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Choosing Not to Choose: A Behavioral Perspective on Parallel Search

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Abstract

A large body of work in the Behavioral Theory of the Firm tradition focuses on processes through which firms search for new opportunities yet largely assumes or implies a fundamentally sequential character to the search process. Firms, however, typically engage simultaneously in multiple R&D projects. To capture the simultaneous pursuit of multiple competing paths, this paper defines parallel search by emphasizing the timing and direction of search efforts. We theoretically and empirically examine the antecedents and consequences of parallel search, focusing on behavioral drivers related to feedback from the environment. Empirical analyses are conducted on patent data in the secondary (rechargeable) battery industry. Findings indicate that environmental feedback is an important input for firm decision-making regarding the nature and direction of search efforts, and that successful parallel search involves balancing a delicate trade-off between risk reduction and productivity gain.

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> "It would be unsafe at this time, in view of the pioneering nature of the entire effort, to concentrate on only one means of obtaining the result."
>
> - J.B. Conant and V. Bush during the early stages of the Manhattan Project (Nelson, 1959)

INTRODUCTION

A significant theme in the Behavioral Theory of the Firm tradition focuses on processes through which firms search for new opportunities. Grounded in behavioral models which are based on the concept of bounded rationality (March & Simon, 1958; Simon, 1947) this stream of research examines how firms cope with an inherent incapacity to optimize fully. A common thread in these behavioral search models is the fundamentally sequential character to the search process, as either assumed or implied by the models. The 'rugged landscape' metaphor (Kauffman, Lobo, & Macready, 2000; Knudsen & Levinthal, 2007; Rivkin, 2000) provides valuable insights as to the manner by which firms scan and move within their opportunity spaces, contrasting the benefits of local versus distant search. Multi-armed bandit models of search and learning (Denrell & March, 2001) investigate how firms choose between local and distant search. However, in these models firms are constrained to occupy but a single location or engage in but one type of search at a time within their opportunity space, resulting in a longitudinal improvement path.[1] Relatedly, aspiration-level models view search as driven by the relation between the firm's performance and its aspiration levels (Greve, 2003). Thus, they do not presume a consecutive search process, and yet these models primarily deal with the triggers of search volume and remain silent regarding the direction of the search process. Hence, existing behavioral search models inform us about the drivers of search processes, their intensity, and

[1] Many NK search models allow firms to evaluate multiple potential locations simultaneously, but the firm is forced to make a single choice as a platform for future search processes instead of continuing down multiple paths.

their accuracy in evaluation of alternatives, yet either largely assume a sequential examination of alternatives or remain agnostic as to the timing and direction of search alternatives.

However, "organizations typically pursue many projects simultaneously" (Schilling, Vidal, Ployhart, & Marangoni, 2003, p. 53). Firms continuously allocate resources among multiple R&D projects, must choose which projects will live on, which will be terminated, and which new ones will be undertaken. Importantly, the simultaneous pursuit of multiple projects goes beyond engaging in research activities in different segments, but often involves investigating multiple potential solutions for the same challenge. For example, pharmaceutical firms often manage a portfolio of projects aimed at the same market (Girotra, Terwiesch, & Ulrich, 2007). A good case is the Manhattan Project, which led to the successful development of the atomic bomb. Undertaken by the United States during World War II, the project employed a "parallel-path strategy" (Nelson, 1961): with the goal of developing a working bomb, different methods of uranium separation were concurrently investigated in various plants across the U.S., and at Los Alamos different groups of scientists and engineers concurrently developed multiple bomb designs (Lenfle, 2011). Concurrent development of projects is undertaken since "the odds of success are low, the development lead times are long, and the correlation between the successes of different concepts is low" (Girotra et al., 2007, p. 1455).

But what leads firms to search in parallel, when are firms more likely to search in parallel, and what are the consequences of parallel search? While the concept of parallel search has received significant attention in the project management and concurrent engineering literatures (e.g., Loch, Terwiesch, & Thomke, 2001; Sommer & Loch, 2004), it seems to be missing from the discussion of search in the strategic management literature, particularly that grounded in the Behavioral Theory of the Firm. On one hand, searching in multiple directions simultaneously may allow the organization to maintain viable alternatives in case some fail, which could reduce the risk of sub-optimizing. Borrowing from the 'rugged landscape' jargon, getting stuck on a local peak is typically the central feature of NK and multi-armed bandit models. By undertaking multiple projects simultaneously, organizations are better able to assess the opportunities in the search space and increase their odds of identifying superior alternatives. On the other hand, spreading a fixed pool of research resources requires coordination and more complex decision-making, can divide managerial focus, and can reduce the potential to capitalize on economies of scale in the research effort.

To unpack the antecedents of parallel search, we focus on behavioral drivers related to feedback from the environment. Firms make decisions in the past about which technological spaces to search in, how to organize the timing of search, and how to identify future opportunities. Based on the feedback that the firm receives from environment about those prior decisions, the firm may choose to search in parallel. In this study, we focus on feedback about the level of success in the firm's prior actions, and about the level of dynamism affecting the firm's current opportunities. We argue that the first will reduce the incentive to engage in parallel search, while the latter will increase the incentives. We also argue that parallel search will decrease the productivity of the firm, but that it may be beneficial to firms under specific circumstances. We investigate these questions with longitudinal data on search paths and strategies of more than one hundred and forty firms in the global secondary (rechargeable) battery industry.

This study offers a first take (as far as we know) at examining parallel search within the Behavioral Theory of the Firm tradition. As such, it contributes to the literature on search and innovation management within the broader strategy literature (Gavetti & Levinthal, 2000;

Siggelkow & Rivkin, 2005) by focusing on the timing and direction of search efforts. We also contribute to the literatures on organizational response to environmental feedback (Argote, 1999) by discussing how feedback on success of prior choices and the dynamism of future opportunities can affect current strategic decision-making within the firm.

THEORETICAL DEVELOPMENT

Drawing from the literature on project management and concurrent engineering (e.g., Loch et al., 2001; Sommer & Loch, 2004) we define parallel search as the simultaneous pursuit of multiple alternatives (two or more projects) which are aimed at providing a solution to the same problem. This builds on Abernathy and Rosenbloom's (1969) definition of a parallel strategy as "the simultaneous pursuit of two or more distinct approaches to a single task", contrasted against a sequential strategy, which they define as "commitment to the best evident approach, taking up other possibilities only if the first proves unsuccessful". At the core of the definition of parallel search are two components. First, *two or more alternatives are pursued concurrently*, so that at any given point in time total R&D investment is split among the alternatives. Nelson (1961, p. 353) emphasizes that "in the parallel-path strategy, information about a development alternative is acquired by doing almost exactly the same things that would be done were the alternative finally chosen, i.e., design and development work". Second, alternatives constitute *different approaches to solving the same problem*, and to answering the same need. In that regard, alternatives are *substitutable paths to the same destination* as each one is, at least initially, considered to have the potential to provide the organization with a technology to complete the task at hand. Full development of competing alternatives may thus lead to the attainment of substitutable technologies. Indeed, two different bomb designs developed concurrently in the Manhattan Project were used in the bombs dropped on Hiroshima and Nagasaki in 1945. Importantly for our definition, we do not consider the concurrent pursuit of multiple alternatives aimed at *different* tasks as parallel search.

