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# Game of skill or game of luck? Distant search in response to performance feedback

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ABSTRACT

Despite its strategic benefits, there is persistent heterogeneity across firms to what extent they engage in distant search activities. According to the default prediction of behavioral theory of the firm (BTF), poor past performance will increase a firm's propensity for distant search, whereas good performance will lead to a decrease. However, a contrasting view is taken within the emerging capability cue perspective, which predicts the opposite. To understand these conflicting views, we emphasize the key role of context that is formed by a firm's sectoral innovation pattern and shapes the dominant cognition of firms' managers. Building on this sectoral innovation perspective and Pavitt's seminal work (1984; 1995) we distinguish between a science-based innovation pattern (here, we focus on the semiconductor industry) and a specialized-supplier innovation pattern (we focus on the machinery industry). The key claim we make is that different sectoral innovation patterns shape other dominant managerial cognitions, leading to a different interpretation of past performance that influences the decision to increase or decrease distant search. Our paper contributes to an understanding of how the competing ideas on different ways in which firms respond to feedback, in view of distant search, can be reconciled. We also contribute to the literature on technological innovation by considering the role of managerial cognition and how differences therein can be associated with different firm choices on their distant search activities.

## 1. Introduction

This paper studies the effect of performance feedback on a firm's propensity for distant search. Searching for novel knowledge forms a central notion in the literature on innovation and is considered a key element in the innovation process (Schumpeter, 1934; Dosi, 1982; Ahuja and Katila, 2004). One of the key findings from this body of literature indicates that firms have a natural inclination to engage in local search, which occurs in the vicinity of what they already know (Levinthal and March 1993). In other words, firms are generally much less focused on distant search, which entails searching for information and knowledge beyond the firm's core domains of expertise (Nelson and Winter 1982; Levinthal and March 1993). As distant search covers novel and unfamiliar domains, it is considered a riskier activity than local search. However, distant search is more likely to generate new insights and contribute to radical innovation development (Afuah and Tucci, 2012; Rosenkopf and Almeida, 2003; Rosenkopf and Nerkar, 2001; Tandon and Toh, 2022). More broadly, distant search supports firms in their anticipation of future environments, and in so doing, it may increase a firm's chances of long-term success (Ahuja and Lampert, 2001; Barirani et al., 2015; Enkel and Heil, 2014; Laursen, 2012; Rosenkopf and Nerkar, 2001).

However, despite the significant benefits of distant search, the conditions that prompt firms to engage in distant search are still not well understood. Here, behavioral theory of the firm (BTF) serves as a useful lens through which to study what drives a firm's propensity for distant search (Cyert and March 1963; Greve, 2003a; Bromiley, 2005). A core premise of BTF is that past performance shapes a firm's strategic behavior, which in turn influences its future performance. According to behavioral theory, firms continue with current activities and tend to avoid risky actions as long as performance is satisfactory, but they will change their activities when performance is perceived as unsatisfactory (Greve, 2003a; Baum and Dahlin, 2007). The implication from BTF is that in response to negative performance, firms increase their propensity to engage in riskier behaviors characterized by more uncertain outcomes—such as organizational restructurings, changes in strategy, the introduction of new practices and routines, the launch of new products, and the termination of existing ones (e.g., Audia et al., 2000; Greve, 2003a; Baum et al., 2005; Joseph et al., 2016; Zhong et al., 2022)—or distant search, like we study in this paper. Meanwhile, considerable support has been found for these hypothesized effects of performance feedback (see Shinkle, 2012; Greve and Gaba, 2017; Kotiloglu et al.,

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2021).

However, standing in contrast to these insights is the so-called capability cue perspective that argues the opposite. That is, this theory suggests that positive cues, such as good performance, may be interpreted by a firm as an indicator of its general ability, which in turn positively influences its risk-taking propensity. In their study, Chatterjee and Hambrick (2011) find a strong positive and robust effect of recent firm performance on a firms' propensity for risk-taking, with the latter indicated by R&D expenditures, capital expenditures, and acquisitions—all subject to highly uncertain returns. In this respect, these findings suggest that there may also be an opposite interpretation of, and response to, performance, whereby strong performance is interpreted as a positive cue that fosters boldness rather than breeding inertia. Also, unsatisfactory performance, in that case, could be construed as a *negative* cue that induces timidity and risk-avoidant behavior (Chatterjee and Hambrick, 2011). The implication for distant search is that, following the capability cue perspective, strong performance leads to its increase, whereas unsatisfactory performance leads to its decrease.

