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A BEHAVIORAL THEORY OF TECHNOLOGY SEARCH: EVIDENCE FROM THE SEMICONDUCTOR INDUSTRY

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Abstract

We build on the behavioral theory of the firm to shed light on the conditions under which firms are more likely to pursue exploratory or exploitative technology search strategies. Drawing on a well-known argument in the performance feedback literature, we predict that firms are more likely to adopt an explorative (exploitative) technology search strategy when their performance is low (high) relative to their peers?. Augmenting existing models, furthermore, we argue that performance feedback consists of cues which need to be interpreted and hence may be more or less ambiguous. Building on this argument, we derive a number of hypotheses explaining how firms? intensity of response to performance feedback varies depending on two distinct kinds of ambiguity - feedback incongruence and feedback variance. An analysis of the semiconductor industry from 1980 to 2002 supports our predictions.

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ABSTRACT

We build on the behavioral theory of the firm to shed light on the conditions under which firms are more likely to pursue exploratory or exploitative technology search strategies. Drawing on a well-known argument in the performance feedback literature, we predict that firms are more likely to adopt an explorative (exploitative) technology search strategy when their performance is low (high) relative to their peers'. Augmenting existing models, furthermore, we argue that performance feedback consists of cues which need to be interpreted and hence may be more or less ambiguous. Building on this argument, we derive a number of hypotheses explaining how firms' intensity of response to performance feedback varies depending on two distinct kinds of ambiguity - feedback incongruence and feedback variance. An analysis of the semiconductor industry from 1980 to 2002 supports our predictions.

Keywords: technology search, behavioral theory, social aspiration, learning, innovation.

INTRODUCTION

Understanding what drives firms' technological search behavior is of key importance from both a strategy and organizational standpoint (Chen & Miller, 2007: 369; Nelson & Winter, 1982; Katila, 2002; Fleming & Sorenson, 2004). While organizational decision makers are typically faced with a plethora of possible technological alternatives among which to choose (Miller and Arikan, 2004), prior research emphasized the crucial importance of two broad search strategies underlying most of these choices. One search strategy – "exploitation" – consists of deepening the firm's existing knowledge base in an attempt to leverage those technological trajectories the firm is already familiar with. The other– "exploration" – focuses on broadening a firm's knowledge base in order to create new technological opportunities in unfamiliar technological areas (Katila & Ahuja, 2002; Laursen & Salter, 2006).

Extant research on these different strategic orientations has mainly evolved along two lines of inquiry. On the one hand, scholars have investigated the performance consequences associated with pursuing explorative and exploitative technology search strategies. By influencing which knowledge elements are combined by a firm (Yayavaram & Ahuja, 2008), as well as the technological and organizational domains from which those elements are drawn (Rosenkopf & Nerkar, 2001), technology search strategies affect firms' responsiveness to both technological threats and opportunities. Accordingly, the choice of whether to adopt an explorative or an exploitative orientation in technological search has been shown to yield systematic performance differentials, including firms' ability to launch new products (Katila & Ahuja, 2002; Katila, 2002), generate impactful innovations (Fleming & Sorenson, 2004) and adapt to environmental changes (Miller & Arikan, 2004).

In addition to explicating the performance consequences of technological exploitation and exploration, a second stream of research investigated which organizational actions and levers are instrumental to their implementation (Tzabbar, 2009; Alexiev, Jansen, Van den Bosch ,Van den Bosch, & Volberda, 2010). For example, an excess of slack human capital in the form of research scientists is found to be generally conducive to exploitative search strategies (Mishina et al. 2004), although when coupled with a high level of managerial discretion, it may also aid in the implementation of explorative strategies (Al-Laham, Amburgey, & Tzabbar, 2010). Similarly, different types of inter-firm alliance are effective when technological search is aimed at exploiting a firm's existing technological opportunities than when the goal is to create entirely new technological opportunities (Hoang & Rothermael, 2005).

While both these research streams have evident merits, a limitation is that they largely take an "ex-post" view on the process of technological search. That is, they focus on what happens *after* the firm has made a decision whether to adopt an exploitative or an explorative search strategy. The goal of this paper is to cover this gap in the literature. Towards this end, we build on the behavioral theory of the firm and, in particular, on performance feedback models explaining decision makers' propensity for risk taking. A central idea in theories of learning from performance feedback is that organizations make decisions by comparing their performance with some goals or aspiration levels (Cyert & March, 1963; Levitt & March, 1988). Especially in highly competitive industries, where "intricate interdependencies among organizations underlie the development of ideas that shape the competitive dynamics among organization" (Podolny, Stuart & Hannan, 1996: 660), firms constantly benchmark their innovative performance against the performance of similar competitors (Clark & Mongomery, 1995; Peteraf & Shanley, 1997), a process that has been called social comparison (e.g., Festinger, 1942; Greve, 1998; Mezias, Chen

& Murphy, 2002). Our argument builds on the well-established view that when their performance is below social aspirations, organizational decision makers will be more willing to engage in risky behaviors with more uncertain outcomes (Kahneman & Tversky, 1979; Bromiley, 1991; March & Shapira, 1992; Greve, 1998, 2003a, 2003b, 2008; Baum, Rowley, Shipilov, & Chaung, 2005; Massini, Lewin & Greve, 2006; Labianca, Fairbank, Andrevski & Parzen, 2009). Applying this argument to explain firms' technology search strategies, we predict when exploitative and/or explorative technology search are more likely to be adopted.

In addition to contributing to our understanding of technology search choices, our model advances performance feedback research in important ways. Prior models implicitly assume performance feedback to be a deterministic reflection of objective performance differentials among the focal firm and its peers. Conversely, we propose that performance feedback consists of signals which need to be interpreted by the focal firm or, to be more precise, by its key decision makers. Consistent with this view, we examine two forms of ambiguity that may diminish the informational clarity of these signals, thereby reducing firms' intensity of response to performance feedback (Greve, 2003b: 3, 152). On the one hand, feedback ambiguity may result from discrepancies across performance dimensions. Consider for example the case of Intel and Advanced Micro Devices in the personal computer microprocessor industry. During the 90s, Intel's innovative performance was far above its direct competitor AMD, along several dimensions: number of key patents, number of product launches and product performance. However, when Intel began to fall behind AMD in terms of market growth, and with increasing variability in its social aspiration level, the firm started to invest a significant amount of resources to explore radically new scientific knowledge, which eventually led to the introduction of new, Hafnium based semiconductor chips (S&P Semiconductor Industry Survey, 2006). As this example suggests, the ease with which a firm can interpret performance feedback depends not only on the magnitude of performance shortfalls, but also on whether the feedback is consistent across performance dimensions (e.g., Gooding, Goel, & Wiseman, 1996; Greve, 2003b: Audia & Brion, 2006).

On the other hand, the ambiguity of performance feedback may increase when the comparison with a firm's peers yields disparate signals (Wood, 1989; Gooding et al., 1996). While prior studies modeled the process of social aspiration by looking solely at the average performance of a reference group of firms (Greve 2003b; Audia & Greve, 2006), we suggest that the ease with which that information can be interpreted by the focal firm depends on how much variability there is around the average. Particularly when the performance of a firm's peers vary significantly above and below the mean, organizational decision makers may face a high degree of uncertainty concerning how well their firm is really doing.

In addition to explicitly accounting for the signaling nature of performance feedback, we draw insights from related lines of inquiry in the sociology of organizations. As Vissa et al. (2010) recently noticed, "there is still a need for research examining whether problemistic search is affected by how the focal organization is embedded in an organizational and environmental context (Gavetti et al., 2007)." Furthermore, although performance feedback models are crucially based on the notion of "peers," thus far consensus is lacking concerning how a firm's external reference group should be identified and modeled (Greve 2003a). To address these problems, we follow a long and well-established research tradition in the sociology of organizations (e.g., White, 1981; Podolny et al., 1996; Stuart & Podolny 1996) and propose that firms' peers can be defined and modeled based on their position, or niche, in social structure.