In this section, we begin by summarizing the findings from the project management literature about parallel search. We then identify three key reasons why applying these findings to contexts of organizational search for technological solutions may be difficult, based on existing literature on search in the Behavioral Theory of the Firm tradition. Finally, we integrate these perspectives to offer novel hypotheses about the likelihood of engaging in parallel search for technological solutions.

Parallel versus Sequential Search

In the project management literature parallel search has mostly been examined using formal models of search. These models aim to find optimal strategies of search, which may be parallel, sequential, or a mix of both (Loch et al., 2001). An optimal strategy is defined as one that minimizes development cost and time given the prior knowledge about each alternative. In models of sequential search a target is set and the first alternative to meet the target is adopted as the solution (Pich, Loch, & Meyer, 2002). Defining an optimal sequential search strategy requires finding the optimal sequence of alternatives. In parallel search multiple alternatives may be pursued simultaneously. Thus, defining an optimal strategy of parallel search includes the optimal selection of a set of projects to undertake at each point in time (Vishwanath, 1988). Once the projects in the chosen set are completed the best is (are) retained. Models of parallel search have rarely been tested empirically, and when they have the focus has been on the efficacy of the single solution created through parallel search efforts (e.g., Boudreau, Lacetera, & Lakhani, 2008).[2]

Existing models of parallel search have three important drawbacks that limit their applicability to organizational models of technological search. First, these models assume that information about the prospects of an alternative is not revealed during its development, but only once development has completed (Loch et al., 2001; Vishwanath, 1988). Thus, projects are assumed to be developed to completion, at which point the new information about the alternative becomes available. This means that in parallel search learning does not take place between projects during development, but only once the set of projects has reached completion. A model of parallel search which includes learning and updating about the efficacy of parallel search decisions would allow information exchange between projects, as well as culling of projects based on the progress of other concurrent projects (Pich et al., 2002). Indeed, "the managerial interest of the parallel approach lies not only in the opportunity to pick the best solution once enough information is available, but also in the possibilities it opens for redeploying resources, combining trials, or adding new ones as the project moves forward" (Lenfle, 2011, p. 371).[3] Thus, there is a need to consider how firms reevaluate their decisions to search in parallel or

[2] A related stream of research is that of systems management, which examines the optimal development strategy of a system's various components. The development strategy takes into account complex dependencies between the components, and involves the simultaneous development of different parts of the system (e.g., Mihm, Loch, & Huchzermeier, 2003). However, the type of concurrent development examined in this stream of research does not fit into our definition of parallel search. Systems management mostly deals with parallel development of *different* components of a system, where each component has a distinct function in the system. Parallel search, as defined above, involves the concurrent development of solution alternatives aimed at performing the *same* task.

[3] An example for the use of such a parallel search strategy with learning between projects can be found in Toyota's development process (Sobek, Ward, & Liker, 1999). Design engineers develop sets of solution alternatives; as design progresses, information is obtained and exchanged between design teams, and the sets of solution alternatives gradually narrow down until convergence is reached.

sequentially as they receive feedback from the external environment on the success or failure of their choices.

Second, the models focus solely on characteristics of the project in determining the appropriate search path. Thus, the drivers of which path is optimal are based on time and cost information about the project. In organizational search, however, a key element is the firm-level heterogeneity in terms of resources, knowledge, and ability, suggesting that search strategy cannot be considered in isolation. In Toyota's case, the principles of parallel design, "along with Toyota's principles for integrating systems and cultivating organizational knowledge, appear to form the basis for Toyota's exceptional vehicle development capability" (Sobek et al., 1999, p. 81). More generally, firms may differ in their ability and their motivation to engage in parallel search efforts (even for the same task), and this underlying firm heterogeneity is a central part of the existing research in management and strategy. Thus, considering how different firms might make different choices in terms of parallel search would be an important element to introducing parallel search activities to the innovation management literature.

Finally, the models ignore the outside environment in which the search activity is taking place. Specifically, the assumption is that the optimal outcome can be determined based solely on the search paths taken within a single organization. This may be true for a single firm's search for (for example) the optimal coding strategy for a new database. When considering search processes between different technological segments that will be inputs to a competitive marketplace and where the underlying technology is subject to an evolutionary path, the nature of the selection process is different. A firm might, for example, make significant progress with its research on Technology A only to discover that competitors have discovered Technology B, which will completely dominate the industry. Thus, there is a need to consider how external feedback on the progress of the firm as well as the progress of other firms affects the decision to pursue or to continue with parallel search efforts.

We seek to address these three elements with our theoretical and empirical approach to parallel search, which we elaborate on below.

Environmental Feedback and Antecedents of Parallel Search

As discussed above, firms are likely to engage in parallel search efforts within the same general problem domain at various points in their organizational history, and there is likely to be important firm-level heterogeneity about the ability and motivation of these firms to engage in parallel search. This section utilizes existing work on capacity and timing constraints, positioning and inertia, and the availability of superior alternatives to build specific hypotheses about the drivers of parallel search for organizations.

Success of Prior Choices

The success or failure of prior choices will have a dramatic impact on managerial motivation to engage in risky and uncertain search behaviors such as parallel search. A central tenet of the Behavioral Theory of the Firm has been the idea of problemistic or problem-driven search (Greve, 2003). Therefore, the efficacy of the firm's prior R&D efforts is likely to affect the propensity of the firm to engage in parallel search. From a behavioral perspective, positive feedback on prior performance is likely to result in inertia as the company continues along the same investment path (Cyert & March, 1963; Nelson & Winter, 1982). Such a pattern is likely to emerge because success creates persistence in strategic decision-making processes (Burgelman, 2002; Miller, 1994), as the managers that oversaw the success have an incentive to maintain the status quo (Hambrick, Geletkanycz, & Fredrickson, 1993). Prior success is likely to diminish the organization's appetite for risky actions (Kahneman & Lovallo, 1993; March & Shapira, 1992), and splitting vital R&D resources between different technological options in parallel search may be too risky for managers to consider pursuing. By contrast, prior failures and poor performance are likely to encourage search behavior, as managers look for means to increase performance (Cyert & March, 1963; Greve, 2003). As a result, we expect that prior success in terms of R&D efforts are likely to discourage the firm from engaging in parallel search.