When attempting to unravel these seemingly inconsistent findings, it is important to note that Chatterjee and Hambrick (2011) conducted their study within an empirical setting of computer hardware and software industries, which is different from the empirical settings used in most feedback studies. Although there is an emerging number of performance feedback studies in (more) high-tech type of industries (e.g., Joseph and Gaba, 2015; Kuusela et al., 2017; Situmeang et al., 2016), most studies in which a positive effect of unsatisfactory performance on risk-taking has been reported tend to be in more traditional, or low-tech, industries, including shipbuilding (Greve, 2003a, 2007), investment banking (Baum et al., 2005), public transport (Baum and Dahlin, 2007), education (Labianca et al., 2009), or manufacturing (Chen, 2008).

So far, performance feedback theory assumes that feedback effects are uniform across industries, which is reflected by Greve's (2003a) claim that the theory holds across a wide range of industries. This assumption implies a certain level of automaticity in firms' responses to feedback and associated, routinized, and uniform search processes (Posen et al., 2018). The theory thus neglects the critical role of managerial cognition in interpreting past performance, also in light of the decision to anticipate future environments through distant search (Gavetti et al., 2012). Here we challenge this dominant assumption by bringing the role of cognition to performance feedback theory. A cognitive perspective assumes that behaviors are premised on beliefs and mental models, describing the relationship between alternative actions and outcomes (Gavetti et al., 2012; Narayanan et al., 2011; Nelson and Winter 1982, Levinthal and March 1993; Saemundsson et al., 2022). It shifts attention to organizational information processing and shared mental representations that shape processes such as (problemistic) search. (Posen et al., 2018). We focus on role of managerial cognition, which has neglected in feedback studies, and argue that this can be different for different firms. That is, different cognitions lead to a different interpretations of performance feedback, that may have different consequences for choices related to, among others, distant search.

To explore the role of managerial cognition, we argue for the importance of sectoral contexts on such cognitions and draw on the well-established literature of sectoral innovation patterns. With its intellectual antecedents firmly grounded in evolutionary theory (Nelson and Winter 1982; Dosi, 1982; Dosi et al., 1988), the literature on sectoral innovation patterns takes an industry-level perspective and argues that firms, operating within various sectors, differ markedly in their sources for innovation, their search intensity and direction, their emphasis on product innovation over process innovation, their means of appropriation as well as their dominant sectoral cognitions (e.g., Pavitt, 1984; Marsili, 2001; Malerba, 2002; Bogliacino and Pianta, 2016; Zhong et al., 2022). Based on these insights, we claim that managerial cognition differs across different sectoral innovation patterns. These cognitions can be considered a mental representation of the industry environment, forming a forward-looking form of intelligence that is based on managers' beliefs about the effectiveness of different industry-specific action-outcome linkages (Gavetti and Levinthal, 2000). As we will argue, these managerial beliefs shape whether they predominantly see distant search as a 'game of skill' or as a 'game of luck,' which colors their interpretation of past performance and shapes their decisions to increase or decrease their distant search activities. This idea helps us understand why firms in certain industries, when faced with negative performance feedback, cut back on distant search activities (following BTF), whereas in other industries, they increase such activities (following the capability cue perspective). By doing so, our study contributes to a better understanding of *why* organizations' responses to feedback differ, in addition to *how*, which has been the focus of many studies to date that have mostly black-boxed such decision-making processes. All in all, this enables us to understand why firms' reactions to performance feedback may not be as invariant across industries as generally assumed (cf. Greve, 2003a), and as also indicated in recent studies (e.g., Cheah et al., 2021).

To study these ideas, we use generalized estimating equation models, and draw on data from we consider two different industries, namely machinery and semiconductors. The choice of these two industries provides us with highly contrasting differences with respect to sectoral innovation patterns. Whereas the machinery industry exhibits characteristics of a specialized-supplier innovation pattern, the semiconductors industry exhibits clear science-based innovation pattern traits (Pavitt, 1984, 1990; Marsili, 2001; Bogliacino and Pianta, 2016). There are 68 companies in our final panel database, including 334 valid observations over 1999–2011.

This paper makes several contributions to the literature. First, as explained, many feedback studies assume a strong degree of automaticity in firms' responses to performance feedback that leads to a highly routinized search process (Posen et al., 2018; Kotiloglu et al., 2021). Here we challenge this assumption by theorizing on the role of managerial cognition and how this differs across different sectoral innovation patterns to explain and reconcile the competing ideas on feedback responses. Second, BTF has emphasized the dominant role of problemistic search, which is stimulated by a problem and is directed toward finding an immediate solution to it (Cyert and March 1963). Although risk-taking and uncertainty form central notions in BTF, activities as foresight and anticipation of the future, including the role of distant search, are largely missing in this theory (Gavetti et al., 2012; Gavetti and Levinthal, 2000). Here, we enrich BTF by developing a more detailed understanding of when firms engage in distant search activities that nurture foresight and support them in developing a better sense of an uncertain future.