The paper proceeds as follows. We begin by introducing our model of technology search based on performance feedback. Against the background of this model we set our baseline hypotheses, and we elaborate on the contingencies which determine the intensity of response to performance feedback. Next we discuss the data – comprising an unusually rich combination of patent and financial information, and the empirical setting – the worldwide semiconductor industry between 1980 and 2002. We conclude by elaborating on the implications of the study, and by suggesting ways in which our model may be extended in future research.

THEORY AND HYPOTHESES

Performance feedback and technology search

Technology search in organizations is a learning process through which firms attempt to solve problems in ambiguous and uncertain technological environments (Huber, 1991; Rosenkopf & Nerkar, 2001). A long tradition of organizational literature has advanced a distinction between two distinct types of search behavior. On the one hand, firms may pursue search activities that explore elements that are beyond the realm of what the firm already knows (March & Simon, 1958; Levinthal & March, 1993: 105), thereby broadening the scope of the firms' knowledge base (Rosenkopf & Nerkar, 2001; Miner, Bassoff, & Moorman, 2001). On the other hand, search efforts may be directed towards getting a deeper understanding of familiar knowledge (Huber, 1991: 99; Laursen & Salter, 2006), for example by systematically reusing and refining technologies the firm has already used in the past (Katila & Ahuja, 2002: 1184).

Due to the uncertainty inherent in innovative activities and the limited cognitive capacity of decision makers (March & Simon, 1958; Nelson & Winter, 1982; Fleming & Sorenson, 2004), firms lack full understanding of the knowledge they process as they attempt to solve technological problems. Therefore, a certain degree of risk taking is intrinsic in technology search. Nevertheless, an exploitative search strategy generally entails a lower level of risk than an exploratory one (March, 1991). Exploiting the same knowledge over and over again reduces the likelihood of errors and false starts and facilitates the development of effective search routines, thereby increasing the reliability of the search process (Levinthal & March, 1981). By contrast, exploring new areas of technological knowledge means relying on non-routinized search patterns and making sense of superficially understood knowledge, which augments the risk of poor solutions and technological dead ends (Martin & Mitchell, 1998).

The idea that explorative technological searches are intrinsically riskier than exploitative ones is key to understanding how firms choose their technological search strategy. Performance feedback models suggest that decision makers are more likely to engage in risky strategies when their organization fails to attain the performance level of (who they perceive as) their peers (March & Simon, 1958; Cyert & March, 1963; Kahneman & Tversky, 1979; March, 1988). For example, firms falling behind the performance of their peers engage more in organizational change (Ketchen & Palmer, 1999; Harris & Bromiley, 2007), vicarious learning (Baum & Dahlin, 2007) and exploratory inter-firm partnerships (2005). In a similar vein, we propose that organizational decision makers choose their technology search strategy by benchmarking the innovative performance of their own firm with that of its peers (Podolny et al., 1996; Stuart & Podolny, 1996). Namely, our hypothesis is that when a firm's innovative performance is perceived to be low relative to the performance of its peers, organizational decision makers will feel compelled to modify the situation. Under these conditions, engaging in high risk, high reward strategies may be seen as the only option to invert the negative tendency, inducing decision makers to invest in more explorative technology search initiatives in unfamiliar knowledge areas. Thus, we advance the following hypothesis:

H1: The more a firm's innovative performance falls behind its social aspirations, the more the firm engages in an exploratory technology search strategy

By contrast, organizational decision makers tend to be risk averse when they perceive their performance to be higher than their aspiration level (Bromiley, 1991; March & Shapira, 1992). Therefore, decisions to support activities based on the firm's prior knowledge technological knowledge will be more likely when a firm's innovative performance is above the performance of its peers in the industry (Levitt & March, 1988; Lant & Mezias, 1992). A high innovative performance relative to one's peers may lead decision makers to provide increasing support to ongoing projects based on existing knowledge and innovation trajectories, so that their potential is more fully realized and the firm's competitive position strengthened. In addition, a positive feedback loop may be triggered that reinforces the importance of what has been learned from previous experience, inducing organizational decision makers to go more and more in depth into those technological areas where the firm is already comparatively strong (Levinthal & March, 1993). As a result, firms experiencing a high innovative performance relative to their peers should be more prone to adopting an exploitative technology search strategy. This leads us to our second hypothesis:

H2: The more a firm's innovative performance is above its social aspirations, the more the firm engages in an exploitative technology search strategy

The ambiguity of performance feedback

Our arguments so far simply extended existing performance feedback models to the choice of a technology search strategy. By so doing, we followed prior research in assuming that the performance feedback received by a firm merely reflects "objective" performance differences between a focal firm and its peers. In what follows, we relax this assumption by acknowledging that a performance feedback is no more than a set of signals that organizational decision makers need to interpret and act upon. As such, it may be more or less ambiguous and easy to understand. Consistent with this view, prior studies brought suggestive evidence that under certain conditions, the evaluation of performance feedback can be problematic (Wiseman & Bromiley, 1996; Gooding, Goel & Wiseman, 1996).

We reckon that two source of signal ambiguity may be associated to performance feedback. A first source pertains to the fact that performance is a multi-dimensional construct rather than a one-dimensional one. When a firm's performance is consistent across all relevant performance dimensions, the feedback is straightforward and easy to interpret. The more discrepancies occur among the performance dimensions, however, the harder it is for organizational decision makers to interpret the signal, i.e., to understand how well the firm is performing (Greve, 2003b: 70-72).

In the context of our study, for example, we have argued that technology search strategies are likely to be influenced by a firm's innovative performance. Albeit salient to the key organizational decision makers within knowledge-intensive firms (Andrews, 1971; Greve, 2003: 70), however, this is not the only performance dimension that may influence technology search decisions. As previous research has shown, also market performance considerations affect the amount and direction of research and technology investments within a firm (Greve, 2003b). Thus, although it seems safe to assume that technology search decisions are primarily influenced by technology-related feedback, it is unlikely that the available market-related feedback will entirely be ignored.

Our argument is that more distal types of performance feedback, such as market-related feedback in our case, exert an influence to the extent that they are *inconsistent* with the primary performance feedback. That is, when organizational decision makers receive a similar performance feedback across different performance dimensions, they will find it easy to interpret the feedback because the signal is unambiguous. When the feedback is contradictory across performance dimensions, however, organizational decision makers are confronted with a highly ambiguous signal concerning how well the firm is doing. As a result, their ability to make decisions based on the performance feedback will be severed.

Going back to our study, this argument suggests that when the market performance feedback is consistent with the innovation performance one, the signal prompted to organizational decision makers will be unambiguous. Accordingly, the intensity of their reaction will be strongest. However, the more the market performance feedback diverges from the innovation-related one, the more attenuated will be the intensity of reaction of organizational decision makers. For example, when both the market and innovative performance of a firm fall behind the performance of its peers, we expect organizational decision makers to strongly react by adopting a riskier but potentially more profitable explorative technology search strategy. By contrast, when the firm is lagging behind its peers on technological grounds, but its market performance is better than its counterparts', we expect the reaction of organizational decision makers to be in the same direction but attenuated. By the same logic, when both a firm's innovative and market performance are high relative to the firm's peers, we expect decision makers to decidedly push for an exploitative technology strategy. But when a high innovative performance is paired with a low market performance feedback, the signal will be more ambiguous and, hence, the move towards an exploitative strategy less definite.

To sum up, we advance the following two hypotheses.

H3a: The tendency of choosing an exploitative technology search strategy when innovative performance is above social aspirations, is attenuated by the degree of inconsistency between innovative and market performance.

