; Zwiebel, 1995) ignore the possibility that this "learning" may provide incentives to prefer certain technological paths. Because which domain a researcher has expertise in can affect her future employability and mobility, we can expect her career concerns to be manifested in technological search activity also through the "learning objective".

A further point to note is that the "learning objective" is even more salient in circumstances where outcomes are poor predictors of capability due to the inherent uncertainty of the task. Technological research is one such circumstance. Firms find it extremely difficult to objectively measure the performance of their researchers and many choose not to (Schainblatt, 1982). If it is difficult for firms to objectively measure the performance of their own researchers, how much of a signal would outcomes provide to external labor markets? The external labor market, however, can form expectations about the knowledge-set of the researcher from the technological domains she has worked in and the technologies that she has employed in the past. It can then verify her competence to a certain degree through an interview or examination process before hiring. Thus, the very experience of a researcher in a particular domain gives her knowledge about the domain which can then enable her to seek further career opportunities. On the other hand, successes or failures in specific research projects are problematic and noisy metrics to use in judging the competence of a researcher (Schainblatt, 1982) given the inherent uncertainty of the research process (Freeman and Soete, 1997). Indeed, even failure in a technological project can increase the skills and knowledge of a researcher as a famous comment attributed to Edison aptly points out: "I have not failed, not once. I've discovered ten thousand ways that don't work."

The importance of learning on the job is well recognized by scholars (Waldman and Gibbons, 2006; Lazear, 2009; Becker, 1962) studying compensation and wage patterns of employees. This strand of literature examines the willingness of employees to invest in firm-specific learning and how this learning impacts the current and future wages of the employees (Waldman and Gibbons, 2006; Lazear, 2009). Since the focus of this literature is on explaining the compensation patterns, it pays less attention to how the learning incentives influence the evolution of tasks performed within the firms. As a result, how the learning objectives of researchers influence the evolution of a firm's technological profile is not examined.

Scholars in this stream of literature largely treat a firm's task requirements as exogenous to the employees' actions (Lazear, 2009). Recent models (Lazear, 2009; Waldman and Gibbons, 2006) have begun treating the nature of tasks as endogenous to external labor environment but these models too do not examine how the employees may alter their task definitions. For instance, Lazear (2009) models firms' task-requirements as a set of generic skills with each firm giving idiosyncratic weights to each generic skill. The firm-specificity in this model comes from the degree to which the weights assigned by the firm differ from the weights assigned in the external world. In thick external labor markets the idiosyncrasy of a firm's weight assignments decreases because each skill has a sufficient demand in the external world. However, in this model, the weights assigned by the firm are fixed and not changed by the employees. In my model, the researchers can be viewed as endogenously changing the weights. They either attempt to make their skills and knowledge more important to the firm or attempt to take the firm's assignment of weights closer to that of the external world. In this study, I examine how the state of the labor market and firm-level characteristics jointly influence this evolution.

When we combine the career concerns literature with the technological search literature, we can clearly see that the way researchers perceive and respond to changes in external labor markets is also conditioned by their past career history and the contexts in which they conduct their research. Past history and the research contexts influence researchers' future learning ability (Cohen and Levinthal, 1990), communication patterns within the firm (Bunderson and Sutcliffe, 2002; Tushman, 1979a,b) and the expectations from the market of their abilities (Kim, 1989). These factors impact how much the researchers are influenced by external opportunities as well as their best responses to the opportunities and threats in the external environment. The career concerns literature however does not deeply examine the behavioral consequences of the past history and firm-level heterogeneity in its models. In this study, I also include the examination of how a researcher's and the firm's idiosyncratic characteristics moderate the influences of external labor markets on the researcher, leading to different behavior in different firms from different researchers.

1.2.2 Contributions to the Technological Search Literature

This study adds to our understanding of the innovation process within firms in four distinct ways. First, by attending to the motivations of researchers explicitly, it uncovers new mechanisms through which the environment impinges on the innovation process within the firms. Studies of innovation have largely ignored the impact of labor markets on the direction of technological search inside the firm. One theoretical mechanism, the induced innovation model (Ruttan, 1997; Ruttan and Hayami,

1984) does imply that the labor market conditions change the direction of innovation by altering the relative costs of a factor of production, i.e. labor. However, the labor market's direct impact on the motivations of researchers and their subsequent technological choices is not well studied.

Second, this research directs attention toward the perspective that learning obtained through technological search (Cohen and Levinthal, 1990) is an important director of a researcher's efforts. The two most prominent theories that explain the direction of innovation efforts - "technology-push" and "demand-pull" - focus on criteria associated with the physical outcome of technological search, not on the benefits obtained by the process of searching. The "technology-push" theory (Walsh, 1984; Jaffe, 1986) focuses on the ease (costs) of producing the innovation outcome given the current state of knowledge. The "demand-pull" theory on the other hand focuses on the profit-potential of the innovation (Christensen and Bower, 1996; Schmookler, 1962). In both cases, the focus is the physical outcome of research efforts. Consequently, these theories do not incorporate the incentives provided by the "learning" benefits gained through the process of innovating regardless of the physical outcome. These learning benefits can present important incentives for the researchers to focus attention on certain technological developments.

Cohen and Levinthal (1990) convincingly argued that the process of innovating also provided learning benefits to the researchers. They highlighted two implications of these benefits. The first implication is direct: it enables the researchers to absorb related external knowledge. This is the gain in "absorptive capacity". The second implication is indirect: the learning gained through research efforts provides incentives to invest in research independent of the physical outcome of research. This effect is especially relevant for individual researchers who can invest in research efforts also to gain this learning. This is the "incentive effect".

The first "absorptive capacity" effect has been a focus of considerable amount of research in the last few years. It has been demonstrated that past research experience in certain areas allows firms to learn from others through alliances (Lane and Lubatkin, 1998) and acquisitions (Ahuja and Katila, 2001). The ability of research units within the firms to learn from each other and from external sources is also attributed to past experience in similar technologies (Almeida and Phene, 2004). Research on the second indirect "incentive" effect is however limited. This is perhaps because the literature has not paid deep attention to understanding how the motives of researchers impact their technological search behavior. My study brings the "incentive effect" to the forefront by arguing that learning about certain technologies is an important motivation guiding the research efforts of researchers. In other words, I suggest that technology not only "pushes" but also "pulls".

Third, this study introduces a different mechanism through which demand conditions of an industry influence the innovation efforts (Schmookler, 1962; Christensen and Bower, 1996). The previous mechanisms focus on the profit potential of the innovations (Cohen and Levin, 1989). I suggest a different mechanism by arguing that as the demand conditions of an industry change, they may also change the labor market conditions for the researchers. This influence on labor markets, in turn, influences the patterns of research activities conducted by researchers. Thus, demand conditions not only influence the direction of innovation directly through altering the profit potential of innovations but also through its influence on the labor market conditions. Examining this new mechanism at depth is important because of two reasons. First, it reveals a path through which demand conditions in one industry may influence the nature of technological research in a different industry. Second, it points toward a hitherto unconsidered linkage between the "demand-pull" (Christensen and Bower, 1996; Schmookler, 1962) and the "technology-push" (Jaffe, 1986) influences.

Through its impact on labor market, the state of demand in an industry can influence the nature of research in related industries. Greater demand for the products of an industry could lead to better labor market conditions for the researchers skilled in the technologies underlying those products. The better labor markets in these technologies may attract researchers from different, albeit related, industries to learn about these technologies, leading those researchers to expand the technological breadth of their search. But, this is not all.

When researchers from varied backgrounds are attracted toward any particular technology, attempts to adapt and apply this technology to many different uses increase. As the researchers explore the diverse uses of that technology, they explicate and expand the technological opportunities associated with it (Nelson, 1962; Cohen, 1995; Levinthal, 1998). These diverse efforts clarify what the technology is best used for, the different ways that the technology can be adapted or modified and the basic scientific principles underlying the technology (Nelson, 1962). In this way through its impact on the labor markets for researchers, the demand condition in an industry alters the technological opportunities associated with technologies that underlie that industry. The first step in understanding this linkage is to understand how the researchers within the firms respond technologically to stimuli from their labor markets.

Fourth, this study provides a different perspective on how the organization of R&D within firms influences its technological search activities. Research connecting the organization of R&D activities with technological search efforts has largely viewed the organization structure as a means to create distinct sets of knowledge bases within the firm and therefore as a means to bound the search within those sets (Argyres, 1996; Toh, 2007). Thus specialization (Toh, 2007), inter-unit integration (Toh, 2007) and centralization (Argyres and Silverman, 2004) of R&D activity is treated as means to enable researchers to access and combine (or not) various knowledge elements together. In this dissertation I provide an alternate perspective on organization structure. Apart from facilitating or hindering (Argyres and Silverman, 2004;

Toh, 2007) the combination of knowledge, the way R&D activity is organized and distributed also triggers career concerns among the researchers and serve as motivating agents for the researchers.

The organization of R&D activities serves as a trigger for the career concerns of researchers in the firm through two related but distinct mechanisms. One, the division of labor in the R&D activity restricts the knowledge that an inventor within the firm is able to acquire and this restriction impacts her future employability and career advancement within the firm (Waldman and Gibbons, 2006). Second, the organization of R&D activity also delineates the "social space" that the inventor uses for social comparison - other inventors that she works with inside the firm provide a basis for comparison (Paruchuri et al., 2006). The relative opportunities that the other researchers get within the firm also serve as a mechanism to trigger career concerns for the inventors. For instance, if a researcher is in a unit that is not at the core of the research activities of the firm, the researcher may be less confident of his or her chances of advancement within the firm or even continued employment at times when the environment becomes less munificent. This in turn can create career concerns for the researcher.

1.3. Theory and Hypothesis

In this study, I assert that in order to understand the technological search process within firms, scholars should attend to the motivations of researchers. The main premise underlying this assertion is that the researchers within the firms have enough autonomy in conducting technological search for their motives to matter. This premise has strong theoretical foundations. Technological search involves significant uncertainty regarding the correct technological path to adopt; one can attempt to solve the same problem through multiple approaches (Nelson, 1959a,b; Siemsen, 2008). Choosing one approach out of these requires specialized knowledge and expertise which resides to a greater extent with the researchers compared to the management (Cohen and Sauermann, 2007). This asymmetry in technical knowledge implicates autonomy for the researchers.

Apart from being necessary, the autonomy may indeed be beneficial to the firm. Innovation is a creative effort and creativity is fostered when researchers are intrinsically motivated to work on problems (Amabile et al., 2005; Cohen and Sauermann, 2007; Morgan, 1992). Having ownership of the research project is integral to being intrinsically motivated (Damanpour, 1991). Autonomy allows the researchers to take ownership of the projects (see Ahuja et al., 2008). Additionally, by allowing autonomous research endeavors, firms can uncover hidden synergies and expand their repertoire of capabilities. These synergies and expanded capabilities help insure the firm against adverse changes in the environment (Burgelman, 1983b; Conner, 1988).

The professional norms guiding the researchers' behaviors also encourage autonomy for the researchers (Bailyn, 1985). Researchers are expected to be curious and enterprising (Morgan, 1992). Stories of defiance and doggedness circulate among them and reinforce the need for autonomy. The firms also expect the researchers to be enterprising and creative. Indeed that is the mandate the firms provide to their researchers – to invent.

Of course, this autonomy is not complete. The management does exercise control through selecting which innovative efforts to pursue further and which to curtail. However, the inherent asymmetry of knowledge, the potential though unpredictable benefits of allowing autonomous behavior and the very nature of inventive task gives the researchers enough autonomy, albeit within bounds, to conduct their technological search. Indeed theories of technological evolution within firm (Gavetti et al., 2007; Burgelman, 1983b) regard the autonomous search of technologists within the firm as the major source of variation within firms. Although the top management selects among the various choices generated by technologists in the firm and sets up the bounds within which the technologists search, it does not exercise fine-grained control over the technological search conducted by researchers (Burgelman, 1983b, 1996). Researchers therefore still enjoy considerable autonomy at the technological level: which technologies to employ, which technologies to build on etc (Burgelman, 1983b; Bailyn, 1985; Hauser, 1998; Cohen and Sauermann, 2007; Siemsen, 2008).

Empirical research also supports this premise (Cohen and Sauermann, 2007). In a series of studies, Burgelman (1983a,b, 1996) demonstrated the existence of autonomous research initiatives within the firms. Bootlegged operations conducted by researchers within firms sometimes even in defiance to top management directives have been documented by many scholars of innovation (Nayak and Ketteringham, 1997; Fleming, 2002; Christensen and Bower, 1996; Burgelman, 1983b). Indeed, these scholars find that in many cases, the researchers first invented the products and processes and then asked for resources to be allocated to turn them into viable business opportunities. In the disk drive industry for example, Christensen and Bower (1996) found that the researchers had already invented the disruptive technology inside the firms even though the firms later chose not to allocate resources to market those technologies. Surveys of researchers within the research labs (Bailyn, 1985) also support this premise. By interviewing with research personnel in research labs, Bailyn (1985) has demonstrated the existence of autonomy for researchers. In fact, in her interviews, she found that quite a few scientists complained of too much strategic autonomy. These studies show that within the broad parameters set by a firm's strategy, researchers do influence the nature of technological search that they conduct and their autonomous efforts are a major source of generating new business opportunities for the firm. Consequently, understanding the researcher's motives is essential to understanding the nature of technological search within firms.

The research personnel are driven by many different motives and the order of importance of these motives varies with time (Morgan, 1992). These motives can be categorized into three distinct kinds: extrinsic, intrinsic and social (Cohen and

Sauermann, 2007). Extrinsic motivations are motivations such as pecuniary benefits and career concerns, intrinsic motivations are those arise from the task of invention itself - the thrill and excitement of creating something original and social motivations arise from the desire to achieve a social position among peers (Cohen and Sauermann, 2007; Paruchuri et al., 2006). The labor market conditions facing the researchers influence all the three motivations.

The labor market conditions most directly influence the extrinsic career-concern motivations by impacting the future employability, job mobility and the opportunity structure facing researchers (Kim, 1989; Rosen, 1983; Waldman and Gibbons, 2006; Lazear, 2009). However, labor markets also indirectly impact the social and intrinsic motivations. The state of the labor market impacts social incentives by altering the importance of external job opportunities relative to career opportunities within the firm. This change in relative importance, in turn, influences which social networks – internal or external – is considered more important by a researcher.

The state of the external labor market exerts two influences on the intrinsic motivations of researchers: first, it alters the salience of intrinsic motivations for researchers and second, it affects the bargaining power of researchers. By altering the perceptions regarding job security, the labor market conditions change the salience of intrinsic motivations in choosing research projects(Unsworth and Clegg, 2010). Researchers are more likely to attach greater weight to creative considerations when they perceive maintaining continuous employment to be easy (Unsworth and Clegg, 2010). Further, the perceived ease of maintaining continuous employment also impacts their propensity to take risks. A good labor market serves as insurance for researchers allowing them to take risks while a bad labor market decreases their propensity to take risks. Although original research projects with no preceding guidance are inherently more challenging and interesting, they also entail greater risk of failure. Hence, researchers are more likely to undertake inherently interesting but challenging projects in good labor markets. Additionally, the external labor market conditions alter the bargaining power of researchers within the firms. This change in bargaining power impacts the extent to which researchers can garner resources and permission to work on projects that are intrinsically interesting to them.

These arguments clearly indicate that labor market conditions influence all the three kinds of motivations. The state of the labor market influences the importance of each motivation relative to others. It also changes the manner in which the motivations manifest themselves in the technological search of researchers. It is therefore imperative that we examine the influence of labor markets on technological search behavior at greater depth.

1.3.1 Main Effects

I develop a theoretical model to examine the impact of external labor market conditions on the nature of technological search within firms. In this model, the state of the labor market impacts technological search through two primary mechanisms. First it alters the importance a researcher attaches to flexibility relative to deepening her knowledge in a narrow specialized domain. Second, it alters the importance of opportunities for career advancement provided by external labor markets relative to those provided by the firm. In addition to these main mechanisms, the model incorporates individual and firm-level heterogeneity to explore how the individual and firm-level characteristics moderate the impact of these two effects.

The first mechanism leads the state of the labor market to influence the extent to which researchers expand their technological search into new technological domains - the technological breadth of their search. If the labor market in a researcher's technological domain is good, she is more inclined to deepen her skills in her specialized domain rather than expand her skill set in a broad range of technologies (Kim, 1989; Rosen, 1983; Garicano and Hubbard, 2009). This is because (a) good labor markets ensure a good match for her skills and (b) deeper knowledge increases her marginal productivity in her specialized domain (Kim, 1989). Similarly bad labor markets lead researchers to prefer a broader skill set allowing them greater employment options (Kim, 1989; Marx et al., 2009). The state of the external labor market, therefore, influences the proclivity of researchers to either focus on a narrow specialized technology or learn about a broader range of technologies. This, in turn, impacts what the pool of technological knowledge that the researchers draw upon for innovations is composed of. In good labor markets, the pool consists of deep knowledge from a narrow specialized domain whereas in bad labor markets, the pool includes ideas from a broader set of technologies. I call this the technological "composition" effect.

By increasing the incentives to learn about certain technologies, the state of the labor market also encourages researchers to employ those technologies in solving their technological problems. Since working on a technology also provides experiential learning about that technology (Argote, 1999; Cohen and Levinthal, 1990), a researcher may be inclined to employ a particular technology in her work for the associated learning benefits. I call this the "learning objective" effect. Although strict controls can reduce the "learning objective" effect, they are unlikely to completely eliminate it. This is because researchers need to be provided autonomy given the uncertainty and information asymmetry of the research process (Cohen and Levinthal, 1990). For the reasons discussed above, the "learning objective" effect also works in the same direction as the "composition" effect. In good labor markets, the researchers are more likely to prefer deepening their knowledge of their domain whereas in bad markets, they are likely to want to learn about the technologies beyond their narrow specialized domain. Thus, the "learning objective" effect in combination with the "composition effect" leads researchers to expand the technological breadth of their search in bad labor markets and deepen their search in a narrow technological domain in good labor markets.

The second mechanism leads the state of the labor market to impact the organizational breadth (Rosenkopf and Nerkar, 2001) of a researcher's technological search: the extent to which the researcher borrows from ideas external to the firm. The condition of the external labor market influences the importance a researcher attaches to internal labor markets relative to external labor markets. As the external job opportunities reduce, the importance of internal labor market and the incentives to maintain employment within the firm increases (Halaby, 1988; Hausknecht et al., 2008) and the opportunity cost of working within the firm decreases (March and Simon, 1958). This causes researchers to pay more attention to the information networks within the firm and focus on improving one's relative position within the firm. The desire to improve their relative position inside the firm and to preserve their jobs encourages researchers to try and increase the firm's dependence on their unique skills. To achieve this, researchers are likely to undertake more firm-specific projects and attempt to increase the use of their inventions and knowledge in several research projects within the firm.

On the other hand, a good labor market outside increases the opportunity cost of working inside the firm and increases the marginal benefit of paying attention to and learning about technological problems and solutions that exist outside the firm. Thus, in good markets, a researcher's pool of knowledge is likely to contain a greater proportion of external knowledge elements. Together, these arguments imply that bad labor markets lead the researchers to search more internally for technological ideas relative to good labor markets.

1.3.2 Individual and Firm Level Moderators

My theoretical model explicitly recognizes that researchers and firms are heterogeneous and therefore individual and firm-level differences matter. The individual-level and firm-level differences moderate the impact of labor markets on a researcher's technological search by influencing two factors. First, the differences can influence a researcher's need to pay attention to and respond to the external labor market conditions. For instance, the extent to which a researcher is secure in her job and enjoys a position of influence within the firm influences her sensitivity to external labor markets. Second, the differences influence a researcher's capability to change her research agenda in response to changes in the labor market conditions. For instance, the way research is organized within a firm can influence the researcher's access to different knowledge elements within the firm. This access, in turn, influences how easy it is for the researchers to alter their research agenda and find projects that they like; in other words, their ability to change the research agenda in response to labor market conditions.

I consider the impact of two individual-level characteristics: the relative position of a researcher within the firm and the degree to which a researcher is specialized in her skills. The first factor influences the researcher's sensitivity to the changes in the external labor market. A higher relative position in the firm provides a researcher job security and influence within the firm, influence which may be compromised should she change jobs. Therefore, her need to track external job market opportunities is reduced.

The second individual-level factor: the degree of individual specialization, influences both the need and the ability to respond to changes in the external labor market conditions. On the one hand, higher degree of specialization makes a researcher more sensitive to fluctuations in the labor market: the threat of job loss when the job opportunities in her domain shrinks is more consequential(Marx et al., 2009) and the gains obtained from finding a better match for her specialized skills in growing job opportunities is higher(Kim, 1989). Thus, we can expect the specialists to react more to the job market fluctuations. But, on the other hand, too much specialization also restricts the ability of a researcher to expand into new technological domains or to find firm-specific projects to contribute to(Cohen and Levinthal, 1990; Kim, 1989). Thus, although individual level specialization may increase a researcher's propensity to react to the labor market conditions, beyond a threshold the inflexibility may pose a binding constraint.

One important firm-level factor that impacts the degree to which conditions in the external labor market influence the search behavior of a firm's researchers is its technological prominence. Working in technologically prominent firms provides the researchers visibility among the external research community (March and Simon, 1958) and the status of the firm is transferred on the researchers (Podolny, 1993). Technological prominence also makes firms likely subjects of imitative behavior and thus increases the demand for their researchers in the external labor markets (Knott and Posen, 2009). The technological prominence of firm, therefore, positively influences its researcher's career prospects in the external labor markets independent of the state of the labor market. The independent positive impact of the technological prominence implies that the state of external labor markets is less salient for the researchers of prominent firms. When the labor market worsens, the independent positive impact shields the researchers from the downswing. Similarly, when the labor market improves, the improvement is recognized less by the researchers of prominent firms. Further, the technological prominence of the researchers' employers ensures a positive demand for their firm-specific knowledge, an assurance that reduces their need to track which technological domains are popular in the external environment and change their search accordingly. These arguments suggest that the technological prominence of a firm reduces the impact of external labor markets on the nature of technological search conducted by its researchers.

Another factor that affects how external labor markets influence the technological search behavior within firms is the extent to which the firm's research community consists of specialists. Whether a firm's research context consists mostly of specialists or generalists has significant impact on the communication patterns within the firm (Bunderson and Sutcliffe, 2002) and consequently on the social cohesion (Coleman, 1988) and the bonding of the researchers with the firm. The social cohesion, bonding and the degree of communication with the colleagues inside the firm influence the degree to which a researcher trusts the firm to buffer her from the vicissitudes of the external labor markets and therefore her perceived need to act individualistically. This in turn influences how important the researcher considers keeping track of the external labor market conditions and responding to them.

Apart from explicitly testing predictions about these individual-level and firm level factors, my study also recognizes that there may be other firm-level factors impacting how external labor markets influence the firm's technological search. I control for these factors by including a number of firm-level controls such as the amount of financial slack in a firm, firm's profitability, the level of stock options provided by the firm and firm size. In addition, I adopt a longitudinal empirical design to track the impact of the labor market on the researcher's behavior over time. These empirical strategies should help alleviate the concerns about unobservable firm-level factors influencing the results.

A further point to note is that external labor market opportunities in a technological domain may also be correlated with other factors such as the technological opportunities inherent in the domain, factors that can influence a firm's technology strategy and therefore the search behavior of its researchers(Rosenberg, 1974; Jaffe, 1986). Of course, these factors do not theoretically contradict the career-concern mechanism; both firm strategy and researchers' labor market concerns can operate simultaneously. However, the presence of these potentially correlated mechanisms do point toward the need to isolate the impact of career concerns triggered by labor markets.

Empirically, I control for the technological richness of the domain as well as the firm's strategic thrust into these domains in my specifications. In addition, identifying the influence of the above moderating factors also allows me to theoretically isolate the influence of researchers' labor-market induced career concerns from alternate explanations. The increased job security and attachment with the firm associated with a researcher's higher standing within the firm and the individualism associated with the degree of specialization of research colleagues impact a researcher's responsiveness to labor markets directly but are unlikely to influence a firm's incentives to respond to the changes in the technological landscape. For instance a firm is unlikely to direct its best researchers (those with the highest internal standing) to be systematically less responsive to the changes in the environment. Thus identifying these moderating effects also help isolate the labor-market induced career concerns mechanism.

1.4. Implications from the study

This study helps in providing a more complete explanation of firm's technological search behavior (Nelson and Winter, 1982; Rosenkopf and Nerkar, 2001; Nerkar, 2003; Katila, 2002) by bringing the researchers to the forefront in the discussion. Earlier explanations have mostly analyzed the question from the perspective of top management of the firm, giving importance to factors such as competitive pressures and customer concerns (Cohen, 1995; Christensen and Bower, 1996; Schmookler, 1962; Ruttan, 1997). That this perspective is incomplete is suggested by three empirical findings: first, the bottom-up process of allocation of resources where projects are proposed by lower level employees and then "sold" to the top management (Bowers, 1970; Burgelman, 1983); second, the normative need for and the provision of autonomy to researchers in industrial research labs (Bailyn, 1985; Burgelman, 1983a); third, the knowledge asymmetry associated with research - researchers are lot more capable of choosing the appropriate technologies than the top managers (Cohen and Sauermann, 2007). Instead of taking the perspective of top management, my study takes the perspective of researchers by examining how their career concerns triggered by fluctuations in the external labor markets influence their technological search behavior. In doing so, this study fills an important lacuna in our understanding about a firm's technological search behavior.

By taking the perspective of the researchers, this study combines and contributes to two distinct strands of literature: the technological search literature (Cohen, 1995; Ahuja et al., 2008; Cohen and Levinthal, 1990; Rosenkopf and Nerkar, 2001; Nerkar and Paruchuri, 2005; Almeida and Kogut, 1999) and the career concerns literature (Holmstrom, 1999; Siemsen, 2008; Zwiebel, 1995). The technological search literature shows that the composition of the pool of technological ideas a researcher uses for inventing is a direct consequence of which information networks (Fleming et al., 2007b) she participates in and which technological developments she pays attention to (Cohen et al., 1972; March, 1981; Morgan, 1992). This literature, however, does not deeply examine why researchers prefer certain networks and certain technologies over others. The answer to this question can be obtained by the implications from the career concerns literature (Becker, 1962; Waldman and Gibbons, 2006) which indicates that concerns about future employability and career advancement can drive technology choices (Zwiebel, 1995; Siemsen, 2008) as well as network choices (Podolny and Baron, 1997; Seibert et al., 2001). Combining ideas from both these literatures also contributes significantly to both. Since I have elaborated on the contributions earlier (section 1.2), I limit my discussion here to general implications for the strategy literature over and beyond the ones discussed earlier.

One significant puzzle in technology strategy is that on many occasions, well established firms of great technological repute and considerable technological talent fail to respond to new technological developments (Henderson and Clark, 1990; Christensen and Bower, 1996). Most explanations address the issue from the perspective of management (Henderson and Clark, 1990; Christensen and Bower, 1996), giving reasons for why the information noticed by researchers at the front-lines is not acted on internally. Either internal structure of communication (Henderson and Clark, 1990) or focus on major customers (Christensen and Bower, 1996) results in the firm ignoring the information gathered at the front-lines. Although instructive, these explanations ignore any heterogeneity at the front-line researcher level. What if the researchers themselves fail to pay attention to the advent of new technologies? If so, the problem is not only at the level of assimilation of new technologies once they enter the firm but also at the entry points themselves - the front-line researchers may not even wish to try out the new technologies. My study potentially points toward this possibility. For instance, the study demonstrates that the researchers of prominent firms value internal labor markets more than the external labor markets. As a result, the researchers are more focused on building internal networks and on improving their relative position within the firm than on keeping abreast of technologies that are being employed in the external environment.

My study also emphasizes the need to include the impact of the state of labor markets and the implied career consequences in studies of decision making within firms. Traditionally, external job opportunities have been shown to influence the willingness to exert effort, the decision to participate (March and Simon, 1958; Halaby, 1988; Hausknecht et al., 2008) and wage costs for the firm. But my study clearly shows that the labor market significantly influences the incentives of decision makers, incentives that can alter both the basis and the process of decision making. For instance, in order to increase their worth in the labor market and move up the corporate ladder through changing jobs in good markets, managers can choose projects on the basis of how visible the projects are in the external markets and how likely the projects are to yield short term gains even if the projects are harmful in the long term. In this context, it might be interesting to study whether the risky financial products responsible for the recent financial crisis were created by managers who later moved on to manage bigger funds in other firms. Similarly, when labor markets turn sour, managers may indulge in more ingratiating activities with their superiors, compromising the quality of decision making within firms.

Chapter 2

Literature Review

My dissertation examines how the labor market impinges on the technological search behavior of technologists within firms. The basic argument is that the labor market triggers the career concerns of researchers, which in turn influence how they conduct their technological search: do they confine themselves to building on familiar technologies or do they explore new ones and broaden their search, do they build on technologies that have been developed within their firms or do they span the boundaries of their firms in search for ideas?

In this examination I combine and build on the ideas from two literatures: the technological search literature and the career concerns literature. In this chapter, I review the concepts, the theories and the findings in these two literatures that are relevant to my study. In doing so, I seek to uncover certain aspects of technological search that have not been given adequate attention in the academic literature, aspects which when explored deeply will significantly increase our understanding of both the literatures. I begin by reviewing the technological search literature and follow it up by discussing the career concerns literature.

2.1. Technological Search

A firm's ability to innovate is crucial to its competitive performance and even survival in high technology environments characterized by rapidly changing technologies and a constant supply of disruptive innovations. Given the crucial role of innovation in these environments, a vast amount of attention has been given to understanding why and how firms gain this ability. Scholars interested in technology strategy (Fleming and Waguespack, 2007; Rosenkopf and Nerkar, 2001; Nerkar and Paruchuri, 2005; Katila, 2002; Ahuja and Katila, 2001) and evolutionary economists (Nelson and Winter, 1982) have developed a very useful model of innovation employing the metaphor of search. This model has gained a lot of prominence in recent years and has significantly added to our understanding of how the process of innovation unfolds within organizations and how the innovative capabilities develop over time.

In this model, an innovation is modeled as a combination of preexisting ideas (Nelson and Winter, 1982). These combinations are a result of a recombinant process where researchers discover the combinations by searching through various knowledge components in many different domains (Rosenkopf and Nerkar, 2001; Fleming and Sorenson, 2001).

The technology management literature (see Ahuja et al., 2008) has investigated this model quite extensively. This investigation has sought answers to three basic set of questions: (i) what are the characteristics of this search process, (ii) what are the different consequences of this search process, and (iii) what are the determinants of the nature of search?

In this section I review the main answers given to these questions and the concepts developed in providing these answers. In doing so, I uncover certain areas in which our understanding of this model is limited. Further, in line with the notion that new ideas are offshoots of existing ideas (Levinthal, 1998), I show that the current literature itself points toward new directions of exploration to increase our understanding of the technological search process.

2.1.1 Characteristics of Technological Search

Evolutionary economists and management scholars have emphasized that firms differ considerably from each other in the way they search for technological ideas. Although much of the earlier work focused on the productivity differences between firms, some scholars have pointed out that firms (Nelson and Winter, 1982; Dosi, 1988; Rosenkopf and Nerkar, 2001) and researchers within the firms (Tushman and Scanlan, 1981) differ significantly from each other in which areas or domains they search for ideas. They have shown that although most technologists look for new ideas close to their existing domains of expertise, few cross group boundaries (Tushman and Scanlan, 1981) and combine ideas from disparate sources (Rosenkopf and Nerkar, 2001; Katila, 2002).

In recent years, an increasing number of scholars have employed patents as maps of technical activity to identify a number of dimensions on which firms differ in their technological search. Rosenkopf and Nerkar (2001) have shown that firms differ from one another in the extent to which they cross their organizational and technological boundaries in search for new ideas. While some firms build further on the ideas developed within the organizational confines, others also draw upon other firm's inventions. Similarly some firms concentrate attention on closely related technologies while others search in a much broader set of technologies. Other scholars have shown that firms differ in their search in the geographical dimension (Ahuja and Katila, 2004; Almeida, 1996) – the extent to which firms limit their search to close geographical areas, the temporal dimension (Nerkar, 2003) – the extent to which firms limit their search to newly developed technologies, and the scientific dimension (Henderson and Cockburn, 1994; Ahuja and Katila, 2004) – the extent to which firms rely on science to get new ideas for technological inventions.

This tremendous heterogeneity in the nature and loci of search suggests that there is no one optimal way of searching, or more precisely, no optimal *known/established* way of searching for technological ideas. For if there was one, one would expect firms to converge on the optimal method of searching over time. This suggestion is further supported from the research that shows the technological search to be an extremely uncertain process. The process of research involves two distinct forms of uncertainty (Nelson and Winter, 1982; Freeman and Soete, 1997). One is the technical uncertainty regarding the feasibility of technological research – is it even possible to combine these preexisting ideas into a technological combination? Second is the usage (or demand) uncertainty regarding what future uses the technological combination can be put to (Nelson and Winter, 1982; Nelson, 1959b; Freeman and Soete, 1997); what are the purposes this combination can serve (Nelson, 1959b) ?; What will be the demand for this combination in the future (see Freeman and Soete, 1997 , Chapter 10)?

These uncertainties also mean that there is no clear one to one mapping between the technological ideas that constitute a new combination and the purposes that can be served by the combination. The same invention can be used for multiple purposes (Nelson, 1959b) and the same purpose can be served by different technological combinations; there is equi-finality in the technological search processes (Nelson and Winter, 1982; Fleming, 2001; Freeman and Soete, 1997). This lack of one to one mapping has clear theoretical implications for scholars interested in understanding how technological search unfolds. It implies that one cannot understand why certain technological domains are searched and not others solely by understanding the end-use demands that the technological combination is to serve. Nor can one predict which purpose a combination will be used for purely by identifying the loci of search for technological ideas. A complete understanding will require explaining both the ends: what determines the purposes of an invention?, and what determines which technological areas are searched? Explaining one in terms of other may be too difficult in view of the lack of one to one mapping.