## 2. Theory

Studies on evolutionary economics have emphasized the role of path-dependence in technological search and innovation processes (Nelson and Winter 1982; Dosi, 1982). The implication that follows from this literature is that past search outcomes form the starting points for new search activities. The causal mechanism here is shaped by the fact that firms rely on previous idiosyncratic experiences in existing knowledge domains, which serve as the basis for determining important factors for future search (March and Simon, 1958; Levinthal and March 1993). So, when searching for novel knowledge, firms search locally and will generally be less inclined to search beyond their established domains of expertise and experience.

This ties into what has been called 'problemistic search' in BTF, which is defined as "search that is stimulated by a problem [...] and is directed toward finding a solution to that problem" (Cyert and March 1963, p. 121). It can be characterized as myopic search that is biased by organizational experiences and current understandings of causality and that is aimed at seeking solutions that are similar to previously used ones. This general idea of problemistic search also resonates with findings by Greve (2003a). In his seminal study on performance feedback and innovation, Greve (2003a) qualified problemistic search as the channeling of R&D resources to projects near completion as a middle ground between solving urgent performance problems and the long lead times that typically come with R&D activities. Problemistic search, then, as a key construct in the behavioral theory of the firm, can be seen as a form of local search.

However, problemistic search is unlikely to generate the variety that is needed to address novel problems and to create new innovations, and may therefore also be less effective in future environments where solutions to problems are generally beyond the familiarity of current practices (Haveman, 1992; Laursen, 2012; Levinthal and March 1993; Posen and Levinthal, 2012; Posen et al., 2018). Consequently, problemistic search will generally not advance foresight through the development of new insights and knowledge that can help firms anticipate and prepare for future environments. On the other hand, distant search means searching in unfamiliar domains and gives organizations access to new knowledge beyond their current expertise. The strategic benefit that distant search offers is the development of a forward-looking orientation that may contribute to the ability to adapt to future environmental changes (Chen, 2008; Jissink et al., 2019). However, any action that departs from current routines and established ways of operating carries uncertain consequences and will thus be considered risky.

Risk-taking and uncertainty also form a central idea in performance feedback theory. According to this theory, firms continue with current activities and tend to avoid risky actions as long as performance is satisfactory, but they will change their activities when performance is perceived as unsatisfactory (Greve, 2003a; Baum and Dahlin, 2007). Hence, the default prediction is that poor performance will lead to lower confidence in current routines and ways of operating, which pushes a firm to undertake a greater level of risk-taking and, therefore, increases its propensity for distant search. In contrast, good performance strengthens a firm's confidence in the value of its current strategy and operations, which attenuates its risk-taking propensity and, therefore, decreases its propensity for distant search. These predictions also resonate with the pillar of behavioral theory that is informed by prospect theory. This theory predicts that individuals who have more to lose become more risk-averse, and vice versa (Kahneman and Tversky, 1979).

A contrasting view, however, suggests that strong performance can also be interpreted as a positive cue that nurtures confidence and leads firms to increase distant search, whereas unsatisfactory performance may serve as a negative cue that may lead to a decrease in it (Chatterjee and Hambrick, 2011). While this discussion is beyond the scope of their study, Chatterjee and Hambrick (2011) suggest that this difference in how firms respond depends on whether their decision-makers "believe they are playing a game of skill rather than a game of luck" (Chatterjee and Hambrick, 2011, p. 208). In this way, they loosely allude to different beliefs that firms' managers can have in how much the environment facilitates them to achieve specific outcomes. Do they believe they are in an environment that permits them to achieve certain outcomes if they are skilled or, instead, are they in an environment in which their skills do not influence the achievement of certain outcomes, but mostly by skills of others, reflective of a 'game of luck?'

This ties into the idea by Gavetti and Levinthal (2000) that cognition is especially important for distant search, as cognition can be understood as a forward-looking form of intelligence based on managers' beliefs about the effectiveness of different industry-specific action-outcome linkages. Cognitions, or cognitive representations, have been shown to be a critical determinant of managerial choice and action (Tversky and Kahneman, 1986; Huff, 1990). In particular, a firm's choice of strategy is often a by-product of its managers' representation of their problem space (Simon, 1991). An important implication that follows is that decision makers' cognitive representations also color how they perceive risks and uncertainties, which affects their interpretation of past performance and their decision to invest in distant search.

To make sense of these conflicting predictions between BTF and a capability cue perspective, we bring in the role of context (Johns, 2006). We argue that the dominant cognitive model on the risks of distant search and the meaning attached to past performance is shaped by the sectoral context in which firms operate. To address this role of the sectoral context, we draw on the literature of sectoral innovation patterns, which carries the central idea that industries differ markedly in the dominant innovation patterns that characterize them. These patterns are formed by the sources of knowledge inputs, the nature and attractiveness of innovation opportunities, and the means of appropriation (Pavitt, 1984; Marsili, 2001; Malerba, 2002). Based on the seminal work by Pavitt, and the recent revision of his work by Bogliacino and Pianta (2016), five different innovation patterns can be distinguished, namely specialized-equipment suppliers, science-based firms, scale-intensive firms, information-intensive firms, and supplier-dominated firms.