H3b: The tendency of choosing an explorative technology search strategy when innovative performance is below social aspirations, is attenuated by the degree of inconsistency between innovative and market performance.

A second source of ambiguity potentially attenuating the impact of performance feedback has to do with the variance originating from a firm's peers (Wood, 1989; Gooding et al., 1996). Social aspirations have been commonly measured using the average performance of its peers (Greve 2003b; Audia & Greve, 2006). This approach reflects the assumption that what matters is the "objective" performance differences among a focal firm and its peers. The view that performance feedback often represent ambiguous signals that must be interpreted, however, suggests that the variance in peers' performance may also matter for performance feedback dynamics. A high variance in the performance of one's peers may increase the ambiguity of the performance feedback signal by making it difficult for decision makers to understand how well their firm is performing. Consistent with this view, it has been recently argued that when the performance of one's peers varies significantly above or below the mean, looking at average values results in coarse-grained information which organizational decision makers may find hard to make sense of (Moliterno & Beckman, 2008). Similarly, Greve (2003b) argued that the presence of extreme values above and below the mean may result in contrasting indications on how to adjust aspiration levels (Greve, 2003b). Furthermore, "level biases" are often associated with extremely high-performing and low performing organizations, which tend to give an anchoring value and a greter role to extreme outcomes in the process of social aspiration formation (Kahneman & Tversky, 1979; Greve, 2003b: 52). When level biases point to contrasting directions, the quality and reliability of the feedback is likely to be perceived as lower, so that overall relevance of performance feedback in decision making is likely to be reduced.

Summing up, these arguments suggest that a high variance in social aspiration formation results in increased ambiguity in feedback interpretation, which ultimately leads to lower responsivesess in terms of decision makers' propensity for risk taking. Therefore, firms facing high variance will react less promptly to performance shortfalls, i.e., their tendency towards technological exploration will be diminished. Similarly, when a positive performance feedback is paired with a high variance in the performance of one's peers, decision makers' push towards exploitative technology search strategies should be reduced. As a result, we advance the following hypotheses:

H4a: The tendency of choosing an exploitative technology search strategy when innovative performance is above social aspirations, is attenuated by the degree of variance in the performance of one's peers.

H4b: The tendency of choosing an explorative technology search strategy when innovative performance is below social aspirations, is attenuated by the degree of variance in the performance of one's peers.

METHODS

Setting

To test our hypotheses, we focus on a comprehensive sample of global semiconductor device firms between 1976 and 2002. This setting lends itself to analyzing how performance relative to aspiration levels affects technology search for three reasons. First, firms' ability to generate technological innovations is crucial to command a competitive advantage in this industry, and yet there is persistent heterogeneity in the way technology search is carried out by firms in the industry (Hall & Ziedonis, 2001). Second, the setting is characterized by well-defined technological niches, wherein firms build on similar knowledge and resources and develop competitive relationships among themselves (Stuart & Podolny, 1996). This makes this industry a setting where social comparison with competitors dealing with similar technologies is relevant for the decision makers engaged in technology search decisions. Third, all relevant players in this industry routinely patent their inventions at the United States Patent and Trademarks Office (henceforth, USPTO) (Hall & Ziedonis, 2001).On these grounds, we followed prior research and used patent data to empirically reconstruct firms' search strategies and innovative performance over time.

Sample and Data

In an attempt to provide a complete and accurate representation of all the relevant players , our study considers all US, European and Asian firms, which patented their inventions at the USPTO. Industry accounts suggest that the inclusion of non-US firms is crucial to understand how aspiration levels are set and social comparison works in the semiconductor field, since the development of the industry "would no doubt have been smaller if the technological leadership of the United States had not come under challenge by the emergence of international competition" (Langlois & Steinmueller, 1999: 19).

To select our sample, we used the following procedure. We first consulted historical company profiles of authoritative specialized market data providers (such as Integrated Circuit Engineering Corporation, Gartner Research and the Semiconductor Industry Association) to identify a list of semiconductor firms that were active between 1975 and 2002. We then used the Directory of Corporate Affiliation to detect the subsidiaries of each firm in the initial list. Financial data about these firms and their subsidiaries were retrieved from COMPUSTAT North America, annual reports, SEC filings for US firms, and COMPUSTAT Global, Osiris and the Japan Company handbook for non US firms. Further, we consulted business directories (Hoovers Premium, Who owns Whom US, UK and Asia), industry sources (ICE annual volumes) and prior research (Hall & Ziedonis, 2001) to identify each firm's founding date, and to establish whether a firm should be categorized as (i) "vertically integrated", which produce semiconductor devices primarily to incorporate them in other products; (ii) "integrated device manufacturer" (IDM), i.e., firms specialized in the design, manufacture and commercialization of semiconductors; (iii) "fabless", i.e., firms specialized exclusively in designing semiconductor devices; or (iv) "others", i.e., semiconductor service providers.

To collect patent information on this sample of firms, we used two independent data sets: the NBER Patent and Patent Citations Data Set (Hall, Jaffe, & Trajtenberg, 2001), and the National University of Singapore's Patent Data Set (Lim, 2004). Using patent data from a single country is a standard practice in prior research (e.g., Ahuja, 2000; Katila & Ahuja, 2002), as this practice guarantees consistency, reliability and comparability (Griliches, 1990). To identify semiconductor-related patents, we used the list of USPTO subclasses developed by Macher (2006). Namely, we counted the number of patents granted in any of the listed subclasses to each of the identified firms and subsidiaries, and we selected those firms that had at least one patent between 1975 and 2002. We thus generated an unbalanced panel of 190 firms over the period 1975-2002.

Dependent Variables

Many researchers have argued that exploration and exploitation should be regarded as the end points of one conceptual continuum (March, 1991). This view, however, has been challenged by a growing number of studies in which exploration and exploitation are conceptualized and measured as two distinct dimensions (see Gupta, Smith & Shelley, 2006 for a comprehensive review). We follow this latter line of reasoning, arguing that "firms can vary in their degree of use and reuse of their existing knowledge, just as they can vary in their exploration of new knowledge" (Katila & Ahuja, 2002: 1183). Consistent with this view we assume that, at least in principle, a firms' technological search strategy may be at the same time explorative and exploitative.

Exploitative Technology Search Strategy. The variable Exploitative Technology Search Strategy replicates Katila and Ahuja (2002) search depth measure and accounts for the accumulation of search experience with the same knowledge elements. Following prior research, we measure the extent to which a firm engages in exploitative technology search as the average number of times a firm repeatedly used the citations in the patents it applied for. We created the variable by calculating the number of times that, on the average, each citation in year t+1 was repeatedly used during the previous five years. The following formula was used:

$$Exploitative\ Technology\ Search_{i\ t+1} = \frac{\sum_{y=t-4}^{t} repetition\ count_{iy}}{total\ citations_{i\ t+1}}$$

Since our patent data start in 1975, and we need at least a five year patent history to build the measure, we start measuring Exploitative Technology Search in 1980.

Exploratory Technology Search Strategy. The variable Exploratory Technology Search Strategy, which corresponds to the theoretical notion of exploration of new knowledge, was the proportion of previously unused citations in a firm's focal year's list of citations. We assessed the share of citations in a focal year's citations that could not be found in the previous five years' list of patents and citations by that firm. The variable was calculated as follows, based on Katila and Ahuja (2002) search scope measure:

$$Exploratory\ Technology\ Search_{i\ t+1} = \frac{new\ citations_{i\ t+1}}{total\ citations_{i\ t+1}}$$

Exploratory Technology Search has a range between 0 and 1. The use of these measures can be illustrated by considering a firm with ten patents. Each of the ten patents further cites ten other patents. On the average, eight out of the ten citations are new to the firm; that is, it has not used them during the past five years. The measure of Exploratory Technology Search is thus 0.8. Of the remaining two “old” citations in each patent, on the average, the firm has used one of them twice and the other three times. Thus, the Exploitative Technology Search measure for this firm is 0.5.