The uncertain and equi-final nature of technological search follows directly from the behavioral foundations of how technologists search for ideas. A substantial body of research (Cyert and March, 1963; Nelson and Winter, 1982; Burgelman, 1983b; Fleming, 2001; Nerkar, 2003) shows that technologists conduct the search in a boundedly rational manner. They find it extremely difficult to converge to an optimal solution since the number of possible combinations of existing ideas is too large (Fleming and Sorenson, 2001, 2004). Thus there is a significant amount of trial and error (Fleming, 2001; Fleming and Sorenson, 2001) leading to almost serendipitous discoveries. The combinatory explosion (Fleming and Sorenson, 2001; Ahuja and Katila, 2004) along with the hit and trial nature of search ensures that the technologists do not all search in the same technological domains to get ideas. The technologists' past experiences (Shane, 2000) and future expectations about the technology (Brown et al., 2006) guide their search efforts. The boundedness of rationality (March and Simon, 1958; Cyert and March, 1963) clearly implies that the technological combinations that are attempted are to a large extent a consequence of which technological ideas technologists pay attention to (March, 1981) and learn about (Cohen and Levinthal, 1990). Explaining which technological domains technologists search in should therefore also include explaining the attention patterns and learning preferences of technologists.

The importance of understanding the attention patterns and the preferences of technologists within the firm is also indicated by research that shows that a significant portion of the technological search is a bottom up process (Burgelman, 1983b; Fleming, 2002; Christensen and Bower, 1996). Although the top management of the firm sets up the general strategic framework, decides on the overall market space to be served by the firm's efforts and the context of work including the reporting and reward structures, considerable autonomy and discretion is still provided to researchers, especially regarding technological matters. Within the broader strategic framework of the firm, the details of technological search are driven by technologists who have significant influence on how technological search is conducted within firms (Hauser, 1998; Bailyn, 1985).

The autonomy that is afforded to the technologists has strong theoretical reasons. Technological search involves significant uncertainty regarding the correct technological path to adopt; one can attempt to solve the same problem through multiple approaches (Nelson, 1959b; Siemsen, 2008). Choosing one approach out of these requires specialized knowledge and expertise which resides to a greater extent with the technologists compared to the management (Cohen and Sauermann, 2007). This asymmetry in technological knowledge implicates autonomy for the technologists.

Apart from being necessary, the autonomy may indeed be beneficial to the firm. Innovation is a creative effort and creativity is fostered when researchers are intrinsically motivated to work on problems (Cohen and Sauermann, 2007; Amabile et al., 2005; Morgan, 1992). Having ownership of the research project is integral to being intrinsically motivated (Damanpour, 1991). Autonomy allows the researchers to take ownership of the projects (see Ahuja et al., 2008). Additionally, by allowing autonomous research endeavors, firms can uncover hidden synergies and expand their repertoire of capabilities. These synergies and expanded capabilities help insure the firm against adverse changes in the environment (Burgelman, 1983a, 1996; Conner, 1988).

The professional norms guiding researchers' behaviors also encourage autonomy for the researchers (Bailyn, 1985). Researchers are expected to be curious and enterprising (Morgan, 1992). Stories of defiance and doggedness circulate among them and reinforce the need for autonomy. The firms also expect researchers to be enterprising and creative. Indeed that is the mandate the firms provide to their researchers – to invent.

That the technologists within the firm have considerable autonomy in technological decisions is also corroborated by empirical research (Cohen and Sauermann, 2007), both through direct observations of the technological search process (Burgelman, 1983b; Bailyn, 1985; Christensen and Bower, 1996; Debackere et al., 1996) and indirectly through the evidence that personal social networks of researchers matter in the technological search process.

In a series of studies, Burgelman (1983b,a) demonstrated the existence of autonomous research initiatives within the firms. Bootlegged operations conducted by researchers within firms sometimes even in defiance to top management directives have been documented by many scholars of innovation (Fleming, 2002; Christensen and Bower, 1996; Burgelman, 1983b; Nayak and Ketteringham, 1997). Indeed, these scholars find that in many cases, researchers first invented the products and processes and then asked for resources to be allocated to turn those inventions into viable business opportunities. In the disk drive industry for example, Christensen and Bower (1996) found that the researchers had already invented the disruptive technology inside the firms even though the firms later chose not to allocate resources to market those technologies. Surveys of researchers within the research labs (Bailyn, 1985) also support this premise. By interviewing with research personnel in research labs, Bailyn (1985) has demonstrated the existence of autonomy for researchers. In fact, in her interviews, she found that quite a few scientists complained of too much strategic autonomy.

These studies show that within the broad parameters set by a firm's strategy, researchers do influence the nature of technological search that they conduct and their autonomous efforts are a major source of generating new business opportunities for the firm.

The research which shows that personal networks of research personnel matter for technological search (Fleming et al., 2007b; Tushman, 1981) provides indirect evidence of the autonomy for technologists. This research demonstrates that the personal networks of technologists influences both the productivity (Ahuja, 2000) and the originality (Fleming et al., 2007b) of their inventions. This indirectly indicates that technologists do have substantial influence on the technological search process.

For if the researchers did not have any influence, why would their personal networks and their boundary spanning behavior matter? Surely the ideas provided through social networks would be of little import if the researchers did not have the autonomy to attempt to combine them together. Indeed, it is difficult to reconcile the evidence that private networks of technologists matter in technological search with the idea that technologists are mere robots who *only* do the bidding of the top management.

Of course, this autonomy is not complete. The management does exercise control through selecting which innovative efforts to pursue further and which to curtail. However, the inherent asymmetry of knowledge, the potential though unpredictable benefits of allowing autonomous behavior and the very nature of inventive task gives researchers enough autonomy, albeit within bounds, to conduct their technological search. Indeed theories of technological evolution within firm (Gavetti et al., 2007; Burgelman, 1983b) regard the autonomous search of technologists within the firm as the major source of variation within firms. Although the top management selects among the various choices generated by technologists in the firm and sets up the bounds within which the technologists search, it does not exercise fine-grained control over the technological search conducted by researchers (Burgelman, 1983b, 1996). Researchers therefore still enjoy considerable autonomy at the technological level: which technologies to employ, which technologies to build on etc (Bailyn, 1985; Burgelman, 1983b; Cohen and Sauermann, 2007; Siemsen, 2008; Debackere et al., 1996). Indeed, if employees who do not have a clear mandate to create new knowledge do succeed to some extent in "crafting" their own job (Wrzesniewski and Dutton, 2001; Berg et al., 2010), then surely it is not surprising that employees who are entrusted to and expected to think of new ideas will be able to exercise discretion in their technological choices.

The foregoing review clearly indicates that if we are to understand how technological research unfolds within the firm, we should endeavor to understand the technologists' attention patterns and their preferences for certain technological areas. An important clue is provided by an important property of the technological search process; searching for combinations also teaches the searcher about the technological area (Cohen and Levinthal, 1990) even if the attempt at creating the combination fails.

Technologists are not oblivious to this learning benefit. Perhaps the most famous evidence is the quote attributed to Edison: "I have not failed, not once. I've discovered ten thousand ways that don't work." Further evidence is provided by the research (Stern, 2004; Moen, 2005) that shows that technologists are willing to forgo wages in order to work in research intensive firms (Moen, 2005) in order to gain human capital. Thus, to the extent that researchers prefer to learn about certain technological domains over others, they may search in those domains for ideas for the learning benefit such a search provides. Countervailing this tendency are of course, considerations of risk. Searching in new domains may provide learning benefits but may also be more risky and more prone to failure (Freeman and Soete, 1997; Levinthal and March, 1993). So we should expect technologists to weigh the costs of failure with the benefits of learning in choosing their domains of search.

Research has also shown that technological search is social in nature (Ahuja, 2000; Fleming et al., 2007b; Fleming and Waguespack, 2007). Deeply analyzing the implications of the social nature provides us other clues to discover patterns in the technologists' behavior. It is relatively non-controversial that technologists care about their relative standing within groups (Paruchuri et al., 2006; Cohen and Sauermann, 2007). Paruchuri et al. (2006) found that technologists' productivity fell when they lost their relative position among the firm's researchers on account of acquisitions.

What is perhaps under-appreciated is that how and where a technologist searches for ideas also influences her social standing. Tushman and Scanlan (1981) found that those engineers who were external communication stars, i.e. were the most active in communicating with professional communities outside the organization were not well respected within their group unless they were also active as internal communication stars. Fleming and Waguespack (2007) show that boundary spanners who combined ideas across technical groups faced mistrust and were not given leadership positions when the technical groups were also socially separated from each other. If technologists consider their social standing to be important and if how and where they search impacts their social standing within groups, it follows that social motivations can influence the technologist's search behaviors.

Although technologists consider their social standing within a group to be important, research also suggests that technologists differ from each other in which social group – internal or external to the firm – they prefer. Tushman and Scanlan (1981) also demonstrated that 75 % of the external stars were not internal stars as well even though this would have increased their respect internally. Tushman and Romanelli (1983) suggest that researchers choose which social groups to interact with. Gittelman and Kogut (2003) provides evidence that scientists within a firm are also influenced by the norms of their profession in deciding on their research projects. Since which social groups the technologists choose to interact with also influences the pool of technological ideas that the technologists obtain, we should expect the factors that influence the technologists' preferences for social groups to also influence their loci of search.

Through this brief overview of the characteristics of the technological search process, I hope to have established the following points. Technological search has been usefully described as a combinatory process. Gaining a complete understanding of this combinatory process should include explaining why technologists search in certain particular technological domains and not others.

The technological search process is an uncertain process which is conducted by boundedly rational technologists. These technologists do have considerable autonomy in technological decisions. Hence, explaining why technologist search in certain areas and not others requires understanding the technologists' motives and attention patterns.

Technological search not only produces combinations but also teaches the searchers about the technological areas that they search in. This learning is an important benefit for the researchers. Further, technological search is a social process in that it is affected by and affects social connections of the technologists. Hence, understanding the social implications of conducting technological search as well as factors that influence the technologist's preferences of social groups will provide important clues to their search behaviors.

2.1.2 Consequences of Technological Seach

The literature on technological search (Rosenkopf and Nerkar, 2001; Nerkar and Paruchuri, 2005; Almeida and Phene, 2004; Paruchuri, 2010; Ahuja and Katila, 2004) has clearly demonstrated that firms differ a great deal in the manner they search for technological ideas. Some seek new technological combinations from technologies that are developed inside the organizations while others cross organizational boundaries, some seek new ideas from closely related technologies while others seek to combine ideas from seemingly unrelated technological areas. This heterogeneity in itself would not be of interest to strategy scholars if it did not have significant consequences for firm performance. In this section therefore I review the flourishing literature that relates the manner of technological search to firm-level consequences.

The notion that firm performance is related to its search behavior is quite old. Building on the behavioral foundations of bounded rationality (March and Simon, 1958; Cyert and March, 1963), Nelson and Winter's (1982) models demonstrate that the search and selection processes within firms can account for the diversity of firms' behavior and performance. Jim March, in his influential article (March, 1991) posited that agents that are able to strike a balance between searching close to their current knowledge set (exploitation) and searching unfamiliar distant knowledge areas (exploration) are more likely to be successful. Subsequent research (Rosenkopf and Nerkar, 2001; Ahuja and Lampert, 2001; Fleming et al., 2007b; Nerkar, 2003)has further identified many different consequences of firms' technological search behavior. Broadly, these consequences can be classified into consequences for firms' innovative performance and consequences for competitive performance.

2.1.2.1 Consequences for Innovative Performance

A considerable number of studies (Rosenkopf and Nerkar, 2001; Nerkar, 2003; Ahuja and Lampert, 2001; Ahuja and Katila, 2004; Ahuja, 2003; Katila, 2002; Katila and Ahuja, 2002; Fleming et al., 2007b) has examined the relationship between the nature of technological search and innovative performance of firms. This literature has demonstrated that a firm's researchers search for technological ideas along a number of dimensions and how far they search from their current position along any dimension significantly influences the firm's innovative performance. A part of this literature has also examined what happens to a firm's innovative performance as its researchers search along two or more dimensions simultaneously.

Using patent data as a map of technology flows, these studies have shown that researchers of different firms vary in the extent to which they build on "proximate" knowledge; the "proximity" lies along several dimensions. Rosenkopf and Nerkar (2001) pointed out that firms could cross both technological and organizational boundaries while searching for ideas. Some other scholars (Katila, 2002; Nerkar, 2003) identified the temporal dimension of search: the researchers could build on technologies of varying age. Yet others (Jaffe, 1986; Phene et al., 2006) have shown that geographic proximity is another important and consequential dimension. Miller et al. (2007) added divisional boundaries to the list of dimensions showing that knowledge sourced from inside the firm but from different divisions produces significantly better innovations than the knowledge sourced from outside the firm or from within the existing division.

In general, this research suggests that a firm's innovative performance increases when its researchers search for technological ideas at a moderate distance along any dimension. Searching too close or too far from the current location may actually hurt the innovative performance both in terms of productivity (Ahuja and Katila, 2001) as well as the quality of innovations produced (Nerkar, 2003; Miller et al., 2007). The underlying theoretical argument is that searching broadly provides innovators with new unfamiliar ideas spurring creative thought and opening up new possibilities for combinations. However, because the innovators are boundedly rational, they may incur too much costs to learn about and integrate the ideas that are too distant from their current set of capabilities thereby reducing the productivity of their efforts.

The conclusions are not so clear when we consider the impact of searching along two or more dimensions simultaneously. Some scholars suggests that simultaneously searching for distant knowledge along two dimensions may hurt performance. For instance, Phene et al. (2006) show that technologically distant knowledge from within national boundaries has a curvilinear impact on the probability of producing breakthrough innovations. However, simultaneously crossing geographical and technological boundaries may be counterproductive. Other studies present more mixed results. Rosenkopf and Nerkar (2001) is an example. They examine the impact of crossing organizational and technological boundaries on the quality of innovations (measured by the impact of the innovations on future technological growth). They find that not crossing organizational boundaries negatively affects the quality of innovations. Crossing organization boundaries but not crossing technological boundaries produces innovations that are most influential within the firm's industry. Crossing both the boundaries produces innovations that are most influential in shaping the technological trajectory outside of the focal industry. Yet others show that crossing two boundaries simultaneously may actually help innovation. For instance, Katila (2002) shows that old intraindustry knowledge hurts innovation but old extraindustry knowledge helps innovation; searching distant knowledge across both time and industry is helpful.

Apart from the quantity and quality of innovations, research has also suggested that the very uncertainty associated with the technological search process is a function of the nature of search, i.e. endogenous to the manner of search. Fleming (2001) suggests that the technological uncertainty stems from "inventor's search processes with unfamiliar components". He proposes that "experimentation with new components and new combinations leads to less useful inventions on average , but it also implies an increase in the variability that can result in both failure and breakthrough." (Fleming, 2001). In other words, the variation in performance could be a function of how inventors search.

Overall, this strand of literature provides strong evidence that the way the inventors search for ideas impacts both the productivity of their efforts as well as the quality of their inventions. In general, searching broadly for technological knowledge is a good idea but the inventors should not venture too far. Going too far in many dimensions may yield spectacular results but is fraught with risks of failure. Further, the very uncertainty of the technological search process could be endogenous to the search behavior of the inventors.

2.1.2.2 Consequences for Competitive Performance

Strategy scholars (Henderson and Clark, 1990; Christensen and Bower, 1996; Ahuja, 2003; Rivkin, 2000) have also argued and shown that the way a firm searches for new ideas also impacts its competitive position. The research has shown that the nature of technological search can influence a firm's competitive position through two broad mechanisms: (a) through sculpting the firm's own capabilities, and (b) through influencing the ability of the competitors.

Firms own capabilities

How and where a firm's research personnel and managers search for new ideas sculpts the firm's capabilities to conduct productive research in the future and to benefit from external knowledge. Cohen and Levinthal (1990) convincingly argued that searching in a technological area teaches the firm's inventors about the area thereby enabling them to conduct further research in that area and to absorb technological knowledge from external sources. This notion has been extensively tested. Scholars have shown that firms high technological skills are better able to absorb knowledge in related technological fields (Phene et al., 2006). Ahuja and Katila (2004) showed that science-based search and geographical breadth of search enables firms to conduct productive research in subsequent periods.

Where the technologists and R&D managers focus their attention also impacts the firm's ability to respond to changes in the competitive landscape (Henderson and Clark, 1990; Christensen and Bower, 1996). Henderson and Clark (1990) showed that the technical personnel's "internal communication channels, problem solving strategies and information filters" reduces the firm's ability to respond effectively to architectural changes in the associated production technologies. Christensen and Bower (1996) show that concentrating attention on existing customers may make the firm vulnerable to disruptive technologies, even when the technologies have been developed in-house.

Competitor's ability

A firm's technological search process not only impacts its own ability to compete but also the ability of competitor firms to compete effectively with it. This is because the manner of search impacts the ability of other firms to appropriate the knowledge developed by the focal firm (Rivkin, 2000; Ahuja, 2003; Zhao, 2006). Rivkin (2000), in a theoretical simulation, shows that if a firm modularizes the search process by reducing the interdependencies between the different modules, it reduces the causal ambiguity associated with its innovations allowing other firms to imitate. Zhao (2006) provides evidence that firms do undertake this strategy as a defensive mechanism. She found that when firms conduct research in countries with weak intellectual property protections, they break up their search into small chunks which are more useful when combined with other chunks developed within the firms rather than as stand-alone inventions. Similarly, Ahuja (2003) showed that the more complex a firm's technological innovations, lesser is the ability of competitors to understand from and build on the firm's technological knowledge.

Another less explored but perhaps equally important mechanism through which a firm's search process impacts competitor's ability follows from the concept of boundedly rational search. Because of bounded rationality, the competitors may be unaware of many existing technological possibilities. However, by conducting search in hitherto hidden technological areas, a firm can draw the competitor's attention to the area by making the competitors aware of the technological possibilities that lie in the area. Polidoro (2006) in an interesting study showed that seeking scientific endorsements of a firm's technological search domain while facilitating institutional legitimacy also attracts competitors toward that domain. The pioneer firm can however hamper the competitor's ability to usurp its dominance in the new technological area through its search behavior. If the pioneer searches extensively in areas close to the new technological domain before moving to farther away domains, it can foreclose the competitors from that area (Ahuja, 2003).

2.1.2.3 Conclusion

I began this subsection with the argument that firms and technologists within them vary significantly from each other in their technological search behavior but this heterogeneity is of little interest to strategy scholars unless it affects the firm's performance. I hope to have demonstrated that the search behavior is indeed very consequential for the firms and not only from the point of view of innovative performance but also from the point of view of competitive performance. Interestingly, the effect on competitive performance is not only due to altering the firm's own ability to develop capabilities or to respond to changes in the external environment but also due to altering the competitor's ability to benefit from the firm's search activities.

2.1.3 Determinants of Technological Search

Given that the researchers differ significantly from each other in how they search for innovations and that these differences have important consequences for the firm, it is important for us to understand the factors that determine why the researchers search in the way that they do. The bulk of the research on the determinants of innovation (see Cohen, 1995, and Ahuja et al., 2008) has concentrated attention on the factors that influence the volume of technological search efforts and the productivity of those search efforts. Much less is understood about the factors that influence the process of search: which technological problems and solutions do the researchers pay attention to? what determines their loci of search? what determines their breadth of search along different dimensions? In this section, I concentrate on the literature that addresses these questions.

Scholars have taken many different approaches to uncover factors that influence how the researchers conduct their search. These factors can be classified into three broad categories: (a) Market-Based explanations that stress the importance of the demand conditions and factor prices facing the firm (Schmookler, 1962; Ruttan, 1997) ,(b) Technology-Based explanations that stress the importance of the available technological and scientific knowledge (Mowery and Rosenberg, 1979; Jaffe, 1986) and (c) Context-Based explanations that stress the importance of the social context of the researchers in shaping the researcher's choice of technological domains (Fleming et al., 2007b). I discuss each of these below.

2.1.3.1 Market-Based Explanations: The role of Demand Conditions and Factor Prices

The idea that the nature of consumer demand influences technological search activity goes back to (Schmookler, 1962). Schmookler (1962) observed that in certain industries, greater demand for goods preceded inventive activities in those industries. This observation led him to argue that demand conditions were the major determinants of technical innovation.

There are two theoretical reasons why demand conditions can be argued to shape the technical activity of researchers (see Cohen, 1995). First, greater size or growth of demand increases the expected marginal benefit of innovating. The cost of innovating is fixed - the same expense is needed irrespective of the demand. But the profits increase with the size of the demand. Hence greater demand increases the incentives to innovate. A corollary to this argument is that a firm's researchers are likely to direct their efforts in inventing products and product features that are demanded by the firm's customers (Christensen and Bower, 1996). Second, the elasticity of demand also impacts the incentives to invest in research. If the demand is more elastic, process inventions that reduce cost are more beneficial while if the demand is more inelastic, product quality improvements may be more beneficial (see Cohen, 1995) .

Another factor used to explain the nature of technological search is the relative prices and shares of the factors of production. The main notion employed here is the idea of "induced innovation" (Ruttan, 1997; Popp, 2002; Newell et al., 1999). The induced innovation hypothesis suggests that as the prices of a particular factor of production rises or if the share of a particular input in the production process is high (Ruttan, 1997), it spurs technological activity to the reduce the use of that input in the production process (Ruttan, 1997; Popp, 2002).

Empirical Examination

Schmookler provided evidence for his mechanism through a number of historical case studies where he tried to show that an increase in demand in an industry led to an increase in patenting activity in the industry. Research examining the role of government on inventive activity has also shown the importance of captive demand, such as provided by the military in case of semiconductor industry, on the total volume of inventive activity in the industry(Langlois and Steinmueller, 1999). However, others (Rosenberg, 1974) show that it is not primarily demand, but the availability of technological knowledge that guided innovative efforts. Yet others (Walsh, 1984) showed that in several industries, some initial breakthrough invention led to greater demand, which then spurred greater inventive activity (Cohen and Levin, 1989).

These industry wide analyses and case studies provide mixed results for the contention that demand conditions were the main determinants of technological activity; the availability of technical knowledge was found to be more critical in explaining the technological activity (Cohen and Levin, 1989; Cohen, 1995). Further still, these studies are conducted at a broad level of analysis: typically at the level of industry. They largely seek to demonstrate that the demand conditions in the industry impacts the volume of technological search in the industry, but not the influence of demand conditions on how the researchers conduct their research - which kind of research projects they work on, how far from their current knowledge base do they search for new ideas?

Firm level examinations of the research process provide greater insight into how the consumer's demands direct the technological search within firms. Christensen and Bower (1996) examined the resource allocation process within few firms of the disk-drive industry to identify the impact of a firm's customers on the innovation process within the firms. They found that firm's resource allocation process is influenced significantly by the demands of their main customers. Thus, even if a firm's researchers invent a new technology, the firm does not easily spend effort in further developing the technology and commercializing it if the technology does not serve the needs of its largest customers.

Although this study provides more convincing evidence that demand conditions influence the technological search activities within a firm, the authors also note that in each of their cases, the firm's researchers had *already* invented the technologies that marketing personnel later found to be not helpful for the firm's current set of customers. In other words, the initial technological search was not driven by customer needs.

The first point they make in developing their model for resource allocation is (page 207):

> Although entrants were the leaders in commercializing disruptive technology, it did not start out that way: the first engineers to develop the disruptive architectures generally did so while employed by a leading established firm, using bootlegged resources. Their work was rarely initiated by senior management.

The second step in their model is (page 207):

> The marketing organization *then* used its habitual procedure for testing the market appeal of new drives, by showing prototypes to lead customers of the existing product line, asking them to evaluate the new models " [emphasis added by me]

In other words, the researchers first invented these technologies and then marketing personnel tested the market for those technologies. Therefore, it is unclear from this study whether demand conditions provide a better explanation for the initial technological search process or for the later commercialization of those technologies.

Qualitative studies that examine the autonomy provided to the researchers (Bailyn, 1985) and the interaction between the engineering and marketing professionals in the firm (Souder and Moenaert, 1992; Moenaert and Souder, 1990; Dougherty, 1992; Souder, 1988; Workman, 1995) provide mixed support for the idea that consumer demands are the major determinants of the researchers behavior. Bailyn (1985) found that the research scientists in her study had a lot of autonomy in choosing and initiating their projects, autonomy that was at times considered too much by the researchers.

Souder (1988) studied the interactions between the marketing and engineers in 289 research projects. He found that about 2/3 of the projects were characterized by lack of appreciation, trust and communication between engineering and marketing personnel. In many cases, the researchers and the marketing professionals hid what they were working from each other and did not take each other's suggestions in their work. The lack of communication and interaction make it less likely that the researchers base their research projects solely on the current demands of the customers. Indeed, Workman (1995) found that in an engineering driven organization, marketing sees its role to be "refining" the inventions of the researchers to make the inventions more sellable in the market rather than "initiating" the projects. The marketing professionals appreciated the fact that they did not know the technologies as well as the researchers did and so "they shouldn't be initiating the new products or providing all the detailed answers such as "telling engineers where to put the switches" ..". This evidence is quite consistent with Christensen and Bower's study described above.

Empirical examination of the induced innovation hypothesis are largely conducted at the industry level of analysis (see Ruttan, 1996 for a review). Ruttan (1996) concluded from his literature review that the evidence supports the notion that relative factor prices exert a substantial influence on the direction of technological change in the agricultural sector and in the natural resource using industries. Other scholars (Popp, 2002; Newell et al., 1999) have found that the oil shock of the 1980's caused increased efforts in discovering energy saving technologies at the industry level.

Why firms differ in the extent to which they choose research projects based on the inducements of external changes in relative prices is relatively understudied. In a recent study, Ahuja et al. (2010) find that the oil shock of the early 1980's cause certain firms (those who have higher degree of related diversification) to invest in paradigm-changing technologies that seek to find alternate and cleaner sources of energy such as solar power.

Theoretical concerns

One theoretical concern with the demand-based explanations of the process of technological search is that these explanations ignore the possibility that technological research also creates new markets where none exist. Indeed, creating new markets is an important mandate to inventors within the firm (Hauser, 1998; Pinchot, 1997). A significant amount of industrial research is done to discover new combinations and products with features that the consumers do not have even a prior inkling of, let alone a known demand for. In many cases, inventions are first created and then markets found for them (Burgelman, 1983b,a; Christensen and Bower, 1996). If this were not so, championing would be lot less important for innovation; firms would first choose the relevant markets and consumer's needs and then invent what the customers want. But as Gifford Pinchot (1997, page 291) puts it:

> This is rarely the way fundamental innovation works because we are not smart enough to invent to order. We are lucky to invent anything with fundamentally new and protectable properties, and when we do so, we must hunt for the most applicable markets.

Related to this is the finding that market uncertainty is usually much greater than technological uncertainty.Freeman and Soete (1997) report a number of empirical findings (see Freeman and Soete, 1997, page 248-249) that find that the market uncertainty (i.e. uncertainty regarding what the consumers will accept and what the revenues from an innovation will be) is many times greater than technological uncertainty (i.e. will this attempt to create this invention succeed?). This is because the researchers have greater control over the technologies that they attempt to combine than the control that firms have over their consumer's tastes. What this implies is that the researchers frequently search for new technological combinations with largely unknown demand functions. If this is indeed so, the idea that demand is the sole determinant of the researchers' search activities is quite suspect.

Another theoretical concern with both the demand-based explanations and the induced innovation hypothesis is that they under-emphasize the role of the state of existing technological and scientific knowledge (Rosenberg, 1974). This has led to an intense debate between technology scholars about what exerts greater influence on technological evolution: demand or technological knowledge (see Cohen, 1995). The basic criticism is that technological search is more likely to be directed by technological feasibility rather than by demand or factor price considerations. Firms coping with the rise in prices of some factor of production will be interested in lowering the total cost of production. Whether the cost of production is lowered through reducing the share of the more expensive factor or not is immaterial. Whichever direction is more technologically feasible and less costly to pursue is what will be pursued (see Cohen, 1995). The importance of technological feasibility is very colorfully described by Pinchot (1997, page 291): "We know an anti-gravity device would be useful and probably well received by customers. We don't work on it because we don't know how to begin."

Summary

The idea that the demand and the relative factor prices shape how and where the researchers direct their search efforts has got mixed support in the literature. Theoretically, the mechanisms have been shown to be suspect in as much as they ignore the technological feasibility on one hand and the uncertainty regarding the consumer's demand functions on the other. Further, the mechanisms also do not account for the findings that technological search is many a time conducted with the hope of discovering new markets.

The empirical research of these mechanisms has also not provided very clear or convincing support to the idea that demand alone directs the researchers' efforts (Cohen, 1995). As discussed above, even Christensen and Bower (1996)'s study is unclear on whether the consumer demand influences the initiation and invention of new technological inventions or does it provide a better explanation of commercialization of the invented technologies.

However, the evidence does show that both the demand concerns as well as technological opportunities together shape the research agenda in firms. The influence of demand should depend on the degree and kind of interaction the researchers have with the marketing and sales functions of the firm as also the bargaining power of the researchers vis a vis the marketing function within the firm. Thus, the factors that cause the researchers to increase their interactions with the firm's sales and marketing personnel and to increase their contribution to the firm's established product trajectories should impact the extent to which the demand of consumers drive their technological search.

2.1.3.2 Technological Opportunities Based Explanations

In contrast to demand based explanations, many scholars (Nelson, 1962; Jaffe, 1986; Mowery and Rosenberg, 1979) have opined that technological search is driven by the technological opportunities created by scientific and technological knowledge. Scholars generally agree that it is "easier" or less costly to innovate in certain industries compared do others (Cohen, 1995) because of the state of scientific and technological knowledge in an industry. This reduced cost of innovation attracts greater inventive activity in those industries.

Scientific knowledge helps innovation by providing heuristics that guide search efforts. Technological search, instead of being a hit and trial process, is informed by known cause-effect relationships. This reduces the probability of false trials. This mechanism in particularly useful when the underlying structure of knowledge is very complex (Fleming and Sorenson, 2004).

Scientific knowledge also points toward many different approaches to solve a problem and therefore creates a wider pool of ideas to choose from. Further scientific research can also throw up a new set of technological problems; researching on one problem can yield new challenges for the researchers to overcome (Nelson, 1962; Ethiraj, 2007). Through these mechanisms, scientific knowledge decreases the cost of the innovation process and increases the productivity of the research efforts. This, in turn, should attract the researchers to explore the possibilities opened up by science.

Much of the initial empirical research on how scientific knowledge affects the research within firms demonstrated that (a) industries differ in technological opportunities and (b) that this difference explains inter-industry differences in R&D intensity and productivity (see Cohen, 1995). Initial attempts classified industries based on technological areas such as chemical, electrical etc and showed that this simple classification is an important explanator for inter-industry differences in R&D intensity and productivity. Others have used different measures such as clusters of patent classes (Jaffe, 1986) to show that firms in certain technological clusters have a higher productivity of R&D efforts than firms in other technological clusters. Yet others have used survey methodology to show that industries differ in the extent to which they use scientific knowledge and the difference matters for the total amount of technological search and the productivity of those search efforts.

These studies have clearly demonstrate that certain industrial sectors have greater technological opportunities and that these technological opportunities do matter for the volume and productivity of technological search. But this strand of research conducts the analysis at quite a broad level. Consequently, it does not address the question of how researchers within firms identify which technological domains are more "opportune" or what decision cues do they follow to cross into different technological domains.

Historical accounts present a more complex picture of the role of scientific knowledge in technological research(see cohen and Levin 1989; Cohen 1995). On the one hand, Rosenberg (1974) has shown that many technological developments would never have happened without certain scientific discoveries. On the other hand, (Nelson, 1962) has shown that the scientific discoveries used in developing transistor technologies were fairly old and that scientific discoveries and technological research follow fairly independent paths and both can influence each other at different points in time (Allen, 1988). For instance, technological developments in the industrial sector can direct the attention of university scientists toward phenomenon not explained by current theoretical knowledge(Nelson, 1962).

Similarly other scholars have shown that while science in general may help research efforts, say by providing technological advice and knowhow, the influence of science differs across industries (Cohen et al., 2002; Lim, 2004; Bercovitz and Feldman, 2007). For instance, university research plays a more important role in industries such as pharmaceuticals (Klevorick et al., 1995; Bercovitz and Feldman, 2007) compared to others (Bercovitz and Feldman, 2007). Relatedly, Gittelman and Kogut (2003) has shown that scientific and industrial research follow different selection criteria and what is considered good research in science may not be what guides industrial scientists. Yet other scholars (Ahuja and Katila, 2004) have shown that when researchers run out of ideas in their research work, they resort to science to seek new innovations.

Thus, the empirical evidence provides a complex view of the connection between university scientific research and industrial research. It is, of course, undeniable that science does help in the creation of many technological developments. But, the differences between different high-tech industries in their use of scientific knowledge (Klevorick et al., 1995; Cohen et al., 2002; Lim, 2004; Bercovitz and Feldman, 2007) and the lag between scientific discoveries and industrial research in some industries (Nelson, 1962; Allen, 1988) shows that the mere existence of scientific knowledge does not a research project make. Ethnographic accounts (Latour and Woolgar, 1979; Owen-Smith, 2001) also demonstrate that the selection of projects in research laboratories is influenced by factors such as the position and credibility of the researcher proposing a particular technical path, and not just by the technological merits of the project. Given the bounded rationality of researchers (Cyert and March, 1963; Nelson and Winter, 1982) and the "combinatorial explosion" of possibilities (Fleming and Sorenson, 2001), understanding the connection between scientific knowledge and the research conducted by industrial inventors also requires us to identify the factors that direct the attention of the inventors(March, 1981) and influence their preferences for certain technologies.