Reflective of the idea that context has a profound impact on organizational behavior (Johns, 2006), below, we will further argue how various two sectoral innovation patterns shape different cognitions on the risks associated with distant search and on the meaning of past performance. Specifically, we distinguish between a science-based innovation pattern and a specialized-supplier innovation pattern, as these sectoral contexts differ profoundly in terms of managerial perceptions on risk and the meaning of performance feedback (Pavitt, 1984, 1995; Bogliacino and Pianta, 2016). In other words, we focus in particular on the selection of these two innovation patterns is both necessary and sufficient, as it allows us to best describe (and observe) the potentially discriminating influence of industry-dominant logics on strategic decision-making processes, to unravel the conflicting findings presented by various BTF scholars.[1] See also Fig. 1, which details our conceptual model.

### *2.1. A science-based innovation pattern: emphasizing endogenous opportunities for innovation—a game of skill*

In this sectoral innovation pattern, the primary source for innovation is formed by firms' own R&D activities. These R&D activities lead to self-created innovations, which are based on the ongoing progress and development of underlying scientific research performed both within the firm and at public research institutes (Pavitt, 1984; Marsili, 2001). Opportunities for innovation within this pattern are often self-generated, as these emerge from the recombination of new scientific knowledge with firms' idiosyncratic and specialized knowledge. This gives rise to a wide range of internal opportunities, such as new self-developed process technology for producing next-generation innovations like, for instance, high-throughput screening in pharmaceuticals (Nightingale, 2000). In addition, it can give rise to new market opportunities within the same industry, such as the creation of new drugs that cure patients' diseases like COVID-19 or to create new opportunities in adjacent industries, such as the application of biotechnology in food processing and environmental cleaning, or the use of new semiconductors in cellphones, self-driving cars, home applications and

[1] Of course, companies are expanding their offerings' scope, triggering industry convergence (Kim et al., 2015). Such convergence could also imply higher levels of managerial mobility across industries—blurring industry boundaries and thereby limiting the discriminating power of sector-derived action-outcome linkages. However, such processes seem to occur mainly between related industries (so-called intra-industry convergence) (Kim et al., 2015). Hence, the sectoral innovation perspective is valid as we selected two highly distant and cognitively remote industries. In this respect, Bogliacino and Pianta (2016) also find that Pavitt's (1984, 1995) taxonomy is still valid for discriminating between sectors. Nevertheless, it seems highly interesting and relevant for future work to study how processes of industry convergence influence change in decision-making heuristics over time.

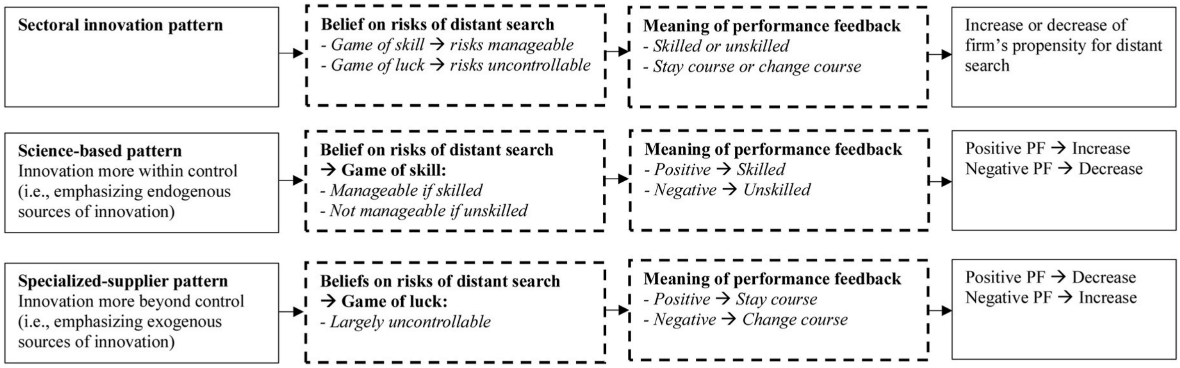


**Fig. 1.** Conceptual model.

industrial processes. Consequently, firms that operate within industries that follow this innovation pattern often act as a key supplier of innovations to firms whose industries operate based on other innovation patterns such as scale-intensive -, information-intensive -, specialized-supplier, and supplier-dependent innovation patterns (Pavitt, 1984, 1995; Marsili, 2001; Malerba, 2002; Bogliacino and Pianta, 2016).