To get an intuition on the technology search strategies adopted by semiconductor firms in the observation period, we plot in figure 1 and figure 2 the average measure of Exploratory Technology Search and exploitative Technology search, by firm type. Over the last three decades the semiconductor industry has witnessed an increasing division of innovative labor between different types of firms (Hall & Ziedonis, 2001): “Fabless” design houses, integrated device manufacturers, vertically integrated electronic device producers and foundries and service providers. The graph shows that all types of firms engage more and more in the exploitation of existing technological knowledge as the industry matures. By contrast, there is more variance across firm types in the extent to which they engage in Exploratory Technology search.

Insert figure 1-2 about here

Independent Variables

Innovative performance relative to social aspirations. Organizational performance feedback arises from the comparison of recent innovative performance with social aspirations. The number of patent applications filed by a firm in a given year is the most intuitive measure of innovative performance in the semiconductor industry and has successfully been used by prior research in the innovation field (Griliches, 1990; Hall, Jaffe, & Trajtenberg, 2001). In a study of performance aspirations, it is important to measure context-specific variables of relevance to decision makers (Greve 2003b) and the generation of new technological knowledge is clearly of utmost importance to both semiconductor producers and fables semiconductor designers (Hall & Ziedonis, 2001). Accordingly, we use the count of patent application filed by a firm in the previous year as the underlying performance measure in the calculation of both our main independent variable measuring performance relative to social aspirations as well as the control variable measuring performance relative to historic aspirations.

Following prior research (Audia & Greve, 2006; Baum & Dahlin, 2007; Greve, 1998; Miller & Chen, 2004) we defined a firm's social aspiration level based as the average performance among an industry-wide peer group. Since comparability appears to be important an important factor affecting decision makers' formation of reference groups for social comparison (see Greve, 2003b: 126-127), we compute the social aspiration level as the weighted average of the innovative performance of all the firms in the industry, where the relative weight of each peer *j* is proportional to the technological proximity between the firm *i* and *j*[1].

$$Social\ Aspiration_{i\,t} = \sum_{j=1}^{N-1} w_{i\,j\,t-1} \times Patent\ Count_{j\,t-1}$$

The logic behind this measure is that the higher the technological proximity between firm j and the focal firm *i*, the higher the relevance that *i* will give to *j*'s performance in forming social aspiration levels. Our measure of innovative performance relative to social aspirations was then computed as follows $Performance\ relative\ to\ Social\ Aspiration_{i\,t} = Patent\ Count_{i\,t} - Social\ Aspiration_{i\,t}$

[1] For each patent with an application date on the 5-year window previous to the year of observation, we tabulated to which 3-digit USPTO technological class it was assigned, and created a vector with the percentage of patents assigned to each class for each firm. Then, we calculated the technological distance between two firms as the normalized Euclidean distance between the vectors just described. $w_{i\,j\,t}$ was computed as the additive inverse of the normalized Euclidean distance, so that technological weights reflect the extent to which the focal firm and its peers operate in similar technological domains.

Figure 1 and 2 illustrate visually how each firm's external reference group was identified and modeled.

Insert figure 3-4 about here

Figure 3 represents a Multi Dimensional Scaling plot representing all firms in our sample between 1995 and 1999 [2]. Squares represent integrated device manufacturers (i.e., Intel, Advanced Micro Devices, Texas Instruments, etc…), crosses represent vertically integrated, diversified corporations (such as Philips, IBM, …), triangles represent foundries and service producers (e.g., UTD, TSMC, …) and diamonds represent fabless firms (e.g., Xilinx, Ndivia, …). Figure 4 represents a closer selection of integrated device manufacturers depicted in figure 1, in the same time window.

In line with prior research (Podolny et al., 1996; Stuart & Podolny, 1996), the position of each firm represents its location on the technology landscape, while distances between firms represent the extent to which two organization exploit similar technological niches. Our intuition is that the group of firms located more closer to a focal firm on the technological landscape represented in figure 1 represents the peer group, that the focal firm monitors to build social aspirations levels. Moreover, we argue that firms located closer to the focal firm have a stronger role in social aspiration formation. For example, in figure 4, when forming social aspiration levels, Dallas Semiconductor would give strong emphasis to the technological performance of Atmel Corporation and Analog Devices Inc., while peers like Micron Technology or Texas Instruments will exert a weaker influence on the process of social aspiration formation.

[2] In line with our measure, the correlation matrix was obtained using dyadic normalized Euclidean distances as starting values. It is worth noticing that similar organizational forms are often not proximate on the technological landscape: in several instances, firms belonging to one type, i.e., fables, have higher technological similarity with other types of organizations, such as Integrated Device Manufacturers, than from other fabless firms. We used R to reproduce MDS plots.

Market Feedback. Building on prior research (Chen & Gallagher, 2002) and from managerial reports describing competition in the semiconductor industry (Gartner Research, 2008), we focus on Sales growth as the key market performance measure which is relevant for organizational decision makers. We compute market based social aspirations as the weighted average sales growth of the group of firm's operating in knowledge domains that are similar to the focal firm:

$$Market\ Social\ Aspiration_{i\,t} = \sum_{j=1}^{N-1} w_{i\,j\,t-1} \times Sales\ Growth_{j\,t-1}$$

We then obtain the discrepancy between a firm's market performance and social aspirations as follows: $Performance\ rel. to\ Social\ Aspiration_{i\,t} = Sales_{i\,t} - Social\ Aspiration_{i\,t}$

Finally, we dichotomize the variable, so that a regime of Positive Market Performance Feedback corresponds to a value of 1, while market performance below peers corresponds to a zero.

Social uncertainty. We define social aspiration uncertainty as the relative variance that decision makers face when evaluating other firms' performance in the process of social aspiration formation. Following prior research (Beckman et al., 2004), we measure social uncertainty as the standard deviation of performance levels of organizations that are similar to the focal firm, normalized by the social aspiration of firm *i*.

Controls

Innovative performance relative to historic aspirations. According to Cyert and March (1963), firms may form aspirations also based on their previous performance. To take into account how performance discrepancy relative to historic aspirations impacts technology search, we derived for each firm a historic performance aspiration level using an exponential weighted moving average (Greve, 2003b: 43) of yearly patent applications:

$$Historic\ aspiration_{i\,t} = \alpha \times Historic\ aspiration_{i\,t-1} + (1 - \alpha) \times Patent\ Count_{i\,t-1}$$

In this formula, α is a weighting coefficient indicating how the current period aspiration is updated. When $\alpha = 0$, historical aspiration adapts instantly to performance, whereas when $0 < \alpha < 1$, current period aspirations are impacted by prior period aspirations at a level equal to alpha. We modeled historical aspirations at 0.25 increments of α, and chose among the models based on goodness of overall model fit, in line with prior studies (Audia & Greve 2006; Baum et al., 2005). This analysis suggested that values of $\alpha = 0.25$ generally offered the best fitting models. We then computed the performance aspiration gap as follows:

$$Performance\ relative\ to\ Historic\ aspiration_{i\,t} = Patent\ Count_{i\,t} - Hist.aspiration_{i\,t}$$

Innovative Labor Slack. When slack resources are available within the firm, they may be deployed in technology search processes and result in the exploration of new knowledge (March, 1981; Greve, 2003b: 54). The most commonly used measure of resource slack divides the number of employees by firm sales relative to the industry average (Mishina, Pollock & Porac, 2004; Welbourne, Neck, & Meyer, 1999). However, the aggregate number of employees across all occupations does not necessarily reflect the amount of resources involved in technology search activities. For example, for vertically integrated firms and integrated device manufacturer, the number of employees includes marketing and sales personnel, or workers, who are not involved in innovation activities. Since researchers and inventors are the resource input for technology search, instead of the number of employees, we compute slack human capital as the total inventors-to-patents ratio for a given firm relative to its industry, using the following equation:

$$Innovative\ Labor\ Slack_{i\,t} = \frac{Inventor\ to\ patent\ ratio_{i\,t}}{\frac{1}{N}\sum_{j=1}^{N} Inventor\ to\ patent\ ratio_{j\,t}}$$

This measure takes industry-level differences in slack resources into account and provides an indicator of whether a firm possesses above- or below-average slack, relative to industry norms.