Another source of technological opportunities for the researchers is the technological research conducted in other firms, i.e. external spillovers. Initial research (Jaffe, 1986) to explore the impact of spillovers on a firm's research was conducted at a broad level of analysis with the primary purpose to show that spillovers exist and that they matter. This strand has shown that spillovers are geographically bounded and being located in the geographical and the technological proximity to other research intensive firms helps a firm increase its innovative productivity (Jaffe et al., 1993; Jaffe, 1986).

More recent research has endeavored to further explore the patterns of knowledge flows between firms. Rosenkopf and Almeida (2003) show that when a firm draws upon external (i.e. other firms') knowledge, it is more likely to draw upon the knowledge of firms which are geographically and technologically closer, the knowledge of firms which are its allies and the knowledge of firms whose researchers have been hired by the focal firm. Almeida (1996) shows that the subsidiaries of foreign firms in the US are more likely to build on geographically local knowledge than domestic firms, presumably because their intent to move to US is to scout for new knowledge. Almeida et al. (2002) show that multinational corporations are more likely to draw upon the knowledge of their foreign subsidiaries compared to their foreign allies and more likely to draw upon the knowledge of their foreign allies than the knowledge of other foreign firms.

Although this strand of research has significantly increased our understanding about the patterns of knowledge flow between firms, our knowledge of how external spillovers impact the kind of projects researchers choose within their firm remains limited. For instance, while we know that firm's research productivity increases when external technologically related knowledge sources are rich and diverse (Almeida and Phene, 2004), we do not know much about the mechanisms that relate the spillover opportunities in the external environment to the breadth of technological search within firms. Why, if at all, do changes in spillover opportunities external to the firm influence the researchers inside the firm to alter their search patterns: either expand or restrict their search in certain dimensions? What factors condition this response? [1]

Much of this research invokes two key mechanisms to predict the patterns of knowledge flow: the increased availability of knowledge in the external environment (e.g through geographic proximity) coupled with the increased technical ability to absorb external knowledge (e.g through technological proximity). However, recent research (Tzabbar, 2009; Song et al., 2003) which examines why firms differ in how much they learn from their hired employees indicates that these two mechanisms are not sufficient to explain how firms exploit the knowledge of hired researchers.

Song et al. (2003) show that firms are less likely to build on the hired researcher's prior knowledge if the firms have a more established research trajectory and if the hired researcher's expertise is in the core areas of the hiring firm. Tzabbar (2009) show that hiring scientists with distant knowledge does not help the firm to move to new technologies when the hiring firm's research labs are dominated by few "star" scientists. This is because if we assume that the stars do not appreciate technologies

[1] Henderson and Clark (1990) point out that the information filters, communication channels and the routines for problem solving leads the researchers to not recognize certain key technological developments in the external world, those that changes the product architecture: the way components are put together to form a product. This study refers to a specific form of external knowledge that is missed by the researchers within the firm; it therefore explains why certain specific forms of technological developments are not adopted by incumbents. However, the study does not tell us in general whether growth or decline in inventive activity outside of the firm leads the researchers to alter their breadth of technological search or the kind of research projects that they choose.

that differ from their own expertise, the domination by the few stars restricts the autonomy, free flow of information and the motivation to integrate new technologies among the non-star scientists within the firm.

These studies examine the impact of organizational context on the efficacy of a specific mechanism: learning through hired scientists. Thus, they do not address the question of why, if at all, the process of technological search inside the firm is impacted by the growth or decline in technological opportunities in the external environment. Nevertheless, these studies do indicate that the motivations of researchers and the impact of the organizational context of research need to be understood if we are to explain how and when the technological activity outside the firm influences the way researchers inside the firm conduct their research.

Theoretical concerns

At an aggregate level of analysis (for instance at the level of the industry), the argument that the presence of technological opportunities and scientific knowledge increases technical activity has a very intuitive appeal (see Cohen, 1995). If science opens up new possibilities in a particular industry and makes finding new technical combinations easy, it seems but natural that it will increase the productivity and the volume of technical efforts in that industry. Although this mechanism provides an explanation for the volume and the productivity of research efforts at the industry level, it does not translate easily into explaining the researcher's choice of technical projects and her process of search.

A deep examination of the mechanisms suggest that even if we keep the issue of technical capability (Cohen and Levinthal, 1990) aside, mere increase in technological opportunities is not sufficient to explain the researchers' choice of technological projects and her process of search. Of course, in one rather vacuous sense, the existence of technical opportunity is necessary: if the current state of knowledge clearly suggests that some innovations are impossible, a researcher will not succeed in creating the innovation and if the researcher knows that, she will not attempt the project. But it is also true of technical research that technical opportunities are usually not clear ex ante (Nelson, 1962, 1959b; Nelson and Winter, 1982). Many technical opportunities appear as a *consequence* of the recombinant process (Nelson, 1962; Fleming, 2001; Cohen, 1995). When researchers attempt certain technical combinations, the limits and possibilities of the technologies become clearer. This inability to predict ex ante what the technical opportunities in a particular domain are without first attempting to recombine the ideas from the domain is in essence the technological uncertainty of research. If researchers find it difficult to predict ex ante which domains have greater *technological* opportunities, it is difficult to expect them to change their technological search process on the basis of technical merits alone.

The uncertainties posed by the bounded rationality of the researchers are further compounded in certain high-technology industries such as electronics by the frequent and fast changes in technological knowledge (Campbell and Brown, 2001; Brown et al., 2006), by the recurrent appearances of new technological approaches, by the variety of domains that can yield technological opportunities (Fleming, 2001; Fleming et al., 2007b; Fleming and Sorenson, 2001) and the complexity of the interrelationships between technological ideas (Fleming and Sorenson, 2004). These realities make identifying the domains with the best technological opportunities even more difficult. If many different technological domains present similar opportunities ex ante and if new technological domains keep showing up frequently, the process of technological search cannot purely be explained on the basis of technical merit alone. The issues of attention and preference for certain domains of knowledge over others become important.

When we take the issues of the researcher's attention and preferences seriously, we realize that the "ease" of finding a combination may not be the only mechanism driving the technological choices of the researchers. This is not only because the "ease" is difficult for the boundedly rational researcher to predict ex-ante. It is also because the process of searching in a domain can provide the researchers with certain other benefits, benefits that arise from the process of search itself rather than from the outcome of search. For instance, searching in a domain can provide learning benefits to the researchers (Cohen and Levinthal, 1990), which the researchers can use to further their career objectives (Becker, 1962; Waldman and Gibbons, 2006). Similarly, paying more attention to firm-specific technological problems and technological trajectories can also help the researcher secure her place within the same firm. These motivations cannot be derived by the "ease of search" mechanism alone.

Summary

In this section, I have discussed the role played by the technological opportunities in influencing the research activities of the researchers in industrial laboratories. The basic idea is that in certain industries, the available scientific and technological knowledge makes searching for combinations easier. This increases both the productivity and the volume of research efforts in those industries. Spillovers in an industry also create technological opportunities for the firms. The empirical research has shown that firms do exploit these opportunities. However, why if at all the technological opportunities cause the researchers to change the process of their technological search (i.e the kind of research projects that they undertake and the technological domains they concentrate on) is not well understood by the literature.

Recent research into the specific mechanism of learning by hiring and a deeper examination of the theoretical mechanisms that underlie the technological opportunity literature suggests that the motivations and attention patterns of the researchers need to be incorporated in the models that relate the technological opportunities to the process of technological search. Doing so will complement the current mechanisms that underlie the technological opportunities literature: the technological and scientific knowledge opens up the *potential* for successful combinations, the motivations and attention patterns explain whether the potential is in fact *realized*.

2.1.3.3 The Context of Research Based Explanations

Researchers do not conduct technological research in isolation. They receive professional information from other researchers both inside and outside of the firm (Tushman, 1978; Katz and Tushman, 1979). They interact with different social groups such as customers, suppliers, manufacturing and marketing personnel within the firm as well as professional colleagues within and outside of the firm (Tushman and Scanlan, 1981) to conduct their technological search. Their context determines their access to technological ideas (Fleming et al., 2007b) as well as the choice of research projects (Argyres and Silverman, 2004; Toh, 2007). In other words, the broader context that they work in shapes the research that they conduct through a myriad set of influences.

Correspondingly, scholars have also attempted to understand the influence of context on technological research through multiple perspectives. These perspectives can be usefully organized into two categories: (a) the impact of social interactions - the patterns of collaborative relationships (Fleming et al., 2007b; Uzzi, 1997) and work-related communication patterns of the researchers with different social groups (Tushman and Scanlan, 1981) and (b) the impact of the organizational structure of research within firms - the division of labor and the distribution of research activity within the firms (Argyres and Silverman, 2004; Toh, 2007) and the way the knowledge base is structured within the firm (Yayavaram and Ahuja, 2008).

Scholars have investigated the role of the social context of conducting research on a number of different outcomes such as the volume of technological activity and the productivity of research activity. My concern however is with the nature of technological search. In this section therefore, I review only the relevant concepts and literatures that discuss the impact of the context on the nature of technological search activity: the kind of research projects that the researchers undertake and the breadth of their technological search activities. I discuss the influences of both social interactions and the organizational structure of research activities in shaping the nature of search.

Social Interactions and Communication patterns

That the social relationships of the researchers have an important influence on the way they conduct technological search is quite well-accepted in the literature on technology-management. These social relationships serve as conduits of information (Allen, 1970; Ahuja, 2000; Fleming et al., 2007b), influence (Tushman and Romanelli, 1983; Paruchuri, 2010; Nerkar and Paruchuri, 2005; Tzabbar, 2009) and norms (Coleman, 1988; Uzzi, 1997; Gittelman and Kogut, 2003; Hansen, 2002) for the researchers and influence their search efforts.

Collaborative ties with other researchers inside the firm are an important source of technological ideas for the researchers (Fleming et al., 2007b; Hargadon and Sutton, 1997; Hansen, 2002). Open collaborative networks (Burt, 2001) of other researchers who themselves do not collaborate with each other provide access to diverse sets of non-redundant information to the researchers (Fleming et al., 2007b). A researcher with access to such an open network is more likely to draw upon a broad set of unconnected ideas for her inventions. On the other hand, closed networks of other researchers who also collaborate with each other increases trust and promotes knowledge sharing. If the closed network consists of researchers who come from varied background and experiences, even the closed network can provide access to a wide array of knowledge elements. A researcher with access to such a network then benefits both from the diversity of knowledge as well as norms of knowledge sharing. Fleming et al. (2007b) test these arguments and find that access to open networks or to closed networks of researchers with broad experiences leads them to combine previously unconnected knowledge elements together.

Apart from providing information and facilitating knowledge exchange, the social context also enables the researchers to influence the research agenda of the firm (Latour and Woolgar, 1979; Tushman and Romanelli, 1983; Nerkar and Paruchuri, 2005; Tzabbar, 2009; Owen-Smith, 2001). Nerkar and Paruchuri (2005) find that the technologies developed by central inventors find greater traction within the firm. Similarly, Owen-Smith (2001) in an ethnographic study shows that the position of a researcher within the laboratory affects the resistance she faces when she proposes new ideas to members. Tzabbar (2009) finds that when the researcher's community within the firm is stratified, the researchers of the firm are less likely to be influenced by the knowledge of newly hired research personnel. He suggests that it is because the presence of "stars" reduces the autonomy of and the knowledge sharing between the non-stars which in turn prevents the diffusion of new ideas brought about by the newly hired scientists. Case study accounts (Taylor, 2010) also show that the researchers compete with each other in "selling" and "championing" their research projects and knowledge within the firm. Although this competition sometimes leads the firms to cancel certain technological endeavors, it also enables the competing groups to learn from each other.

Research on the work-related communication patterns of the researchers (Tushman and Scanlan, 1981; Tushman, 1979a) indicate that the researchers not only interact with other researchers inside the firm but also with external groups such as customers, suppliers, the professional communities outside of the organization and with other operational areas within the firm such as marketing and sales. The different social groups provide different sets of input to the technological search activity (Tushman, 1977). For instance, interactions with other researchers and scientists outside the organization are likely to provide information about the technological developments outside of the organization (Henderson and Cockburn, 1994; Tushman and Scanlan, 1981), the interactions with the marketing and sales personnel are likely to provide information about the customer needs and help identify the main profit-making product lines of the firm (Dougherty, 1992; Griffin and Hauser, 1996) and the interactions with other researchers inside the firm are likely to provide information about the various technological projects and technologies built inside the firm (Taylor, 2010).

Greater communication with colleagues internal to the firm is likely to provide access to knowledge about the technologies, expertise and important technological projects inside the firm as well as inform about the strategically important product lines and research trajectories within the firm (Taylor, 2010). On the other hand, interactions with professional communities and universities outside the firm is likely to inform about the broad technological trends in the industry Tushman (1977); Fleming et al. (2007a), which technologies are being adopted by other firms in the industry and the technological problems that are important to other firms in the industry.

The research on the patterns of communication among researchers also shows that not all researchers show the same patterns of communication (Tushman and Romanelli, 1983; Tushman, 1977). Some researchers communicate more with the external professional communities, others interact more with other researchers within the group and yet others with both (Tushman and Scanlan, 1981; Tushman, 1977). The latter are the "gatekeepers" who play an instrumental role in bringing the information outside of the organization inside the organization.

These communication patterns also change when the circumstances facing the researchers change. Tushman (1979b) on examining the communication patterns within the research projects inside a corporate R&D lab shows that as the techniques and skills required by the researchers change, the communication within the research group becomes more free-flowing and decentralized. Further Tushman (1979a) found that under these changing requirements, the researchers also reduced their communication with professional communities outside the organization such as the universities. In contrast, the research groups increased their communication with operational areas such as customers and vendors.Brown and Utterback (1985) using survey methods show that in firms where the R&D personnel perceive greater overall uncertainty, the researchers reduce informal contacts outside of the laboratory such as through attending symposia but increase the number of papers published and periodicals read. These studies show that the communication patterns of researchers is contingent on the circumstances facing them.

Since social interactions and communication with different social groups are such an important source of information for the researchers, which groups they interact with and which information networks they pay attention to should influence the set of technological ideas that they draw upon while searching for new combinations.

Thus the factors that change who the researchers communicate with and the factors that change which social groups and information networks they attend to should also considerably influence the kind of research projects they undertake and the technologies that they draw upon. However the literature has paid little attention in identifying the factors that change the researcher's communication patterns and connect the changes with the technological search process.

Organization of Research Activities

The literature connecting organizational structure to innovation is vast (see Ahuja et al., 2008). However much of the earlier literature focuses on the volume and productivity of innovative efforts rather than on the impact of structure on the nature of search: which kind of research projects are undertaken by the researchers and what are the sets of technologies that the researchers draw on.

The basic idea in this earlier research is that mechanistic structures with strict bureaucratic controls and formalism restricts the information flows and also creates motivational problems because they do not provide autonomy and a feeling of ownership to the researchers (Damanpour, 1991, 1996). In contrast, organic structures that allow discretion and free-flowing information motivates the researchers by giving them autonomy and ownership of their research projects (Burns and Stalker, 1994). Closer examinations of these ideas suggested that while organic structures are good in generating ideas, mechanistic structures may be better at implementing the innovative ideas (see Ahuja et al., 2008 for details). This research however did not connect organizational structures to the nature of technological search and the choice of research projects.

More recent investigations (Argyres, 1996; Argyres and Silverman, 2004; Yayavaram and Ahuja, 2008; Toh, 2007) into the impact of organizational structures have related structural parameters of the organizations to the nature of search. Argyres and Silverman (2004) study the effect of centralization of research laboratories in multi-divisional firms. They argue that when research labs are decentralized and housed within divisions, the researchers are pressured to serve the needs of the division's customers. As a result they conduct product specific research to meet the division's customer needs instead of choosing research projects that solve more basic research problems. Centralizing the research laboratories on the other hand allows the researchers the freedom to explore and not constrain their search to meet the present needs of the customers. This allows the researchers in centralized laboratories to create innovations that have a broader impact and also to search more broadly. They find that centralization allowed the researchers to search more broadly in an organizational sense, i.e. draw upon knowledge from outside the organization. However, they found weak results for the technological breadth of search.

Toh (2007) has demonstrated that research labs that have more diverse technological skills are more likely to develop innovations that have broad applications. This is because specialization increases the depth of contextual knowledge of the researchers leading to inventions that can be narrowly applied to the context whereas generalists have greater breadth of knowledge that allows them to work on projects that has greater breadth of application. Yayavaram and Ahuja (2008) show that the way a firm structures its knowledge base, i.e. the way it couples the different knowledge elements together influences the malleability of the knowledge base.

These studies investigate the impact of organizational structure borrowing ideas from the knowledge based view of the firm. The general mechanism is that structures create distinct sets of knowledge bases within the firm and therefore bound the search within those sets (Toh, 2007; Yayavaram and Ahuja, 2008). The structure of research also focuses the researcher's attention to certain information networks Argyres and Silverman (2004) and not on others (Ocasio, 1997). This focus shapes the kind of research that the researcher undertakes.

However, apart from delimiting knowledge spaces and focusing attention, organizational structures also delimit the social space surrounding the researcher; they determine who the researcher's colleagues are. This has implications for the motivations of the researchers. First, division of labor among the colleagues influences the communication patterns between the colleagues, patterns which influence the degree of trust and affinity that the researcher has for her colleagues (Bunderson and Sutcliffe, 2002; Taylor, 2010). This in turn can affect the researcher's responsiveness to inducements external to the firm. Second, the social space also delineates the space that the inventor uses for social comparison. The relative opportunities that the other researchers get within the firm also serve as a mechanism to trigger career concerns for the inventors. For instance, if a researcher is in a group that is not at the core of the research activities of the firm, the researcher may be less confident of his or her chances of advancement within the firm or even continued employment at times when the environment becomes less munificent. This in turn can create career concerns for the researcher. This impact of organizational structure on the motivations of the researchers and the consequent impact on the technological search process has not been examined deeply in the literature.

2.2. Career Concerns

The review of the technological search literature clearly indicates that the technological search process is a boundedly rational process mired by uncertainties and information asymmetries. The researchers know more about the technological developments than the top management and other functional groups in the organization. Their work involves creativity and is frequently frustrating. Firms therefore give them autonomy and ownership over their projects to motivate them to put effort in face of frequent failure.

However the researchers are boundedly rational and not aware of all available technological options and neither do they know which of the technological options is optimal. Given the autonomy, information asymmetry and bounded rationality, which technological opportunities the researchers focus on and learn about and which channels of information they pay more attention to become important determinants of the kind of research projects they choose and the technologies they draw upon. I argue that the researchers' choices of technologies that they wish to learn about (Kim, 1989; Rosen, 1983; Siemsen, 2008; Zwiebel, 1995), the technological problems that they focus on (Taylor, 2010; Tzabbar, 2009) and the information channels that they engage with Seibert et al. (2001) are influenced by their career concerns triggered by changes in the labor market for technological skills.

In this section, I briefly review the concepts and findings from the career concerns literature relevant to my study. Then I follow it up by discussing the importance to the researchers of career advancement in general and the labor market in particular.

2.2.1 Career Concerns: Concepts

As important as the explicit incentives (e.g. bonuses and wage contracts) are the implicit incentives provided through the career concerns (Holmstrom, 1999; Gibbons and Murphy, 1992; Dewatripont et al., 1999). The importance of career concerns has been demonstrated in a number of different contexts such as mutual fund managers

(Chevalier and Ellison, 1999), political strategies within organizations (Zanzi et al., 1991) and technological researchers (Moen, 2005; Gittelman, 2006). In addition, scholars have developed a number of theoretical models (Holmstrom, 1999; Gibbons and Murphy, 1992) that provide insights into the mechanisms through which career concerns create incentives.

The main idea behind the career concerns models is that the desire to advance further in one's career such as through promotion or through getting a better job creates incentives for the employees. The basic model is a signaling model (see Gibbons, 2005). One's current performance provides the employers (current and prospective) a signal of capability – the employers infer the capability of the individual based on the performance achieved by the employee. The employee therefore wishes to have a good "impression" on the employers and thus exerts greater efforts.

Holmstrom (1982) showed that employees have incentives to exert greater effort earlier in their career when the labor market is most uncertain about their capabilities. Over time, as the market learns about the employees' capabilities, the incentives to provide efforts to make a favorable impression weakens. Gibbons and Murphy (1992) build on this insight to suggest that since the implicit incentives of career concerns die out at later stages in the career, the firm can supplement the implicit incentives with explicit performance based incentives at the later stages. They test their model with CEO compensation data. They show that the compensation of the CEO is more sensitive to the firm's performance when the CEO approaches retirement. Dewatripont et al. (1999) modify the basic model to examine how the signal to noise ratio of the signal provided through performance changes when the capability and the efforts are complements (i.e. when exerting more efforts yields better results for more capable employees) and how these changes impact the incentives to provide efforts.

Although many of the models are primarily concerned with the *volume* of efforts, some scholars (Siemsen, 2008; Zwiebel, 1995) have built models that recognize that employees, especially technological researchers, have discretion in choosing their task profile and the choice may be made based on career concerns. Siemsen (2008) analyzes a mathematical model to suggest that low quality technologists may choose to employ overly difficult technological solutions in solving a problem in order to obfuscate their low quality. Employing a difficult technology prevents the market from attributing a failure to the researcher's low quality. Zwiebel (1995) models the problem of technological choice to suggest that researchers are more likely to prefer standard technological solutions even if they are inferior to non-standard technologies so as to allow the market to accurately benchmark their performance. Chevalier and Ellison (1999), through an empirical study, show that career concerns influence the portfolio allocation choice of mutual fund managers.

These studies including those that model the impact of career concerns on technological choice, invoke the signaling effect of performance as the key mechanism driving their conclusions. The capability of the employees do not change in their models. Yet, considerable research on technological capability development (Cohen and Levinthal, 1990; Levinthal and March, 1993; Argote, 1999) shows that the researchers' capability to search in a technological domain increases with search in that domain. Models that connect career concerns to technology choice (Zwiebel, 1995; Siemsen, 2008) ignore the possibility that this "learning" may provide incentives to prefer certain technological paths. Because enhanced knowledge about certain technological domains can affect the future employability and mobility of a researcher, we can expect her career concerns to be manifested in technological search activity also through the "learning objective".

A further point to note is that the "learning objective" is even more salient in circumstances where outcomes are poor predictors of capability due to the inherent uncertainty of the task. technological research is one such circumstance. Firms find it extremely difficult to objectively measure the performance of their researchers and many choose not to (Schainblatt, 1982). If it is difficult for firms to objectively measure the performance of their own researchers, how much of a signal would outcomes provide to external labor markets? The external labor market, however, can form expectations about the knowledge-set of the researcher from the technological domains she has worked in and the technologies that she has employed in the past. It can then verify her competence to a certain degree through an interview or examination process before hiring. Thus, the very experience of the researcher in a particular domain gives her knowledge about the domain, knowledge that can then enable her to seek further career opportunities. On the other hand, successes or failures in specific research projects are problematic and noisy metrics to use in judging the competence of a researcher (Schainblatt, 1982) given the inherent uncertainty in the technological search process (Freeman and Soete, 1997). Indeed, even failure in a technological project can increase the skills and knowledge of a researcher as a famous comment attributed to Edison aptly points out: "I have not failed, not once. I've discovered ten thousand ways that don't work."

Another assumption in the above literature is that a competitive 'market' for the employee's skills always exists (Gibbons, 2005; Dewatripont et al., 1999). These examinations, especially the ones that relate career concerns to technological choice, do not incorporate the state of the external labor markets explicitly in their models. Since both the internal and the external labor market assess the capability of the employee, the existence of the internal market alone is sufficient to create incentives for the employee. For the purposes of understanding the impact of career concerns on the volume of efforts therefore, the state of the external labor market does not matter. But if our endeavor is to understand the impact of career concerns on the nature of technological search: the choice of technological problems and solutions, the state of the external labor market may be important.

The state of the external labor market can influence the relative importance of internal and external labor markets to the researchers. For example, if the external job opportunities are decreasing, internal labor markets become more important (March and Simon, 1958; Hausknecht et al., 2008; Scholl, 1983). Whether the researcher is more interested in advancing her career within the firm or in exploiting the opportunities that lie in the external market should influence the researcher's attention patterns and choice of information channels that she engages with (Taylor, 2010; Seibert et al., 2001; Podolny and Baron, 1997). For instance, learning about who knows what within the firm, which technological problems and solutions underlie critical money-making products in the firm and which technological solutions best fit with the existing technological projects in the firm is more likely to help one progress within the firm.

The distinction between internal and external labor markets and the corresponding incentives to invest in firm-specific and generic human capital is recognized by another strand of labor economics literature (Becker, 1962; Waldman and Gibbons, 2006; Lazear, 2009) which examines the implications of human capital acquisition. The main thrust of this literature is to explain the firm's and the employee's willingness to invest in firm-specific and generic human capital and the design of the best wage contract that achieves the optimal investments. Since the focus of this literature is on explaining the design of wage contracts to stimulate human capital investments, it pays less attention to how the tasks performed within the firms evolve.

Indeed, scholars in this stream of literature largely treat a firm's task requirements as exogenous to the employees actions (Lazear, 2009). Recent models (Lazear, 2009; Waldman and Gibbons, 2006) have begun treating the nature of tasks as endogenous to external labor environment but these models too do not examine how the employees may alter their task definitions. For instance, Lazear (2009) models firms' task-requirements as a set of generic skills with each firm giving idiosyncratic weights to each generic skill. The firm-specificity in this model comes from the degree to which the weights assigned by the firm differ from the weights assigned in the external world. In thick external labor markets the idiosyncrasy of a firm's weight assignments decreases because each skill has a sufficient demand in the external world. However, in this model, the weights assigned by the firm are fixed and not changed by the employees.

Apart from the economics literature, the management literature also indicates that the career concerns of the employees guide their decisions to stay within the firm or explore the external labor markets (Scholl, 1983; Taylor et al., 1996; Robson et al., 1996; Benson et al., 2004), guide their conduct within the firm (Fox and Staw, 1979; Hausknecht et al., 2008) and impact their organizational commitment (Taylor et al., 1996). Scholl (1983) shows that employees who have greater upward mobility chances within the firm tend to stay with the firm instead of searching for external job opportunities. Robson et al. (1996) shows that accountants are less likely to leave the organization just before they are about to complete their job experience requirements to get certification; the accountants are more likely to quit soon after getting certified. Benson et al. (2004) shows that employees in a high-tech manufacturing firm left the firm after getting their tuition for skill-enhancing courses reimbursed unless the firm also gave them promotion after the course. Hausknecht et al. (2008) show that the negative relationship between job satisfaction and absenteeism reduces when unemployment is high. Fox and Staw (1979) show that greater job insecurity induces a greater need to justify decisions and therefore leads the managers to escalate their commitments to their earlier choices. Taylor et al. (1996) show that when managers continue with the same job inside a firm, they feel that their careers are not advancing and this reduces their organizational commitment and increases their turnover.

The evidence from this literature seems clear that career concerns regarding future employability, mobility and advancement provides significant incentives to employees and professionals, incentives that considerably alter their organizational commitment as well as their professional conduct inside the firm.

Recent management research (Arthur, 1994; Lazarova and Taylor, 2009; Sullivan and Baruch, 2009) on careers suggests an even greater role for career concerns in general, and, for labor markets in particular in motivating employee behavior, especially of professionals. While much of the early management literature on careers focused on career paths within a single organization in a stable environment (Arthur, 1994; Podolny and Baron, 1997) recent research acknowledges that careers are shaped in a much broader context of labor markets where the environment facing the employees especially in the fast-changing high-technology world is hardly stable (Arthur, 1994; Hallock, 2009; Brown et al., 2006; Kalleberg, 2009; Idson and Valletta, 1996). In such an environment where skills become obsolete very fast (Tushman and Anderson, 1986) and the economic turbulence is the order of the day (Brown et al., 2006), assuming firms are benevolent institutions which provide job security and keep their promises of deferred payment (e.g through promotions) could be quite dangerous for the employee (Arthur, 1994). Research (Idson and Valletta, 1996) has shown that even a long tenure in the job is no security in time of downturns. Indeed organizational theorists (Pfeffer, 1997), economists (Hallock, 2009) and sociologists (Kalleberg, 2009) have observed that the old employment contract of providing security in lieu of loyalty now stands eroded and thus normative ideals that favor individualism have become more prevalent (Kunda and Maanen, 1999; Kunda et al., 2002).

For instance, some observers of organizational culture in high-tech firms have noted that (Kunda and Maanen, 1999 , page 73):

> The rhetoric of organizational communities and cultures is being replaced – swiftly it seems – by the rhetoric of markets and entrepreneurs. ... The imagery of love and marriage fades into obscurity, replaced by an imagery of temporary, short-term affairs or one-night stands. Thus, prevailing rhetorics of motive no longer cite the commitment to corporate communities and the orderly career ladders they provide; instead they emphasize the legitimacy of seeking “sexy projects” and “hot technologies” wherever they may be found.

Further, they note that in such environment the "responsibility for the design and development of a career involving continuous employment, learning, progression, upward or lateral mobility shifts away from the employer to the individual" (Kunda and Maanen, 1999 , page 75).

Clearly, the importance of keeping track of external labor market conditions and worrying about employability clearly assume greater importance in such industries. Also, the discussion clearly indicates that it should be of no surprise that the responses by professionals to turbulent environments, such as those facing the researchers in high-tech industries, are strategic (Robson et al., 1996; Benson et al., 2004).

The above discussion clearly demonstrates the importance of incentives provided by career concerns. Theoretical models have shown that not only do these career concerns provide incentives to exert greater effort but also impact the direction of efforts. In particular, models suggest that the researchers in the firm can choose their technological problems based on the implications for their career. However, much of this research is either based on the signaling mechanism (Siemsen, 2008; Zwiebel, 1995) or assumes that the researchers do not have any discretion in changing their task description. I argue that the learning provided by conducting research in a particular technological domain also impacts the researcher's career and therefore provides incentives to the researchers to choose their technological domains.

In addition, I have argued that the literature in labor economics, especially the one that relates the career concerns to the problem of technological-choice, has paid little attention to the impact that the state of the external labor markets has on this choice. However, there are strong reasons to believe that the state of the external labor market can influence the researchers choice of information channels as well as the technological domains that they focus on. Recent management literature on boundary-less careers (Arthur, 1994) and the change in the "employment contract" (Pfeffer, 1997; Hallock, 2009) suggest that the impact of external labor markets and the learning objective is even greater in industries characterized by economic turbulence (Brown et al., 2006).

2.2.2 The career concerns of researchers and the importance of labor markets

One of the popular assumptions regarding the motivations of researchers in the industrial labs is that the researchers are primarily moved by the "taste for science" (Roach and Sauermann, 2010) and the desire for autonomy. It is generally assumed that the firm with its bureaucratic controls do not allow the researchers in their labs to interact with academia and professional scientific community (Stern, 2004; Aghion et al., 2008) and if only these restrictions were relaxed, the researchers would significantly increase their interactions with professional communities and bring new ideas inside the firms.

Like most other generalizations, this characterization is only partly true. If intellectual challenge and taste for science is an important motivator for the researchers, so are concerns about career advancement and employability. Bailyn (1985, 1991), through a number of interviews demonstrates that the research personnel in the R&D labs do not only value the technological challenge but also promotions and extrinsic rewards. Indeed, most of the researchers in her study (Bailyn, 1991) preferred to take the managerial route to advance their careers because of the prestige and power involved. Even those who preferred to advance in their careers through following the technological path were often not quite pleased with the rewards that were offered. She reports comments such as the following in her paper (Bailyn, 1991).

A researcher professing his liking for managerial track reportedly said (Bailyn, 1991 , page 3):

> Managers move much more quickly and have better working conditions - get cars, secretaries, a dining room, and phones. They have carpets and curtains.

A researcher who chose the technical ladder said (page5):

> I would definitely choose the technical ladder. There is supposed to be one here but I do not see it in effect. They are not as high as managers.

These quotes suggest that it is not only the taste for science that moves the researchers but also cars, secretaries and dining rooms. Even the researchers who prefer to follow the technical ladder within the firm are cognizant of the benefits that they are foregoing.

Interviews with the researchers regarding their desire for autonomy (Bailyn, 1985) also suggest that the researchers were suspicious of their autonomy because too much autonomy could lead them in directions which yielded less rewards. For instance, Bailyn reports the researchers in the research labs to state (Bailyn, 1985, page 132):

> Management gives you enough rope to hang yourself, for one can do a lot of work without direction and find out after the fact that work will not *reap rewards*. [emphasis added by me]
> They may tell you are doing well, to carry on, and then *in the merit review* write that you are not working on a *bread and butter project.* [emphasis added by me]

These quotations suggest that surely it is not only intellectual challenge and scientific freedom that motivates the researchers but also promotions with the associated cars, secretaries and dining rooms and rewards that come from working on "bread and butter" projects.

That concerns about career progression and employability influence the industrial researchers should not be that surprising in light of research (Gittelman, 2006) that shows that even for academic scientists, the norms and institutions that govern the careers of the scientists shape their professional conduct and knowledge sharing behavior. In a comparative analysis of institutions governing the mobility and career progression of academic scientists in bio-technology in France and the U.S, she shows that the career systems in the U.S. were more supportive of academic researchers "forming close professional ties" with new entrepreneurial firms in the industry. These differences in the career systems influenced the knowledge-sharing patterns of French and US academic scientists with the US scientists interacting more with the entrepreneurial firms than the French. If the career concerns affect the "real" academic scientists, it is hardly surprising that they should have an influence on the researchers in the industrial labs. This is even more evident when we consider research(Roach and Sauermann, 2010) which shows that compared to the PhD students in science and engineering who stay back in academia, the PhD students who go to work in the industrial labs have a weaker "taste for science" and a greater concern for extrinsic rewards.