Success of prior decisions may manifest itself in different ways. One would be based on the ability of the firm to generate high-value innovations, often measured as forward citations received by the firm's patents. Firms whose prior patents are more highly cited have been more productive in terms of their prior R&D decisions and efforts. A second way would be based on whether managers see the environment as validating or invalidating their strategic positioning decisions within the technological space. Effectively, firms that already focus most of their resources on the largest technological segments in the industry are likely to view their position as advantageous. Such a strong position based on prior choices and the evolution of the external technological space are likely to increase persistence of choices, as these firms already occupy strong positions and do not need to engage in risky, exploratory search. Thus we offer two specific hypotheses based on the logic of success of prior decisions leading to reductions in the incentives to engage in parallel search.

H1: The higher the productivity (in terms of citations) of the firm's prior patenting efforts, the less likely the firm is to engage in parallel search.

H2: The larger the technological segments in which the firm has recent experience, the less likely the firm is to engage in parallel search.

The above perspective on prior successes and incentives to engage in parallel search require an important caveat. If the firm's prior successes were built off of parallel search investments, then the success-built routines that emerge from that process will encourage further investment in parallel search. Success builds routines based on the actions that generated the successful outcome in the first place (Kim, Kim, & Miner, 2009; Zollo, 2009), so if parallel search is correlated with strong performance in the firm's history, then the firm will continue to search in parallel. Indeed, if success in prior parallel search leads to the continuation of parallel search efforts, this confirms that the driver of parallel search is not simply the success or failure of the firm's prior efforts, but is based on managerial perceptions of the causes of those successes and failures.

> *H3: Prior experience in parallel search will positively moderate the effect of prior productivity – as firms are more productive and have engaged in more parallel search, they are more likely to continue to search in parallel.*

Dynamism of Future Opportunities

If the success of prior choices creates inertia and decreases the incentives to engage in parallel search, the risk and uncertainty associated with future opportunities increase that incentive. Increased uncertainty about the future can lead firms and managers to pursue strategies that reduce organizational risk, and in dynamic technological environments, the potential for supporting a specific technological segment that does not eventually bear fruit becomes a primary concern for managers (Arthur, 1989). We relate the perceived dynamism of future opportunities to changes in the level of growth experienced by the firm and the technological segments that it occupies. Higher levels of growth in a technological space generally lead to entry by potential competitors, experimentation with different technological configurations, and other realities that are related to environmental uncertainty (Geroski, 1995; Klepper, 1996; Suárez & Utterback, 1995). By contrast, low levels of growth represent stability and predictability.

In the relationship between higher growth and the decision to search in parallel, there are potentially contrasting forces at play. On one hand, aggressive growth demands significant resources from the firm. Wu (Levinthal & Wu, 2010; Wu, 2007) suggests that capabilities in

R&D will be constrained, so that higher growth in the firm's own technological segments reduces the likelihood of switching to another segment. On the other hand, such growth focuses a great deal of managerial attention on the technological space, which provides the potential for better access to resources. Such managerial attention has been shown to be important at the project level to facilitate new product development success (Krishnan & Ulrich, 2001; Song, Montoya-Weiss, & Schmidt, 1997), and at the organizational level to facilitate transition into new technological spaces (Eggers & Kaplan, 2009). Combining these two perspectives, our argument is that the increased environmental uncertainty and increased managerial attention on technological choices will encourage managers to search in parallel to reduce the risk of backing the wrong technological path, but that engaging in parallel search may have consequences based on over-extending in-house R&D resources (Levinthal & Wu, 2010) as discussed for H7 below.

As was true with measuring the success of prior decision earlier, we offer two different means of assessing the dynamism and risk in the firm's opportunity set. First, the growth trajectory of the firm is indicative of the expanding and changing opportunities that the firm has available to it. Thus, firms experiencing steeper growth trajectories have a higher degree of uncertainty about the exact nature of their future opportunities, and will be encouraged to pursue multiple technological paths to reduce organizational risk. Second, the level of growth in the firm's external environment – the degree to which the technological segments in which the firm is most active are dynamic and growing rapidly – represents the degree of external dynamism facing the firm.

H4: The higher the firm's growth trajectory within the industry, the more likely it is to engage in parallel search.

H5: The higher the growth rate of the technological segments in which the firm has recent experience, the more likely it is to engage in parallel search.

Firms are not only aware of the growth rates in the segments in which they are involved, but they compare those growth rates with the rates in other technological areas in which they are not directly involved. Thus, higher growth rates of technological segments beyond the firm's scope, relative to the growth rates of the firm's own technological segments, tend to decrease the motivation to engage in search. Thus, the driver of uncertainty-related search may be driven not just by the firm's own technological segment experiences (H5 above), but also by the level of dynamism in the opportunities that the firm chose not to pursue, similar to the way in which social performance may affect aspiration levels in addition to historical performance (e.g., Baum & Dahlin, 2007; Greve, 2003). For this reason, we offer a hypothesis that is the other side of the coin from H5 – for the technological segments in which the firm has chosen *not* to invest, increases in the growth and dynamism of those segments decreases the perceived need to engage in parallel search. This is true both because the perceived risk in the existing technological segments for the firm declines, and because the potential parallel investment segments are increasing in their dynamism, which limits the appeal as a strategy to reduce organizational risk.

> *H6: The higher the growth rate of the technological segments in which the firm <u>does not</u> have recent experience, the less likely it is to engage in parallel search.*

<u>Consequences of Parallel Search</u>

In general, engaging in parallel search has three major consequences. First, it involves moving into a technological segment in which the firm has less direct knowledge and in which existing routines based on inferences made from the firm's experience with other technological segments (Levitt & March, 1988) may be inadequate. This results in an initial learning process in which the firm is developing efficient routines to process information obtained in the new technological space and is assimilating the new knowledge. During this process the firm's initial investments in the segment are less effective in generating outputs (Lieberman, 1989).

Second, transitioning from focused search to parallel search is a strategic change. Such a change may require that the firm overcome core rigidities (Leonard-Barton, 1992), develop new capabilities suitable for parallel activities, and adjust its "dominant logic" (Bettis & Prahalad, 1995) to efficiently process information received through multiple channels. This transitional phase may be taxing on firm resources and managerial attention, and may consequently entail a reduction in output efficiency until it is complete.

Third, the firm is forced to split its R&D investment between two or more technological segments. To the extent that there are economies of scale in R&D investment (Nightingale, 2000), the effect of splitting this investment will be detrimental to the performance of the firm. This splitting of R&D investment between multiple categories simultaneously also divides managerial attention between the different segments, which results in reduced access to important resources for each segment (Eggers, 2012).

Thus, we argue that, while engaging in parallel search may have benefits such as reducing the risk of pursuing the wrong technological path in an evolving and uncertain industry, the effect of parallel search on the productivity of the firm's current innovative efforts will be negative.