R&D Search Intensity. Technology search may also be driven by institutionalized search processes (Greve, 2003b: 54), which are rooted in stable, long term research programs and corporate investments in R&D. For this reason, we include the ratio between a firm's R&D expenditure and its net sales as a control.

Size. Firm size may have either a positive or a negative effect on the scale and scope of a firm's R&D activities, which in turn may affect search (Greve, 2008). To control for this, our models included firms' average number of employees in a given year.

Age. To account for the role of organizational experience in search processes (Cyert & March, 1963) we controlled for age, measured as the number of years elapsed between a firm's incorporation and the end of each year t.

Knowledge Heterogeneity. Firms' whose knowledge base comprises heterogeneous knowledge domains may have developed a direct experience on how to explore new knowledge (Phelps, 2010). For this reason, we control for the extent to which a firm's knowledge base is distributed across distinct 3-digit USPTO technological classes by adding a Blau (1959) index of knowledge heterogeneity in our models. The measure ranges between 0 and 1, where larger values indicate greater knowledge base heterogeneity.

Knowledge Stock. The extent to which a firm redeploys existing knowledge elements depends certainly on the amount of knowledge that a firm has accumulated over time. To take into account the amount of knowledge available within the firm, we include the count of total citations used by a firm's patent in the last five years.

Self Citations. Firms may differ in the extent to which they build on their own knowledge, rather than on external knowledge (Hall et al., 2001). To make sure that our estimates are not biased by these strategies, we constructed a variable, Self-ratio, which measures what share of a firm's backward patent citations are directed towards the firm's own prior patents in a given year (Hall et al., 2001).

Firm Type Dummies. As we mentioned in the previous paragraphs, to account for differences across these different organizational forms, we included a set of dummies indicating firms' organizational type. Fabless is the omitted category.

Time Dummies. We use a set of time dummies to control for unobserved time-varying effects which may affect firms' decision to engage in exploratory or exploitative search strategies.

US. Since all our measures are built on USPTO patents, but our sample includes worldwide semiconductor firms, we introduce a US dummy to capture systematic, country-level effects which may engender differences in firms' technology search behavior.

IBM. Since IBM holds more than 20% of the patents in our sample, we have some concerns that it may impact our results. To control for this outlier, we introduce a dummy that is 1 for IBM, 0 otherwise.

Model specification and estimation

Our first dependent variable, Exploratory Technology Search, is bounded between 0 and 1, while our second dependent variable, Exploitative Technology Search, is non-negative. Following recent empirical work dealing with similar dependent variables (Argyres & Silverman, 2004; Laursen & Salter, 2006), we thus used several alternative modeling approaches that have been used in prior research. As a first choice, we estimated a fractional response model on panel data, based on the logistic transformation of Exploratory Technology Search (Papke & Wooldridge, 1996; Greene, 2008) and a panel random effect regression for Exploitative Technology Search (the variable does not have an upper bound, rendering the logistic transformation unfeasible). We display results obtained with other approaches as robustness checks. Notice that to reduce concerns of reverse causality and to avoid simultaneity, all independent variables are lagged by one year. We used STATA 11 to estimate all equations.

RESULTS

In table 1, we report the mean, standard deviations and range of variables of interest. It is worth noticing that the correlation between the tendency to rely on Exploratory Search Strategies and on Exploitative Search strategies is as low as 0.09: that is, in line with prior research (Katila & Ahuja, 2002; Gupta et al., 2006) in our empirical context these strategies seem to be distinct and may be concurrently pursued. We explored potential multicollinearity problems by computing the mean variance inflation factors (VIF) for each model. In all cases, the mean VIF for our models falls well below 5, which is considered unproblematic by conventional standards (Studenmund, 2001).

Insert table 1 about here

Table 2 displays results of our models predicting firms' tendency to choose an Exploitative Technology Search Strategy or an Exploratory Technology Search Strategy.

Insert table 2 about here

Starting with our control variables, our models show that a firm's Knowledge Stock has a positive, statistically significant effect on the extent to which a firm engages in Exploitative

Technology Search Strategy and a negative and significant effect on the firm's engagement in Exploratory Technology Search Strategy. Thus, firms with little prior technological knowledge are more likely to explore new knowledge areas and are less likely to reuse the knowledge they acquired in the past. Similarly, firms who developed an ability to build on their existing knowledge, tend to expand their knowledge base by deepening their understanding of prior knowledge, whereas they are less likely to explore new knowledge. By contrast, firms' age does not have a significant effect on firms' technological search strategy.

In line with slack based models of firms' search behavior, Inventive slack has a positive and statistically significant effect on Exploratory Search Strategy. Corroborating results of prior research (March, 1981; Greve, 2003b: 54), when slack resources are available within the firm, these inventive resources are deployed in technology search processes and result in the exploration of new knowledge. However, innovative slack does not have a significant effect on the tendency of choosing an exploitative technology search strategy. We reckoned that because in the semiconductor business firms' vary greatly with respect to the diversity of technology domains they engage in, it would be important to control for the *Knowledge Heterogeneity* of a firm's knowledge base. Our estimates show that Knowledge Heterogeneity has a positive effect on firms' tendency to engage in Exploitative Technology Search Strategies, though the effect is not statistically significant. Most importantly, firms whose knowledge base spans distinct technology domains are significantly more likely to explore new knowledge domains in their building up new technological knowledge. Finally, firms' size does not influence any of our independent variables, as indicated by the lack of significance of *Size* across our main models. We also attempted to capture possible unobserved firm-specific factors by adding a set of firm type dummies and a US geographic dummy, which correspond to 1 if the company headquarters are located in the United States. The effect of these variables was not significant across all models.

Moving now to our variables of interest, Model 2 shows a negative, statistically significant effect of positive performance feedback on the tendency of a firm to choose an Exploratory Technology Search strategy ($\beta=0.002$, $p<0.01$). Thus, our first hypothesis is corroborated: The more a firm's innovative performance falls behind its social aspirations, the more the firm engages in an exploratory technology search strategy. By contrast performing above social aspirations tends to reduce firms' tendency to engage in exploratory Search strategies. Similarly, and in line with our second hypothesis, model 7 shows that the more a firm's innovative performance is above its social aspirations, the more the firm increases its tendency towards exploitative technology search strategy ($\beta=0.002$, $p<0.05$). To explore the impact of performing above social aspiration, Model 3 and Model 8 examine the distinctive effect of performing above and below aspiration on both types of technology search strategies. We insert two predictors in each model: one predictor is equal to the Positive performance Feedback, and zero otherwise. The second predictor is equal to the performance shortfall, and zero otherwise. These models corroborate results of model 2 and 7: firms performing above their peers significantly reduce Exploratory Technology Search and increase Exploitative Search. However, in contrast with prior findings (Greve, 2003b) our data do not show a significant difference in the slopes of these two variables.