A further point to note is that not all industrial researchers are the same. PhD holding scientists differ from the non-PhD engineers in their outlook toward research (Allen, 1988). While the scientists, through a strong period of socialization, may have acquired a greater "taste for science", engineers are probably more motivated by career advancement and employability motives. It has also been shown that industries differ in the extent to which they rely on academic research for ideas. While the biological sector (medicine) is influenced to a great degree by academic research (Bercovitz and Feldman, 2007), industries such as semiconductors are driven more by industrial research (Langlois and Steinmueller, 1999). Since different industries differ in the extent to which they depend on academic research for ideas, the influence of the "taste of science" motivations should not be generalized across researchers of all the industries.

Research also suggests that concerns about careers and employability influence the researchers' decision to both join a firm (Moen, 2005) as well as their professional relationships within the firm (Joshi et al., 2008). Moen (2005) suggest that engineers take a pay cut to work in technologically intensive firms in order to build human capital. Although Stern (2004) suggests that scientists take a pay cut to work in firms that allow them to indulge in their "taste for science", it is possible to interpret these findings differently. All the scientists in this sample are PhD students in the biological sciences who are seeking their first full time employment. Research on careers show that an individual goes through career stages (Cohen, 1991; Veiga, 1983). In the early career stage, the individual is exploring for the correct niche and likes to keep the options open (Cohen, 1991). If this is so, it can be expected that at the point of choosing the first full time job, the PhD biologists may not wish to "burn their bridges" with the academic community. If they are indeed testing the waters in the industrial setting, they may prefer jobs that allow them to keep their options open in the academia as well. It is instructive to note that for the biological scientists in the US, leaving academia for industry is not a one-way street (Gittelman, 2006). In other words, the finding that the PhD students agreed to take a pay cut in order to continue their relationships with science also has a career-concern based explanation.

Concerns about career and employability also impacts the professional conduct of the researchers within the firms (Joshi et al., 2008; Taylor, 2010; Katz and Allen, 1985). Joshi et al. (2008) through their interviews with researchers find that the researchers increased their interaction with other colleagues in the same firm but with different expertise in order to update their knowledge of currently popular technologies. Taylor (2010) found that researchers within a firm kept a close tab on and paid special attention to the activities of technical groups within the same firm who were developing a competing product but with different technologies. The researchers also took political action to throttle the competing group's efforts when they felt threatened. In this process, they learnt about the new technologies as well. Katz and Allen (1985) found that in a matrix structure, the researchers decided on which technological path to take based on their perceptions of who had greater impact on their rewards: the functional technology manager or the project manager. Recent research on creativity (Unsworth and Clegg, 2010) also shows that the engineers try to judge whether engaging in creative tasks was good for them or not before undertaking any creative task. These studies provide ample evidence that career concerns are indeed important factors in the researchers choices.

The state of the external labor market for technological skills is an important concern for the researchers in technology-intensive industries such as semiconductors (Brown et al., 2006; Campbell and Brown, 2001; Ryoo and Rosen, 2004). These industries are characterized by a fast changing technological landscape where current technologies are constantly threatened by new ones. In such circumstances, the researchers are constantly threatened by obsolescence since the returns to experience with older technologies are uncertain and short-lived (Brown and Campbell, 2001; Campbell and Brown, 2001). Further, firms in such industries frequently hire new researchers with the latest skills and relegate the existing workforce to legacy projects which are typically less interesting and promise less career advancement (Campbell and Brown, 2001).

In a fast changing technological landscape, the economic turbulence is high; new firms frequently come up, old firms either die or are restructured. Losing a job usually implies a pay cut (Brown et al., 2006; Hallock, 2009) or long periods of unemployment if the skills are obsolete. This imposes tremendous psychological and economic costs on the researchers.

The fast paced technological developments imply that the half-life (the time after which the skills become half as useful) for technological knowledge is quite short - usually 5-6 years long or in some cases even shorter. In such a scenario, maximizing earning while the skills that you possess are still valuable in the labor market becomes important (Campbell and Brown, 2001). Similarly updating your skills while maintaining employment when the technological skills you have approach obsolescence is also important.

The growth and decline in the demand for technological skills in the labor market provide important cues to the researchers of what the half-life of their technological knowledge is. Another factor that makes keeping track of the labor market important is that mobility is frequently misconstrued as advancement in career (Taylor et al., 1996). The technology-based periodicals and journals indicate to the researchers which technologies are 'hot' in the labor market and which are not. In addition, the researchers also frequently "probe" the market by sending out resumes to test how up to date their skills are. The effect of growing and declining job market is well illustrated in the following quotes from an article in "EE times" (a trade journal) (Costlow, 2000) that describe the survey results from a salary and compensation survey.

Quote from an engineer to the author regarding the growing period

> "The last three years have been incredible. I have gone from $72k (with seven years experience) to $115k (now with 10 years experience.) Changing jobs is by far the best way to get the big salary jumps," wrote one of our first respondents on the Web.

A little later in the article, the author notes this about declining labor market conditions:

> ...it easy to forget that in 1992, engineers were more concerned with holding a job than whether they would get close to a 10 percent raise. Unemployment averaged 7.5 percent through most of that year. A full 31 percent of our readers said they were "not at all secure" about their jobs.

And, what is the advice given to the engineers facing declining job opportunities? An article in the "CIO" magazine suggests (Tynan, 2008) [2]:

> Start by taking notice of the projects that get the most attention from management and ask to be a part of them, advises Betsy Richards, director of career services at Kaplan University.
>
> "Ask to be transferred to a critical area, or volunteer for extra duties to support these activities," Richards says. "You'll be viewed as an employee who goes the extra mile while inoculating yourself against expendability when the pink slips get handed out."

[2] The article can be found at:
http://www.cio.com/article/466823/IT_Careers_7_Tips_for_Job_Security_in_a_Bad_Economy

The research discussed above and the rather colorful examples show that the researchers are not only motivated by the intellectual challenge and taste for science but also by extrinsic rewards and concerns about advancing in the career and future employability. The concerns about their careers also influences their interaction patterns (Joshi et al., 2008), technological decisions (Katz and Allen, 1985) as well as their attention patterns (Taylor, 2010). Some research also shows that the external market for their skills and the threat of obsolescence is an important career concern for them especially in industries characterized by fast-paced technological change.

2.3. Putting it all together

In the sections above, I have reviewed the literature on technological search and career concerns to elaborate on the key concepts relevant to my dissertation and to identify relationships that have not been given significant theoretical attention but are pointed at by the extant literature.

One major development in the study of innovations is the modeling of the innovation process as a combinatory search process (Nelson and Winter, 1982; Rosenkopf and Nerkar, 2001; Fleming, 2001). The literature has significantly elaborated this model by paying attention to (a) identifying the key characteristics of the process, (b) showing that the manner of searching is consequential to performance and (c) identifying the factors that cause the researchers to search in the way that they do.

The literature has characterized the technological search process inside industrial laboratories to be a boundedly rational process (Nelson and Winter, 1982; Nelson, 1962; Fleming and Sorenson, 2004) which is extremely uncertain (Freeman and Soete, 1997) and where the optimal search path is not known (Fleming and Sorenson, 2001, 2004). The researchers are provided significant discretion in their work (Bailyn, 1985; Burgelman, 1983b) because they have superior knowledge of the technologies (Cohen and Sauermann, 2007; Workman, 1995), because providing autonomy motivates them (Damanpour, 1991; Ahuja et al., 2008) and because autonomous research projects can open up new markets and uncover new synergies (Burgelman, 1983b; Cohen and Sauermann, 2007; Pinchot, 1997). Of course, this autonomy is bounded within the larger framework of corporate strategy such as the broad product markets the firm serves (Burgelman, 2002). But nevertheless, within the framework, the researchers do have the discretion with regards to which technologies to search in (Siemsen, 2008).

The literature has also shown that the researchers in firms differ in the way that they search for new ideas (Rosenkopf and Nerkar, 2001; Nerkar, 2003; Katila, 2002). Some draw upon knowledge from inside the firm while others cross organizational boundaries. Similarly some search for ideas within a specialized technological domains while others cast their nets over a broader set of technological domains. This heterogeneity is quite consequential for the firm's innovative and competitive performance (Rosenkopf and Nerkar, 2001; Ahuja, 2003). The literature on the consequences of technological search implies that it is important to understand why researchers differ in their search process from a strategy point of view. The bounded rationality and autonomy of the researchers implicate the importance of identifying and investigating the factors that impact the motivations, preferences and the attention patterns of the researchers.

The research on the determinants of the nature of technological search follows three broad strands: (a) market based explanations (b) technological opportunities based explanations and (c) the context of research and social interactions based explanations.

Initial research on the impact of demand on innovation was typically done at a broad level of analysis with the prime objective of showing the impact on the volume of research rather than on how research is conducted within firms (Cohen, 1995, see). This research has not yielded any consistent results (Cohen and Levin, 1989; Cohen, 1995). Deeper analysis by observing the innovation process inside the firm presents a complicated picture. Demand forces do seem to play a role in the technological search process but not an overly deterministic one. Many observers including Christensen and Bower note that the researchers first initiate research projects and create inventions which are then tested for sellability in the market. It is at this second "impetus" stage that the demand forces seem to play their biggest role (Christensen and Bower, 1996). The research on relationships of researchers with marketing and sales personnel is also consistent with this view (Dougherty, 1992; Workman, 1995; Souder, 1988).

Since the researchers concentrate more on technologies and the marketing personnel more on the product markets, the extent to which demand forces influence the nature of technological search should therefore depend on the extent to which the researchers attend to and incorporate the information provided by the marketing personnel in the firm. The changes in the external job opportunities may be one such factor that influences this behavior of the researchers (Tushman, 1979b,a; Brown and Utterback, 1985). Since the decline in external opportunities motivate the employees to increase their participation inside the firm (March and Simon, 1958), we can expect the researchers to pay more attention to the information provided by the marketing personnel when the external job opportunities reduce. In this way, the impact of current demand on the nature of technological search may be conditioned by the state of the external labor market.

Much of the research on the impact of technological opportunities on innovation has occurred at a broad level of analysis (Jaffe, 1986). This literature has shown that it is easier (less costly) to conduct research in certain industries and this "ease" increases the volume and productivity of research efforts in those industries. Although some scholars have opined that the exogenous discoveries in science attract the researchers (Rosenberg, 1974), others (Nelson, 1962; Allen, 1988) have shown that science is not always a direct driver of research efforts (Lim, 2004; Bercovitz and Feldman, 2007; Klevorick et al., 1995; Cohen et al., 2002). Spillovers from research conducted in other industrial laboratories are another source of technological opportunities (Cohen, 1995). Most of the research on spillovers show that spillovers exist, that they matter and that they occur through a number of means: alliances, informal relationships and hiring. Much less is understood however on how spillovers change the process of technological search inside the firm and the conditions under which the researchers pay attention to external technological opportunities. Recent research on whether firms learn from their hired researchers (Song et al., 2003; Tzabbar, 2009) indicate the importance of examining the motivations of researchers and the organizational factors in understanding how spillovers impact the technological search that the researchers conduct.

The bounded rationality of the researchers implies that which information channels the researchers participate in and which technological developments the researchers pay attention to should be important determinants of which information spillovers they use in their technological search. However what makes certain information channels - those within the firm or those outside the firm - more important to the researcher is not clearly understood. It is important to identify these factors if we are to understand why certain researchers are more susceptible to external information sources than others. Much of the research has given capability based or routine-based reasons to explain these differences in the search behavior and paid less attention to motivations and intentions of the researchers. But bounded rationality does not imply that decision making is not affected by the "logic of consequences" (March and Simon, 1958; Gavetti and Levinthal, 2004). Consequently, incorporating motives and intentions of the searchers in the models of search can lead to new and important insights(Gavetti and Levinthal, 2004).

The research on social context (Fleming et al., 2007b; Ahuja, 2000) shows the importance of personal networks and social interactions on the nature of technological projects that the researchers undertake. The nature of social networks with other collaborators - open vs closed networks - affects the creativity of the search process. Communication patterns with different social groups provide different kinds of information that goes into the research projects: interactions with external professional communities provide knowledge about the technological developments outside the firm (Fleming et al., 2007a), interactions with research colleagues inside the firm provide avenues to learn different techniques (Fleming et al., 2007b) and to learn about the technologies being developed inside the firm (Taylor, 2010) and the interactions with the sales and marketing personnel provide information about the product lines and consumer demands within the firm (Dougherty, 1992). However, not all researchers choose to interact with all the groups. Some choose to interact externally, others internally and yet others do both. Further the communication patterns change with circumstances.

These findings point toward two important relationships: (a) who the researchers interact with affects the information she gets and consequently the kind of technological search she does, and (b) researchers differ in their preferences of social groups with which they interact and their patterns of interaction changes with circumstances. These two relationships together suggest that it may be insightful to identify and examine the factors that cause the researchers to alter their preferences for social groups and communication patterns and then relate these changes to the kind of technological search that they conduct. Important clues regarding these factors can be obtained if we combine this idea with the findings (discussed in the section on characteristics of technological search: 2.1.1) that the technological search process provides learning and social benefits to the researchers.

The learning and social benefits are important for the researchers from the point of view of their careers. The career concern literature has provided ample evidence that concerns about careers and employability provide important motivation to employees. The literature largely employs the signaling mechanism: if we assume that better performance leads to better assessment of the employee's ability by the market, we can expect employees to exert greater efforts to achieve better performance. Especially relevant for our discussion is the problem of technology-choice - the career concerns literature suggests that researchers choose their technologies based on what 'signal' the resulting performance will provide. This literature, especially the one concerning the technologists (Siemsen, 2008; Zwiebel, 1995), does not give importance to the learning and social benefits obtained by the researchers by conducting technological research

While human capital acquisition theories (Waldman and Gibbons, 2006; Lazear, 2009) do emphasize the difference between acquiring firm-specific and general human capital, they do not examine how these incentives change the task profile of the firm and consequently do not examine how these incentives can alter the researcher's technological search behavior.

The learning benefits of technological search are quite important to researchers especially in industries characterized by fast-paced technological change (Joshi et al., 2008; Campbell and Brown, 2001). In such industries, the technological skills become obsolete quite fast reducing the returns to experience (Brown and Campbell, 2001; Brown et al., 2006). Hence exploiting one's knowledge once the knowledge is popular in the labor market and updating one's knowledge while still maintaining employment once the knowledge approaches obsolescence become very important for the careers of researchers in such industries (Campbell and Brown, 2001). Thus the researchers have to keep track of the changes in the labor market conditions and respond accordingly.

These considerations imply that the state of the labor market should influence the choice of the technologies that the researchers wish to learn, the choice of the social groups that they prefer to interact with and the choice of the social groups that the researchers wish to have a reputation in. Since time and effort are limited (Cyert and March, 1963; Ocasio, 1997) the researchers cannot choose to know about all the technologies and pay equal attention to all the information channels (Burt, 2001; Hansen, 2002). Given the fast paced nature of technological change in high-tech industries, understanding how the changes in the market for technological skills affect these choices should lead to important insights into the nature of technological search.

Chapter 3

Theory and Hypothesis

In this study, I assert that attending to the motivations of researchers is necessary to understand the technological search process within firms. The main premise underlying this assertion is that researchers within firms have enough autonomy in conducting technological search for their motives to matter. This premise has strong theoretical foundations and empirical validation (see section 2.1.1).

Research personnel are driven by many different motives and the order of importance of these motives varies with time (Morgan, 1992). These motives can be categorized into three distinct kinds – extrinsic, intrinsic and social (Cohen and Sauermann, 2007). Extrinsic motivations are motivations such as pecuniary benefits and career concerns, intrinsic motivations are those arise from the task of invention itself - the thrill and excitement of creating something original and social motivations arise from the desire to achieve a social position among peers. The labor market conditions facing researchers influence all the three motivations.

The labor market conditions most directly influence the extrinsic career-concern motivations by impacting future employability, job mobility, and opportunity structure facing the researchers (Kim, 1989; Rosen, 1983; Waldman and Gibbons, 2006; Lazear, 2009; Garicano and Hubbard, 2009). However, labor markets also indirectly impact the social and intrinsic motivations. The state of the labor market impacts social incentives by altering the importance of external job opportunities relative to the career opportunities within the firm. This change in relative importance, in turn, influences which social networks - internal or external - is considered more important by a researcher. The state of the external labor market exerts two influences on the intrinsic motivations of researchers: first, it alters the salience of intrinsic motivations for researchers and second, it affects the bargaining power of researchers. By altering the perceptions regarding job security, the labor market conditions change the salience of intrinsic motivations in choosing research projects. Researchers are more likely to attach greater weight to intrinsic motivation when they perceive maintaining continuous employment to be easy (Unsworth and Clegg, 2010). Additionally, the external labor market conditions alter the bargaining power of researchers within the firms. This change in bargaining power impacts the extent to which researchers can garner resources and permission to work on projects that are intrinsically interesting to them.

In this chapter, I analyze the impact of labor market conditions on the researchers' technological and organizational breadth of search. First, I present the hypotheses for the impact of external labor market conditions on the tendency of researchers to cross into new technological domains and then I focus on the tendencies of researchers to cross the organizational boundaries in their search for technological ideas.

3.1. Labor Market and the Technological Breadth of Search

One significant way in which researchers differ while searching for new technological innovations is how broadly they search in the technological dimension (Rosenkopf and Nerkar, 2001; Argyres and Silverman, 2004). Some researchers confine their search within a narrow range of familiar technologies and become specialist experts in those technologies. Yet others expand their search among a broader set of technological domains.

Whether a researcher confines herself to a narrow set of technologies or chooses to expand her search into a broader set is significantly affected by the state of the labor market. The labor market conditions alter the importance a researcher attaches to deepening her knowledge in a narrow specialized domain relative to broadening her repertoire of skills (Kim, 1989; Garicano and Hubbard, 2009; Rosen, 1983). On an average, when the labor market conditions are good, a researcher attaches greater importance to specialization. However, when the labor market conditions worsen, she values a broader skill set more than specialization.

If the job opportunities in a researcher's technological domains are numerous, her returns to specialization are also likely to increase. This is because of a combination of two effects. First, specialization in a narrow set of technological domains increases a researcher's marginal product in those technologies (Kim, 1989; Garicano and Hubbard, 2009) because the depth of her knowledge about the technologies increases. Second, a good labor market ensures that the researcher is able to appropriate rents from the increased marginal product because an improved labor market increases the probability that she finds a job that utilizes her skills well (Halaby, 1988); in other words the probability of finding a good match increases. The increase in marginal product and a higher probability of exploiting this increased marginal product increase the value of specialization. On the other hand, the value of a broader skill-set is lower when the labor market conditions are good. A broader skill-set allows a researcher to market her skills in a broad set of firms (Marx et al., 2009), an ability which comes in handy when jobs are in short supply but of less use in good labor markets. Hence, in good labor market conditions, researchers are likely to attach greater importance to specialization compared to a broader skill-set.

The relative value of specialization and a broad skill-set is reversed when the job opportunities facing a researcher decline. On the one hand, the decline in job opportunities implies that a researcher is less likely to find a good match for her skills and therefore appropriate the value of increased marginal product through specialization. On the other hand, the flexibility given by broader technological knowledge increases the ability of a researcher to market her skills in a broad set of firms (Marx et al., 2009). This increased potential for mobility insures her against job loss.

Increasing one's repertoire of skills insures against job loss not only by increasing external mobility chances. It also reduces the probability of a job loss. Increased breadth of knowledge enables a researcher to interact with and contribute to projects in different groups within the existing firm (Bunderson and Sutcliffe, 2002; Hargadon and Sutton, 1997). Hence, increasing one's diversity of skills increases the ability to move *inside* the firm itself. This further insures a researcher against losing her job.

The insurance against job loss is particularly valuable when the job opportunities in the external environment are decreasing because the decline in job opportunities makes the consequences of losing a job more dire. Whether or not a researcher is able to move within a firm if her research project is canceled is less relevant to the researcher when external job opportunities are increasing. Similarly, the ability to find another job is less relevant when finding employment is not a concern.

The state of the labor market therefore influences the proclivity of researchers to either focus on a narrow specialized technological domain or learn about a broader set of technologies. When the labor market conditions facing a researcher are good, she is more likely to concentrate her attention on deepening her skills (Kim, 1989). If however the labor market conditions are bad, a researcher is likely to engage in broadening her skill set (Kim, 1989). She is likely to read about a broader set of technologies and talk to researchers who work in other domains to learn about different technologies. This proclivity to either focus or broaden one's knowledge base is also likely to influence the pool of technological knowledge that a researcher draws upon in searching for new technological innovations. In good labor markets, the pool is likely to be restricted to a few technological domains while in bad labor market conditions, the pool is likely to be broader.

Since working with certain technologies also provides experiential learning about those technologies (Argote, 1999; Cohen and Levinthal, 1990), a researcher's willingness to expand her knowledge domain or further deepen her knowledge in a narrow domain is also reflected in her choice of technological problems and the choice of technological solutions that she employs to solve the problem. In other words, a researcher may choose to conduct her search in particular domains in order to gain greater knowledge of that domain.

Although firms may reduce this latter effect of working on certain technologies in order to learn from it by employing strict controls, they are unlikely to completely eliminate it. This is partly because firms need to provide researchers autonomy in choosing the technologies because of uncertainty and information asymmetry associated with the research process (Cohen and Sauermann, 2007).

But there are other more substantive reasons for not exerting stifling controls as well. The uncertainty involved in the research process implies that it is not clear that the researcher's behavior is necessarily detrimental to a firm's interests (Burgelman, 1983b; Freeman and Soete, 1997). Researchers do not necessarily experiment to hurt the firm; rather their interest is in producing fruitful research for the firm. Technological researchers are expected to be (Morgan, 1992) and normally are (Joshi et al., 2008; Campbell and Brown, 2001; Cohen and Sauermann, 2007) curious about newer technologies; career concerns provide the added motivation to justify the effort in learning the new technologies.

If a researcher chooses a particular research path with the desire to learn a particular technology and explore the possibilities of that technology, it does not necessarily hurt the firm. Rather the desire can provide the motivation, intellectual challenge and the tenacity necessary to confront the inevitable challenges and frustrations of any technological search process. Since research involves experimentation and can yield serendipitous discoveries, not allowing the inventors to experiment with unfamiliar technologies could be counter-productive. Further, allowing the researchers to expand their knowledge of technologies can also help the firm insure itself against sudden changes in the technological space.

These arguments leads us to the following predictions:

Hypothesis 1. *The greater is the decline (growth) in the researcher's job opportunities in the external environment, the greater (lesser) is the expansion of the researcher's search into new technological domains.*

These arguments are not completely deterministic in the sense that every researcher facing a declining labor market will *necessarily* expand her knowledge base. Rather these arguments are probabilistic and assert that in general, researchers facing decline in the job markets will attempt to expand their knowledge base. Some researchers, especially the ones who are already specialized in their domains, may indeed choose to further specialize in their technological domains to become recognized experts in the domains(see the subsection 3.1.1.1 below). Such specialization may also protect the researchers against job loss.

However, these capability considerations do not completely refute the assertion that an average researcher is more likely to specialize in good labor markets and less likely to do so in bad labor markets. First, even if capability constraints due to prior specialization prevent a researcher from expanding her skill sets in bad labor markets, they certainly do not encourage her to expand their skills when the labor markets for the skills are good. Thus the capability constraint argument only applies to the case when labor markets are worsening and not when labor markets are improving. Second, a decline in external demand for skills in her technological domains provides the researcher a cue that the skills may be approaching obsolescence. While being excellent in an obsolescent skill may prevent immediate job loss, the excellence certainly does not ensure career growth and intellectually challenging projects in the future.

It can also be argued that the reduction in external job opportunities may make the researchers more risk averse and therefore prevent them from experimenting with new technologies. However, this argument ignores the risks of *not* expanding one's skill sets in bad environments. Further, the risk of failure is not really such a big risk when we take into account the way firms evaluate researchers (Schainblatt, 1982). Since it is difficult to judge the worth of an inventor solely based on the output (Schainblatt, 1982) and indeed punishment based on failure may be counterproductive (Manso, 2009), it is unlikely that a failed attempt alone will incur risks. Further more, the attempt to broaden the skill set also implies that a researcher will have learnt something new. For the firm, failure is sunk cost - it has already happened. But the researcher is a different researcher because of the newly acquired skills.

3.1.1 Individual Level Moderators

3.1.1.1 Individual Level Specialization

A recurring theme in the evolutionary economics (Nelson and Winter, 1982; Helfat, 1994), capabilities (Ethiraj et al., 2005; Dierickx and Cool, 1989) and learning literature (Levinthal and March, 1993) is that the actions and choices of an actor is constrained and shaped by the prior knowledge and capabilities of the actor. In particular, scholars (Toh, 2007) have demonstrated that the breadth and depth of knowledge exert a significant influence on the kind of technological search researchers perform (Toh, 2007; Cohen and Levinthal, 1990). The level of individual specialization has also been shown to impact the communication patterns and the cohesiveness of relationships employees share with the rest of the firm (Bunderson and Sutcliffe, 2002). These communication patterns and relationships, in turn, can influence the importance of external job opportunities for the researchers. Thus, a researcher's level of specialization should have an important impact on how she reacts to changes in external job market opportunities.

Responding to the changing job market conditions is predicated on two imperatives: (a) that the researchers pay attention the change in the job market conditions and (b) that the researchers have the capabilities to respond in the direction they desire. A researcher's degree of specialization impacts both the conditions. I discuss both the influences below.

The extent to which a researcher pays attention to the external job market conditions should be influenced by the extent to which she is vulnerable to the changes in job market conditions (Joshi et al., 2008; Brown et al., 2006). Researchers who specialize in a narrow set of technologies are affected to a greater extent by the fluctuations in the external job market conditions in comparison to researchers with a broad set of skills (Marx et al., 2009). Since a specialist's productivity is greater in a narrow set of technologies, it is in her interest to be employed in a firm that utilizes her deep knowledge adequately; finding a better match for her skills is more important to her (Halaby, 1988; Kim, 1989). Consequently she has a greater incentive to keep track of opportunities that provide a better match for her skills.

Similarly, a specialist is more vulnerable to adverse changes in the job market conditions than a generalist (Marx et al., 2009). Compared to a generalist, a specialist's narrow albeit deep skill set indicates reduced adaptability to the employers (Kim, 1989). A decline in job opportunities in her narrow domain also implies that it is more difficult for her to find an adequate match for her skills in the external market (Marx et al., 2009; Kim, 1989; Garicano and Hubbard, 2009). These factors increase her dependence on the firm. Thus purely from an economic point of view, narrower the domain of a researcher's skills, greater are her incentives to keep track of the changing job market conditions. Similar conclusions follow from the organizational effects of specialization as well.

Research on how individual level functional diversity influence the communication patterns within firms (Bunderson and Sutcliffe, 2002) show that individual level specialization reduces the communication with others. Although Bunderson and Sutcliffe's research pertained to cross-functional managerial teams, similar mechanisms apply to innovative teams as well.

The theory of absorptive capacity (Cohen and Levinthal, 1990) and it's subsequent empirical validation (Lane and Lubatkin, 1998) shows that some amount of prior knowledge in a technological domain is essential for a researcher to understand and contribute to problem-solving in that domain (Grant, 1996). Consequently, researchers with expertise in a narrow set of technologies would find it difficult to understand and contribute to the technological problems faced by researchers in different technological domains. The specialists are also less likely to understand how their knowledge could be useful to others thereby reducing their communication with other researchers (Bunderson and Sutcliffe, 2002). Social categorization theory also suggests similar impact of specialization on communication patterns (Bunderson and Sutcliffe, 2002).

A researcher who has worked in a number of different technological domains is less likely to identify with any particular domain and therefore be more open minded about other technologies. She is also less likely to view the technologists working in different technologies as "others". This is because she is likely to possess some knowledge that is common between herself and other researchers in the firm (Bunderson and Sutcliffe, 2002; Dougherty, 1992). The specialists, on the other hand, are more likely to be "labeled" as experts in a particular technology and approached by others only for their specific knowledge about the technology. Other researchers are less likely to engage in general technological discussions with the specialists.

These social dynamics within the research unit is likely to make the specialist researcher more isolated within the firm. Her identification is likely to be greater with the larger profession rather than with the firm. Reduced communication with the rest of the firm is also likely to prevent the development of emotional attachment and trust(Zaheer and Venkatraman, 1995; Zaheer et al., 1998) with the firm. As a result, a specialist researcher is likely to pay more attention to the external job market conditions compared to a generalist.

The above discussion would suggest that as the individual level specialization of a researcher increases, she is more likely to pay attention to the external environment and therefore be more responsive to the fluctuations in the external labor market conditions. When the external job opportunities in a researcher's domains are good, specialists are even less likely than generalists to venture into new technological domains but when the external job opportunities worsen, the specialists are even more likely to attempt to broaden their knowledge base.

These arguments however ignore the constraints that specialization presents on the capabilities of the researchers. The absorptive capacity (Cohen and Levinthal, 1990) considerations imply that as the degree of specialization of a researcher increases, she becomes more and more constrained in her ability to learn about and contribute to different technological domains. Some degree of broadness increases the researcher's ability to understand the problems of a new domain and combine her prior knowledge with different knowledge sets to discover an innovative idea.

These constraints on the capability are less relevant when the labor market in the technological domains is growing and the researcher does not want to broaden her knowledge base. But the constraints become quite relevant when a researcher's incentives are to broaden her skill set in face of downswings in the labor markets. In these circumstances, it is likely that beyond a threshold, the constraints posed by specialization becomes binding and the researcher instead of expanding her skill set chooses to further deepen her knowledge of the domain and become the recognized expert of the domain. Doing so increases the likelihood that she is retained by the firm as long as the firm needs someone with skills in her technological domain.

In combination, the three set of arguments - the economic incentives effect, the organizational communication effects and the capability effect - imply that upto a threshold, increases in individual specialization increases the likelihood that the researchers broaden the technological breadth of their search when the job opportunities in their domains fall, but beyond the threshold the likelihood falls.

Hence, I make the following predictions:

Hypothesis 2. *The researcher's expansion into new technological domains in response to declining external job opportunities is moderated by her degree of specialization; the expansion increases with specialization upto a threshold and then decreases.*

3.1.1.2 Relative Position of the Researcher

Research documenting the motivations of researchers has highlighted the importance of social incentives (Cohen and Levinthal, 1990) particularly a researcher's relative standing in the firm (Paruchuri et al., 2006; Tzabbar, 2009). A higher performance position of the researcher within the firm provides her high local status (Hambrick and Cannella, 1993; Paruchuri et al., 2006; Nerkar and Paruchuri, 2005) within the firm. It gives her the power to set research agenda and garner resources from the firm. Further a higher performance relative to others provides her an expert status (Tzabbar, 2009). Other researchers in the firm respect her opinion and come to her for advice (Tushman and Romanelli, 1983). This higher performance position also provides the researcher higher job security making her less vulnerable to adverse changes in the external job market conditions. This respect and standing is very important to a researcher and losing it adversely hurts her innovative performance (Paruchuri et al., 2006).

Research has also shown that researchers make significant attempts to preserve their relative standing within the firm (Taylor, 2010). Central researchers try to influence the research direction in the firm so that the firm builds further on their specific knowledge (Paruchuri, 2010). The more productive researchers also prevent the firm from moving into new direction through hiring new talent (Tzabbar, 2009). Established researchers indulge in political action to prevent competing research groups to bring in new ideas (Taylor, 2010). This research clearly demonstrates the importance of high relative social standing to the researchers. But other implications also follow from this stream of research.

This research also implies that the high relative standing of researchers is not only a function of their talent and capabilities. It is almost trivial to observe that the relative standing is also influenced by the performance of others in the firm. But the research discussed above also shows that researchers do influence the resource allocation process within the firm to maintain their position (Paruchuri, 2010; Taylor, 2010). Thus, the relative standing also depends on the relationships that researchers build within the organization, the trust and the confidence that they have of the top management and their ability to influence the resource allocation process in the firm. Hence, a significant portion of their standing is firm-specific. In another firm, they would need to reestablish the confidence and trust and the relationships needed to achieve the same influence (Paruchuri et al., 2006). This implies that outside job opportunities hold less charm for researchers with high local social standing within the firms and they would therefore be less sensitive to changes in the external job market conditions.

Another reason why a high local technical standing reduces the importance a researcher attaches to external job market conditions is that a researcher with a higher local standing is also more *visible* to external employers (March and Simon, 1958). A higher local technical standing affords a researcher greater opportunities to interact with the external world. A firm is more likely to entrust dealings with external technological constituents to its recognized experts. This in turn increases the visibility of high performing researchers in the external world. Since it is not only the researchers who look for employment but also the employers who look for researchers (March and Simon, 1958; Gibbons, 2005), the increased visibility in the external world implies that the researcher is less vulnerable to and dependent on the state of the external labor market for job opportunities.

One big motivation to track labor markets and react to shifts in labor market conditions is preparing oneself for any adverse shocks and forced unemployment. Forced unemployment imposes tremendous psychological and financial costs to researchers (Brown et al., 2006). Keeping track of labor markets and acquiring the skills that keeps one employable allows a researcher to be prepared for the unfortunate circumstance of losing her job. Research shows that greater insecurity reduces engineers' resistance to learning new technologies (Agarwal and Prasad, 1997). This motivation of tracking shifts in labor market conditions will be less important for researchers who are more confident of maintaining their employment(Ashford et al., 1989).

A researcher is likely to be more confident of her ability to avoid forced unemployment in adverse shocks when a large number of researchers in her firm are less productive than her. When faced with adverse shocks, firms may be forced to reduce their R&D expenses and lay off their less productive researchers. Being more productive than many other researchers also gives a researcher greater influence within the firm (Paruchuri et al., 2006; Tzabbar, 2009). This allows her to influence the research agenda of her firm (Tzabbar, 2009) and thereby protect herself from adverse shocks and restructuring. Firms are also more likely to accommodate their more productive researchers in other projects and teams if they have to restructure.