H7: On average, patents developed through parallel search processes will be less valuable than patents developed through a more focused innovative process.

DATA & SETTING

Research Setting

The context of our empirical examination is the secondary (rechargeable) battery industry. According to Freedonia the battery industry was $86.2 billion worldwide in 2010 and $13.2 billion in the US alone in 2011, and is expected to rise 4.8% annually through 2015. This includes both primary (non-rechargeable) and secondary (rechargeable) batteries. According to Frost and Sullivan secondary batteries compose the lion's share of the global battery industry, accounting for 76.4% of the market in 2009, and are expected to increase to 82.6% by 2015.

Lead-acid batteries account for roughly half the rechargeable battery market, and are mainly used in automotive applications (e.g., starting, lighting, and braking). Non-lead-acid batteries serve various markets, notably portable consumer electronics, power tools, and electric- and hybrid-vehicles. As portable electronic devices become increasingly energy-hungry and as the electric vehicle industry is rapidly expanding, demand drives the growth of non-lead-acid batteries. They are required to deliver increasingly more power and have longer life, while recharging faster and being smaller, lighter, and cheaper. Freedonia expects the demand of non-lead-acid batteries to outpace that of primary and lead-acid batteries by 2014.

The secondary battery industry constitutes an ideal setting for our study for two main reasons. First, the industry is characterized by high dynamism and uncertainty. The industry concurrently invests in multiple technologies, and clear winners are difficult to identify. Sodium-based batteries were under intense development in the 1970's and 1980's. Interest in the sodium-sulphur variant of the technology waned in the 1990's since performance remained marginal, and interest shifted to sodium-nickel-chloride. Demand for nickel-cadmium increased steadily during the 1980's and until the mid 1990's, but later dwindled due to increased demand for nickel-hydride and lithium-ion batteries, which were first commercialized in 1990-1991 following development progress in the 1980's. Lithium-ion batteries have seen explosive growth in recent years, yet relatively high manufacturing costs and safety concerns lead firms to continue the search for better solutions. The difficulty of identifying a superior technology increases the uncertainty of investment in each technology. Such a dynamic industry provides a perfect setting for our study as parallel search in multiple technological segments allows firms to reduce the risk of committing to a single technology. By investing in multiple technologies, firms are also able to evaluate the trade-offs between different technologies. For example, for the electric vehicle market, R&D efforts seek a technology that "will give the best combination of performance, life, and cost with adequate safety and minimal environmental impact, " yet "the three leading elements are inextricably linked, and improvements in any one come at the expense of one or both of the others" (Hunt, 1998, p. 22).

Second, the technologies in the secondary battery industry are defined by distinct chemistries. Each chemistry is associated with specific energy storage characteristics (e.g., energy density, internal resistance, cell voltage, etc.), requires a specific charging mechanism, and has different regulatory requirements for shipping and disposal due to different toxicity levels. As a result, secondary battery technologies are classified into well-defined categories that are defined by the active component of the battery cell. This allows us to distinguish between investments in different technologies, as well as to identify concurrent investment in multiple technologies.

Data Source and Sample

Our sample is based on patent data from the Derwent Innovation Index covering all secondary (rechargeable) battery patent applications filed between 1981 and 2010, and every organization or individual listed on those patent applications (over 7,500 organizations and individuals and 70,000 patents). Derwent provides a high-resolution classification system that allows us to distinguish between patents belonging to different technologies. We use the classification of secondary battery cells' active component to define technological categories. Our final sample includes six technological categories: alkaline (including nickel-cadmium and nickel-metal-hydrogen), lead-acid, high-temperature sodium-sulphur, metal-halogen, non-aqueous components (including lithium ion and other lithium-based components), and a category grouping all other secondary cells (referred to as categories below)[4].

Derwent uses patent families to group identical patent applications filed in different countries in order to prevent double counting (our sample has over 70,000 patent families grouping nearly 600,000 patent applications). The analyses below are based on patent families. We limit our final sample to applications filed by 2005 to allow counting forward citations for patents (as detailed below). We focus our analysis on for-profit firms that file at least 20 patent applications in the industry over the entire sample period. The first exclusion is meant to focus our analysis on firms with a presumably homogenous objective of profitable growth, and therefore excludes data on patent applications filed by government agencies, universities and research institutes, and individuals to focus only on for-profit firms. These patents are, however, included to measure industry growth trends in each technological segment, as discussed below. The second exclusion focuses our attention on the firms that have significant battery investments, as many firms may have a few battery patents but actually weigh their decisions on where to invest their technological resources based on factors not directly involved in batteries (such as computer companies, car companies, etc.). Firms are included in the sample only for the period between the first year in which we observe patent applications filed by the firm and the last year in which we observe applications by the firm, resulting in an unbalanced panel. The final sample has 2,135 firm-year observations on 144 firms.

[4] An additional category has been dropped due to its late introduction to the Derwent database in 2005, which results in too few applications categorized under it in our sample

Dependent Variables

The dependent variable for Hypotheses 1-6 is a dummy indicating, for each year, whether the firm applied for patents in two or more of the six technological categories described above (*parallel search*). The dummy is zero if the firm did not apply for any patents in that year, or if the firm applied for patents in only a single category.[5] This dummy is then used as the independent variable to test Hypothesis 7.

As the dependent variable for Hypothesis 7, we measure patent value using forward patent citations. Our dependent variable is the number of citations received by the firm's patents that were filed in that year (*forward citations*)[6]. Following Fleming and Sorenson (2004), we limit our citations count to the five years following the application date. This avoids the problem of older patents having more citations, while still allowing sufficient time to assess the technological and economical value of the patent (Hall, Jaffe, & Trajtenberg, 2005; Trajtenberg, 1990). We consider citations by all patents included in Derwent's secondary battery classification, rather than only patents by firms in our sample, to accurately capture a patent's value in the field.

Independent Variables

Prior forward citations. To assess the productivity of the firm's prior knowledge creation investments, we use the total citations received for patents filed by the firm in the previous 3 years, normalized by the number of patents and logged to deal with skewness. This is used to test Hypothesis 1.

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[5] In the Robustness section, we discuss an alternate specification that counts the number of categories in which the firm patents in that year. The results are qualitatively similar.
[6] Our sample includes both patent applications and granted patents. Forward citations exist only for granted patents, rendering applications that were not granted as having no value.