The dominant characteristics of this sectoral innovation pattern—particularly strong self-reliance in relation to innovation, entry barriers for outsiders, and generally effective means of appropriation—create a context wherein innovation opportunities are mostly endogenously created by the actions and recombination activities of firms. This sectoral innovation pattern shares commonalities with a creation context in which agents do not wait for exogenous events to form opportunities but, through acting and enactment, form and create new opportunities themselves (Alvarez and Barney, 2007). In addressing the opportunities, managers learn that their initial ideas on newly identified opportunities may not be justified and need further adjustment and development. Such feedback fuels a learning process that makes them and their firms more skilled over time (Alvarez and Barney, 2007). Thus, this sectoral context gives rise to a cognition that implies that investing in distant search and innovation will pay off for those who are skilled. The general belief is that new action-outcome linkages can be identified and enacted through learning, experimentation, and skill development. The emphasis on learning and new skill development also means that risks of distant search are considered as manageable.

The meaning attached to performance feedback is that good performance validates the belief that one is skilled. Hence, good performance is seen as a capability cue and enhances confidence that risks of distant search can be managed, which serves as an incentive to invest in distant search. In contrast, negative performance diminishes confidence that one is skilled enough to manage the risks of distant search, making managers timider to further invest in distant search. Instead, they may prefer to place safer bets by investing in local search. This leads to our first hypothesis:

**Hypothesis 1**. In a science-based innovation pattern, positive performance feedback is positively related to a firm's propensity for distant search.

### 2.2. *A specialized-supplier innovation pattern: emphasizing exogenous opportunities for innovation—a game of luck*

In this sectoral innovation pattern, the main source of innovation originates from (large) external users. That is, specialized suppliers follow their users' needs, who serve as key sources of innovation (Pavitt, 1984). In other words, users provide the operating skills and experience, testing facilities, and possibly also design and development resources for specialized suppliers; while specialized suppliers respond to users' needs by offering their specialized expertise and experience to support external users in creating continuous improvements in product design and product reliability (Marsili, 2001). As a result, innovations typically take the form of newly designed, existing products in response to users' needs.

To address those needs, specialized suppliers rely not only on their own knowledge but also on knowledge and expertise that exists beyond their industry, such as that of firms from scale-intensive industries or from science-based industries (Pavitt, 1984). Whereas these users and firms from outside the industry make significant contributions to innovations, specialized suppliers make only a minor contribution (Pavitt, 1984). Moreover, the appropriation of innovations is generally limited and mainly occurs by developing firm-specific skills in responding sensitively and quickly to users' needs and continuous improvements of product design and reliability (Marsili, 2001). This pattern is typically found in the traditional machinery, manufacturing, housebuilding, and agriculture industries.[2] Firms operating within this pattern contribute only marginally to their product and process innovations, which are mainly formed by continuous improvement and refinement of products, their designs, and working features (Pavitt, 1984, 1990; Marsili, 2001; Bogliacino and Pianta, 2016).

In such a sectoral innovation pattern, both the key sources and opportunities for innovation and the means of appropriation are largely beyond the control of these specialized-supplier firms. This creates a sectoral context that shares commonalities with a discovery context as innovation opportunities are made mainly by others, whereas specialized suppliers need to respond quickly and sensitively to these exogenous opportunities once discovered (Alvarez and Barney, 2007). In search for and discovery of new opportunities, these firms generally put more emphasis on local search. This focus on local search will only make room for a focus on distant search when firms have sufficient 'alertness' to become aware of new, exogenous opportunities (Shane, 2003). This sectoral context, as such, feeds a cognition that innovation relies primarily on the skills of others and that exogenous opportunities need to be discovered, implying that one's skills do not much influence the successful outcomes of distant search. Hence, learning and new skill development regarding distant search are considered to be of little importance as distant search and its inherent risks are considered largely uncontrollable. Consequently, the dominant managerial belief is that distant search is a 'game of luck.'

The meaning attached to performance feedback is that good performance validates the belief that one is effective in this sectoral environment, which forms an incentive to stay course and not to engage in

[2] Greve's (2003a; 2003b) empirical setting, formed by his sample of Japanese ship manufacturers, was characterized by the industry's long history of its firms' adopting foreign innovations in their processes and products. In a follow-up study, he reported a strong bias toward "exploitation innovations" in this industry, which "did not involve any firm learning or development of new technology" (Greve, 2007, p. 958).

distant search. Good performance reaffirms the dominant cognition that customers and other firms from beyond the industry are the major sources of innovation, which mutes the propensity to invest in distant search. In contrast, negative performance diminishes confidence that this strategy is still effective, creating alertness (Shane, 2003). Alertness induces a need to leave the path of local search and engage in distant search instead (Levinthal, 1997), as this could potentially generate novel and unforeseen solutions that may contribute to restoring future performance.