These arguments suggest that as the local standing of a researcher rises, the increased job security and influence within the firm reduces the salience of external labor markets for her. Hence, I predict,

Hypothesis 3. *The researcher's expansion into new technological domains in response to declining external job opportunities is moderated by her relative performance position within the firm; the expansion decreases with higher relative performance.*

3.1.2 Firm Level Moderators

3.1.2.1 Firm-Level Average Specialization of Researchers

Just as a researcher's own degree of specialization impacts her response to the fluctuations in the external job market conditions, so does the division of labor in her work context. In other words, apart from her individual degree of specialization, the extent to which she works in a community consisting of specialist researchers (as opposed to a community consisting of generalists) also has an additional impact on her responses to threats and opportunities in the external labor market.

It is by now a non-controversial notion that the actions and choices of individuals are not only influenced by their individual attributes but also by the attributes of the social context in which they are embedded (Granovetter, 1985). If a researcher works in a social context characterized by high levels of internal communication and collaboration, she is more likely to build social ties with the group (Coleman, 1988; Zaheer et al., 1998), ties which can impact the researcher's decision to attend to changes in external job market conditions. Since the degree of individual level specialization in a group influences the extent of internal communication in a group, it should also have a significant and independent effect on the salience of external markets to a researcher.

As I have discussed in subsection (3.1.1.1) above, one consequence of increased division of labor within firms is the reduced communication between the employees of the group (Cohen and Levinthal, 1990; Bunderson and Sutcliffe, 2002). When researchers in a group work on specialized technological problems, they develop a deep knowledge and understanding of those problems but at the cost of not possessing knowledge about a broad set of technological problems (Toh, 2007). This decreases the extent to which the knowledge sets of the researchers overlap. Because successful communication requires some degree of overlap of knowledge sets (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998; Ahuja and Katila, 2001; Grant, 1996), this reduces the communication between the researchers.

As researchers increase their depth of knowledge at the cost of breadth of knowledge, they also get recognized and characterized as "experts" of their respective fields. This categorization provides them a source of power and therefore increases their identification with their fields of expertise. This increases the likelihood that researchers perceive other researchers within the same firm but in different technological domains as experts of "other" domains (Bunderson and Sutcliffe, 2002). Thus, although they may go to the "other" experts for specific technological advice when needed, general communication of an informal nature is reduced.

The reduced communication, the reduced overlap of knowledge sets between researchers, and the social categorization reduces the social cohesion in the group (Coleman, 1988). Reduction in social cohesion reduces the trust between different participants in the social group (Uzzi, 1997). As a consequence, researchers working in a social context characterized by high division of labor and specialization are likely to feel less bonded to the firm and the research unit as a whole. This reduced bonding with the group directly implies that the researcher is more likely to respond to changes in the external environment.

As the labor market improves, she is more likely to exploit the conditions to look for better opportunities. Similarly, the reduced trust and social ties with others mean that the researcher is less likely to feel secure in the firm. These factors clearly imply that researchers in research groups characterized by greater division of labor and higher individual level specialization are likely to pay greater attention to and respond to changes in the external labor market conditions. Hence I predict,

Hypothesis 4. *The researcher's expansion into new technological domains in response to declining external job opportunities is moderated by the extent to which the firm's research community consists of specialists; the expansion increases with the extent to which the firm consists of specialist researchers.*

3.1.2.2 Technological Prominence of the Firm

Sociological research on labor markets (Halaby, 1988; Kalleberg and Sorensen, 1979) show that the labor markets are segmented and the job opportunities differ from one set of workers to another. An important finding is that wages, benefits and job opportunities differ based on which kind of firm an employee works for (Fujiwara-Greve and Greve, 2000; Haveman, 1995; DiPrete, 1993), a difference that should alter the importance of external labor markets for researchers and therefore influence their pattern of technological search. I argue below that working for a firm that is prominent in a researcher's technological domain significantly shapes her response to external labor markets.

Working in technologically prominent firms provides researchers visibility among the external research community (March and Simon, 1958). Technological prominence makes the firm a likely subject of imitation (Knott and Posen, 2009; Stuart, 2000) and make the researchers within the firm more visible to the external environment. In addition, because technologically prominent firms are the more likely objects of imitation, researchers within those firms are in demand in the outside world not only for their technological skills but also for their knowledge of the firm's internal technologies (Knott and Posen, 2009).

Research on the effects of status show that affiliation with high status actors helps an actor gain visibility and opportunities in the marketplace, opportunities that would otherwise be not available to the actor (Podolny, 1993). The same mechanism helps researchers in technically prominent firms as well. The high status of the employer leads the external environment to attribute high quality to the researchers as well (Podolny, 1993) and thus increase their employability in the external world.

Both of these factors – increased visibility and the transfer of status – help the researchers in prominent firms in external labor markets. These factors imply that the technological prominence of the firm positively influences its researcher's career prospects in external labor markets independent of the state of the labor market. The independent positive impact of the technological prominence implies that the state of external labor markets is less salient for researchers of prominent firms. When the labor market worsens, the independent positive impact on researchers' career-prospects shields them from the downswing. Similarly, researchers in technically prominent firms are less dependent on the improvements in the external labor markets for their mobility.

These arguments suggest that the technological prominence of a firm reduces the impact of external labor markets on technological breadth of search conducted by its researchers. Thus, I predict,

Hypothesis 5. *The researcher's expansion into new technological domains in response to declining external job opportunities is moderated by the technological prominence of the firm; the expansion decreases with the technological prominence of the employing firm.*

3.2. Labor Market and the Organizational Breadth of Search

It has become increasingly clear that industrial innovation is not conducted in isolation; spillovers between firms are an important source of knowledge for innovators. Yet, research has also shown that researchers differ in the extent to which they cross the organizational boundaries in search for new ideas (Rosenkopf and Nerkar, 2001; Argyres and Silverman, 2004). In this section, I argue that the state of the external labor market facing the researcher significantly affects her propensity to cross the organizational boundaries in search for technological innovations.

The state of the external labor market influences the importance a researcher attaches to the internal labor market relative to external labor markets. When external job opportunities decline, the importance of internal labor market increases and so do the incentives to maintain the current employment (Halaby, 1988; Hausknecht et al., 2008; Costlow, 2000; DiPrete, 1993). On the one hand, the opportunity cost of working within the firm reduces since there are lesser opportunities in the external world to find a better match for one's skills (March and Simon, 1958; Kim, 1989; Lazear, 2009). On the other hand, the cost of losing the current job increases since the difficulty of finding another increases.

As the internal job market and preserving the current job become more important to researchers, they pay greater attention to information networks within the firm. To preserve the job and to advance within the firm, a researcher needs to be aware of what projects are important to the firm (Bailyn, 1985), which managers and people hold greater influence within the firm (Katz and Allen, 1985) and what technologies are being developed in other research groups of the firm (Taylor, 2010). This information allows a researcher to locate alternative projects and research groups within the firm that could use her skills in the unfortunate event that the management pulls the plug on her research projects. This knowledge is firm-specific and is generally learnt through conversations and gossips inside the firm (Podolny and Baron, 1997). Thus, to gain this knowledge, researchers have to plug themselves in the information networks internal to the firm.

Influencing the direction of research and making one's knowledge more important to the firm is always important to researchers (Paruchuri et al., 2006; Paruchuri, 2010). However, this influence assumes even more importance with the increase in the relative importance of the internal job market. If a researcher's knowledge base and inventions are used extensively inside the firm, it secures the researcher's employment within the firm. It also increases her influence within the firm. Consequently, when the external job opportunities worsen, researchers make even greater effort to "sell" their skills within the firm and discover new innovative uses of their knowledge base in various research projects within the firm.

The increased importance of internal labor markets and of preserving the current job also influences the kind of projects that researchers wish to contribute to. Since firms are profit making entities, those research projects that contribute to the bottom-line of the firm are more likely to be continued and receive resources (Christensen and Bower, 1996). Being associated with and contributing to such profit making products therefore enables the researchers to secure their positions within the firm, a security that is especially important when external job market conditions are bad. Hence, in bad external labor market conditions, we can expect the researchers to interact to a greater degree with marketing, sales and other operational areas within the firm and work on product-specific innovations instead of engaging in exploratory research.

Relatedly, researchers are also more likely to associate themselves with established research trajectories within the firm. Research trajectories generally indicate the accepted direction of technological search (Dosi, 1988; Song et al., 2003) and indicate to the researchers which research directions are well funded within the firms (Song et al., 2003). Identifying and associating with those research trajectories helps secure a researcher's place in the organization, security that is more valuable when the external job opportunities decline (Tynan, 2008).

Although not tested directly, these arguments are consistent with the research on how the research scientists change their communication patterns when the skills needed for their jobs undergo significant change. Tushman (1979a) found to his surprise that researchers of high performing projects reduced their professional external communication (to universities and professional societies) and increased their communication with the operational external constituents such as customers and vendors when they faced significant changes in their skill requirements. Further the communication within the research units became more free flowing and decentralized (Tushman, 1979b). If these findings are interpreted broadly, they suggest that when faced with threatening circumstances, researchers increase their interactions with operational units of the firm which are directly related with the money-making areas of the firm (e.g. customers) instead of engaging in exploratory research (e.g. engage with universities) and also increase their communications with their peer networks within the firm.

Engaging with and contributing to product-specific innovations implies that researchers spend less attention in indulging in broad search for ideas; rather the researchers build narrowly on firm-specific technologies (Argyres and Silverman, 2004). The increased attention to internal information networks and the increased incentives to sell one's knowledge bases in diverse internal projects also suggest that researchers are more likely to build on firm-specific technologies when they face tough external labor markets.

The technological search behavior of the researchers changes however when the external job market conditions are good. In good labor markets, researchers perceive the ease of movement from the firm to be greater (March and Simon, 1958). Their cost of losing the current job reduces on one hand and the opportunity cost of working in the firm increases on the other. The relative importance of the internal labor markets therefore decreases with increasing external job market opportunities. Researchers therefore find lesser need to make efforts to preserve their jobs, to plug deeply into internal information networks and to sell their knowledge base within the firm.

Good external labor markets also encourage the researchers to pay greater attention to the technological developments outside the firm boundaries. Keeping abreast of the technological developments outside the firm allows the researchers to fully avail the opportunities presented by the growing labor market (Brown et al., 2006; Campbell and Brown, 2001). Both the marginal benefit of learning about the technological developments in the industry and the opportunity cost of not doing so is likely to increase when the job opportunities are greater; not learning about technological developments in the external environment may result in foregone opportunities.

Greater job opportunities in the external labor markets also gives researchers more freedom to explore. Compared to when external labor market conditions are bad, in good labor market conditions, researchers are likely to be less concerned about being associated with current profit-making products. Instead, they may find it more interesting to explore the possibilities for inventing and developing the next blockbuster product for the firm. They may find importing and adapting external unfamiliar technologies to produce new products more intellectually challenging than incrementally building on current product lines (Campbell and Brown, 2001).

Although this exploration is intellectually challenging, it is also more risky and not only because the technology is unfamiliar. New products also face market uncertainty and thus the firms may shut down the research projects if the products don't succeed in the market (Freeman and Soete, 1997). In bad labor markets, researchers may be unwilling to work in such risky projects while good labor markets may provide the needed insurance to work on these intellectually stimulating but potentially risky projects. These arguments are also consistent with the recent research on creativity among engineers (Unsworth and Clegg, 2010) which shows that engineers decide on whether or not to initiate creative tasks based on a cost-benefit calculus.

The growth in external job opportunities also provides researchers with greater bargaining power to work on intellectually stimulating projects. Working on prior firm inventions leads to more and more incremental work (Ahuja and Katila, 2004) and leads to intellectual exhaustion (Campbell and Brown, 2001) and boredom. When the labor market conditions are good, researchers' willingness to work on such projects diminishes.

The foregoing arguments imply that when the external labor market conditions facing the researchers are bad, the researchers narrow their search to firm-specific technologies but when the labor market conditions facing them are good, they explore more broadly and cross the firm boundaries to innovate. Thus, I predict,

Hypothesis 6. *The greater is the growth in the researcher's job opportunities in the external environment, the greater is the organizational breadth of the researcher's* *search (i.e more likely is the researcher to draw upon knowledge external to the firm).*

3.2.1 Individual Level Moderators

3.2.1.1 Individual Level Specialization

As I have argued earlier (see subsection 3.1.1.1), a researcher specializing in a narrow set of technologies is more likely to be sensitive to the fluctuations in external labor markets compared to a researcher who has a greater diversity of skills. This is a consequence of two factors: (a) the economic consequences of labor market fluctuations are greater for specialists and (b) the impact of specialization on communication and bonding with rest of the firm. Below, I briefly recall these mechanisms and then discuss the specific impact of individual level specialization on the organizational breadth of search in greater detail.

The state of the external labor market has greater economic consequences for specialists. Since finding a better match for her skills increases the wages and productivity of a specialist, she is more likely to search for a better fit when job opportunities abound (Kim, 1989). Similarly, her narrow range of skills also makes her vulnerable to downswings in the labor market since her mobility is hampered more than that of a generalist (Marx et al., 2009).

A specialist's narrow range of skills also reduce her ability to comprehend and contribute to the research projects of her colleagues in the research lab, a constraint that reduces her communication with her colleagues (Cohen and Levinthal, 1990; Bunderson and Sutcliffe, 2002). Because of this reduced communication, a specialist is likely to experience lower level of bonding and identification with the firm compared to generalists.

Both of the above factors make the state of the external labor market more salient to a specialist researcher compared to a generalist. Thus, we can expect that as the specialization of a researcher increases, she is more likely to cross the organizational boundaries for technological ideas in good labor markets and concentrate attention on firm-specific technologies when the labor markets are bad.

Similar conclusions can be drawn when we consider the expectations that the external labor market has of a specialist compared to a generalist. A specialist is expected to be an expert in her specialized domain and is hired by other firms for this expertise (Kim, 1989). Employers expect her to know the latest developments that have taken place in that domain in the larger industry so that she can be the "go to" person for any technological problems in her domain.

However, this expertise and knowledge is more likely to be evaluated during the hiring process rather than during the day to day operations of the firm. This evaluation does not take usually recur frequently in the day to day working of a firm. Once a specialist is part of the firm, it is generally assumed that she is an expert in the technologies. To question her skills repeatedly is to alienate her and to destroy the camaraderie of the group. Thus, gaining knowledge about the technological developments that have occurred in the wider industry is especially important for a specialist when she is exploring the job opportunities in the external environment.

The external market however hires a generalist more for her flexibility, her ability to quickly adapt and come up to speed in any research project she is assigned to (Kim, 1989). Since she is not expected to be an expert with deep knowledge in any technological domain, it would not be surprising to the potential employers that she is unaware of certain technological developments in a particular domain. Indeed with her broad skills she would be expected to pick up the knowledge in her job. Thus a generalist has lesser incentives than a specialist to learn about the various developments in the external world when the job opportunities are growing.

Deep knowledge in a technological domain also provides researchers increased ability to comprehend and assimilate unfamiliar technologies in their domains (Cohen and Levinthal, 1990). Technologies that are external to the firm are unfamiliar and there is limited access to "teachers" for those technologies. In contrast, technologies that are developed in house have associated experts of those technologies inside the firm (Allen, 1988; Almeida and Phene, 2004). Deep knowledge of the technological domain allows a researcher to "connect the missing dots" of spotty and thin information that characterizes external information. Thus specialization and depth of knowledge also increases the ability of the researcher to understand external information without the presence of a "teacher".

Yet, too much specialization may hurt the absorptive capacity of a researcher (Cohen and Levinthal, 1990). Although specialized knowledge increases a researcher's comprehension of external knowledge in the same domain, too much specialization also reduces the amount of combinatory material with which to combine the external knowledge (Cohen and Levinthal, 1990). Thus, beyond a threshold, specialization may hit a binding constraint and reduce the ability of the researcher to respond to the changes in the external labor market.

Thus I predict,

Hypothesis 7. *The researcher's expansion of search beyond the firm in response to growing external job opportunities is moderated by her degree of specialization; the expansion increases with specialization upto a threshold and then decreases.*

3.2.1.2 Relative Position of the Researcher

As has been discussed before (see subsection 3.1.1.2), a researcher's relative technical standing in the firm is likely to have a significant impact on her sensitivity to the changes in the external labor market conditions.

For a researcher, a high relative technical standing within the firm reduces both the charms of a growing external labor market as well as the threats of a shrinking external labor market. On the one hand, a high relative standing allows a researcher to influence the research agenda of the firm (Nerkar and Paruchuri, 2005; Tzabbar, 2009; Tushman and Romanelli, 1983), an influence greatly valued by researchers. (Paruchuri et al., 2006; Cohen and Sauermann, 2007). On the other hand, the higher relative standing also reduces the threat of losing one's job and therefore the salience of declining external labor market opportunities.

Furthermore, the relative standing is not only a function of the talent and capabilities of a researcher but is also a function of one's position in the inter-firm inventor collaboration network within the firm (Nerkar and Paruchuri, 2005; Paruchuri, 2010). The standing is built by gaining the trust of the top management (Taylor, 2010) and influencing the research agenda within the firm (Taylor, 2010). Thus, the relative standing of a researcher is quite firm-specific. The researcher will need to re-establish the influence in another firm should she decide to separate from the firm. These factors in combination reduce the charms and the threats of the external labor markets, thereby reducing the salience of the state of the external labor markets for her.

Together, this discussion implies that the researchers with higher relative standing within the firm are less likely to respond to growing external labor markets with increasing the organizational breadth of search or to shrinking external labor markets by restricting their search to firm-specific technologies. Hence I predict,

Hypothesis 8. *The researcher's expansion of search beyond the firm in response to growing external job opportunities is moderated by her relative performance position in the firm; the expansion decreases with higher relative performance.*

3.2.2 Firm Level Moderators

3.2.2.1 Firm-Level Average Specialization of Researchers

As discussed earlier (3.1.2.1), a social context characterized by specialists leads to lesser internal communication (Bunderson and Sutcliffe, 2002) and greater isolation of the researchers from the firm. The reduced communication and isolation reduces the social cohesion in the group (Coleman, 1988) and fosters a more individualistic culture among the researchers in the firm. Thus the emergent culture in the group is more of individualism and professional competence and less of cooperation and team bonding. This culture also reduces the degree to which the researchers in the group trust each other.

Thus, an average researcher working in such a group is more likely to feel that she has to fend for herself and take responsibility for her own career rather than depend on the firm to buffer her from technological uncertainties (Arthur, 1994; DiPrete, 1993). She is more likely to have a professional commitment rather than local organizational commitment. This implies that she is more likely to pay attention to the job opportunities that lie in the external labor market.

If the external labor market is growing, a researcher who is fending for herself is more likely to increase her efforts to find the best match for her abilities in the industry. This implies that she will increase her interaction with the external professional communities and want to learn about the technologies that are being used in the broader external environment. Thus, a researcher working in a research laboratory of specialists is more likely than a researcher working among generalists to draw upon external technologies when there is growth in the job opportunities in the external environment.

Similarly, a researcher in a group of specialists is more likely to feel threatened when the job opportunities in the environment decline. Thus, she is more likely to take strategic action to preserve her job within the firm. She is more likely to engage with the information channels within the firm to uncover technological projects that can utilize her skills and knowledge. She is also more likely to try and contribute to the established technological trajectories within the firm. Thus, compared to researchers who work in a more cohesive group of generalists, researchers working among specialists are more likely to feel threatened by a declining job market and narrow draw upon firm-specific knowledge for their innovations.

Thus, I predict

Hypothesis 9. *The researcher's expansion of search beyond the firm in response to growing external job opportunities is moderated by the extent to which the firm's research community consists of specialists; the expansion increases with the extent to which the firm consists of specialist researchers.*

3.2.2.2 Technological Prominence of the Firm

The technological prominence of the firm buffers researchers from the vicissitudes of external labor market by providing an independent source of job market opportunities (see section 3.1.2.2). When the job markets decline, the technological prominence of the firm gives researchers visibility (March and Simon, 1958; Podolny, 1993) and thus reduces the effect of reduced job opportunities. The provision of independent job market opportunities and the associated buffer also reduces the researchers' need to keep track of the changes in the external labor market. Further, leaving prominent firms also implies surrendering the status associated with working in such a firm. Therefore, growth in job opportunities in the external labor market holds lesser lure for researchers in such firms.

In sum, these arguments imply that an average researcher in a technically prominent firm is less likely to be responsive to the changes in labor market conditions while making technological choices. Her technological search behavior is less likely to be strategic. Thus, I predict,

Hypothesis 10. *The researcher's expansion of search beyond the firm in response to growing external job opportunities is moderated by the technological prominence of the firm; the expansion decreases with the technological prominence.*

Chapter 4

Data and Methods

In this chapter, I discuss the empirical strategy I adopt to test my predictions. I begin by discussing the setting for my study and my reasons for choosing the setting in section 4.1. In section 4.2, I then describe the sources of data I use. I recap the theoretical model and describe my empirical model in section 4.3. I conclude in section 4.4 by describing the variables I use in my tests and the operationalization of those variables.

4.1. Setting

I test my hypotheses on a longitudinal sample of the patenting behavior of inventors of all publicly traded firms in the "Electronic Components and Accessories" industry (SIC 367) over a time period of 1992 - 2002. There are a number of reasons why this industry is appropriate to test my theory and to study the response of industrial researchers to changes in the labor market conditions.

The electronics industry is characterized by fast-paced technological developments. Technological strength and innovativeness are paramount to firms for competitive performance and even survival in this industry. Consequently, firms in the electronics sector invest heavily in research and development activities. The R&D intensity of this sector is significantly above (almost double) the average in the manufacturing sector (Blonigen and Taylor, 2000). Given the importance of R&D and technological performance to firms in this industry, the behavior and concerns of researchers are quite relevant for the overall performance of firms in this industry.

The heavy R&D spending in the industry is also coupled with a large number of firms that invest in innovation. The R&D expenditures is not concentrated in a select few firms but is quite widespread. For instance, a National Science Foundation report of 1999 (Shepherd, 1999) found that out of the top 500 R&D spending firms, the largest number (217) were in information and electronics sectors. This number is quite large compared to other industries. For instance motor vehicles and surface transportation industry had 22 firms who were among the top 500 R&D spenders. The second largest industry was medical substances and devices with 87 firms in the top 500 R&D spenders.

A large number of R&D spenders implies that there is sufficient variety in the way research is conducted in these firms. As a result, there is sufficient variance in the moderating factors such as individual specialization, individual skills, and technological prominence of firms. This variance provides a good opportunity to study how individual and firm level heterogeneity influences a researcher's response to career concerns triggered by labor market fluctuations.

Understanding a researcher's response to labor market fluctuations in the Electronics industry is also important and relevant to understanding the technological evolution in the industry because this industry relies more on technological developments conducted in the industrial labs rather than on academic research (Langlois and Steinmueller, 1999). Further, this industry has undergone significant technological upheavals which have triggered significant technological responses by technologists within the firms (Burgelman, 1996). In addition, the responses of researchers in this industry can also be observed over the years through the patent data because patenting inventions for protection of intellectual property is also important and common in this industry.

The importance of technological innovation to the firms in this industry, the considerable heterogeneity in the conduct of R&D, the importance of industrial labs in driving the technological trajectory in the industry, the presence of significant technological changes that trigger researchers' career concerns and the observability of the researchers' technological search behavior over time makes the electronics industry an adequate setting to test my hypotheses.

4.2. Data and Sample

To test my hypotheses I combine data from multiple sources. I match the financial data from COMPUSTAT with the patent data obtained from PATSTAT. I collect and match the patent data with the data on patent classes from CASSIS. In addition, I use firm-patent match data from NBER and the inventor-patent match data provided by Lai et al. (2009).

I draw my sample of firms from COMPUSTAT data. The sample consist of firms that list SIC 367 as a major line of business for the firm. I draw my sample from the time period of 1992 - 2002 for which all the data including data on stock options is available (the stock option data was not available before 1992). In addition, I collect data (especially on patents) from 1976 - 2006 in order to trace most of the inventing history of the researchers and the citation patterns of the inventions.

Th time period of study includes the major downswings (early 1990s and early 2000s) in the electronics sector as well as the upswing of the mid 1990s and therefore provides an adequate test for the impact of fluctuations in the job market conditions. The COMPUSTAT provides longitudinal data about financial variables such as R&D expenses, sales and profits of the publicly traded firms in the USA. I use this data to construct a number of controls for my statistical tests.

Apart from financial data, I use the data on patents filed by the inventors in the firms to test my ideas. The patent data has been commonly employed to understand the nature of knowledge flows as well as the technical search process (Almeida and

Kogut, 1999; Argyres and Silverman, 2004). Patents contain data about (a) the researchers who collaborate to create the patent: their name and cities of residence , (b) firms where the patents were created (c) the date at which they were filed and granted, (d) citations to 'prior art' relevant to the focal invention, and (e) the technological classes that pertain to the invention. Through citations, patents provide a trace for knowledge flows: which technical ideas have been drawn upon to create the invention. The technological classes represent the technical domain of the inventions.

I match the data from COMPUSTAT with the patent data obtained from the PATSTAT database. Although the PATSTAT database consists of patents filed round the world, I limit my sample to consider only the patents filed in the USPTO. Since the sample is drawn from US firms, this does not create a problem for my study. The PATSTAT database also provides information regarding the citations to prior art patents. I use the USPTO classification provided by the CASSIS database dated April, 2010 to obtain a consistent classification scheme across years.

I match the firms with the patent data using the match provided by NBER firm-patent patent match data (2006). The initial firm-patent match data (1999) was updated by the NBER scholars using a NSF grant to correctly trace mergers, acquisitions and major restructuring efforts in the firms and thus accurately match the patents to firms. As a result of this matching, the sample of firms is restricted to those public firms who have also filed for patents in the USPTO.

Using the patent data, I identify the unique inventors of the relevant patents. I also trace the complete inventing history of each inventor to construct inventor-specific measures of an inventor's past experience, productivity and specialization. To do this, I utilize the inventor-patent match data provided by Lai, D'Amour, and Lee (2009). Lai et al. (2009) have developed a comprehensive algorithm to disambiguate the names of inventors and match them accurately with patents. This algorithm uses a comprehensive set of information such as an inventor's name, address and the collaborators that the inventor has worked with etc. to achieve an accurate match.[1]

4.3. Model Definition

In this section I describe and discuss the statistical models that I employ to test my hypotheses and the reasons for doing so. I test my hypotheses by analyzing the data on longitudinal inventing behavior of scientists in electronics industry using regression models suitable for count data (Cameron and Trivedi, 1998). Before describing the empirical models in greater detail though it may be helpful to briefly recap my theoretical model and the hypotheses that I seek to test.

4.3.1 Theoretical Model

My dissertation seeks to examine the impact of external labor market conditions on technical search behavior of researchers inside firms. In particular, I analyze the impact of growth and decline in external job market opportunities on a researcher's technical and organizational breadth of search. Additionally, I investigate how the above impact is modified by two individual level factors: (a) the researcher's relative position in the firm, and (b) the degree of specialization of the researcher. Further, I investigate the role of two firm-level characteristics : (a) the technical prominence of the firm, and (b) the extent to which the firm's researchers are specialists. The theoretical models are shown in figures 4.1 and 4.2.

Figure 4.1 shows the impact of decline in job opportunities on the researcher's propensity to expand their search into new technological domains. H1 shows the main effect: as the job opportunities for a researcher declines, she expands into new technological domains. The model predicts that this main effect is moderated by two individual-level and two firm-level factors. At the individual level, an individual's degree of specialization increases this propensity to expand upto a threshold and

[1]This algorithm has been improved over a number of iterations. Earlier versions of this match has been used in a number of papers which examine the behavior of inventors (Fleming et al., 2007b; Marx et al., 2009)

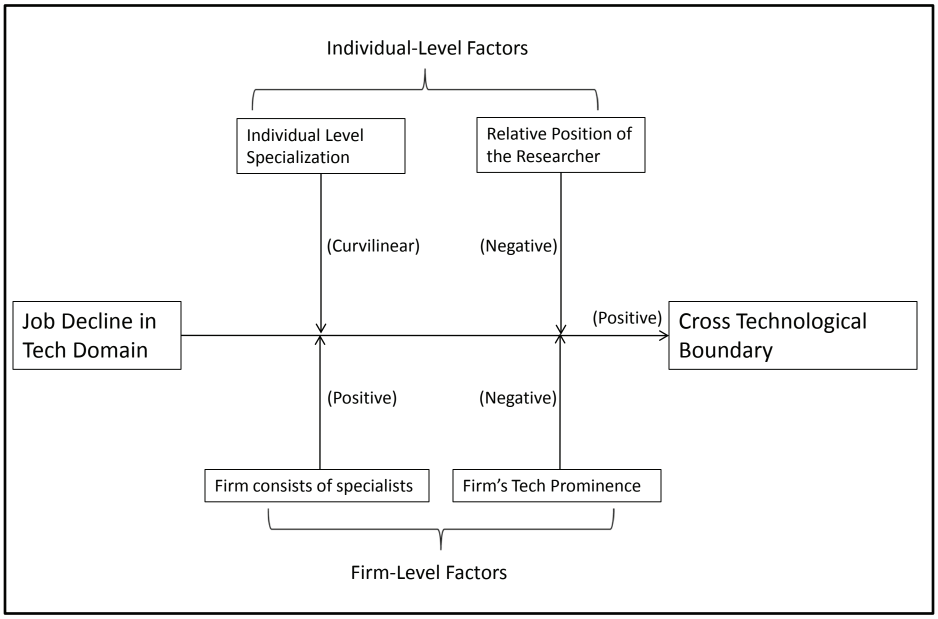

Figure 4.1: The Impact of Labor Market on Technological Breadth of Search

then declines(H2). On the other hand, a higher position of the researcher among other researchers reduces this propensity to expand into new technological domains with the decline in opportunities(H3). At the firm level, the greater is the extent to which a firm's research environment consists of specialists, the greater is the propensity of its researchers to expand into new technological domains (H4). On the other hand, greater is the technological prominence of the firm, smaller is the propensity of its researcher to expand into new technological domains when the job opportunities decline (H5).

Figure 4.2 shows the impact of growth in job opportunities on a researcher's propensity to expand their search beyond the firm's boundaries. H6 shows the main effect: as the job opportunities for a researcher increase, she expands her search beyond the organization. The model predicts that this effect is moderated by two individual-level and two firm-level factors. At the individual level, specialization increases this propensity to expand upto a threshold (H7) while a higher position

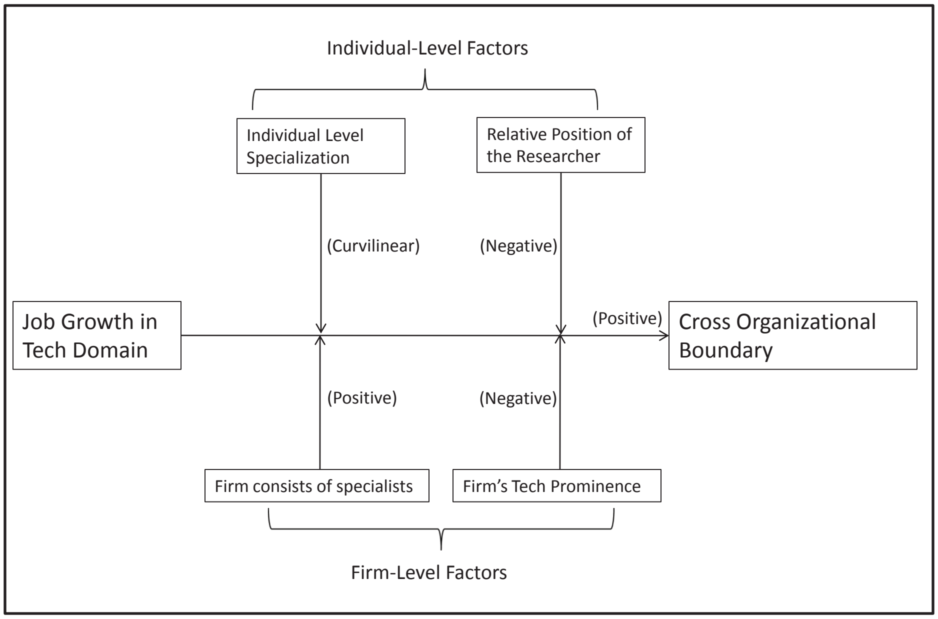

Figure 4.2: The Impact of Labor Market on Organizational Breadth of Search

of the researcher among other researchers reduces this propensity to expand (H8). At the firm level, the greater is the extent to which a firm's research environment consists of specialists, the greater is the propensity of its researchers to search beyond the firm's boundaries in growing labor markets (H9). On the other hand, greater is the technological prominence of a firm, smaller is the propensity of its researchers to search beyond the firm's boundaries when the job opportunities grow (H10).

4.3.2 Empirical Model

I empirically test my theory and hypotheses through a longitudinal analysis of the inventing behavior of inventors in industrial firms of a single industry using regression techniques. My theory and analyses pertains to the career motives and consequent behaviors of individual researchers. Hence the unit of analysis of my study is the researcher within the firm; I measure the dependent variables: technical breadth and organizational breadth of search based on the patents that the researcher has filed in the current year in a firm.

I limit my analysis to the behavior of researchers in a single industry. Limiting the analysis to a single industry enables me to control for unobserved inter-industry differences. Industries differ significantly in their appropriability conditions and in the proclivity of firms to patent their inventions. Because I utilize the information contained in patents to trace the inventing behavior of researchers, these industry-specific factors that influence patenting can confound my analyses. Limiting the analysis to a single industry helps me eliminate the influence of such industry-specific factors.

The longitudinal design of the study enables me to control for a number of unobserved firm and individual specific factors that may influence a scientist's technological search behavior. Although I am able to observe a number of individual level factors such as an individual's level of specialization, many individual specific characteristics cannot be measured. These unobserved characteristics such as a scientist's need for challenge in a task may condition her response to changes in job opportunities. Not accounting for these unobserved characteristics can therefore confound the relationship between job opportunities and technological search behavior. I use the longitudinal character of the data to account for this unobserved heterogeneity by including the firm, inventor pair fixed effects in the empirical model.