Model 4 and 9 insert the interaction between the dummy Positive Market Performance feedback and the difference between a firm's innovative performance and its social aspirations. As results show, in both cases predictions from performance feedback is strengthened when feedback is not ambiguous. In other words, the tendency of choosing an exploitative technology search strategy when innovative performance is above social aspirations, is stronger innovative and market performance are aligned ($\beta=0.001$, $p<0.1$). In addition, the tendency of choosing an explorative technology search strategy when innovative performance is below social aspirations, is attenuated by the degree of inconsistency between innovative and market performance ($\beta=-0.001$, $p<0.05$).

Finally, Model 5 and 10 insert the interaction between the difference between a firm's innovative performance and its social aspirations. Supporting H4b, the tendency of reducing Explorative Technology Search efforts when innovative performance is above social aspirations, is attenuated by the degree of variance in the performance of one's peers. However, H4a is not supported: firms performing above their peers in an uncertain environment do not seem to reduce their tendency for Exploitative Technology Search strategies, even in highly uncertain environments.

Robustness analyses

Since one of our dependent variables is bounded between 0 and 1, and the second is non negative, we used a panel, fractional response model and a panel random effect model. We estimated a panel regression with firm fixed effects to make sure that our results are consistent in the presence of unobserved heterogeneity. The consistency of the random effect estimates was confirmed through a Hausman test (1978). In a another set of models, we used a generalized least squares approach to take into account possible heteroskedasticity and autocorrelation across panels. Autocorrelation may be a problem since we analyzed our data based on partly overlapping time windows. While this is a standard practice in research based on patent data (e.g., Katila & Ahuja, 2002), it may engender temporal autocorrelation. Finally, we followed prior research (Argyres & Silverman, 2004; Laursen & Salter, 2006) and estimated one-side and two-side Tobit models for both our dependent variables. Results are in line, in terms of sign and significance, with the ones displayed in the main tables.

DISCUSSION AND CONCLUSIONS

Departing from the predominant ex-post view on the process of technology search, the present paper examined the factors that drive firms' decision to adopt and exploitative or an explorative technology search strategy. Towards this end, we built on the flourishing stream of literature going under the rubric of performance feedback models (Greve, 2003b), arguing that firms make decisions by comparing their performance with that of their peers – a process often named "social aspiration" (Cyert & March, 1963; Levitt & March, 1988; Greve, 1998; Mezias, Chen & Murphy, 2002). We tested our predictions on a comprehensive sample of global semiconductor device firms between 1976 and 2002. To measure the technological output and search of firms, we assessed their patenting behavior. Following previous research, we quantified the intensity of an exploitative search strategy as the extent to which a firm reuses the same patent sources over and over again. As evidence of explorative search strategies, we took the number of patent sources used by a firm that did not belong to the firm's existing knowledge portfolio (Katila & Ahuja, 2002). To define the peer group for the firms, we assessed firms' closeness to each other in technology space by measuring the extent to which they patent in the same technological classes. Using these variable constructs, we found support for our prediction that peers' innovative performance influences which technological search strategy firms adopt, as well as the intensity with which they pursue it. These results are stable and robust to alternative specifications.

Drawing from previous research on performance feedback models (Kahneman & Tversky, 1979; Bromiley, 1991; March & Shapira, 1992; Greve, 1998, 2003a, 2003b, 2008; Baum, Rowley, Shipilov, & Chaung, 2005; Massini, Lewin & Greve, 2006; Labianca, Fairbank, Andrevski & Parzen, 2009), we argued that when the performance of a firm is perceived to be below its social aspiration level, organizational decision makers are more willing to engage in risky behaviors with more uncertain outcomes. Conversely, risk averse solutions are more often sought when one's performance is perceived to be superior to that of its peers. Applying this argument to explain firms' technology search strategies, we demonstrated that exploitative technology search strategies are more likely to be adopted when a firm's innovative performance is lower than that of its peers. When a firm is more innovative than its peers, however, exploitative technology search strategies tend to be preferred.

In addition to shedding new light on the antecedents of technology search strategies, we advanced performance feedback research in important ways. Prior models implicitly assumed performance feedback to be a deterministic reflection of "objective" performance differentials among the focal firm and its peers. Conversely, we argued that performance feedback consists of signals that need to be interpreted. Accordingly, the intensity of firms' response to performance feedback depends on its degree of ambiguity. When the ambiguity of performance feedback is low the responsiveness of organizational decision makers is strongest, whereas it whitens as the level of ambiguity increases. To explore this argument, we examined two sources of ambiguity that diminish the informational clarity of performance feedback. The first results from the fact that performance is a multidimensional construct and discrepancies may occur across performance dimensions. For example, we argued that when both the market and innovative performance of a firm fall behind the performance of its peers, the performance feedback has low level of ambiguity. As a result, firms strongly react to the feedback by adopting a riskier but potentially more profitable explorative technology search strategy. When the firm is lagging behind its peers on technological grounds but its market performance is better than its counterparts', however, the ambiguity of the performance signal increases and, hence, the reaction of organizational decision makers is significantly attenuated.

We reasoned that the ambiguity of performance feedback also increases when the comparison with a firm's peers yields disparate signals (Wood, 1989; Gooding et al., 1996). Thus, although prior studies modeled the process of social aspiration by looking solely at the average performance of one's peers (Greve, 2003b; Audia & Greve, 2006), we argued that the ease with which performance feedback can be interpreted depends on how much variability there is around the average. When one's peers vary significantly above and below the mean, organizational decision makers face a high degree of uncertainty concerning how their firm is really doing. As a result, the intensity of their reaction to the performance feedback will be reduced. Conversely, when most of a firm's peers have a comparable performance, the ambiguity of the feedback received by the focal firm will be low. Hence, its impact on the firm's technology search strategy will be strong.

In addition to explicitly accounting for the signaling nature of performance feedback, we advanced the literature on problemistic search by drawing insights from related lines of inquiry in the sociology of organizations. As Greve et al. (2010) recently noticed, "there is still a need for research examining whether problemistic search is affected by how the focal organization is embedded in an organizational and environmental context (Gavetti et al., 2007)." Furthermore, although performance feedback models are crucially based on the notion of "peers," thus far consensus is lacking concerning how a firm's external reference group should be identified and modeled (Greve, 2003a). To address these problems, we followed a long and well-established research tradition in the sociology of organizations (e.g., White, 1981; Podolny et al., 1996;

Stuart & Podolny, 1996) and proposed that firms' peers can be defined based on their position, or niche, in social structure. Using a relational construction of firms' technological positions based on patent data, we conceptualized firms as located on technology space. Thus, rather than adopting ad hoc methods to infer a firm's peers, we were able to infer this information from their position in social structure.

In addition to this immediate benefit, connecting the concept of peers used in performance feedback theories to notions used in the sociological literature may result in more profound theoretical advances. Although a core theoretical claim in the sociology of organizations is that firms' strategies are constructed by interpreting signals from other market participants (see, e.g., White, 1981, 1992; Podolny, 1993; Podolny et al., 1996), ensuing research has left this argument largely unattended. Thus for example, sociologists developed a status-based view of the firm arguing that firms' behaviors act as signals affecting the evaluation of their offerings by other market participants (Podolny 1993, Zuckerman 1999). However, scant attention has been paid to studying how organizations are affected by the signals they receive from their peers. By connecting a performance feedback view to existing sociological models of firms' behavior, interesting cross-fertilizations could be generated. For example, our results show that organizational decision makers have troubles interpreting performance feedback when there is much variance in the performance of one's peers. From a sociological perspective, this suggests that a firm's ability to make strategic decisions may depend on their position in social structure. Namely, firms embedded in structural positions whereby performance differentials are limited should be best equipped to respond rationally to the performance signals accruing to them, which in turn should result in increased adaptiveness. Conversely, the strategy formulation process may be more cumbersome for firms located in positions where performance differentials are significant. Future research should explore this argument and, more generally, opportunities for cross-fertilization between performance-feedback and sociological theories of firm behavior.