In-scope segment size. We measure the extent to which a firm is searching in large technological segments using a weighted sum of the industry's shares of the six categories. Specifically, we calculate a weighted average of the industry-level patent shares of each of the six categories in which the focal firm patented in the prior three years. The basic format is $\sum_{j=1}^{6} \left(w_{ijt} \cdot segmentsize_{jt} \right)$, where *j* denotes the categories (up to six) in which firm *i* is active in the previous three years, the weights (*w*) are based on the percent of firm *i*'s patents in the past three years filed in category *j*, and $segmentsize_{jt}$ denotes the industry-level share of patents in category *j* in the previous three years versus patents filed in all six categories. This variable (*in-scope segment size*) captures the extent to which the firm is patenting in technological spaces in which the industry is making more progress relative to other fields. Higher values indicate that the firm is more active in categories defining larger spaces, and lower values indicate that the firm is searching less in these categories. This variable is used to test Hypothesis 2.[7]

*Experience * Forward Citations.* To assess the moderating effect of prior experience in parallel search on the effect of prior productivity we interact *prior forward citations* with an experience measure (*experience)*. We measure experience as the number of years out of the previous 3 in which the firm searched in multiple categories (i.e., for how many of the previous 3 years *parallel search* was 1). This variable can be viewed as a sum of non-decaying versions of *parallel search* which are lagged one-, two- and three years. The main effect of *experience* is used as a control for potential firm inertia and the resulting autocorrelation in organizational decisions. The interaction of *experience* with *forward citations* is used to test Hypothesis 3. Higher values of the interaction effect indicate that more productive firms that have more experience in parallel search will be more likely to continue searching in parallel. We mean-

[7] Formal definitions of the concepts and measures may be found in the appendix.

center the two variables to improve the interpretability of the main effects when the interaction term is included.

Firm growth trajectory. We assess the growth trajectory of the firm's own patenting activities using a measure that is analogous to *in-scope segment size* but that focuses on the firm's growth trajectory instead of segment size. Specifically, we compute $\sum_{j=1}^{6}\left(w_{ijt} \cdot firmgrowth_{jt}\right)$, where j denotes the categories (up to six) in which firm i is active in the previous three years, the weights (w) are based on the percent of firm i's patents in the past three years filed in category j, and $firmgrowth_{jt}$ denotes the firm's growth trajectory in category j in the previous three years versus its growth trajectory in category j in the three years before that. This measure (*firm growth trajectory*) captures the rate of advancement a firm is experiencing in the six technological segments relative to the extent of activity in each segment. Higher values correspond to steeper growth trajectories in technological segments in which the firm is more active, whereas lower values correspond to slower growth rates in such segments. This is used to test Hypothesis 4.

In-scope segment growth. To capture the firm's focus on growing and dynamic technological segments, we construct a measure that is analogous to *firm growth trajectory* but that focuses on segment growth instead of firm growth. We calculate $\sum_{j=1}^{6}\left(w_{ijt} \cdot segmentgrowth_{jt}\right)$, where j denotes the categories (up to six) in which firm i is active in the previous three years, the weights (w) are based on the percent of firm i's patents in the past three years filed in category j, and $segmentgrowth_{jt}$ denotes the industry-level growth of patents in category j in the previous three years versus patents in category j in the three years before that. This measure (*in-scope segment growth*) captures the rate at which each of the six technological segments is advancing, weighted by the scope of the firm's activities in each segment. Thus, higher values indicate that the firm has more experience in rapidly advancing segments, whereas lower values indicate that the firm has less experience in these segments. We use this measure to test Hypothesis 5.

Out-scope segment growth. We measure the industry-level growth in the categories in which the firm is *inactive* with a weighted sum of the industry's growth in these categories, where the weights are the industry's shares of each corresponding category. Thus, it is analogous to *in-scope segment growth* but where the categories only include those in which the firm is inactive and the weights are simply the industry-level shares in those categories. This variable (*out-scope segment growth*) captures the extent to which the firm is 'missing out' on rapidly growing segments. Higher values indicate that segments in which the firm has less experience are more active and more rapidly advancing, while lower values indicate that these segments are less active and have a slower growth rate. We use this measure to test Hypothesis 6.

Control Variables

Our approach with our control variables focuses on controlling for three types of potentially confounding factors – those affecting overall search volume (and thus parallel search only incidentally), those affecting the ease of parallel search for the firm, and those related to underlying unobserved firm heterogeneity. The third set are discussed when we discuss the econometric model itself. The other two are discussed below.

First, we seek to control for factors that might affect overall search volume. As a control for firm size we include a measure of the firm's average number of patents per year in the previous 3 years (*size*). This measure is logged to correct skewness. We also control for firm age (*age*), measured from the first year in which we observe patents by the firm. Work on organizational inertia suggests that larger and older firms may be less likely to engage in active search processes (Hannan & Freeman, 1977). At the same time, larger firms may have more resources that they could dedicate to parallel search, so it is ambiguous what effect to expect from these controls.

Second, firms may find parallel search easier or harder based on factors unrelated to feedback from internal and external elements. Our controls in this category include *experience*, which we discussed above and captures a learning process in terms of the firm's ability to search in parallel. Additionally, the decision to search simultaneously in multiple technological spaces may be affected by the characteristics of the technological spaces themselves. Some technologies may be more similar than others, building on common knowledge bases. Searching concurrently in similar technological spaces may render knowledge gained in one space useful in the other, allowing for greater exchange of knowledge between the two projects and faster progress (Breschi, Lissoni, & Malerba, 2003; Cohen & Levinthal, 1990; Kim & Kogut, 1996). We control for the proximity between technological spaces in which the firm is active and those in which it is inactive by including a measure of inter-category citation probabilities (*proximity*). For every category-pair we measure the probability with which patents from one category cite patents from the other category. We then compute a weighted sum of the citation probabilities between categories that the firm has active projects in and categories in which the firm is inactive. The weights are the firm's share of patents in each category (a formal description is included in the appendix). Higher values indicate greater proximity between current search activities and technological spaces in which the firm is inactive. We have also constructed a similar proximity measure based on the probabilities of patents being classified under multiple categories. The correlation of the two measures was 0.89, hence we proceed with using only the aforementioned citations-based measure.

Additionally, we include two dummies to control for specific "edge cases" where our unbounded measures above fail to capture a specific, potentially-relevant circumstance. First, we include a dummy (*recent inactivity*) for years where the firm did not patent at all in the prior three years (and thus has a zero for the majority of the independent variables). The results of our analysis are qualitatively similar if we simply exclude these observations. Second, we include a dummy (*recent progress halt*) noting when the firm had a previous investment in a category in years *t-4* to *t-6*, but did not invest in that category in *t-1* to *t-3*. The exclusion of this variable does not materially affect our results.

Analysis Methods

Hypotheses 1-6 concern factors affecting the binary decision whether to engage in parallel search. Since the dependent variable is a binary outcome we employ a logistic model (the xtlogit routine in STATA). We use the fixed-effects version of the model to control for unobserved firm heterogeneity. While the conditions for a Hausman test are not met, an augmented regression test (Batalgi, 2005, p. 67) favors the fixed-effects model over the random-effects model.