I now specify the reduced-form equations of my empirical models. The two dependent variables - technological breadth of search and the organizational breadth of search - are regressed against the growth in job opportunities. The moderating effects are tested by including the interaction terms of the moderators and the growth in job opportunities. To test the non linear predictions - hypothesis 2 and hypothesis 7 - I include the interactions of the individual-level specialization variable and its squared term with the job growth variable in the model. To reduce multicollinearity I mean-deviate the covariates that are interacted together. The details about the statistical model and the variable definitions follow.

Technical Breadth of Search

$$
\begin{aligned}
\text{TechBreadth}_{i,j,t} = {} & \beta_0 + \beta_1 \text{JobGrowth}_{i,t-2} \\
& + \beta_2 \text{JobGrowth}_{i,t-2} \times \text{IndivSpec}_{i,t-2} \\
& + \beta_3 \text{JobGrowth}_{i,t-2} \times \text{IndivSpec Squared}_{i,t-2} \\
& + \beta_4 \text{JobGrowth}_{i,t-2} \times \text{RelPos}_{i,j,t-2} \\
& + \beta_5 \text{JobGrowth}_{i,t-2} \times \text{AvgSpecialization}_{j,t-2} \\
& + \beta_6 \text{JobGrowth}_{i,t-2} \times \text{TechProminence}_{j,t-2} \\
& + \mathbf{\Gamma} \text{Moderator Main Effects} + \gamma \text{controls}
\end{aligned}
$$

Here, “i” indexes the individual researcher; “j” indexes the firm

The coefficient β_1 corresponds to hypothesis 1 which predicts β_1 to be negative; greater job growth is associated with lesser expansion into new domains or conversely greater job decline is associated with greater expansion into new domains. The coefficients β_2 and β_3 correspond to hypothesis 2 which is a non-linear prediction. Hypothesis 2 predicts β_2 to be negative and β_3 to be positive; the main effect is increases and then decreases with specialization. The coefficient β_4 corresponds to hypothesis 3. Hypothesis 3 predicts β_4 to be positive. The coefficient β_5 corresponds to hypothesis 4. Hypothesis 4 predicts β_5 to be negative. Finally, the coefficient β_6 corresponds to hypothesis 5. Hypothesis 5 predicts β_6 to be positive. Table 4.1 below lists all the predictions related to technological breadth of researchers' technological search behavior.

Table 4.1: Predictions for Technological Breadth

Hypothesis Number	Variable	Coefficient	Prediction
H1	Job Growth	β_1	Negative
H2	JobGrowth X Indiv Special	β_2	Negative
H2	JobGrowth X Indiv Special Sq	β_3	Positive
H3	JobGrowth X Indiv Rel Pos	β_4	Positive
H4	JobGrowth X Avg Indiv Special	β_5	Negative
H5	JobGrowth X Tech Prominence	β_6	Positive

Organizational Breadth of Search

$$
\begin{aligned}
\text{OrgBreadth}_{i,j,t} &= \beta_0 + \beta_1 \text{JobGrowth}_{i,t-2} \\
&+\beta_2 \text{JobGrowth}_{i,t-2} \times \text{IndivSpec}_{i,t-2} \\
&+\beta_3 \text{JobGrowth}_{i,t-2} \times \text{IndivSpec Squared}_{i,t-2} \\
&+\beta_4 \text{JobGrowth}_{i,t-2} \times \text{RelPos}_{i,j,t-2} \\
&+\beta_5 \text{JobGrowth}_{i,t-2} \times \text{AvgSpecialization}_{j,t-2} \\
&+\beta_6 \text{JobGrowth}_{i,t-2} \times \text{TechProminence}_{j,t-2} \\
&+\mathbf{\Gamma}\text{Moderator Main Effects} + \gamma\text{controls}
\end{aligned}
$$

Here, "i" indexes the individual researcher; "j" indexes the firm

The coefficient β_1 corresponds to hypothesis 6 which predicts that β_1 to be positive. The coefficients β_2 and β_3 correspond to hypothesis 7 which is a non-linear prediction. Hypothesis 7 predicts β_2 to be positive and β_3 to be negative. The coefficient β_4 corresponds to hypothesis 8. Hypothesis 8 predicts β_4 to be negative. The coefficient β_5 corresponds to hypothesis 9. Hypothesis 9 predicts β_5 to be positive. Finally, the coefficient β_6 corresponds to hypothesis 10. Hypothesis 10 predicts β_6 to be negative. Table 4.2 below lists all the predictions related to technological breadth of inventors' technological search behavior.

My dependent variables - technological breadth and organizational breadth - are count variables (which I describe in the section 4.4.1). Thus, any statistical model

Table 4.2: Predictions for Organizational Breadth

Hypothesis Number	Variable	Coefficient	Prediction
H6	Job Growth	β_1	Positive
H7	JobGrowth X Indiv Special	β_2	Positive
H7	JobGrowth X Indiv Special Sq	β_3	Negative
H8	JobGrowth X Indiv Rel Pos	β_4	Negative
H9	JobGrowth X Avg Indiv Special	β_5	Positive
H10	JobGrowth X Tech Prominence	β_6	Negative

has to account for two characteristics of the dependent variables: (a) non-negativity, and (b) discreteness. To account for these two characteristics, I use the following specification of the conditional mean:

$$\mathbb{E}\left[Y|X\right] = e^{\beta'\mathbf{X}} \tag{4.1}$$

The exponential form of the conditional mean ensures non-negativity. The exponential form of the conditional mean also implies that the estimated coefficients of the variables in the model can be interpreted as semi-elasticities: the proportional change in dependent variable per unit change in the independent variables (Cameron and Trivedi, 1998). This can be seen by differentiating equation 4.1 with respect to the independent variable.

$$\frac{\partial\mathbb{E}[y|\mathbf{x}]}{\partial x_j} = \beta_j e^{\beta'\mathbf{x}} \tag{4.2}$$

Using equation 4.1, we can rewrite 4.2 as

$$\frac{\partial\mathbb{E}[y|\mathbf{x}]}{\partial x_j} = \beta_j \mathbb{E}\left[Y|X\right]$$

Hence,

$$\beta_j = \frac{\partial\mathbb{E}[y|\mathbf{x}]}{\partial x_j}\frac{1}{\mathbb{E}\left[Y|X\right]}$$

Thus, β_j is the semi-elasticity: the proportional change in $\mathbb{E}[Y|X]$ for a unit change in x_j. When the conditional mean function includes interaction terms, the coefficient of the interaction term indicates how the semi-elasticity of the conditional mean with respect to one independent variable changes with the value of the moderator variable.

For instance consider the following conditional mean (This example is derived from (Cameron and Trivedi, 1998, p. 81)).

$$\mathbb{E}[Y|X] = e^{\beta_1+\beta_2 x_2+\beta_3 x_3+\beta_4 x_2 x_3} \tag{4.3}$$

Differentiating with respect to x_2 and rearranging we get

$$\frac{\partial \mathbb{E}[y|\mathbf{x}]}{\partial x_2}\frac{1}{\mathbb{E}[Y|X]} = (\beta_2 + \beta_4 x_3)$$

Thus the semi-elasticity of the conditional mean with respect to x_2 depends on the value of x_3. Further, β_4 is the degree to which the semi-elasticity of the conditional mean with respect to x_2 changes per unit change in x_3; in other words β_4 measures the moderating effect of x_3 on the semi-elasticity of the conditional mean with respect to x_2.

Apart from non-negativity, the statistical model should also account for the discreteness of the dependent variables. This can be done by modeling the dependent variables to come out of a poisson or a negative binomial distribution.

Research has shown that the poisson model is more robust to distributional assumptions (Cameron and Trivedi, 1998, p. 59). But the poisson model imposes the constraint that the mean and the variance of the distribution be equal: the condition of equidispersion. This condition is rarely met in practice.

The negative binomial model is “the standard parametric model to account for overdispersion” (Cameron and Trivedi, 1998, p.71). It models the variance to be the function $\mu + \alpha\mu^2$ (here μ is the mean). It models the density to be a complex function of α and μ. The negative binomial model reduces to a poisson model when $\alpha = 0$. The test for $\alpha = 0$ therefore allows one to test for overdispersion. In this study the data shows overdispersion and thus I employ the negative binomial model. However I also apply the poisson model for robustness.

The longitudinal design of the study enables me to control for a number of unobserved firm and individual specific factors that may influence a scientist's technological search behavior. Both the poisson and negative binomial models allow the modeling of individual and firm specific effects.

These longitudinal models incorporate a term for the individual heterogeneity in the model. In other words, the conditional mean function is modified to include a term specific to each individual i.e.

$$\mathbb{E}\left[y_{it}|\alpha_i, x_{it}\right] = e^{\gamma_i + \beta' \mathbf{x}_{it}} = \alpha_i e^{\beta' \mathbf{X}} \tag{4.4}$$

Here, $\gamma_i = \ln \alpha_i$

Two longitudinal panel models - random effects and fixed effects - can be used to model unobserved individual heterogeneity. The random effects model estimates the parameters using both the cross-sectional variance between individuals and the variance within the individuals across time. The fixed effects model on the other hand uses only the within variance. As a result the random effects model is more efficient than the fixed effects model.

The random effects model however is consistent only when the unobserved heterogeneity is not correlated with the independent variables. It provides biased estimates if the unobserved heterogeneity and the other regressors in the model are correlated with each other. The fixed effects model on the other hand provides consistent estimates even if the unobserved heterogeneity is correlated with other regressors in the model (Cameron and Trivedi, 2009; Kennedy, 2003).

From the above discussion it is clear that the random effects model is the more efficient choice if the unobserved heterogeneity is not correlated with the other regressors in the model, a requirement which is often violated in practice. Hausman test can be used to verify whether this requirement is met. The Hausman test tests whether the estimates of the two models differ significantly from each other. The fixed effects model always provides consistent estimates. But the random effects model provides consistent estimates only when the unobserved heterogeneity is not correlated with the independent variables. In this case, the two estimates should be close to each other. The Hausman test essentially tests whether this is true. If the two estimates are significantly different from each other the fixed effects model may be the appropriate choice. In this study tests indicate that the fixed effects model is the appropriate choice. I run the random effects model in addition to the fixed effects model for robustness.

I control for a number of factors in the study both at a firm and at an individual level. I control for the total R&D effort of the firm by using the lagged R&D expense of the firm as a control. Past studies have indicated that a firm's tendency to explore may be related to the amount of slack in a firm. Thus, I control for slack by controlling for the liquidity ratio (current asset/current liability) of a firm, as well as its profitability. I control for the size of a firm using the log of its sales as a control. These controls are also lagged. I include a dummy variable to indicate whether the firm has foreign R&D (measured by the presence of any patent invented outside of the USA). I also include a measure of total technical diversity of a firm as a control because total diversity provides a researcher a more diverse set of combinatory material to search for combinations. I measure a firm's total diversity as the concentration index (Herfindahl index) of the distribution of patents filed in the last three years among the different technological classes.

The growth in job market opportunities in a technical domain could also be correlated with a number of factors such as the inherent technological opportunities in the domain. These factors can also induce the firm to increase its investments into these domains. Thus, I control for the strategic thrust of a firm in a researcher's technological domain by calculating the growth in the proportion of patents filed by a researcher's firm in her domain during the last 3 years.

Further, I control for the technological richness of a researcher's technological domain. Researchers may be inclined to work in a domain because the domain is rich in providing technological ideas to them. I control for this effect by including the number of patents filed by all the firms in the researcher's technological domain during the previous 3 years to control for the technological richness in a researcher's technological domain.

Additionally the firm can institute certain incentive schemes such as stock options to retain talent within firms. These schemes can also alter the researcher's technological search behavior. I control for this by including a measure of stock option intensity in the firm. I calculate the stock option granted per employee in a firm using the strategy employed by Bergman and Jenter (2007). I use the data on stock options granted to the top 5 managers from ExecuComp database and then use the "pcttotop" variable to extrapolate the stocks granted to rest of the firm. I then divide this amount by the total number of employees of a firm. Bergman and Jenter (2007) show that this method yields results that are highly correlated with other methods using hand-collected data from annual reports. I use lagged values of this variable.

At the individual level, I control for the number of patents filed by the researcher that year because the productivity of the researcher in the year can be correlated with the number of technological classes that the researcher works in and the number of external citations that her patents make. I also include the total number of citations cited by the researcher in that year in the specifications on the organizational breadth of search (see 4.4.1). In addition, I also control for the number of technological classes that the researcher has worked on in that year in the specification for technological breadth of search. I also control for the age of the researcher. I measure the age of the inventor as the number of years since the researcher's first patent. Additionally, I include year dummies to control for unobserved changes in the broader environment.

4.4. Variable Definitions and Operationalization

4.4.1 Dependent Variables

I am interested in two aspects of technical search of the researchers: the technological breadth of search and the organizational breadth of search. Below, I explain how I operationalize these two constructs.

I measure the technological breadth of search through the following operationalization:

$\text{TechBreadth}_{i,j,t}$ = The number of new technological classes (classes in which the researcher has not worked on during the last 3 years) that the researcher "i" in firm "j" has worked on during the year "t"

To measure the organizational breadth of search, I use the following operationalization.

$$\text{OrgBreadth}_{i,j,t} = n_{i,j,t}$$

where $n_{i,j,t}$ equals the number of citations made by the researcher "i" to patents that do not belong to the employing firm, "j", in the year "t"

4.4.2 Independent Variables

JobGrowth To measure the growth in a researcher's job opportunities in the external environment, I calculate the growth trend in R&D expense in the classes that the researcher has worked on during the last three years. The basic logic of using increases in R&D expenditure as a measure of increasing career opportunities is that the growth in R&D expenses is also accompanied the growth in employment opportunities for the research personnel. An OTA (Office of Technology Assessment) report (of Technology Assessment U.S. Congress, 1993) shows that in the pharmaceutical industry, an increase in R&D costs was also associated with an increase in the employment if R&D personnel (even though the inflation adjusted wages of the research personnel largely remained constant). It assessed that "the increases in the numbers of employed research personnel" was one of the three main potential causes of the rise in the cost of researching and developing drugs in the pharmaceutical industry (page 65).

To corroborate this in my data, I compare my independent variable (which I describe below) with the growth in overall employment in the electronics industry in the time period. I collect data from the Bureau of Labor Statistics (Jacobs, 2003) on the total employment in the "Electronics Components and Accessories" industry for the time-period of interest. This data includes the total employment (i.e. not only the research personnel employed but all the employees). This data is available annually till 2001. I use this data to calculate the growth in total employment over the last three years for each of the years from 1992 – 2001. I also calculate the mean of the *JobGrowth* variable (described below) per year for the period 1992 – 2001 for the researchers in electronic firms [2]. I then calculate the correlation between the two series of numbers: the growth in total employment and the annual mean of *JobGrowth* variable. The correlation is 40.8 %.

Although the correlation does not seem very high, this indicates considerable positive association especially in view of the fact the data from BLS is at a very aggregate level. The BLS data is the total employment data and not specific to the employment patterns of the researchers. The factors influencing the employment opportunities of research personnel can differ considerably from the factors that drive the employment

[2] This includes the researchers from firms who are eventually dropped from later analyses due to lack of data on other variables

conditions of all the employees. This is because labor markets are segmented (Kalleberg and Sorensen, 1979; Smith, 1983) and different occupations can have different employment patterns. For instance, the outsourcing of manufacturing can influence the employment patterns of manufacturing personnel without necessarily impacting the labor markets of research personnel.

Another point to note is that the growth in the total employment figures (from the BLS) does not sharply measure the changes in job opportunities in the industry. This is because the change in total employment figures is the result of both job creations and job losses and does not distinguish between the two. Thus changes in total employment figure does not even measure the total jobs added let alone sharply measure which segment within the industry is growing and which is not. This point is especially relevant for this study because even a modest change in total employment may actually be caused by considerable turbulence in the employment opportunities of individual researchers. Researchers have a certain set of skills may see dramatic growth in job opportunities whereas other researchers having different skills may see a dramatic fall in their opportunities. Thus using an aggregate employment growth number will not provide a sharp enough measure of job opportunities for the researchers. The positive association of employment growth of researchers with the growth in R&D suggests that calculating the growth trend in R&D expense in a researcher's technological domain should be a good proxy for the growth in her job opportunities.

The positive association of the growth in R&D expense with the growth in employment opportunities is due to the fact that by far the largest component of R&D expense in the manufacturing sector is the wages of the research personnel (Dougherty et al., 2007; NSF, 2011; Goolsbee, 1998). Goolsbee (1998) after reviewing a number of reports concludes that a reasonable estimate is that about $\frac{2}{3}$ of R&D expenses are because of the wages of research personnel. The NSF report shows that the largest component of R&D expense averaged over all industries as well as in the electronics industry is the wages of the researchers. The OTA finding of the positive association of increased R&D cost with increased employment of researchers (of Technology Assessment U.S. Congress, 1993) pertained to the pharmaceutical industry where the wages of R&D personnel constituted 40 % of the R&D expenditure. This positive association should in fact be greater in the electronics industry where the weightage of wage cost is about 10 % higher (NSF, 2011). This discussion strongly suggests that increase in R&D expenses in a technological domain indicate increases in demand and career opportunities for researchers skilled in that domain and thus forms a reasonable proxy for growth in opportunities for a researcher in that domain.

Below I describe the construction of the independent variable that is measured based on patents filed in years t-3 through t-1 for the dependent variables in year t.

I construct the measure in the following steps.

Step1. First I create the list of technological classes that the researcher has filed patents in during the last 3 years, i.e. during the years t-1, t-2 and t-3. Let us call this set of technological classes $S_{i,t-2}$, where

$$S_{i,t-2} = \{\text{C : C is a technical class that "i" has patented in during the last 3 years}\}$$

Step2. Next, I calculate for each of the years in the three year period, the amount of R&D spent by each external firm, "k", on the classes belonging to $S_{i,t-2}$. Let us call this , $\text{R\&D}_{k,S_{i,t-2},x}$.

A firm does not disclose how its R&D is distributed among the various classes. Thus I devise an algorithm to distribute a firm's R&D expense among its technological classes.

First, I distribute a firm's R&D expense among its patents. To take into account the possibility that some patents may require more resources than others, I distribute a firm's R&D among its patents based on the complexity of each patent, i.e. the number of technological classes that a patent is in. Then in the second step, I distribute the amount of R&D allocated to an individual patent equally among the classes that pertain to that patent. Finally, to calculate the total R&D expense of a firm allocated to an individual class, I sum together the R&D amounts allocated to that class in the second step across all the patents in the firm [3].

For instance, consider a firm which has two patents in a year: patent 1 and patent 2. Patent 1 is in two classes, X and Y. Patent 2 is in one class, Y. The total R&D of the firm is \$3. I first divide \$3 among the patents based on the number of classes that pertain to each patent: patent 1 is allocated \$2 and patent 2 is allocated \$1. Then for each patent, the amount is distributed equally among its classes. So, both X and Y are allocated \$1 each from the \$2 allocated to patent 1. The \$1 allocated to patent 2 is allocated to the class Y. To calculate the amount allocated to class Y, the amounts allocated to class Y is summed over all patents, i.e. \$1 (from patent 1) + \$1 (from patent 2). Class Y, therefore, is allocated \$2 overall; \$1 comes from patent 1 and \$1 from patent 2. When the amounts allocated to class X are summed together over all patents, we arrive at \$1 overall (\$1 from patent 1 + \$0 from patent 2).

Step3. In the third step, I sum the $\text{R\&D}_{k,S_{i,t-2},x}$ for all the "k" firms in the external environment, i.e. for all the firms in the industry excluding the employer firm. I adjust this value for inflation to 1975 dollars (using data from inflationdata.com). This gives me the total R&D expense devoted to the relevant classes in the industry for each year from t-3, t-2, t-1. Let us call this sum $\text{TotR\&D}_{S_{i,t-2},x}$. In other words

$$\text{TotR\&D}_{S_{i,t-2},x} = \Sigma_{k=1}^{n-1}\text{R\&D}_{k,S_{i,t-2},x}$$

Step4. In this step, I construct the trend line of R&D expenditure in the relevant classes by regressing $\text{TotR\&D}_{S_{i,t-2},x}$ on year (i.e "x"). The slope of the trend line

[3] Please note that this method is equivalent to distributing the R&D among the classes in proportion to the number of patents filed in that class.

gives me the measure of the Job Growth for the researcher "i".

4.4.3 Moderating Variables

RelPos: The relative position of the researcher in the firm I measure this construct as the number of researchers in the firm that are less productive than the researcher during the last 3 years. I include the number of inventors in the firm as an additional control because the number of less productive researchers compared to the focal researchers can also be a function of the total number of researchers in the firm. Greater the number of researchers that are less productive than the focal researcher controlling for the total number of inventors within the firm, the higher is the relative position of the researcher in the firm.

IndivSpec: The researchers degree of individual specialization I measure this construct as the degree of concentration of the researcher's patents in a few classes. In other words,

$$\text{IndivSpec}_{i,t-2} = \Sigma_{l=1}^{n} s_{i,l,t-3::t-1}^{2}$$

where l indexes the technical classes that the researcher patents in during the previous three years, and,

$s_{i,l,t-3::t-1}$ = Proportion of patents of researcher "i" in a particular class "l"

Average Specialization of the researchers in the firm I measure this as the average individual level specialization of the researchers in the firm, where the individual level specialization is as calculated above.

Tech Prominence of the firm To measure the technological prominence of a firm, I calculate the firm's market share of patents in the patent classes that the researcher has worked in during the last 3 years based on the patents filed during the last 3 years.

Chapter 5

Findings

In this chapter I report the findings of the statistical tests I outlined in the previous chapter. I begin by briefly recapitulating my research questions and my predictions in section 5.1. In section 5.2, I provided the descriptive statistics of the data. In this section I provide information about the time trends of the dependent and independent variables of the study. Additionally I provide information about the means and variances of the variables of interest. In section 5.3, I describe the results of running the statistical tests on technological breadth of search. In section 5.4, I describe the results of running the regressions on the organizational breadth of technological search. In both these sections - section 5.3 and 5.4 - I discuss the findings related to each hypotheses. I conclude each of these two sections by summarizing and discussing the findings. I conclude the chapter by discussing the limitations of this study and outline few future research possibilities in section 5.5.

5.1. Brief Recap

Before reporting the findings of the statistical tests, it may be helpful to briefly recall the research questions and the main predictions of the theoretical model. In this study, I explore how the external labor market conditions and the characteristics of the individuals and that of the firms they work for jointly impact how the researchers search for innovations in technology-intensive industries. I include two individual-level characteristics in my investigation: the level of specialization of the researcher and the relative position of the researcher inside the firm. I seek to answer the following two research questions:

(a) How does the state of external labor market impact the tendency of researchers within firms to search along each of two dimensions: technological - the extent to which researchers cross technological domains and organizational - the extent to which researchers draw upon technological ideas outside the firm?

(b) How is this tendency influenced by individual and firm-level characteristics; specifically, the level of specialization of the researcher, the relative position of the researcher inside the firm, the extent to which the research in the firm is conducted by specialists vs generalists and the technological prominence of the firm?

H1-5 relate to the technological dimension of search. H1 predicts the main effect: as the job opportunities for a researcher declines, she expands into new technological domains. At the individual level, an individual's degree of specialization increases this propensity to expand upto a threshold and then declines(H2). On the other hand, a higher position of the researcher among other researchers reduces this propensity to expand into new technological domains(H3). At the firm level, the greater is the extent to which a firm's research environment consists of specialists, the greater is the propensity of its researchers to expand into new technological domains (H4). On the other hand, greater is the technological prominence of the firm, smaller is the propensity of its researcher to expand into new technological domains when the job opportunities decline (H5).

H6-10 relate to the organizational dimension of search. H6 predicts the main effect: as the job opportunities for a researcher increase, she expands her search beyond the organization. At the individual level, individual level specialization increases this propensity to expand upto a threshold (H7) while a higher position of the researcher among other researchers reduces this propensity to expand (H8). At the firm level, the greater is the extent to which a firm's research environment consists of specialists, the greater is the propensity of its researchers to search beyond the firm's boundaries in growing labor markets (H9). On the other hand, greater is the technological prominence of a firm, smaller is the propensity of its researchers to search beyond the firm's boundaries when the job opportunities grow (H10).

5.2. Descriptive Statistics

I test my theory and hypotheses by analyzing the patents filed by the researchers within public firms in the electronics industry in the US Patent Office. The data set consists of 26738 unique researchers who filed for US patents between 1992 and 2002 for the public firms in the electronics industry. These researchers filed a total of 77504 patents in the US Patent Office for these firms. In this section I describe the time trend of the dependent and the main independent variables. I follow this up by discussing the means and variances of the main variables of interest.

5.2.1 Time Trends

Figures 5.1 and 5.2 show how the dependent variables - the technological breadth of search and the organizational breadth of search - vary with respect to time. Figure 5.3 shows how the main independent variable of interest - the job growth variable - varies with time. Although the time period is limited from 1992-2002 due to the availability of data on stock-options, I use the patent data from early 1980s onward to capture the complete effect of previous citations made by the inventions. This enables me to analyze the time trend from before the period of study. To construct these graphs, I first calculate the mean of these variables per year of observation. I then plot these means against the "year" of observation. These graphs thus show how the average levels of these variables vary over time.

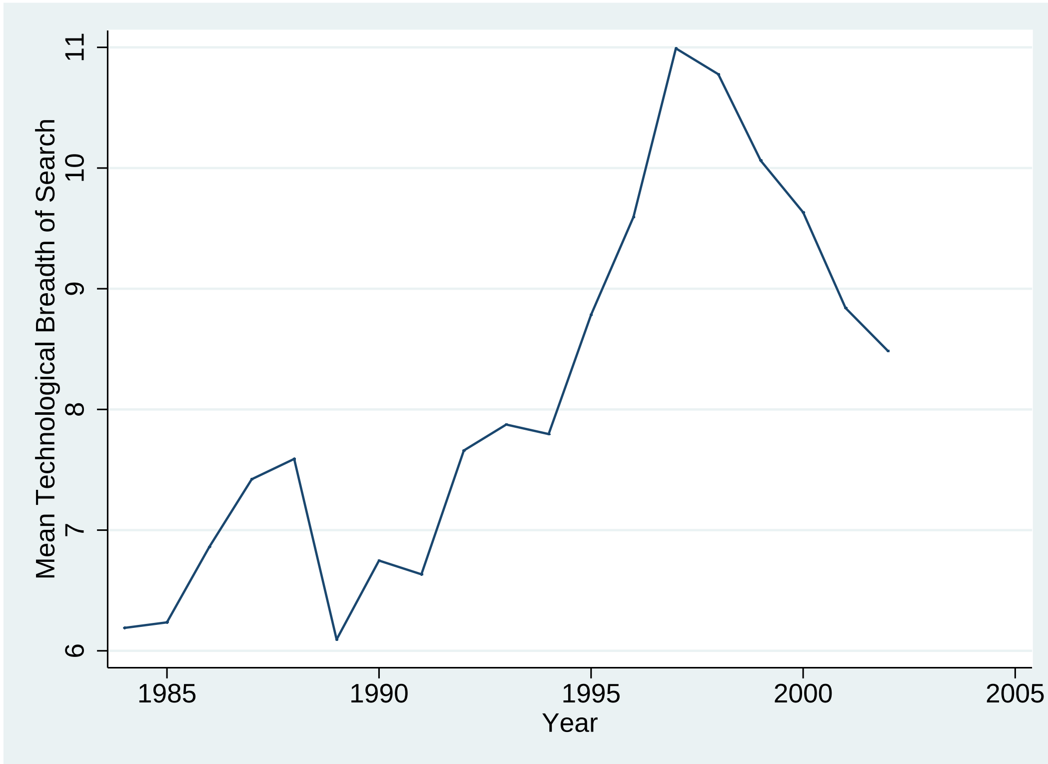

Figure 5.1: Time Trend of Technological Breadth of Search

5.2.1.1 Technological Breadth of Search

Figure 5.1 shows how the mean of the technological breadth of search varies with the year of observation. The mean technological breadth of search increases and decreases from year to year. In the late 1980's - from 1984 to 1989 - the technological breadth rises and falls and then rises at an increasing rate till 1998. After 1998, the technological breadth of search falls yet again.

Although a bit difficult to spot due to the rise and falls in the breadth of search, the overall trend is positive. It implies that on an average, researchers are expanding the technological breadth of their search, i.e. they are venturing into a greater number of technological domains. This increasing trend may be indicative of many external factors. Regardless, the influence of time of observation on the technological breadth of search does indicate the need to include year dummies in the statistical models.

5.2.1.2 Organizational Breadth of Search

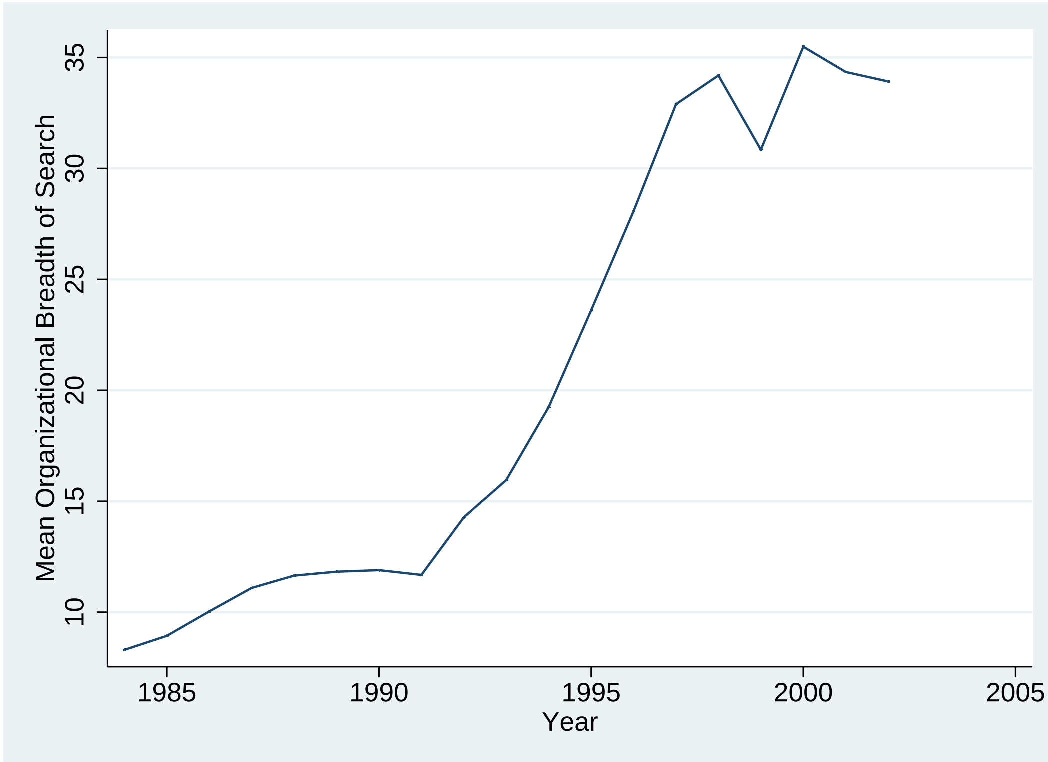

Figure 5.2: Time Trend of Organizational Breadth of Search

Figure 5.2 shows how a researcher's expansion beyond her organizational boundary in search of technological ideas varies with the year of observation. Although this organizational breadth of technological search also rises and falls with time like the technological breadth of search, the trend is quite unmistakably positive. It is clear from the graph that on an average, researchers are increasing their search for technological ideas beyond their own organization.

This increasing trend of crossing the organizational boundary for technological ideas may be due to many factors. For instance the trend may be due to expansion in the pool of external technological knowledge, i.e. the overall technological knowledge residing in external firms. This in turn may be due to the entry of many entrants in the industry with the passage of time. This trend and the above example clearly point toward the inclusion of year dummies in the regression equations as well as the need to control for the technological richness of the focal researcher's technological domain.

5.2.1.3 Job Growth

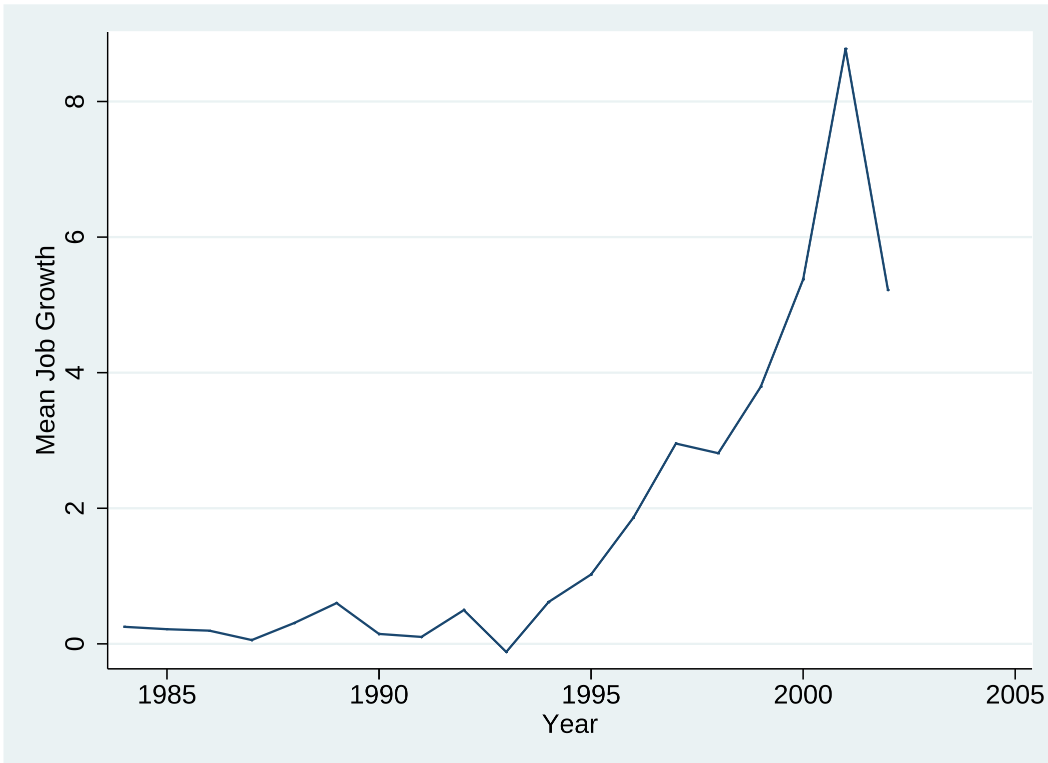

Figure 5.3: Time Trend of Job Growth

Figure 5.3 shows how the mean growth in job opportunities in a researcher's technological domain varies with the year of observation. The graph shows that the growth in job opportunities varies significantly in time. In the 1980's till early 1990's, the average job growth was close to zero and even negative at some points during this time period. In the mid to late 1990s the mean job growth picks up significantly before falling again in early 2000's.