In this sectoral context, we expect the core ideas of performance feedback theory to apply, meaning that as long as performance is satisfactory, managers remain confident and will not be inclined to change their current search routines and existing ways of operating. Past positive performance feeds their self-confidence and will bias their decision-making against changes and novel alternatives (Greve, 1998; Posen and Levinthal, 2012; Joseph et al., 2016). Only when performance drops will managers start to lose confidence in their current strategy, which makes them alert to the search for and discovery of more distant solutions to address their firm's declining performance. All in all, this leads to our second hypothesis:

**Hypothesis 2.** In a specialized-supplier innovation pattern, positive performance feedback is negatively related to a firm's propensity for distant search.

## 3. Empirics

To test our hypotheses and informed by the work by Pavitt (1984), Marsili (2001), and Bogliacino and Pianta (2016), we collected data from the semiconductor (SIC 3674) and industrial machinery (SIC 3510–3590)[3] industries. These two industries accurately reflect our distinction between a science-based innovation pattern and a supplier-dominated one (Pavitt, 1984; Marsili, 2001; Bogliacino and Pianta, 2016), enabling us to test our hypotheses. There are 68 companies in our final panel database, spanning years 1999–2011, and including 334 observations.[4] The semiconductor panel subset comprises 35 companies (168 observations) and the industrial machinery subset includes 33 companies (166 observations). Our database mainly includes US-based firms (64 firms), but it also contains firms located in Switzerland, Ireland, and Panama (two, one, and one firm, respectively).[5] The panel is unbalanced owing to, among other things, mergers and acquisitions.

Specifically, our database consists of all organizations represented in the Compustat database in the selected industries (1999–2011). For all organizations, we (hand) collected additional information, such as the annual reports, form 10-Ks and proxy statements, and patent information. Companies like Texas Instruments Inc. and Deere & Co. are included in the database. Our sampling approach implied that we selected such larger companies, which are also more likely to regularly and systematically file for patents (we use patents to create a proxy for distant search) than are smaller firms.

We combined data from Compustat and BoardEx with USPTO patent data to construct our database. We used data provided by the Fung Institute, which includes granted patents from USPTO. For the companies in our sample, which typically operate internationally, USPTO data serve as a suitable proxy for company search behavior and innovation performance (Nooteboom et al., 2007). Data were merged using company identifiers (to combine those from Compustat and from BoardEx) and string similarity threshold analyses combined with manual coding (to match patent data and Compustat/BoardEx data). We considered subsidiaries by gathering data using Securities and Exchange Commission (SEC) 10 K filings and other publicly available sources (e.g., companies' websites). We only included granted patents—that is, the number of successful patent applications. The corresponding year is the year when a company applied for a particular patent (Nooteboom et al., 2007; Ahuja, 2000).

Despite the limitations of patent data—for instance, not all inventions get patented, for technical or strategic reasons—they have been widely used in the field of innovation studies to uncover, among other things, firm search behavior and technological innovation output (e.g., Eggers and Kaul, 2018; Ahuja and Lampert, 2001; Schoenmakers and Duysters, 2010). However, these limitations mainly apply to cross-sector analyses, as patenting behavior varies substantially across sectors. This study is interested in firms' responses to performance feedback *within* a specific innovation pattern. As such, this limitation does not affect our research. Other studies have used R&D expenses to measure innovation (e.g., Greve, 2003b). However, R&D expenses form a measure that more accurately represents the quantity of *inputs* into the innovation process. Relying on granted patents instead means that we can call upon a measure that comes close(r) to capture a company's realized technological *output*. Therefore, using patents as the basis of our measure for distant search implies that we capture firms' actual risk-taking behavior more accurately.[6]

The fact that we only include granted patents to calculate our measure for a firm's propensity for distant search means that we only measure *successful* distant search attempts when, in fact, firms' actual levels of risk-taking are likely to be (much) higher. Our empirical model, therefore, reflects a rather conservative test of our hypotheses, as the actual relationship between performance feedback and propensity for distant search is likely to be stronger than we find, as firms typically need to engage in numerous distant search attempts before one is successful and becomes observable as a granted patent.