To investigate Hypothesis 7, for which the dependent variable is a citation count, our model of choice is a negative binomial model (the nbreg routine in STATA). To control for unobserved heterogeneity we include firm, year, and size dummies. We do not use the fixed-effect negative binomial model in STATA (xtnbreg) as this model is not a true fixed effect model, but research indicates that including firm dummies to create real fixed effects does not bias the estimators (Allison & Waterman, 2002). To deal with the endogneity of the decision to engage in parallel search, we take the predicted likelihood of engaging in parallel search from the first model and create an inverse Mills ratio, in a Heckman-style (Heckman, 1979) selection model.[8] Also, we exclude observations from this model where the firm did not patent at all in the focal year, to avoid measuring productivity of patenting when the firm doesn't patent at all.

The descriptive statistics (Table 1) and correlations matrix (Table 2) are shown below. The most interesting part of the descriptive statistics is to note that firms search in parallel in twenty four percent of the observations. The correlations table shows a fair number of relatively high correlations (such as the one between *size* and *experience*), but the Variance Inflation Factors (VIFs) are all very low (below 3.5), which suggests minimal concern about multicollinearity. Still, to be safe, we present the results of the regression analysis with one independent variable added at a time to be able to assess potential concerns about multicollinearity.

INSERT TABLE 1 ABOUT HERE

INSERT TABLE 2 ABOUT HERE

RESULTS

First we explore the effect of feedback on the success of prior choices and the dynamics of future opportunities by investigating the factors that determine the decision to engage in parallel search. The results of the fixed-effects logistic model appear in Table 3, reported as odds ratios. In the full model (Model 7) three of the control measures are significant. The controls for age and size are positive and significant ($p<0.01$), indicating that larger and more mature firms

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[8] At this point, we achieve identification through the nonlinearity of the transformation for the inverse Mills ratio, but we are actively working on other instruments to address endoegneity.

exhibit a greater tendency to engage in parallel search. The third significant control (experience) is only marginally significant ($p<0.10$) and only in the final two models. It is negative, however, suggesting that increases in experience with parallel search in recent years *decrease* the likelihood of pursuing parallel search in the current year. As Model 7 includes the interaction with this variable and the productivity of that experience, the interpretation of the effect is somewhat contingent on that interaction term, as discussed below. It does not appear that the proximity of potential parallel categories has any bearing on the decision to engage in parallel search.

INSERT TABLE 3 ABOUT HERE

Hypothesis 1 suggests that more productive firms will be less likely to engage in parallel search, while Hypothesis 3 says that this relationship will only be present if the firm has also been less productive in its knowledge creation efforts during the same period. Meanwhile, the effect of productivity is expected to reverse when the firm has been productive while also having recently engaged in parallel search. The coefficient on *prior forward citations* is insignificant in all models (with and without the interaction), suggesting that productivity alone does not discourage parallel search. In the full model (Model 7), the interaction is positive and significant ($p<0.05$). Thus, firms that have recently engaged in parallel search are more likely to continue searching in parallel if they have been more productive during the same period, while they are less likely to continue to do so if they have been less productive. These results do not support Hypothesis 1, but do support Hypothesis 3, suggesting that successful investments in parallel search may result in the emergence of organizational routines, which encourage further parallel search.

Hypothesis 2 focuses on the effect of the size of the technological segments that the firm has recent experience in on the choice of engaging in parallel search. The coefficient of the measure of the extent to which a firm is searching in large technological segments (*in-scope segment size*) is negative and significant ($p<0.01$), supporting Hypothesis 2 and indicating that firms with recent experience in larger segments are less likely to search in parallel.

Hypotheses 4 and 5 address the effects of dynamism and risk of the firm's search directions on its likelihood to engage in parallel search, predicting that higher growth rates of the firm's own trajectory and of the technological segments in which the firm is active increase the likelihood of searching in parallel. The coefficient on the measure of the growth rate of the firm's patenting activities (*firm growth trajectory*) is positive and significant ($p<0.05$), suggesting that steeper trajectories in the firm's own growth entail higher uncertainty, which the firm addresses through undertaking search in additional directions. The coefficient on the measure of the growth rate of the technological segments in which the firm has recent experience (*in-scope segment growth*) is also positive and significant ($p<0.01$), showing that firm choices are affected by relevant environmental uncertainty, which may be reduced via parallel search. These findings lend support to Hypotheses 4 and 5.

Hypothesis 6 suggests that firms engage in comparisons with their environment and assess the level of uncertainty that they experience relative to that in segments outside their scope of activity. The effect of the growth rate of technological segments in which the firm has not been recently active is negative and significant ($p<0.01$), supporting Hypothesis 6. Higher levels of dynamism in segments outside the firm's scope of activities reduce the perceived uncertainty in the firm's current trajectories, which in turn decreases the perceived risk and the benefit of parallel search.

Having considered the antecedents of parallel search above, we now turn our attention to the consequences of parallel search. Results for the negative binomial model appear in Table 4. Looking at the full model (Model 3), only two of the controls are significant. *Recent inactivity* is positive ($p<0.05$), suggesting that resuming or initiating activity after a period in which the firm did not patent increases patents' value. A possible reason for this effect might be that new patenting activities may be less likely to be incremental innovations and to build on recent advancements, and instead may be driven by discoveries of greater value. The coefficient of *recent progress halt* is negative and marginally significant ($p<0.10$), suggesting that recently ceasing activity in a category reduces the value of current year patents. Of the independent variables from the model for engaging in parallel search, only two are significant. *Prior Forward Citations* is unsurprisingly positive ($p<0.01$), indicating persistence and trend in the firm's ability to generate useful innovative knowledge. Additionally, *out-scope segment size* is significant ($p<0.01$), indicating that greater dynamism in technological segments in which the firm has not been recently active reduces the value of patents. This suggests that the firm might be 'missing out' on impactful high-growth areas and instead remains active in familiar areas that may yield only incremental innovations of relatively lower value.

INSERT TABLE 4 ABOUT HERE

Hypothesis 7 deals with the effect of parallel search on the value of developed patents. The full model (Model 3) shows that, while controlling for the relative magnitudes of firm and industry progress and growth rates, as well as for firm characteristics, the coefficient on the indicator for parallel search is negative and significant ($p<0.05$). This demonstrates that patents produced through parallel search processes are less valuable than those produced through a focused search process, in support of Hypothesis 7. It appears that the benefits of parallel search activities are to be found elsewhere, possibly in reduced risk of failure associated with investment in a single technological segment.

Robustness Checks

As a robustness check we have tested Hypotheses 1-6 using a multinomial logit model (the mlogit routine in STATA) with standard errors clustered by firm. As the dependent variable served the number of technological segments in which the firm is concurrently searching. Results are qualitatively consistent with the findings reported above.