This graph plots the mean of job growth across all technological domains. As a result it hides the differences in job growth across different domains. Some technological domains may decline while others may experience growth, a possibility especially probable in high-tech industries such as the electronics industry. Nevertheless, the trend of the mean job growth closely matches the recessions and expansions in the industry which is expected and reassuring. This dependence of job growth on the year of observation with the influence of time on the dependent variables discussed earlier further reinforces the need to include year dummies in the statistical models.

5.2.2 Summary Statistics

Table 5.1 reports the summary statistics and the correlations between the variables used in the study. The mean of the technological breadth of search is 9.13 while its standard deviation is 13.5. The mean of the organizational breadth of search is 30.6 with a standard deviation of 56.2. The mean of the main independent variable, job growth is 4.213 and the standard deviation is 7.057.

These values indicate that means of the main variables in the study are much lower than the variances. This pattern is also followed by the moderator variables in the study as well. This finding that for most variables, the mean is lower than the variance has implications for the choice of the statistical models. Since the dependent variables are count variables, the poisson and the negative binomial are the two natural choices for the model. The poisson model assumes the mean to be equal to the variance whereas the negative binomial model accounts for the greater variance by incorporating an overdispersion parameter, α, in the model. The test for significance of α is the test for overdispersion. Testing for overdispersion in this study also shows that there is overdispersion in the data. Hence, I employ the negative binomial model in the study.

5.3. Technological Breadth of Search

In this section, I describe the findings from running the regression models on the first dependent variable: the technological breadth of search. These results test hypotheses 1 - 5. I report the results of testing all the hypothesis 1 - 5. Then, I

Table 5.1: Summary Statistics

	Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
Tech Breadth	9.687	13.546	0.000	329.000	1.000																			
Org Breadth	30.652	56.241	0.000	1319.000	0.653	1.000																		
JobGrowth	4.213	7.057	-23.265	120.559	0.279	0.500	1.000																	
IndivSpecialization	0.101	0.111	0.003	1.000	-0.163	-0.170	-0.299	1.000																
IndivPosition	0.482	0.386	0.000	1.678	0.042	0.050	0.143	-0.215	1.000															
FirmAvgSpec	0.142	0.033	0.041	0.360	-0.175	-0.224	-0.321	0.191	0.021	1.000														
FirmTechProminence	0.276	0.206	0.001	1.000	-0.066	-0.044	-0.229	0.188	0.075	0.139	1.000													
Technological Richness	667.361	1001.660	2.000	13469.000	0.311	0.474	0.765	-0.338	0.161	-0.417	-0.227	1.000												
nPatents by Inventor	3.717	5.718	1.000	192.000	0.797	0.845	0.464	-0.189	0.057	-0.203	-0.065	0.452	1.000											
nClasses by Inventor	15.478	22.201	1.000	546.000	0.882	0.813	0.483	-0.234	0.067	-0.246	-0.078	0.518	0.924	1.000										
nCites by Inventor	37.000	69.332	0.000	1670.000	0.629	0.992	0.508	-0.168	0.047	-0.233	-0.032	0.490	0.836	0.801	1.000									
Age of Inventor	6.094	5.140	0.000	27.000	0.009	0.072	0.129	-0.143	0.002	0.033	0.015	0.138	0.049	0.053	0.075	1.000								
Firm's Thrust	0.001	0.023	-0.407	0.338	0.074	0.028	0.006	-0.008	-0.014	-0.003	0.021	0.014	0.065	0.069	0.026	-0.052	1.000							
Total no. Inventors	685.509	484.998	3.000	1679.000	-0.011	-0.029	0.011	0.006	0.908	-0.022	0.115	0.034	-0.037	-0.025	-0.031	-0.077	-0.016	1.000						
Firm's TechSpecial	0.003	0.005	0.000	0.071	-0.086	0.004	-0.014	0.074	-0.365	0.229	-0.094	-0.056	-0.017	-0.073	0.013	0.028	0.029	-0.411	1.000					
Liquidity Ratio	2.603	1.314	1.219	36.188	-0.077	0.057	0.091	0.005	-0.118	0.026	-0.207	0.098	-0.012	-0.038	0.061	0.033	-0.027	-0.123	0.386	1.000				
Profitability	0.083	0.126	-1.971	0.304	-0.022	-0.035	-0.047	0.070	0.295	0.172	0.082	-0.133	-0.033	-0.043	-0.037	-0.088	-0.004	0.321	0.001	-0.093	1.000			
R&D expense	1114.643	1189.244	1.774	4006.000	-0.068	-0.101	-0.034	0.033	0.872	0.149	0.071	-0.038	-0.099	-0.100	-0.107	-0.046	-0.018	0.943	-0.294	-0.074	0.307	1.000		
logSales	8.509	1.296	3.292	10.426	-0.023	-0.063	-0.047	0.017	0.801	0.038	0.274	-0.028	-0.060	-0.042	-0.062	-0.031	-0.007	0.882	-0.559	-0.309	0.375	0.804	1.000	
Foreign	0.975	0.155	0.000	1.000	0.046	0.017	0.042	-0.022	0.185	-0.093	0.054	0.055	0.020	0.038	0.019	-0.003	-0.065	0.209	-0.450	-0.351	0.036	0.142	0.327	1.000
Stock Option Per Employee	39292.370	77359.020	180.956	3.00e+06	-0.041	0.028	0.107	-0.018	-0.020	-0.005	-0.155	0.086	0.000	-0.022	0.028	0.000	-0.078	-0.028	0.215	0.463	-0.230	0.052	-0.157	-0.136

report and discuss the results of the many robustness tests that I conduct. Finally, I summarize and discuss the results.

As I discussed in the previous chapter, I utilize the longitudinal nature of the data to account for the unobserved heterogeneity of the firm, researcher pairs. This can be done by incorporating fixed effects or random effects in the model. While the fixed effects model is always consistent, the random effects model is only consistent when the unobserved heterogeneity is not correlated with the explanatory variables. The random effects model is however more efficient. I conduct hausman tests to test for the need to incorporate fixed effects into the model. The hausman tests indicates that the fixed effects model is more appropriate for this data. Further, the discussion in the subsection 5.2.2 shows that negative binomial is the appropriate choice. Hence I report the results of running the fixed effects negative binomial model below.

Table 5.2 reports the results of running the negative binomial fixed effects model. Model 1 includes only the main independent variable. In models 2 - 6, I introduce the moderators one at a time and model 7 reports the results of the complete model.

5.3.1 Results for Hypothesis 1

Hypothesis 1 pertains to the main effect of job growth on a researcher's proclivity to search in new technological domains. It predicts that as the external job opportunities for a researcher increase, she is less likely to expand her search into new technological domains. In other words, it predicts the coefficient of the $JobGrowth$ variable to be negative.

From the complete model (model(7)) of the table 5.2 we can see that the coefficient on the $JobGrowth$ variable is negative and significant providing support for the hypothesis. The coefficient is negative and significant for four out of the other 6 models. In model(2) and model(3), the coefficient retains is sign but loses significance. Overall the results suggest that as the job market improves, researchers reduce the number of new technological domains that they expand into. In other words, their

Table 5.2: Technological Breadth: Negative Binomial Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
JobGrowth	-0.01***	-0.00	-0.00	-0.01***	-0.01***	-0.01***	-0.01*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
JobGrowth X IndivSpec		0.07+	0.07+				0.18***
		(0.04)	(0.04)				(0.04)
JobGrowth X IndivSpecSq			0.02				-0.19
			(0.20)				(0.20)
JobGrowth X IndivPosition				0.01+			0.02***
				(0.00)			(0.00)
JobGrowth X FirmAvgSpec					-0.11***		-0.31***
					(0.03)		(0.04)
JobGrowth X FirmTechProm						-0.04***	-0.09***
						(0.01)	(0.01)
IndivSpecialization	1.35***	1.55***	1.55***	1.31***	1.32***	1.37***	1.71***
	(0.12)	(0.16)	(0.17)	(0.12)	(0.12)	(0.12)	(0.17)
IndivSpecSq	-1.73***	-1.71***	-1.65*	-1.69***	-1.68***	-1.76***	-2.06**
	(0.21)	(0.21)	(0.64)	(0.21)	(0.21)	(0.21)	(0.66)
IndivPosition	-0.27***	-0.28***	-0.28***	-0.29***	-0.24***	-0.26***	-0.25***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
FirmAvgSpec	1.87***	1.92***	1.92***	1.85***	1.76***	1.85***	1.63***
	(0.38)	(0.38)	(0.38)	(0.38)	(0.38)	(0.38)	(0.38)
FirmTechProminence	-0.07	-0.06	-0.06	-0.07	-0.09	-0.15*	-0.27***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Technological Richness	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
nPatents by Inventor	-0.06***	-0.06***	-0.06***	-0.06***	-0.06***	-0.07***	-0.06***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
nClasses by Inventor	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***	0.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age of Inventor	-0.01+	-0.01+	-0.01+	-0.01+	-0.01+	-0.01+	-0.01+
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm's Thrust	1.09***	1.10***	1.10***	1.10***	1.15***	1.09***	1.29***
	(0.27)	(0.27)	(0.27)	(0.27)	(0.27)	(0.27)	(0.27)
Total no. Inventors	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm's TechSpecial	-4.15	-4.51	-4.50	-3.94	-4.86	-3.47	-5.07
	(3.55)	(3.56)	(3.56)	(3.54)	(3.56)	(3.55)	(3.57)
Liquidity Ratio	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Profitability	0.10	0.10	0.10	0.11	0.11	0.06	0.05
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
R&D expense	-0.00**	-0.00**	-0.00**	-0.00***	-0.00**	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
logSales	0.07**	0.07**	0.07**	0.08***	0.07**	0.08***	0.08***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Foreign	0.21***	0.20***	0.20***	0.21***	0.21***	0.20***	0.18**
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Stock Option Per Employee	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.21	0.23	0.23	0.17	0.27	0.14	0.20
	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.20)
Observations	17763	17763	17763	17763	17763	17763	17763

Standard errors in parentheses; All models include (firm, inventor) fixed effects and year dummies

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Two-tailed tests expansion into new technological domains is reduced as the opportunities in their technological domain increase. Hypothesis 1 is, therefore, supported.

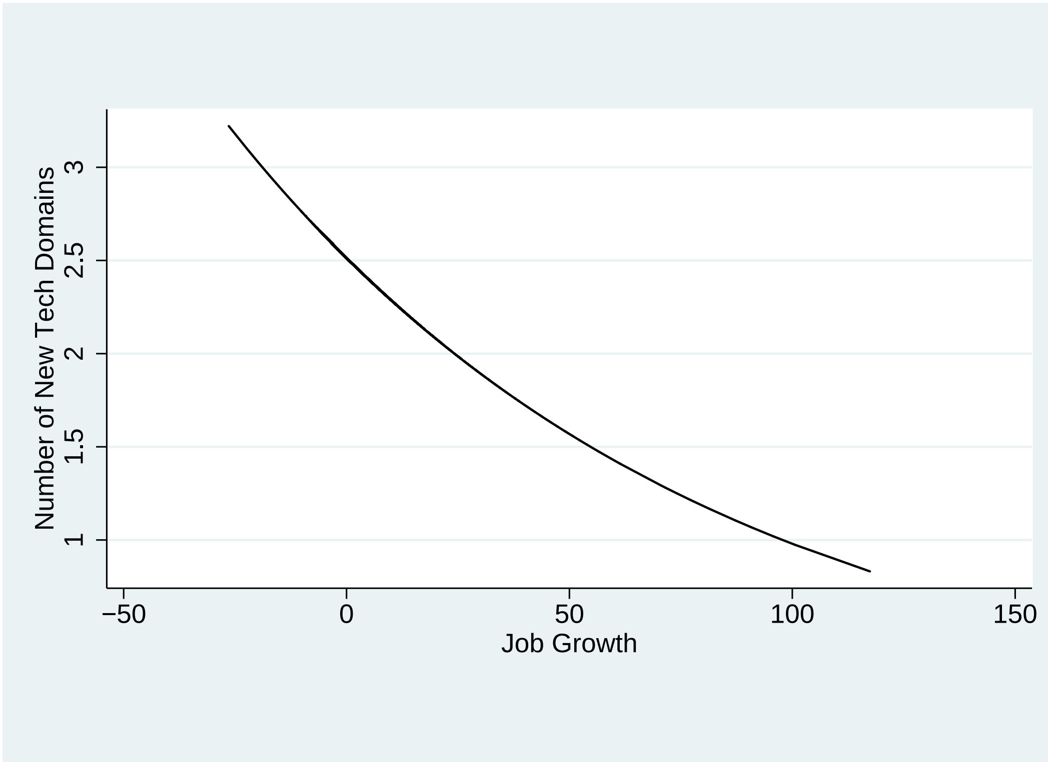

Figure 5.4: Technological Breadth vs. Job Growth

To better understand the results, I plot the predicted expansion into new technological domains against the job growth variable keeping all other covariates at their means. The graph is shown in the Figure 5.4. The solid line plots the relationship between the growth in job opportunities of a researcher and the technological breadth of her search. The downward sloping line clearly shows that as the growth in job opportunities increases, the number of new technological domains entered into by the researchers decreases. This provides evidence for Hypothesis 1.

5.3.2 Results for Hypothesis 2

Hypothesis 2 analyzes the moderating impact of a researcher's level of specialization on the relationship between growth in job opportunities and her technological breadth of search. It predicts a complex curvilinear moderating effect. It predicts that the impact of job growth on a researcher's reduction in search in new technological domain is moderated by her level of specialization; the impact increases with specialization and then decreases. This hypothesis is tested by interacting the *JobGrowth* variable with individual level specialization variable, *IndivSpec* and with the square of the individual level of specialization, *IndivSpecSquared*. The hypothesis predicts that the coefficient of the interaction between *IndivSpec* and *JobGrowth* is negative and that of the interaction between *IndivSpecSquared* and *JobGrowth* is positive.

From the complete model (Model(7)) of table 5.2 we can see that the coefficient of interaction between *IndivSpec* and *JobGrowth* is positive and significant while the coefficient of the interaction between *IndivSpecSquared* variable and *JobGrowth* is not significant. Model(2) and Model(3) also show the same results. Overall hypothesis 2 is not supported by the results. There does not seem to be any curvilinear moderating effect of a researcher's specialization on the impact of job growth on her technological breadth of search. Moreover the positive and significant coefficient on the interaction between the *IndivSpec* variable and *JobGrowth* suggests that specialization increases researchers' expansion into new domains with the increase in job opportunities. I discuss the possible reasons for this intriguing finding below in the section 5.3.7.

5.3.3 Results for Hypothesis 3

Hypothesis 3 analyzes the moderating impact of a researcher's position inside the firm on the relationship between growth in job opportunities and her technological breadth of search. It predicts that the impact of job growth on a researcher's reduction in search in new technological domain is moderated by her position inside the firm; the impact decreases with higher standing inside the firm. The hypothesis predicts that the coefficient on the interaction between *IndivPosition* and *JobGrowth* is positive.

From the complete model (model(7)) of the table 5.2 we can see that the coefficient on the interaction between *IndivPosition* and *JobGrowth* variables is positive and significant providing support for the hypothesis. The same results are obtained in Model(4) as well. Overall the results suggest that as the researcher's standing within the firm improves her sensitivity to external labor market conditions reduce because the higher standing within the firm reduces her desire to move from the firm on one hand and increases her job security on the other. Hypothesis 3 is therefore supported by the results.

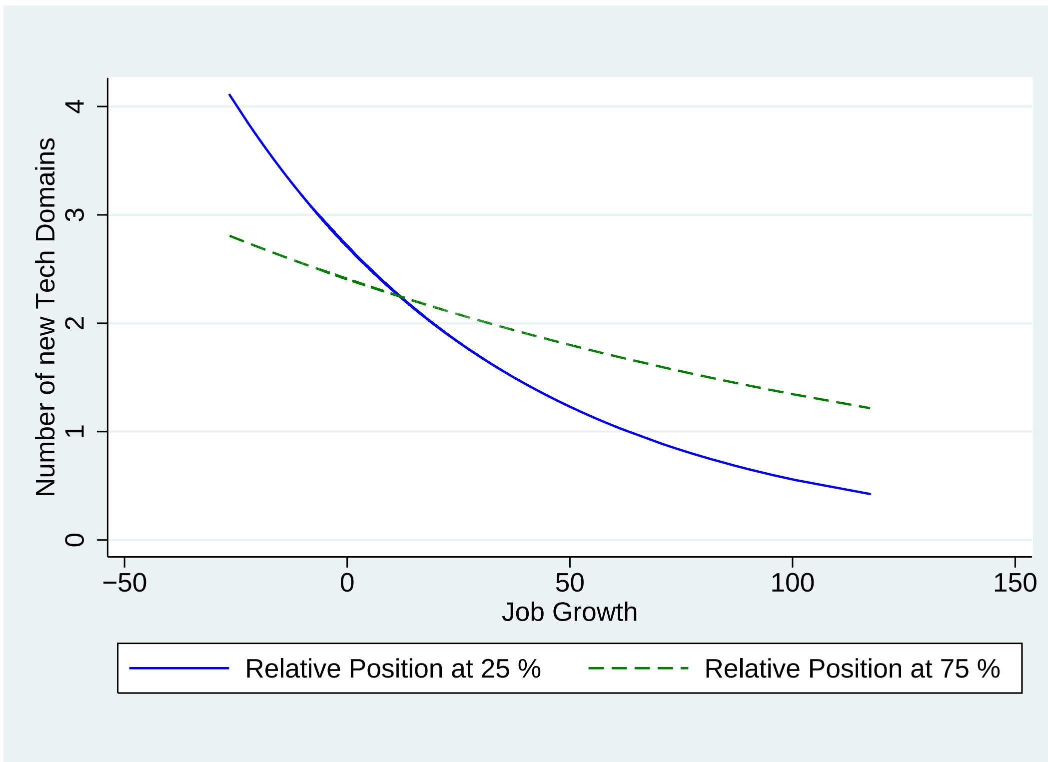

Figure 5.5: Technological Breadth: Moderating Influence of Researcher's Position

The impact of a researcher's relative position in the firm can be seen by plotting the predicted relationship between job growth and technological breadth for different values of researcher's relative position. In figure 5.5, I plot the impact of job growth on technological expansion for two different values of researcher's relative position. All other covariates are kept at their means. The solid line shows the relationship when the relative position is at 25^{th} percentile while the dashed line shows the relationship when the relative position is at the 75^{th} percentile. The slope of the 25^{th} percentile line is much steeper than that of the 75^{th} percentile line. This indicates that the reduction in technological expansion for a researcher at the 25^{th} percentile is much greater than the reduction for a researcher at the 75^{th} percentile for the same change in job growth. This shows that the impact of job growth is reduced as the relative position of the researcher improves.

5.3.4 Results for Hypothesis 4

Hypothesis 4 analyzes the moderating impact of the extent to which a researcher's firm consists of specialists on the relationship between growth in job opportunities and her technological breadth of search. It predicts that the impact of job growth on a researcher's reduction in search in new technological domain is moderated by the average level of specialization of the researchers within the firm; the impact increases with higher average levels of specialization of the researchers. The hypothesis predicts that the coefficient on the interaction between $FirmAvgSpec$ and $JobGrowth$ is negative.

From the complete model (model(7)) of the table 5.2 we can see that the coefficient on the interaction between $FirmAvgSpec$ and $JobGrowth$ variables is negative and significant providing support for the hypothesis. The same results are obtained in Model(5) as well. Overall the results suggest that researchers in firms characterized by higher individual level specialization are likely to pay greater attention and respond to labor market conditions. Hypothesis 4 is therefore supported by the results.

The impact of a firm's average specialization can be seen by plotting the predicted relationship between the growth in a researcher's technological domain and the technological breadth of her search for different values of average specialization of the employer firm's researchers. In figure 5.6, I plot the impact of job growth on technological expansion for two different values of average specialization. All other covariates are kept at their means. The solid line shows the relationship when the average specialization of the employer firm's researchers is at 25^{th} percentile while

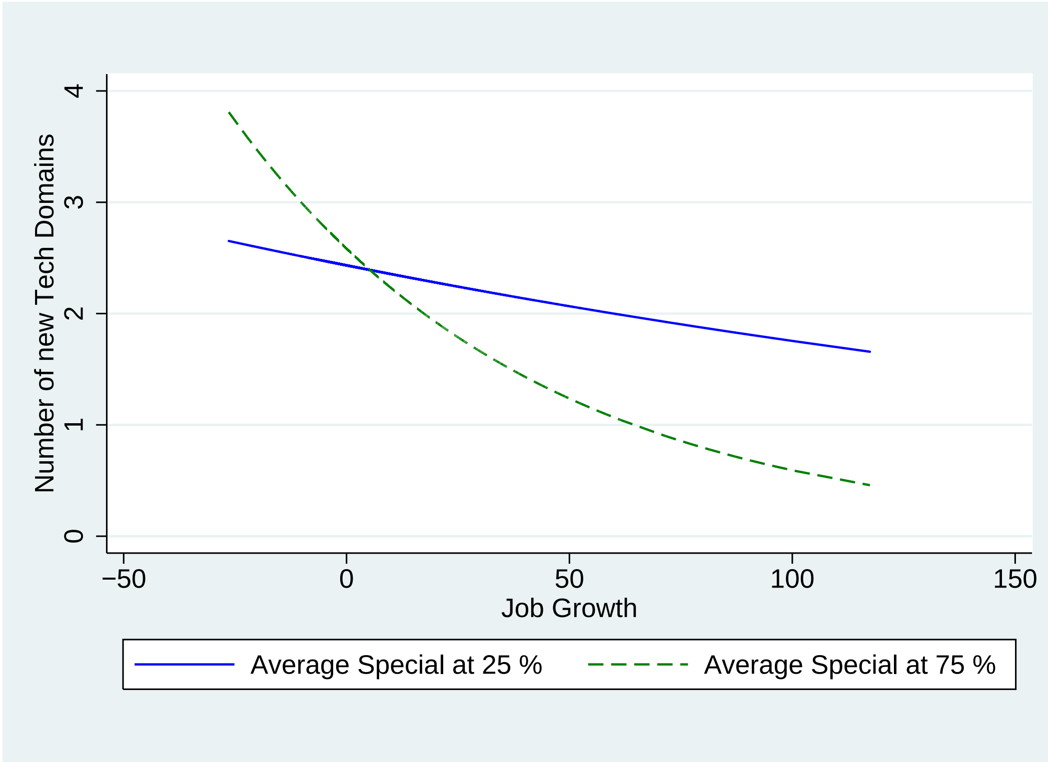

Figure 5.6: Technological Breadth: Moderating Influence of Average Specialization

the dashed line shows the relationship when the average specialization is at the 75^{th} percentile. The slope of the 75^{th} percentile line is much steeper than that of the 25^{th} percentile line indicating that the impact of job growth is higher at higher values of average specialization of the employer firm's researchers.

5.3.5 Results for Hypothesis 5

Hypothesis 5 analyzes the moderating impact of the technological prominence of a researcher's firm in the researcher's domain on the relationship between growth in job opportunities and her technological breadth of search. It predicts that the impact of job growth on a researcher's reduction in search in new technological domain is moderated by the technological prominence of her employer firm in her domain; as the prominence of the firm increases the impact of job growth decreases. The hypothesis predicts that the coefficient on the interaction between $FirmTechProm$ and $JobGrowth$ is positive.

From the complete model (model(7)) of the table 5.2 we can see that the coefficient on the interaction between $FirmTechProm$ and $JobGrowth$ variables is negative and significant. The same results are obtained in Model(6) as well. Overall the results do not support Hypothesis 5. The negative and significant coefficient on the interaction between the $FirmTechProm$ variable and $JobGrowth$ suggests that as labor markets improve, researchers from firms that are prominent in researchers' technological domains expand into new technological domains to a lesser extent than the researchers of less prominent firms. I discuss the possible reasons for this intriguing and anomalous finding below in the section 5.3.7.

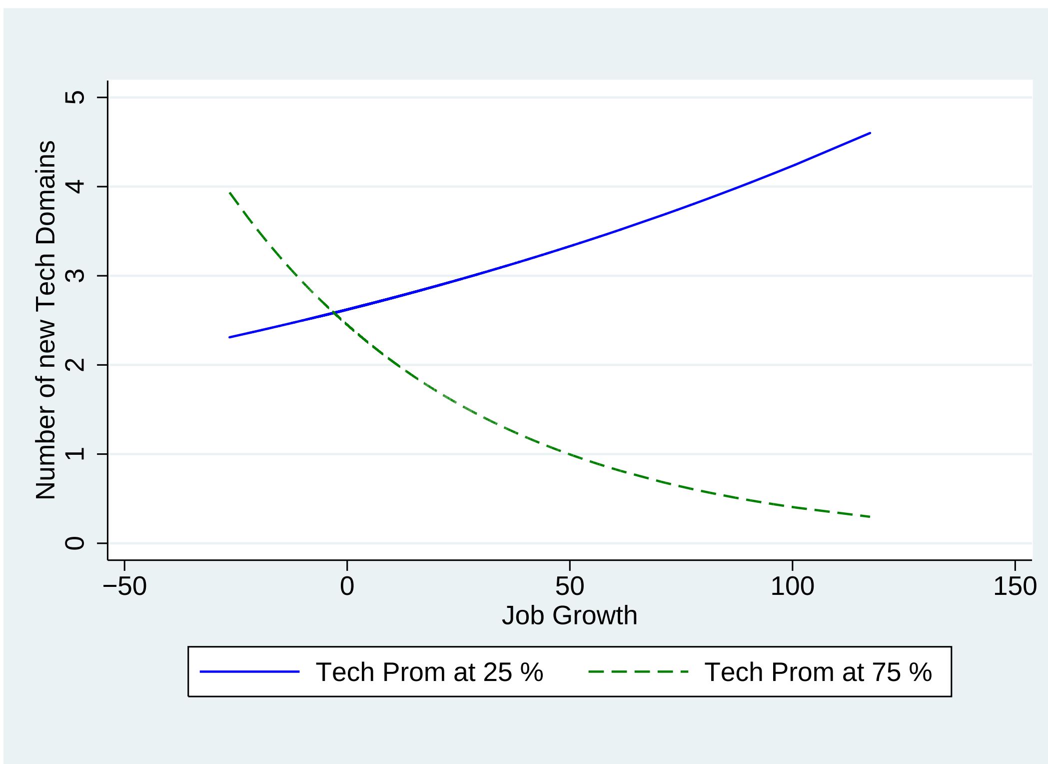

Figure 5.7: Technological Breadth: Moderating Influence of Firm's Technological Prominence

The impact of a firm's technological prominence in a researcher's domain can be visualized by plotting the predicted relationship between job growth and technological breadth for different values of average specialization of a firm's researchers. In figure 5.7, I plot the impact of job growth on technological expansion for two different values of the firm's technological prominence. All other covariates are kept at their means. The solid line shows the relationship when the relative position is at 25^{th} percentile while the dashed line shows the relationship when the relative position is at the 75^{th} percentile. The slope of the 75^{th} percentile line is much more negative than that of the 25^{th} percentile line (which has a positive slope). This indicates that researchers at more prominent firms are much more likely to stick to their current domains when there is growth in the domains. In other words it shows that the impact of job growth is higher at higher values of technological prominence. This result is contrary to the prediction.

5.3.6 Robustness Tests

I test the robustness of the results to alternate specifications. To test the robustness of the results to alternate specifications, I run the negative binomial random effects model and the poisson model on the data. Unfortunately, the fixed effects poisson model did not converge to any results. Consequently I report the results from running the poisson random effects model.

Table 5.3 reports the results obtained by running these alternate specifications on the technological breadth variable. The table reports the complete model for each of these specifications.

Model(1) of table 5.3 reports the results obtained by running the negative binomial random effects model. The results are substantively similar to running the fixed effects model. In this model the coefficient on the main $JobGrowth$ variable is negative and significant as expected. Hypothesis 1 is thus supported. The coefficient on the interaction between $JobGrowth$ and $IndivSpec$ is positive and significant while the coefficient on the interaction between $JobGrowth$ and $IndivSpecSquared$ is negative and significant. This is contrary to expectations from Hypothesis 2. The coefficient of interaction of $JobGrowth$ and $IndivPosition$ is positive and significant supporting Hypothesis 3 while the coefficient of interaction between $JobGrowth$ and

Table 5.3: Technological Breadth: Robustness Tests

	(1) Neg Bin: Random Effects	(2) Poisson: Random Effects
JobGrowth	-0.01*	-0.01**
	(0.00)	(0.00)
JobGrowth X IndivSpec	0.09**	0.14***
	(0.03)	(0.02)
JobGrowth X IndivSpecSq	-0.72***	-0.53***
	(0.14)	(0.09)
JobGrowth X IndivPosition	0.01***	0.02***
	(0.00)	(0.00)
JobGrowth X FirmAvgSpec	-0.26***	-0.28***
	(0.03)	(0.02)
JobGrowth X FirmTechProm	-0.08***	-0.10***
	(0.01)	(0.00)
IndivSpecialization	-0.42***	0.34***
	(0.11)	(0.08)
IndivSpecSq	-1.54***	-1.86***
	(0.46)	(0.29)
IndivPosition	-0.09*	-0.30***
	(0.04)	(0.03)
FirmAvgSpec	-0.59*	-0.26
	(0.24)	(0.17)
FirmTechProminence	-0.44***	-0.45***
	(0.04)	(0.03)
Technological Richness	-0.00***	-0.00***
	(0.00)	(0.00)
nPatents by Inventor	-0.08***	-0.05***
	(0.00)	(0.00)
nClasses by Inventor	0.04***	0.03***
	(0.00)	(0.00)
Age of Inventor	-0.00***	-0.00*
	(0.00)	(0.00)
Firm's Thrust	1.22***	0.43**
	(0.22)	(0.13)
Total no. Inventors	0.00***	0.00***
	(0.00)	(0.00)
Firm's TechSpecial	-6.12***	-6.45***
	(1.62)	(1.31)
Liquidity Ratio	-0.01*	-0.00
	(0.01)	(0.00)
Profitability	0.10+	0.10**
	(0.05)	(0.03)
R&D expense	-0.00***	-0.00***
	(0.00)	(0.00)
logSales	-0.00	-0.04***
	(0.01)	(0.01)
Foreign	0.04	0.13***
	(0.04)	(0.03)
Stock Option Per Employee	0.00	0.00
	(0.00)	(0.00)
Constant	0.66***	1.73***
	(0.11)	(0.08)
Observations	22455	22455

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Two-tailed tests

$FirmAvgSpec$ is negative supporting Hypothesis 4. Finally, the coefficient on the interaction between $JobGrowth$ and $FirmTechProm$ is negative and significant providing results contrary to expectations in Hypothesis 5. Overall Hypotheses 1, 3, and 4 are supported while Hypothesis 2 and 5 are not supported.

Model(2) of table 5.3 reports the results obtained by running the poisson model with random effects. The results are substantively similar to running the negative binomial random effects model. In this model too Hypotheses 1, 3, and 4 are supported while Hypothesis 2 and 5 are not supported.

5.3.7 Discussion of Results

The results broadly support the idea that the career concerns of researchers inside industrial firms triggered by the state of the external labor markets influence the researcher's expansion beyond their current technological domain. I find support for the prediction that greater the external job growth in a researcher's technological domain, the lesser the expansion of search beyond the domain. In addition, I also find support for the prediction that the impact of external labor market conditions on a researcher's expansion into new technological domains is reduced by the researcher's standing within the firm. Furthermore, I also find support for the moderating effect of a researcher's context of work particularly the average degree of specialization of her colleagues. I find that as the average level of specialization within the firm increases, researchers are more likely to react to changes in external labor market conditions.

External labor market opportunities in a technological domain may also be correlated with other factors such as the technological opportunities inherent in the domain (i.e. the technological richness of a domain), factors that can influence a firm's technology strategy and therefore the search behavior of its researchers(Rosenberg, 1974; Jaffe, 1986). Of course, these factors do not theoretically contradict the career-concern mechanism; both firm strategy and researchers' labor market concerns can operate simultaneously. However, the presence of these potentially correlated mechanisms do point toward the need to isolate the impact of career concerns triggered by labor markets. Empirically, I control for the technological richness of the domain as well as the firm's strategic thrust into these domains in my specifications. However, identifying the influence of the above moderating factors also allows me to theoretically isolate the influence of researchers' labor-market induced career concerns from alternate explanations.

The increased job security and attachment with the firm associated with a researcher's higher standing within the firm reduces her responsiveness to inducements offered by external labor markets. The reduced attachment to the firm associated with division of labor increases a researcher's responsiveness to the labor markets. These moderating effects impact a researcher's responsiveness to labor markets directly but are unlikely to influence a firm's incentives to respond to the changes in the technological landscape. For instance a firm that wants to deepen its capability in a growing domain is unlikely to direct its best researchers in the domain (those with the highest internal standing) to systematically move into new domains away from the growing one. Thus identifying these moderating effects help isolate the labor-market induced career concerns mechanism.