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FIGURE 1

Exploitative Technology Search Strategy (average by firm type) 1980-2002

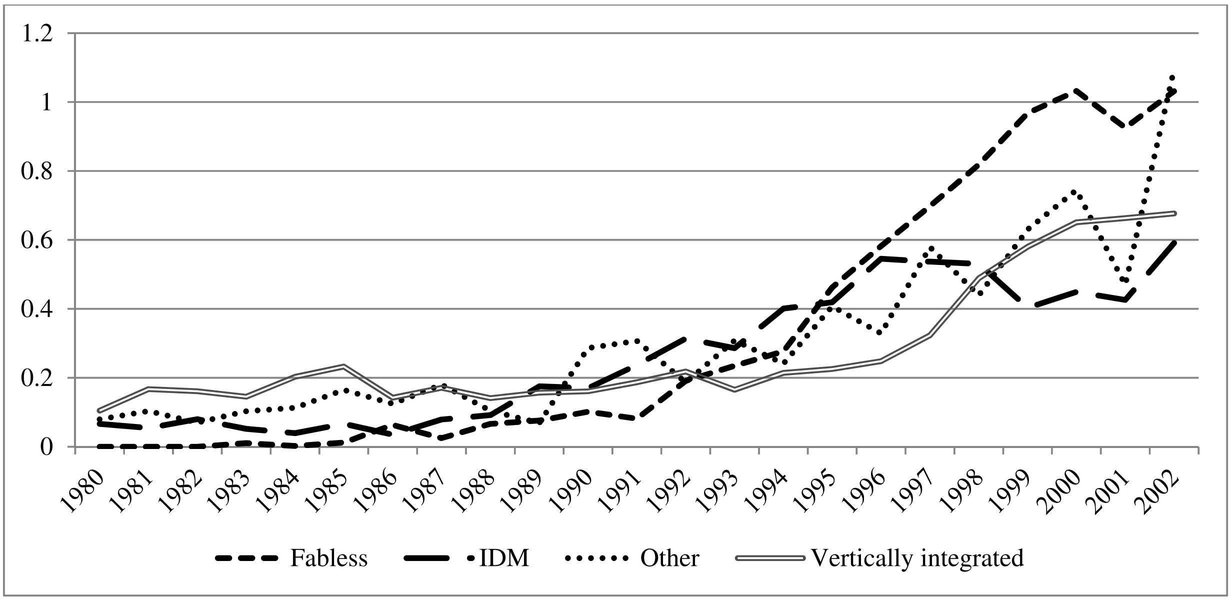

FIGURE 2

Exploratory Technology Search Strategy (average by firm type) 1980-2002

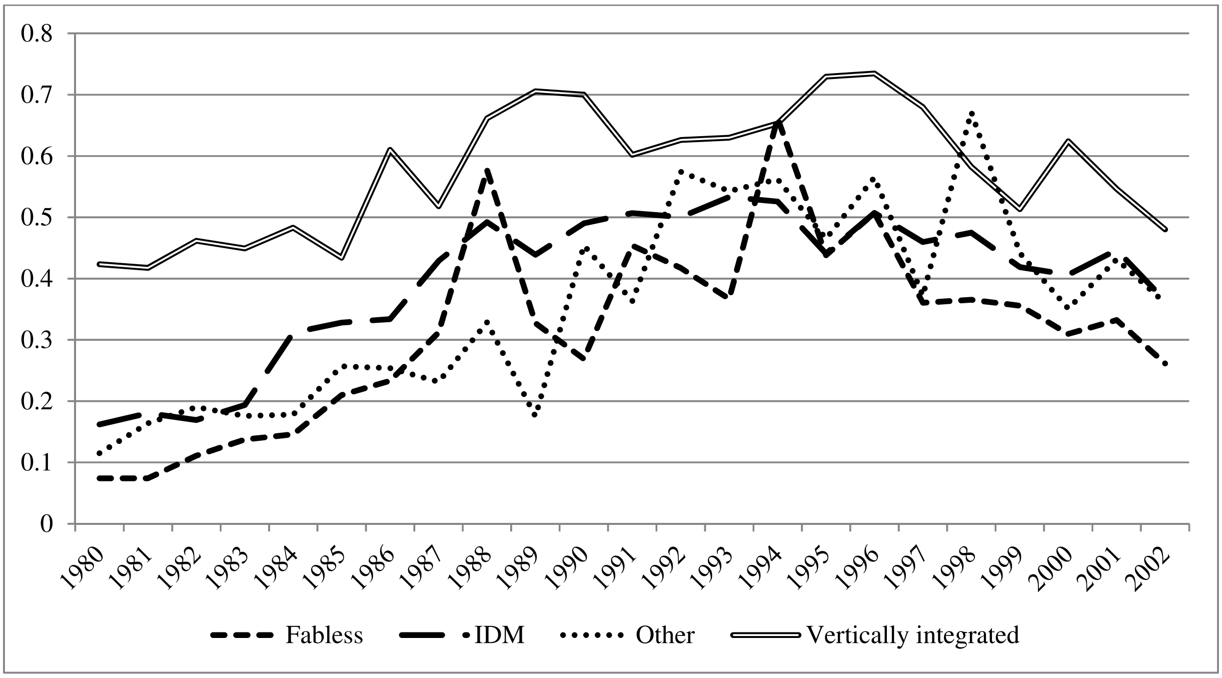

FIGURE 3

Technological position of semiconductor firms in the sample, by firm type (1995-99)

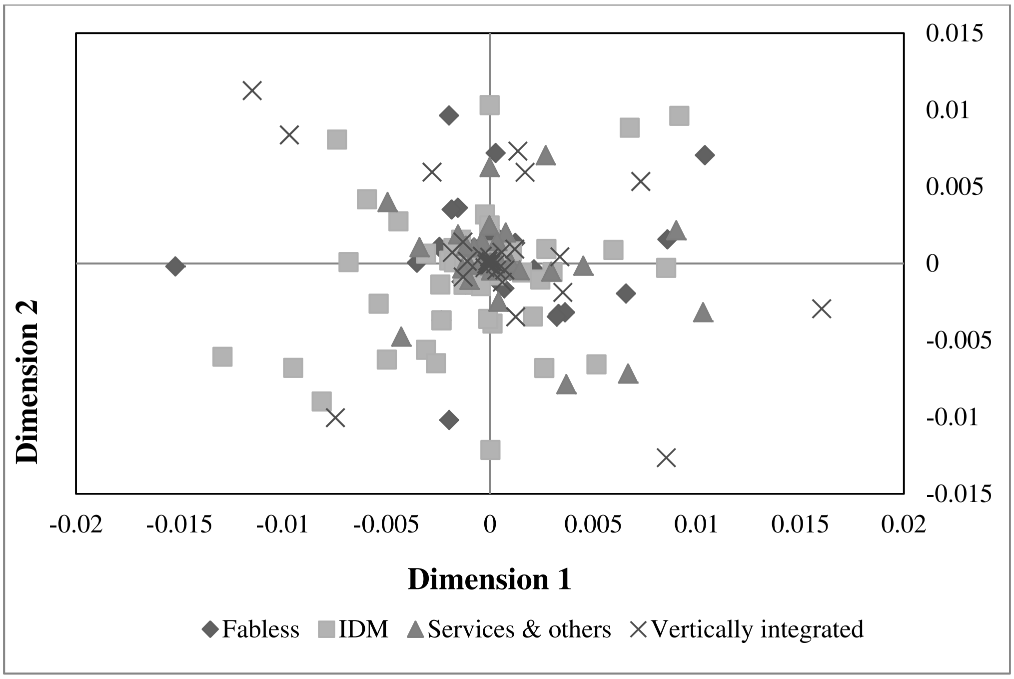

FIGURE 4

Technological position of selected semiconductor firms (1995-99)