DISCUSSION

This study introduces the concept of parallel search to the Behavioral Theory of the Firm tradition. Within this tradition, existing models of search largely assume or imply a fundamentally sequential character to the search process. Motivated by the observation that firms typically undertake multiple R&D projects simultaneously, this study examines the factors that drive firms to engage in parallel search, and the consequences of this strategy. Specifically, the focus is directed towards behavioral drivers related to feedback about the level of success in the firm's prior actions, and about the level of dynamism affecting the firm's current opportunities. Regarding the antecedents of parallel search, findings show that firms are more likely to engage in parallel search following successful prior investments in parallel search, and in the presence of high dynamism in the technological segments they occupy. Firms are less likely to engage in parallel search when occupying strong positions in large technological segments, and when dynamism in other segments is high. Regarding the consequences of parallel search, evidence suggests that parallel search negatively impacts productivity. These findings indicate that environmental feedback is an important input for firm decision-making regarding the nature and direction of search efforts, and that successful parallel search involves balancing a delicate trade-off between risk reduction and productivity gain.

This study has important implications for our understanding of how firms search for technological solutions in an uncertain and evolving environment. Firms certainly search in parallel as well as focus on only one potential solution at a time. The decision about whether and when to search in parallel seems to be dictated less by classic factors that influence overall search volume, such as organization size (Nelson & Winter, 1982) or the technological proximity of potential solutions (Breschi et al., 2003), but instead is highly influenced by feedback from the environment on the success of prior decisions and the dynamism of future opportunities. In general, success builds routines that discourage difficult parallel search efforts (unless the success potentially derives from prior parallel investments), while increases in the growth and uncertainty associated with future opportunities push firms to engage in parallel search to reduce organizational risk. This push to reduce risk, however, comes with a tradeoff – parallel investments are less productive at producing useful knowledge, on average. These findings offer important extensions to our knowledge of search behavior in uncertain and dynamic technological environments. Prior research has largely focused on the difficulties of distant versus local search (Fleming, 2001; Stuart & Podolny, 1996) and the traps that befall organizations searching on rugged landscapes (Ethiraj & Levinthal, 2004; Siggelkow & Rivkin, 2005). We suggest that the parallel versus sequential nature of search is also an important factor to understand when considering organizational search dynamics, and that – like many other aspects of search behavior – the decision to search in parallel is driven at least in part by environmental feedback on performance and opportunities. More work is clearly needed to assess what makes parallel search more or less effective, as well as the other organizational consequences of parallel search (such as the potential reduction in risk of choosing the wrong technology by pursuing multiple options). But this study is a first step towards a broader understanding of the antecedents and consequences of parallel search.

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Table 1. Summary Statistics

	Mean	S.D.	Min	Max	VIF
Parallel Search (DV)	0.24	0.43	0.0	1.0	
Forward Citations (DV)	12.67	39.00	0.0	482.0	
Experience	0.72	1.06	0.0	3.0	2.73
Age	9.30	6.37	0.0	24.0	1.56
Size	1.14	1.19	0.0	5.3	3.33
Proximity	0.73	0.63	0.0	3.0	1.97
Recent Inactivity	0.25	0.43	0.0	1.0	2.59
Recent Progress Halt	0.37	0.48	0.0	1.0	1.09
Prior Forward Citations	0.69	0.72	0.0	3.6	1.32
In-scope Segment Size	29.91	26.00	0.0	87.4	2.09
Firm Growth Trajectory	0.17	1.06	-24.0	2.0	1.12
In-scope Segment Growth	0.16	0.84	-30.5	1.1	1.05
Out-scope Segment Growth	10.47	15.80	-36.5	46.9	1.16

Table 2. Correlations

	Experience	Age	Size	Proximity	Recent Inactivity	Recent Progress Halt	Prior Forward Citations	In-scope Segment Size	Firm Growth Trajectory	In-scope Segment Growth	Out-scope Segment Growth
Experience	1.00										
Age	0.35	1.00									
Size	0.80	0.41	1.00								
Proximity	0.13	-0.11	0.27	1.00							
Recent Inactivity	-0.43	-0.16	-0.61	-0.74	1.00						
Recent Progress Halt	-0.01	0.08	-0.01	0.03	0.10	1.00					
Prior Forward Citations	0.24	0.05	0.36	0.51	-0.61	-0.02	1.00				
In-scope Segment Size	0.28	0.38	0.53	0.59	-0.73	-0.07	0.50	1.00			
Firm Growth Trajectory	0.04	-0.23	0.08	0.12	-0.11	-0.13	0.15	0.04	1.00		
In-scope Segment Growth	0.06	0.03	0.11	0.09	-0.13	-0.00	0.15	0.19	0.07	1.00	
Out-scope Segment Growth	-0.29	-0.11	-0.35	-0.15	0.26	-0.14	-0.24	-0.30	-0.06	-0.01	1.00

Table 3. Likelihood of Engagement in Parallel Search

Fixed effects logistic regression model with firms as the parallel variable; DV = 1 if the firm applied for patents in two or more of the six technological categories, and 0 otherwise.

Parallel Search (DV)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Prior Forward Citations		1.273^{*}	1.341^{**}	1.252^{+}	1.169	1.007	1.055
		(0.142)	(0.152)	(0.144)	(0.139)	(0.129)	(0.138)
In-Scope Segment Size			0.983^{**}	0.983^{**}	0.981^{**}	0.981^{**}	0.980^{**}
			(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Firm Growth Trajectory				1.381^{**}	1.327^{**}	1.227^{*}	1.214^{*}
				(0.111)	(0.107)	(0.100)	(0.098)
In-Scope Segment Growth					1.858^{*}	2.057^{**}	2.078^{**}
					(0.490)	(0.571)	(0.576)
Out-Scope Segment Growth						0.940^{**}	0.939^{**}
						(0.005)	(0.005)
Experience * Prior Forward Citations							1.239^{*}
							(0.133)
Experience	0.937	0.937	0.883	0.884	0.878	0.862^{+}	0.843^{+}
	(0.076)	(0.076)	(0.074)	(0.074)	(0.074)	(0.077)	(0.076)
Age	1.015	1.021	1.061^{**}	1.095^{**}	1.104^{**}	1.079^{**}	1.083^{**}
	(0.014)	(0.015)	(0.019)	(0.022)	(0.022)	(0.022)	(0.022)
Size	1.874^{**}	1.863^{**}	2.078^{**}	1.764^{**}	1.796^{**}	1.996^{**}	2.010^{**}
	(0.213)	(0.212)	(0.247)	(0.217)	(0.222)	(0.262)	(0.264)
Proximity	0.778	0.793	0.890	0.875	0.910	1.173	1.235
	(0.122)	(0.126)	(0.146)	(0.145)	(0.153)	(0.210)	(0.223)
Recent Inactivity	0.798	1.052	0.751	0.714	0.786	1.000	0.910
	(0.287)	(0.403)	(0.298)	(0.282)	(0.313)	(0.436)	(0.399)
Recent Progress Halt	0.959	0.947	0.934	0.987	0.960	0.776^{+}	0.774^{+}
	(0.118)	(0.117)	(0.116)	(0.124)	(0.121)	(0.105)	(0.105)
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2135	2135	2135	2135	2135	2135	2135
Firms	144	144	144	144	144	144	144
LogLikelihood	-844.35	-842.00	-835.83	-825.98	-823.17	-724.37	-722.37