### 3.1. Measures

#### 3.1.1. Dependent variable: propensity for distant search

We construct our measure of a firm's propensity for distant search via the following steps. First, we took the calculated technology profiles of all focal companies in the sample. These calculated technology profiles are based on the primary USPTO classes at the three-digit level. More specifically, if a patent was granted in a given technology class to a focal firm during the year of observation and this grant occurred five or fewer years after that focal company had already successfully obtained a patent within the same technology class, that patent can be considered the result of a local search process (Nooteboom et al., 2007; Ahuja, 2000). If a company was granted a patent within a given technology class in the year of observation but had not received a patent within that same technology class in the previous five years, that patent can be considered the result of distant search, as it implies that the firm was searching for information and knowledge beyond its core domains of expertise. Since knowledge remains relatively new immediately after patenting, classes keep this distant search 'status' for three consecutive years (Ahuja and Lampert, 2001). In our final database, we count 1913 distant search events and 15,589 local search events. We calculate a firm's propensity for distant search by calculating the percentage of 'distant' patents relative to the total sum of patents acquired per firm

[3] We drew data from several subsectors within SIC35 to obtain sufficient data for our analyses. These subsectors include, among others, pumps & pumping equipment (SIC3561), general industrial machinery & equipment (SIC3560), special industry machinery (SIC3559), and farm machinery & equipment (SIC3523), which all resonate well with the specialized-supplier innovation pattern.

[4] Our model setup implied that we 'lost' quite some observations, please see section 3.2, Analysis for more information.

[5] Robustness tests that excluded these four non-US firms from the analyses resulted in highly similar findings.

[6] Furthermore, we do not know how many of the R&D resources, per firm-year, are directed toward local versus distant search—unlike patents, which can more easily be categorized.

(including any patents acquired by subsidiaries) per year (Katila and Ahuja, 2002).

#### 3.1.2. Independent variable: performance feedback

Scholars have relied on various measures to operationalize performance feedback (Short and Palmer, 2003). Here, we use a standard accounting measure that varies annually: return on sales (ROS). ROS is a frequently employed measure of performance and is widely used by managers. More specifically, based on ROS we calculated *social comparison* performance feedback (Greve, 2003b). We focus on social comparison performance feedback because firms' aspiration levels are largely determined by the performance of similar firms (Festinger, 1954; Cyert and March 1963). That is, managers often consider their firm's performance in light of the performance of firms with similar products, markets, and so on (Reger and Huff, 1993; Porac et al., 1995; Clark and Montgomery, 1999). Comparisons with peer firms can be considered of higher strategic importance than prior performance alone, as such performance does not capture the necessary information required for allocation decisions (Arrfelt et al., 2013). Furthermore, peer comparison is likely to invoke stronger managerial emotions and subsequent responses. That is, a firm's senior management may gain or lose legitimacy in the eyes of its stakeholders—and thereby gain or lose the support that is critical to firm survival and success—as a result of the firm's performance compared to that of its peers (Arrfelt et al., 2013; Ye et al., 2021) and thus becomes more self-confident or timid. In other words, we consider organizational performance through the lens of comparison with industry average performance, and we take the position that it results in either self-confidence or timidity—dispositions that subsequently influence a firm's propensity for risk-taking and thus its propensity for distant search.

We calculated social comparison performance feedback as firm performance in terms of ROS minus the mean performance of all firms in the sector during the previous year (Greve, 2003b). A firm's performance is considered satisfactory or good in cases where it is better than that of the firm's rivals (feedback >0), whereas it is considered unsatisfactory or bad in cases where it is lower than the performance of the firm's rivals (feedback <0). Furthermore, we calculated two- and three-year moving averages of social comparison performance feedback to assess the effect of feedback *persistency* on a firm's propensity for distant search (O'Brien and David, 2014). Analyses with a measure of social comparison performance feedback that was based on return on assets (ROA) as robustness tests yielded highly similar results. A detailed appendix, which includes these results, is available upon request.

#### 3.1.3. Control variables

We include control variables at the industry, firm, and top management levels. At the industry level, we include *GDP growth*, as macroeconomic conditions are likely to influence decision-making processes with respect to local versus distant search (Lavie et al., 2010). We also include several controls at the company level: *organization growth*, measured in terms of employee growth, as growing organizations are more prone to engage in distant search activities (Lavie et al., 2010); *R&D intensity*, measured as R&D investments over revenue, as this may affect patent output (Ahuja and Katila, 2004; Nooteboom et al., 2007); and *current ratio*, as a measure of slack resources. We also included several top management team (TMT) variables. More specifically, we consider *TMT size* and *TMT average tenure*. *TMT size* reflects the total number of executives in the TMT and may influence communication speed and effectiveness (Clark and Maggitti, 2012), which may have a bearing on distant search. *TMT average tenure* is the average tenure (in years) of the complete TMT, and it captures the idea that longer-tenured managers are more likely to be committed to the status quo and thus more likely to steer the firm away from risk-taking and distant search. This variable also partially controls for (inter-sector) executive mobility as a source of novel ideas that could challenge the dominant logics that reside within firms. Finally, we include two variables at the CEO level. First, *CEO tenure* captures the same dynamics as the TMT counterpart at the level of the organization's most influential actor. Second, *CEO duality*, a binary variable coded as 1 where the CEO is also the chairman of the board of directors and 0 where he or she is not, indicates the CEO's power to push a particular agenda within the organization (Chatterjee and Hambrick, 2011). We also account for unobserved time effects by including a complete set of year dummies. In view of the persistency of firms' propensity for distant search, we also include the lagged dependent variable. Table 1 provides an overview of our variables, their measures, and main data source.