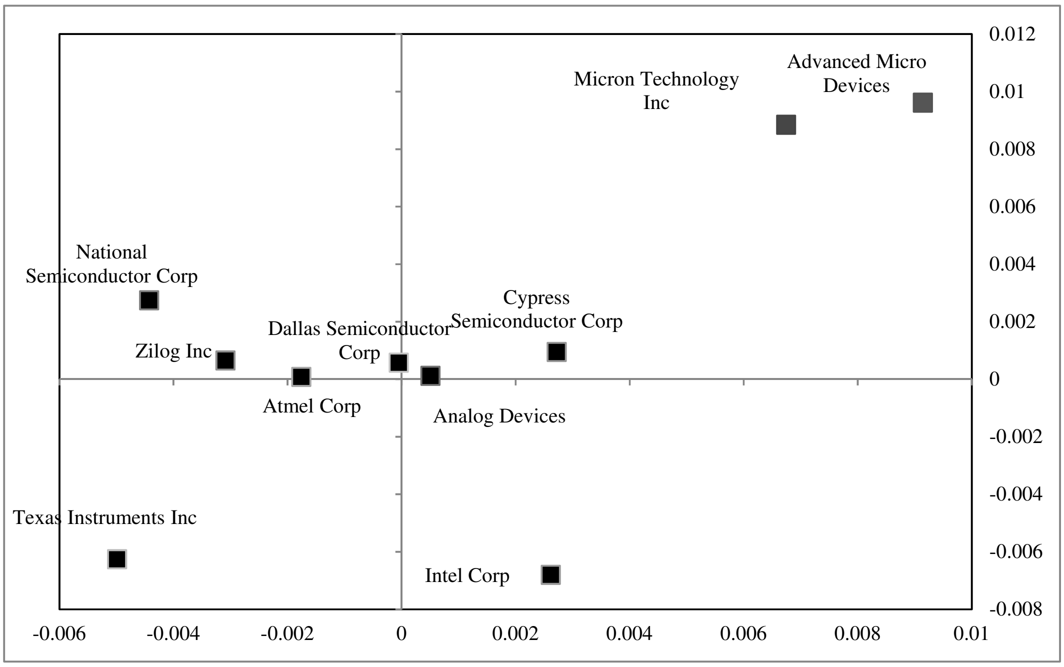

TABLE 1

Variable	Mean	Std. Dev.	Min	Max
Exploitative Technology Search	0.38	0.89	0	10.83
Exploratory Technology Search	0.56	0.40	0	1
Difference Technological Performance - Social Aspiration	3.27	64.11	-467	954.03
Positive Market Performance Feedback	0.40	0.49	0	1
Social Uncertainty	0.76	0.59	0	1.73
Difference Performance - Historical Aspiration	7.15	33.93	-338.72	469.16
Knowledge stock	7.63	9.53	0	193
Age	30.77	30.78	0	155
Inventive Slack	0.83	0.54	0	4.47
Self citations	0.11	0.16	0	1
Knowledge Heterogeneity	0.41	0.35	0	0.94
R&D Intensity	0.47	2.16	-93.95	21.04
Size	28.95	79.80	0	845.68

TABLE 2

Results of panel regression predicting Exploratory Technology Search and Exploitative Technology Search

	Exploratory Technology Search					Exploitative Technology Search				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Difference Technological Performance - Social Aspiration		-0.002***		-0.002***	-0.002**		0.002**		0.002**	0.002**
		(0.001)		(0.001)	(0.001)		(0.001)		(0.001)	(0.001)
Difference Technological Performance - Social Aspiration (>0)			-0.003***					0.002*		
			(0.001)					(0.001)		
Difference Technological Performance - Social Aspiration (<0)			-0.001					0.002		
			(0.002)					(0.002)		
[Diff.Tech. Perf. - Social Aspiration] * Positive Market Performance Feedback				-0.001**	-0.001**				0.001**	0.001*
				(0.001)	(0.001)				(0.001)	(0.001)
[Diff.Tech. Perf. - Social Aspiration] * Social Uncertainty					0.012**					-0.001
					(0.002)					(0.001)
Positive Market Performance Feedback	0.172**	0.177**	0.178**	0.180**	0.180**	0.017	0.014	0.015	0.011	0.011
	(0.074)	(0.074)	(0.075)	(0.075)	(0.075)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
Social Uncertainty	0.000	0.001	0.001	0.001	0.001	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Difference Performance - Historical Aspiration	-0.002**	0.001	0.002**	0.001	0.001	0.003***	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Knowledge stock	-0.019***	-0.020***	-0.020***	-0.020***	-0.020***	0.027***	0.028***	0.029***	0.029***	0.029***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
Age	0.002	0.002	0.003	0.002	0.002	0.000	-0.000	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Inventive Slack	0.205**	0.194**	0.199**	0.197**	0.195**	-0.032	-0.025	-0.024	-0.028	-0.029
	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)	(0.050)	(0.049)	(0.050)	(0.048)	(0.048)

(Table 2 continued)

Self citations	-0.819***	-0.786**	-0.772**	-0.770**	-0.766**	1.452***	1.423***	1.425***	1.412***	1.414***
	(0.316)	(0.315)	(0.315)	(0.316)	(0.315)	(0.453)	(0.451)	(0.453)	(0.454)	(0.455)
Knowledge Heterogeneity	1.364***	1.356***	1.344***	1.343***	1.340***	0.187**	0.204**	0.202**	0.212**	0.208**
	(0.147)	(0.150)	(0.148)	(0.150)	(0.150)	(0.089)	(0.088)	(0.090)	(0.091)	(0.090)
R&D Intensity	-0.011*	-0.011*	-0.011*	-0.011*	-0.011*	0.004	0.004	0.005	0.005	0.005
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Size	-0.000	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IBM	-0.541**	-0.367	-0.340	-0.450*	-0.432*	0.176	0.004	0.011	0.069	0.082
	(0.244)	(0.238)	(0.243)	(0.238)	(0.238)	(0.146)	(0.164)	(0.159)	(0.170)	(0.166)
US	-0.288**	-0.285**	-0.279**	-0.282**	-0.281**	0.017	0.016	0.017	0.014	0.015
	(0.138)	(0.136)	(0.136)	(0.137)	(0.136)	(0.056)	(0.055)	(0.055)	(0.055)	(0.055)
IDM	0.085	0.098	0.097	0.099	0.099	-0.034	-0.045	-0.045	-0.045	-0.044
	(0.167)	(0.167)	(0.167)	(0.167)	(0.167)	(0.103)	(0.101)	(0.101)	(0.101)	(0.101)
Vertically integrated	0.114	0.109	0.120	0.111	0.113	-0.176	-0.171	-0.168	-0.170	-0.168
	(0.260)	(0.255)	(0.255)	(0.255)	(0.255)	(0.123)	(0.123)	(0.121)	(0.122)	(0.122)
Service & Others	-0.037	-0.041	-0.036	-0.041	-0.043	-0.115	-0.106	-0.104	-0.104	-0.105
	(0.207)	(0.206)	(0.207)	(0.206)	(0.206)	(0.136)	(0.132)	(0.130)	(0.132)	(0.132)
Time dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Constant	-0.512*	-0.540*	-0.560*	-0.548*	-0.550*	-0.126	-0.104	-0.108	-0.098	-0.100
	(0.290)	(0.287)	(0.287)	(0.286)	(0.286)	(0.091)	(0.088)	(0.094)	(0.088)	(0.088)
Observations	2,115	2,115	2,115	2,115	2,115	2,115	2,115	2,115	2,115	2,115
Number of firms	190	190	190	190	190	190	190	190	190	190

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1