Odds ratios; Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table 4. The Effect of Parallel Search on Patent Value

Negative binomial regression model with firm, year and size dummies and firm-clustered standard errors; DV = number of forward citations received by the firm's patents filed in the current year

Forward Citations (DV)	(1)	(2)	(3)
Parallel Search			-0.134*
			(0.062)
Prior Forward Citations		0.171**	0.168**
		(0.058)	(0.058)
In-scope Segment Size		0.003	0.003
		(0.003)	(0.003)
Experience * Prior Forward Citations		0.052	0.050
		(0.040)	(0.040)
Firm Growth Trajectory		0.019	0.022
		(0.032)	(0.031)
In-scope Segment Growth		-0.013	-0.021
		(0.127)	(0.127)
Out-scope Segment Growth		-0.016**	-0.017**
		(0.004)	(0.004)
Inverse Mills Ratio		0.818	0.747
		(1.003)	(0.993)
Experience	-0.020	-0.025	-0.030
	(0.039)	(0.040)	(0.040)
Size	-0.010	0.001	0.002
	(0.053)	(0.061)	(0.061)
Proximity	0.041	0.045	0.045
	(0.086)	(0.084)	(0.085)
Recent Inactivity	0.252	0.545**	0.517*
	(0.165)	(0.207)	(0.208)
Recent Progress Halt	-0.081	-0.096^{+}	-0.093^{+}
	(0.055)	(0.051)	(0.051)
Firm Dummies	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Size Dummies	Yes	Yes	Yes
Observations	2142	2142	2142

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

APPENDIX

Definitions

N_{tA} = # of PANs of the focal firm in year t in category A

N_{tA}^{-i} = # of PANs of the industry in year t in category A

$T = \{t-1, t-2, t-3\}$

$T-3 = \{t-4, t-5, t-6\}$

cat = the set of all categories

cat_p = the set of categories that the firm has patented in during T

$cat_{np} = cat \backslash cat_p$ = the set of categories that the firm has NOT patented in during T

In-scope segment size

$$\sum_{A\in cat}\left(\frac{\sum_{t\in T} N_{t,A}}{\sum_{K\in cat}\sum_{t`\in T} N_{t`,K}} \times \frac{\sum_{t\in T} N_{t,A}^{-i}}{\sum_{K\in cat}\sum_{t`\in T} N_{t`,K}^{-i}}\right) = \frac{\sum_{A\in cat}\left(\sum_{t\in T} N_{t,A} \times \sum_{t\in T} N_{t,A}^{-i}\right)}{\sum_{K\in cat}\sum_{t`\in T} N_{t`,K} \times \sum_{K\in cat}\sum_{t`\in T} N_{t`,K}^{-i}}$$

We consider the measure as zero in case the firm did not patent in the previous 3 years.

Firm growth trajectory

$$\sum_{A\in cat}\left(\frac{\sum_{t\in T} N_{t,A}}{\sum_{K\in cat}\sum_{t`\in T} N_{t`,K}} \times \frac{\sum_{t\in T} N_{t,A} - \sum_{t\in T-3} N_{t,A}}{\sum_{t\in T} N_{t,A}}\right)$$

We consider the term in parenthesis as zero in case the firm did not patent in the corresponding category in the previous 3 years. As a result, this measure reduces to a top-line measure of growth in patenting: it measures total battery patents in the prior three years compared to total battery patents in the three previous years (years *t-6* to *t-4* versus *t-3* to *t-1*). Thus, it captures the rate of advancement a firm is experiencing in its overall portfolio.

In-scope segment growth

$$\sum_{A\in cat}\left(\frac{\sum_{t\in T} N_{t,A}}{\sum_{t`\in T}\sum_{K\in cat} N_{t`,K}} \times \frac{\sum_{t\in T} N_{t,A}^{-i} - \sum_{t\in T-3} N_{t,A}^{-i}}{\sum_{t\in T} N_{t,A}^{-i}}\right)$$

Out-scope segment growth

$$\sum_{A\in cat_{np}}\left(\frac{\sum_{t\in T} N_{t,A}{}^{-i}}{\sum_{t`\in T}\sum_{K\in cat} N_{t`,K}^{-i}}\times\frac{\sum_{t\in T} N_{t,A}^{-i}-\sum_{t\in T-3} N_{t,A}^{-i}}{\sum_{t\in T} N_{t,A}^{-i}}\right)$$

Proximity

$\mathrm{Prox}_{\mathrm{AB}}$ = the proximity measure of categories A and B

$$Proximity=\sum_{K\in cat_p}\left(\frac{\sum_{t\in T} N_{t,K}}{\sum_{t\in T}\sum_{K\in cat} N_{t,K}}\cdot\frac{1}{|cat\backslash cat_p|}\sum_{J\in cat\backslash cat_p} Prox_{KJ}\right)$$

$$=\frac{1}{\sum_{t\in T}\sum_{K\in cat} N_{t,K}}\cdot\frac{1}{|cat\backslash cat_p|}\cdot\sum_{K\in cat_p}\left(\sum_{t\in T} N_{t,K}\cdot\sum_{J\in cat\backslash cat_p} Prox_{KJ}\right)$$

Example:

The proximity measure for a firm which patented in categories A and B out of the set of categories A,B,C,D,F,X is:

$$Proximity=\frac{\sum_{t\in T} N_{t,A}}{\sum_{t\in T}\sum_{K\in cat} N_{t,K}}\cdot\frac{1}{4}(Prox_{AC}+Prox_{AD}+Prox_{AF}+Prox_{AX})$$

$$+\frac{\sum_{t\in T} N_{t,B}}{\sum_{t\in T}\sum_{K\in cat} N_{t,K}}\cdot\frac{1}{4}(Prox_{BC}+Prox_{BD}+Prox_{BF}+Prox_{BX})$$

Recent inactivity

Equals 1 if $\sum_{t\in T} N_{t,A}=0$.

Recent progress halt

Equals 1 if $\sum_{t\in T} N_{t,A}=0$ and $\sum_{t\in T-3} N_{t,A}\neq 0$.