Two of the findings reported above are unexpected. First, I do not find support for the curvilinear prediction regarding specialization. The results suggest that specialization reduces the impact of growth in job opportunities; instead of specializing further in growing markets specialists expand into new technological domains when the labor market for them expands. Second, contrary to my expectation, I find that researchers of prominent firms are more likely to stick to their domains when the labor markets are good. Exploring these results further may point toward extending the theory I have developed in this study and also toward new directions of research.

In deriving the prediction for hypothesis 2, I had argued that specialization makes a researcher more vulnerable to the changes in the labor market conditions which make her more responsive to the labor market conditions. Consequently, a specialist researcher is even more likely to stick to her domain in growing labor markets. At very high levels of specialization researchers are likely to find it more difficult to change leading to the curvilinear prediction. The results suggest a more nuanced line of reasoning.

Specialization in general should increase the vulnerability of a researcher to changes in the technological landscape (Marx et al., 2009). A specialist researcher therefore would find it beneficial to add new capabilities in her repertoire and broaden her skill set especially in the high-tech context where the threat of obsolescence is high. A good labor market provides the specialist researcher enough bargaining power and risk-taking ability to do so. In other words while researchers in general might want to deepen skills in growing markets, specialists may use their increased bargaining power in good labor markets to diversify.

While predicting hypothesis 5, I had argued that the technological prominence of the firm in a researcher's domain provides an independent positive impact to her job prospects. This independent positive effect reduces a researcher's sensitivity to the labor market. The results could be pointing toward a more complex argument.

The above argument did not take into account the possibility that technological prominence of the employer firm in a researcher's technical domain may also amplify her incentives to not move into new domains in good labor markets. The technological prominence of the firm in her domain makes it easier for the researcher to be recognized and labeled as an expert in her domain by the market. Moving into different domains would dilute this label, a dilution that a researcher would seek to avoid when the label is especially valuable i.e. when the labor market for the domain is good.

5.4. Organizational Breadth of Search

In this section, I describe the findings from running the regression models on the second dependent variable: the organizational breadth of search. These results test hypotheses 6 - 10. I first report the results of testing all the hypothesis 6 - 10. Then, I report and discuss the results of the many robustness tests that I conduct. Finally, I summarize and discuss the results.

Just like for the specification for technological breadth of search I conduct hausman tests to test for the need to incorporate fixed effects into the model. The hausman test indicates that the fixed effects model is more appropriate for this specification. Further, the discussion in the subsection 5.2.2 shows that negative binomial is the appropriate choice. Hence I report the results of running the fixed effects negative binomial model below.

Table 5.4 reports the results of running the negative binomial fixed effects model. Model 1 includes only the main independent variable. In models 2 - 6, I introduce the moderators one at a time and model 7 reports the results of the complete model.

5.4.1 Results for Hypothesis 6

Hypothesis 6 pertains to the main effect of external job growth on a researcher's proclivity to search beyond the organizational boundary for ideas. It predicts that as the external job opportunities for a researcher increase, she explores the ideas from outside the firm boundaries to a greater extent. In other words, it predicts the coefficient of the *JobGrowth* variable to be positive.

From the complete model (model(7)) of the table 5.4 we can see that the coefficient on the *JobGrowth* variable is positive and significant providing support for the hypothesis. The coefficient is positive and significant for two out of the other 6 models. In model(5), the coefficient retains its sign but loses significance. However for two models, model(1) and model(6), the coefficient is negative and significant. Of course, model(1) and (6) are not complete models. Nevertheless the instability in signs suggest that multi-collinearity may be influencing the results. Although multi-

Table 5.4: Organizational Breadth: Negative Binomial Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
JobGrowth	-0.00***	0.01**	0.01**	-0.00	0.00	-0.01***	0.01+
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
JobGrowth X IndivSpec		0.14***	0.08*				0.06
		(0.03)	(0.04)				(0.04)
JobGrowth X IndivSpecSq			-0.42*				-0.26
			(0.19)				(0.19)
JobGrowth X IndivPosition				-0.00+			0.00
				(0.00)			(0.00)
JobGrowth X FirmAvgSpec					0.16***		0.08*
					(0.03)		(0.03)
JobGrowth X FirmTechProm						-0.05***	-0.04***
						(0.01)	(0.01)
IndivSpecialization	-0.26*	0.12	0.02	-0.22+	-0.22+	-0.24*	-0.04
	(0.12)	(0.14)	(0.15)	(0.12)	(0.12)	(0.12)	(0.15)
IndivSpecSq	0.26	0.32+	-1.01	0.23	0.21	0.24	-0.54
	(0.19)	(0.19)	(0.63)	(0.19)	(0.19)	(0.19)	(0.62)
IndivPosition	-0.01	-0.03	-0.03	0.00	-0.05	0.01	-0.03
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
FirmAvgSpec	0.34	0.42	0.43	0.35	0.45	0.32	0.43
	(0.33)	(0.33)	(0.33)	(0.33)	(0.34)	(0.33)	(0.34)
FirmTechProminence	-0.02	0.00	0.00	-0.02	0.00	-0.11*	-0.07
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
Technological Richness	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
nPatents by Inventor	0.00***	0.00***	0.00***	0.00***	0.00**	0.00**	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
nCites by Inventor	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age of Inventor	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00+	-0.00+
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm's Thrust	0.18	0.17	0.17	0.18	0.15	0.19	0.17
	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)
Total no. Inventors	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm's TechSpecial	5.89*	5.34*	5.43*	5.79*	6.87**	6.82**	6.87**
	(2.56)	(2.57)	(2.57)	(2.56)	(2.55)	(2.55)	(2.56)
Liquidity Ratio	0.02*	0.02*	0.02*	0.02*	0.02*	0.02*	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Profitability	-0.11	-0.11	-0.11	-0.12	-0.11	-0.14+	-0.13+
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
R&D expense	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
logSales	-0.02	-0.02	-0.02	-0.02	-0.01	-0.02	-0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Foreign	0.36***	0.35***	0.34***	0.36***	0.36***	0.35***	0.34***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Stock Option Per Employee	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.51**	0.56***	0.56***	0.55**	0.45**	0.49**	0.49**
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Observations	17818	17818	17818	17818	17818	17818	17818

Standard errors in parentheses

All models include (firm, inventor) fixed effects and year dummies

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Two-tailed tests collinearity does not bias the results (Kennedy, 2003), it reduces the confidence in the results. Overall the results provide mixed support for the prediction that researchers explore technological ideas from outside the firm to a greater extent when their labor market conditions are good.

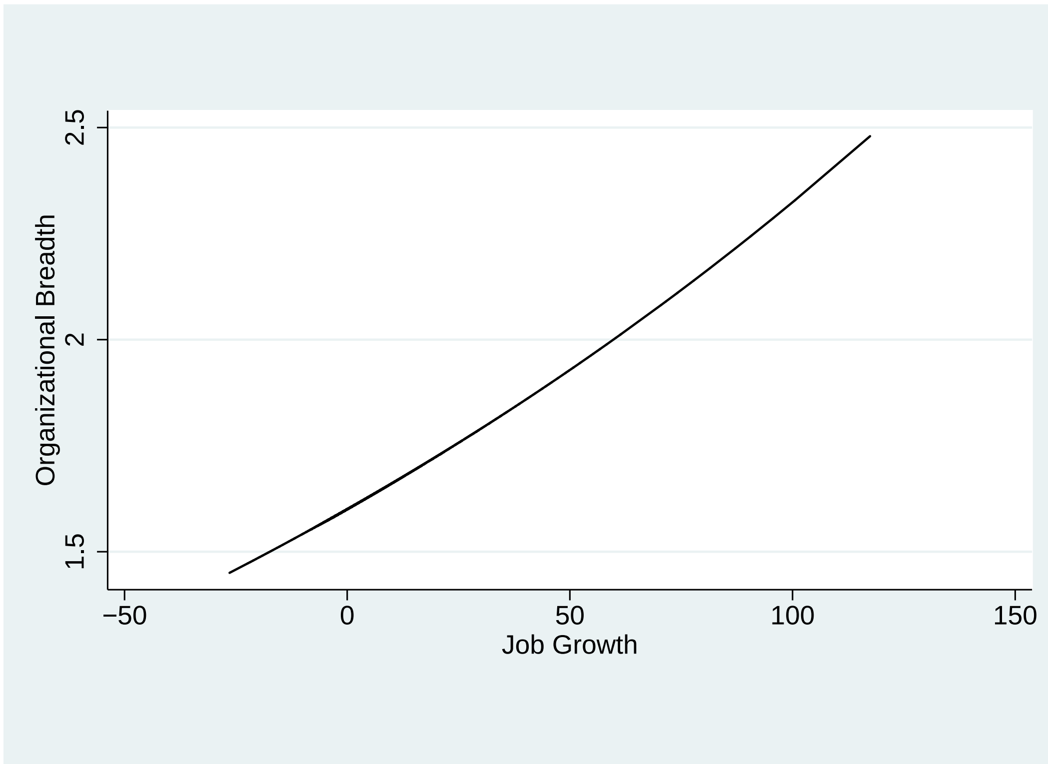

Figure 5.8: Organizational Breadth vs. Job Growth

To better understand the results, I plot the predicted organizational breadth of a researcher's technical search against the job growth variable keeping all other co-variates at their means. The graph is shown in the Figure 5.8. The solid line plots the relationship between the growth in job opportunities of a researcher and the organizational breadth of her search. The upward sloping line clearly shows that as the growth in job opportunities for a researcher increase the extent to which she draws on ideas from outside the firm increases.

5.4.2 Results for Hypothesis 7

Hypothesis 7 analyzes the moderating impact of a researcher's level of specialization on the relationship between growth in job opportunities and her organizational breadth of search. It predicts a complex curvilinear moderating effect. It predicts that the impact of job growth on a researcher's expansion of search beyond her firm is moderated by her level of specialization; the impact increases with specialization and then decreases. This hypothesis is tested by interacting the *JobGrowth* variable with individual level specialization variable, *IndivSpec* and with the square of the individual level of specialization, *IndivSpecSquared*. The hypothesis predicts that the coefficient of the interaction between *IndivSpec* and *JobGrowth* is positive and that of the interaction between *IndivSpecSquared* and *JobGrowth* is negative.

From the complete model (Model(7)) of table 5.4 we can see that the coefficient of interaction between *IndivSpec* and *JobGrowth* is positive but not significant while the coefficient of the interaction between *IndivSpecSquared* variable and *JobGrowth* is negative and not significant. Model(2) and Model(3) also show the same pattern, the coefficients have the same signs but now also have significance. Overall hypothesis 7 is not supported by the results since the complete model does not support it. There does not seem to be any curvilinear moderating effect of a researcher's specialization on the impact of job growth on her organizational breadth of search in the main model. In the incomplete models however the coefficients are significant and in the predicted direction.

5.4.3 Results for Hypothesis 8

Hypothesis 8 analyzes the moderating impact of a researcher's position inside the firm on the relationship between growth in job opportunities and her organizational breadth of search. It predicts that the impact of job growth on a researcher's expansion of search beyond her firm is moderated by her position inside the firm; the impact decreases with higher standing inside the firm. The hypothesis predicts that the coefficient on the interaction between *IndivPosition* and *JobGrowth* is negative.

From the complete model (model(7)) of the table 5.4 we can see that the coefficient on the interaction between *IndivPosition* and *JobGrowth* variables is negative but not significant. In Model(4) the coefficient is negative and significant. These results do not provide support for the hypothesis 8.

5.4.4 Results for Hypothesis 9

Hypothesis 9 analyzes the moderating impact of the extent to which a researcher's firm consists of specialists on the relationship between growth in job opportunities and her organizational breadth of search. It predicts that the impact of job growth on a researcher's expansion of search beyond her firm is moderated by the average level of specialization of the researchers within the firm; the impact increases with higher average levels of specialization of the researchers. The hypothesis predicts that the coefficient on the interaction between *FirmAvgSpec* and *JobGrowth* is positive.

From the complete model (model(7)) of the table 5.4 we can see that the coefficient on the interaction between *FirmAvgSpec* and *JobGrowth* variables is positive and significant providing support for the hypothesis. The same results are obtained in Model(5) as well. Overall the results suggest that researchers in firms characterized by higher individual level specialization are likely to pay greater attention and respond to labor market conditions. Hypothesis 9 is therefore supported by the results.

The impact of a firm's average specialization can be seen by plotting the predicted relationship between the growth in job opportunities for a researcher and the organizational breadth of her technical search for different values of average specialization of the employer firm's researchers. In figure 5.9, I plot the impact of job growth on organizational breadth for two different values of average specialization. All other covariates are kept at their means. The solid line shows the relationship when the average specialization of the employer firm's researchers is at 25^{th} percentile while the dashed line shows the relationship when the average specialization is at the 75^{th} percentile. The slope of the 75^{th} percentile line is much steeper than that of the 25^{th}

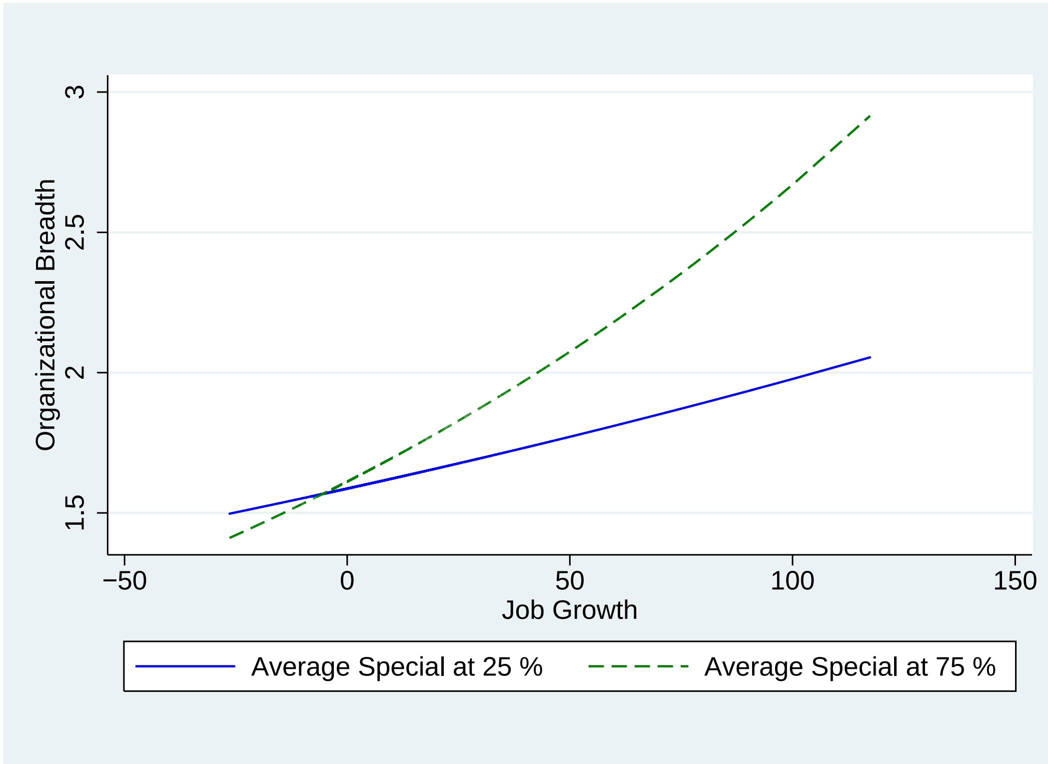

Figure 5.9: Organizational Breadth: Moderating Influence of Average Specialization

percentile line indicating that the impact of job growth is higher at higher values of average specialization of the employer firm's researchers.

5.4.5 Results for Hypothesis 10

Hypothesis 10 analyzes the moderating impact of the technological prominence of a researcher's firm in the researcher's domain on the relationship between growth in job opportunities and her organizational breadth of search. It predicts that the impact of job growth on a researcher's expansion of search beyond her firm is moderated by the technological prominence of her employer firm in her domain; as the prominence of the firm increases the impact of job growth decreases. The hypothesis predicts that the coefficient on the interaction between $FirmTechProm$ and $JobGrowth$ is negative.

From the complete model (model(7)) of the table 5.4 we can see that the coefficient on the interaction between $FirmTechProm$ and $JobGrowth$ variables is negative and significant providing support for the hypothesis. The same results are obtained in Model(6) as well. Overall the results support Hypothesis 10. The negative and significant coefficient on the interaction between the $FirmTechProm$ variable and $JobGrowth$ suggests that as labor markets improve, researchers from firms that are prominent in researchers' technological domains expand beyond the firm to a lesser extent than the researchers of less prominent firms.

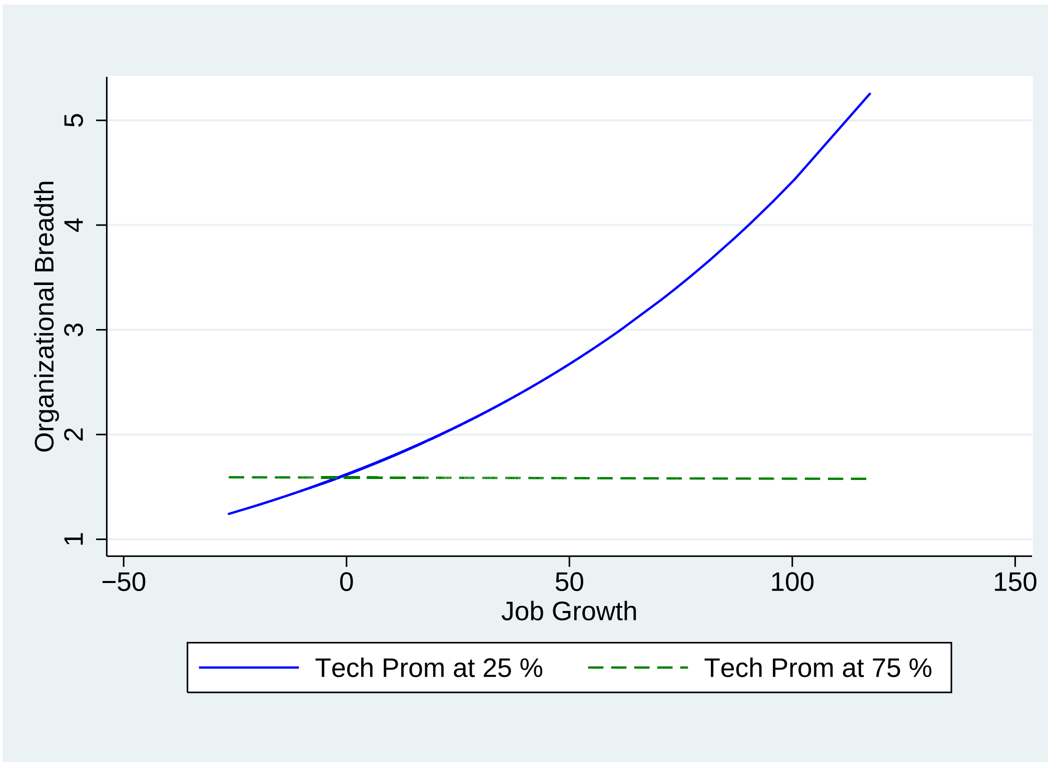

Figure 5.10: Organizational Breadth: Moderating Influence of Firm's Technological Prominence

The impact of a firm's technological prominence in a researcher's domain can be seen by plotting the predicted relationship between the growth in job opportunities for a researcher and the organizational breadth of her technical search for different values of technological prominence of the employer firm. In figure 5.10, I plot the impact of job growth on organizational breadth for two different values of technological prominence. All other covariates are kept at their means. The solid line shows the relationship when the technological prominence of the employer firm is at 25^{th}

percentile while the dashed line shows the relationship when the technological prominence is at the 75^{th} percentile. The slope of the 25^{th} percentile line is much steeper than that of the 75^{th} percentile line indicating that the impact of job growth is lower at higher values of technological prominence of the employer firm.

5.4.6 Robustness Tests

Just like for technological breadth of search, I test the robustness of the results to alternate specifications by running the negative binomial random effects model and the poisson model on the data. Unfortunately, the fixed effects poisson model did not converge to any results. Consequently I report the results from running the poisson random effects model.

Table 5.5 reports the results obtained by running these alternate specifications on the organizational breadth variable. The table reports the complete model for each of these specifications.

Model(1) of table 5.5 reports the results obtained by running the negative binomial random effects model. The results are substantively similar to running the fixed effects model. In this model too Hypotheses 6, 9, and 10 are supported while Hypothesis 7 is not. The results differ from the negative binomial fixed effects model in that in this model I find support for Hypothesis 8 as well. The coefficient on the interaction between $JobGrowth$ and $IndivPosition$ is negative and significant. This provides support for the idea that a higher internal standing within the firm reduces the impact of job growth on a researcher's organizational breadth of search.

Model(2) of table 5.5 reports the results obtained by running the poisson model with random effects. The results are substantively similar to running the negative binomial fixed effects model. In this model too Hypotheses 6, 9, and 10 are supported. The results differ from the negative binomial fixed effects model in that in this model I find support for Hypothesis 7 and 8 as well. The coefficient on interaction between $JobGrowth$ and $IndivSpec$ is positive and significant while the

Table 5.5: Organizational Breadth: Robustness Tests

	(1) Neg Bin: Random Effects	(2) Poisson: Random Effects
JobGrowth	0.01**	0.01***
	(0.00)	(0.00)
JobGrowth X IndivSpec	-0.01	0.05***
	(0.03)	(0.01)
JobGrowth X IndivSpecSq	-0.36**	-0.21***
	(0.12)	(0.06)
JobGrowth X IndivPosition	-0.01**	-0.00***
	(0.00)	(0.00)
JobGrowth X FirmAvgSpec	0.15***	0.07***
	(0.03)	(0.01)
JobGrowth X FirmTechProm	-0.03***	-0.01*
	(0.01)	(0.00)
IndivSpecialization	-1.06***	-0.54***
	(0.10)	(0.05)
IndivSpecSq	0.20	0.21
	(0.39)	(0.21)
IndivPosition	0.29***	0.17***
	(0.04)	(0.02)
FirmAvgSpec	-0.87***	0.01
	(0.22)	(0.11)
FirmTechProminence	-0.02	-0.01
	(0.04)	(0.02)
Technological Richness	-0.00***	-0.00***
	(0.00)	(0.00)
nPatents by Inventor	0.00	0.01***
	(0.00)	(0.00)
nCites by Inventor	0.00***	0.00***
	(0.00)	(0.00)
Age of Inventor	-0.00	0.00**
	(0.00)	(0.00)
Firm's Thrust	-0.01	0.21***
	(0.19)	(0.06)
Total no. Inventors	0.00***	0.00***
	(0.00)	(0.00)
Firm's TechSpecial	10.43***	3.26***
	(1.36)	(0.86)
Liquidity Ratio	-0.01	0.00
	(0.00)	(0.00)
Profitability	0.07	-0.02
	(0.05)	(0.02)
R&D expense	-0.00***	-0.00***
	(0.00)	(0.00)
logSales	-0.12***	-0.04***
	(0.01)	(0.01)
Foreign	0.22***	0.34***
	(0.04)	(0.02)
Stock Option Per Employee	0.00**	0.00**
	(0.00)	(0.00)
Constant	1.19***	2.67***
	(0.10)	(0.06)
Observations	22455	22455

Standard errors in parentheses

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Two-tailed tests coefficient on the interaction between $JobGrowth$ and $IndivSpecSquared$ is negative and significant. This provides support for the prediction that as the specialization of a researcher increases, she is more sensitive to the labor markets and thus increases her organizational breadth of search when the external job market conditions are good. But this impact is reversed with too much specialization. The coefficient on the interaction between $JobGrowth$ and $IndivPosition$ is negative and significant. This provides support for the idea that a higher internal standing within the firm reduces the impact of job growth on a researcher's organizational breadth of search.

5.4.7 Discussion of Results

I find mixed support for the main prediction that as the external job opportunities for a researcher increase, she explores the ideas from outside the firm boundaries to a greater extent. While the coefficient of $JobGrowth$ in complete model of the negative binomial fixed effects regression is positive and significant, the result is not stable across all models reducing the confidence in the main result. Although the complete models of other specifications also show evidence for the main hypothesis, gathering more fine grained data in future work and reexamining this question in greater detail will certainly help instill greater confidence in this conclusion.

The results across specifications show stable and strong support for Hypotheses 9 and 10. The results suggest that researchers in firms characterized by higher individual level specialization are likely to pay greater attention and respond to labor market conditions. Furthermore as the labor market in a technological domain improves, researchers of that domain who are from firms that are prominent in the domain expand beyond the firm to a lesser extent than the researchers of less prominent firms.

The findings do not support in general the prediction pertaining to the curvilinear moderating impact of individual level specialization. This when coupled with the intriguing finding regarding individual level specialization for the technological breadth of search suggests an important line of future investigation.

5.5. Summary and Limitations

The statistical tests provide good evidence for the idea that researchers within firms are influenced by their career concerns in making technological decisions. Specifically the tests show that fluctuations in a researcher's external labor market opportunities impact the kind of research projects she undertakes.

The tests support the idea that researchers deepen their skills in their technological domains if the job opportunities in the domain are good and expand into new domains when the labor market conditions deteriorate. The study shows that this impact of labor markets is reduced by a researcher's internal standing and amplified by the average specialization of her colleagues in the firm. Intriguingly, the tests show that the impact of labor markets on the technological breadth of search is amplified by the technological prominence of the firm in the researcher's domain.

The results provide mixed support for the prediction that researchers expand their technological search beyond the organizational boundaries when the external job market conditions are good. This impact of the labor markets is increased by the average level of specialization in the firm and reduced by the technological prominence of the firm. The internal standing of a researcher inside the firm was found to reduce the impact of labor market conditions on the organizational breadth of search only in few models.

The results do not support the curvilinear moderating impact of individual level specialization on the relationship between external labor market conditions and the technological decisions of researchers. This finding points toward the need to investigate the impact of specialization more deeply possibly through more fine grained data and interviews.

This study utilizes patent data to trace the technological search behavior of researchers inside firms of a single industry. Although this allows me to control for many unobserved factors that may influence the search process, it also limits the study in certain ways. While patent data allow a scholar to trace the innovative behavior over time in a large sample, it does not cover all the innovative activity. Many inventions are not covered by patents. The choice of electronics industry as a setting limits this problem to an extent because protecting intellectual property through patents is important in this industry. Of course the problem is not completely eliminated though.

Another limitation follows from utilizing the patent data to trace the technological search behavior of the researchers. The technological and organizational breadth of a researcher's search can be observed only in the years that the researcher has filed for a patent since the variables are constructed based on the patents filed by the researcher that year. This implies that the search behavior of the inventors which are not filed as patents is not observed and is not analyzed. This behavior can be observed through field studies or through survey data. However this concern is limited in the electronics industry to the extent that patenting is important to firms in this industry.

Another problem with patent data is that the proclivity to patent differs across industries and thus the observed pattern may be influenced by industry specific idiosyncrasies. Limiting my study to one industry reduces this problem but can limit the generalizability of the findings. This study examines the incentives and concerns of industrial researchers and may not apply completely to researchers who are strongly linked with the academic research communities such as the researchers in pharmaceutical industries (Allen, 1988). However this may be less of a concern than it appears in view of recent research that shows that even academic scientists are influenced in their decisions by the institutional environment governing their careers(Gittelman, 2006).

Chapter 6

Conclusion

This study helps in providing a more complete explanation of technological search behavior in firms (Nelson and Winter, 1982; Rosenkopf and Nerkar, 2001; Nerkar, 2003; Katila, 2002) by bringing researchers to the forefront in the discussion. Earlier explanations (Cohen, 1995; Christensen and Bower, 1996; Schmookler, 1962; Ruttan, 1997) have focused on analyzing technological search behavior from the perspective of firm's top management, giving importance to factors such as competitive pressures and customer concerns. That this perspective is incomplete is suggested by three empirical findings: first, the bottom-up process of allocation of resources where projects are proposed by lower level employees and then "sold" to the top management (Burgelman, 1983b; Nayak and Ketteringham, 1997); second, the normative need for and the provision of autonomy for researchers in research labs (Bailyn, 1985; Burgelman, 1983a); third, the knowledge asymmetry associated with research – researchers are lot more capable of choosing appropriate technologies than top managers (Cohen and Sauermann, 2007). Instead of taking the perspective of top management, my study takes the perspective of researchers by examining how their career concerns triggered by fluctuations in external labor markets influence their technological search behavior. In doing so, this study fills an important lacuna in our understanding about a firm's technological search behavior.

By taking the perspective of the researchers, this study combines and contributes to two distinct strands of literature: the technological search literature (Cohen, 1995; Ahuja et al., 2008; Cohen and Levinthal, 1990; Rosenkopf and Nerkar, 2001; Nerkar and Paruchuri, 2005; Almeida and Kogut, 1999) and the career concerns literature (Holmstrom, 1999; Siemsen, 2008; Zwiebel, 1995). The technological search literature shows that the composition of the pool of technological ideas a researcher uses for inventing is a direct consequence of which information networks (Fleming et al., 2007b) she participates in and which technological developments she pays attention to (Cohen et al., 1972; March, 1981; Morgan, 1992). This literature, however, does not deeply examine why researchers prefer certain networks and certain technologies over others. The answer to this question can be obtained from the implications from the career concerns literature (Becker, 1962; Waldman and Gibbons, 2006), which indicates that concerns about future employability and career advancement can drive technology choices (Zwiebel, 1995; Siemsen, 2008) as well as network choices (Podolny and Baron, 1997; Seibert et al., 2001).

I analyze the technological search behavior of researchers from the electronics industry over a period ranging from 1992 – 2002. I find that when external job opportunities in a researcher's technological domains grow, she reduces her expansion into new technological domains. This impact of external job opportunities is reduced by her position inside the firm. On the other hand, degree of average specialization of researchers inside the firm amplify this effect. My analyses also broadly support the proposition that in good labor markets the researchers increase their attention on the technologies developed outside the firm[1]. This impact of labor markets on the organizational breadth of search is amplified by the extent of division of labor within the firm and reduced by the technical prominence of the firm.

These findings have important implications for our understanding of technological evolution and for technology management. The findings identify a new influence of

[1]This result is found in most of the statistical models but not all.

the external environment on the innovation process within firms: the influence of external labor markets. Identifying this influence would have been quite difficult by taking the perspective of only the top management of a firm.

These findings also suggest that the choice of technological domains is also driven by learning and skill acquisition that is provided by searching in those domains. When we take the top management's perspective, we focus on how the choice of technologies is driven by the costs of searching in a domain (the technological opportunity literature (Rosenberg, 1974; Jaffe, 1986)) or the profit potential inherent in a domain (Schmookler, 1962). This study, by focusing on researchers, shows that it is not only the technological richness and the profit potential that drive technological choice but also the learning provided by searching for innovations within a technological domain.

This study also implies that managers need to pay attention to the career concerns of researchers when they put in place strategies to manage the innovation process. For instance, the study shows that the strategies and structures such as extensive division of labor which firms employ for efficiency in the research process can also have unintended consequences of making the researchers more sensitive to inducements provided by the labor markets.

Scholars of innovation have held intense debates on the relative importance of demand-pull and technology-push on technological search. My study contributes to this debate through two ways. First, it points toward conditions under which demand may have greater or smaller influence on technological search. Researchers concentrate more on technologies while the marketing personnel more on the product markets. Therefore the extent to which demand influences technological search should depend on the extent to which researchers attend to, seek, and incorporate the information provided by the marketing personnel in the firm. The changes in the external job opportunities may be one factor that influences this behavior of researchers (Tushman, 1979b,a; Brown and Utterback, 1985). Since the decline in external opportunities motivate employees to increase their participation inside the firm (March and Simon, 1958), we can expect researchers to pay more attention to the information provided by the marketing personnel when the external job opportunities reduce. In this way, the impact of current demand on the nature of technological search may be conditioned by the state of the external labor market.

Second, this study introduces a different mechanism through which demand conditions of an industry influence the innovation efforts (Schmookler, 1962; Christensen and Bower, 1996). The previous mechanisms focus on the profit potential of the innovations (Cohen and Levin, 1989). I suggest a different mechanism by arguing that as the demand conditions of an industry change, they may also change the labor market conditions for the researchers. This influence on labor markets, in turn, influences the patterns of research activities conducted by the researchers. Thus, demand conditions not only influence the direction of innovation directly through altering the profit potential of innovations but also through its influence on the labor market conditions. Examining this new mechanism at depth is important because of two reasons. First, it reveals a path through which demand conditions in one industry may influence the nature of technological research in a different industry. Second, it points toward a hitherto unconsidered linkage between the "demand-pull" (Christensen and Bower, 1996; Schmookler, 1962) and the "technology-push" (Jaffe, 1986) influences.

Through its impact on labor market, the state of demand in an industry can influence the nature of research in related industries. Greater demand for the products of an industry could lead to better labor market conditions for the researchers skilled in the technologies underlying those products. The better labor markets in these technologies may attract researchers from different, albeit related, industries to learn about these technologies, leading those researchers to expand the technological breadth of their search. But this is not all.

When researchers from varied backgrounds are attracted to any particular technology, attempts to adapt and apply this technology to many different uses increase. As researchers explore the diverse uses of that technology, they explicate and expand the technological opportunities associated with it (Nelson, 1962; Cohen, 1995; Levinthal, 1998). These diverse efforts clarify what the technology is best used for, the different ways that the technology can be adapted or modified, and the basic scientific principles underlying the technology (Nelson, 1962). In this way, through its impact on the labor markets for researchers, the demand condition in an industry alters the technological opportunities associated with technologies that underlie that industry. The first step in understanding this linkage is to understand how industrial researchers respond technologically to stimuli from labor markets, a task that I undertake in this study.

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