### 3.2. Analysis

We used generalized estimating equation (GEE) models with robust standard errors, clustered by firm, as we have multiple observations for each firm that are likely correlated over repeated measures (Liang and Zeger, 1986; Katila and Ahuja, 2002; Martínez-Noya and García-Canal, 2021). In such cases, GEE models consider firm-specific factors as reflected in any remaining correlation or heteroscedasticity between the within-firm residuals (Hardin and Hilbe, 2002; van de Wal et al., 2020). Compare this approach to that of a fixed-effect estimator, which does not take firm-specific factors as reflected in any remaining correlation or heteroscedasticity into account, resulting in biased model outcomes (Hubbard et al., 2010). We also adopted the following measures to alleviate potential endogeneity problems (Xu et al., 2019; Zhong et al., 2022). First, all explanatory variables and controls were lagged to reduce the possibility of reverse causality by better reflecting the logic that the firm's strategic choices and actions precede the observable

**Table 1**
Overview of variables, measures, main data source, and example references.

| | Variable | Measure(s) | Main data source(s) | Example reference |
|---|---|---|---|---|
| 1. | Distant search | Percentage of 'distant' patents relative to the total sum of patents acquired per firm, per year. | USPTO (Fung institute); SEC 10K | Nooteboom et al. (2007) |
| 2. | R&D Intensity | The annual reported level of R&D investments divided by revenue, per year. | Compustat | Phelps (2010); Nooteboom et al. (2007) |
| 3. | Performance feedback | ROS minus the previous year's mean ROS of all firms in the sector. (Robustness test with ROA.) | Compustat | Greve (2003b) |
| 4. | GDP growth | GDP growth, based on annual GDP levels. | Compustat | Gielnik et al. (2012); Greve (2008) |
| 5. | Firm growth | Employee growth, based on annual number of employees. | Compustat | Audretsch et al. (2014) |
| 6. | Current ratio | The natural logarithm of the current ratio. | Compustat | Iyer and Miller (2008) |
| 7. | TMT size | The number of senior/vice executives in the TMT. | BoardEx | Clark and Maggitti (2012) |
| 8. | TMT tenure | The average tenure, in years, of all TMT members. | BoardEx | Chatterjee and Hambrick (2011) |
| 9. | CEO tenure | The tenure, in years, of the CEO. | BoardEx | Chatterjee and Hambrick (2011) |
| 10. | CEO duality | A binary variable that is coded '1' if the CEO is also the chair of the board of directors. | BoardEx | Chatterjee and Hambrick (2011) |

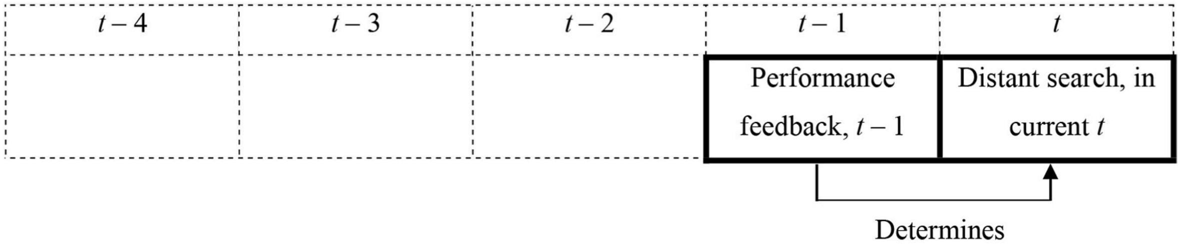


**Fig. 2.** Example of a model with a simple, 'traditional,' delay structure.

outcomes of search activities. Second, as explained, we control for TMT, firm, and industry-level effects that influence decisions with respect to distant search. Finally, to account for unobserved time effects and potential omitted variable bias, we included a complete set of year dummies as well as an industry dummy.

To test our hypotheses, we also consider a delayed effect of performance feedback on a firm's propensity for distant search. This choice follows from the observations that cognitions change relatively slowly, also on matters like action-outcome relationships, as they are subject to complex learning processes and delays (Levinthal and March 1993). As such, we systematically assess a one-, two-, three-, and four-year lag between the dependent and independent variables.[7] We also use the two- and three-year moving average of performance feedback as proxies of *feedback persistency*. In this respect, we were also interested in learning if more persistent feedback, likely more forcefully driving learning and cognition development, better explains a firm's propensity for distant search. Consider Figs. 2 and 3. The former denotes a typical delay structure, in which the independent variable is lagged by one year. Compare that to the second figure, which details a model that utilizes a more complex delay structure, involving a two-year delay between the current level of a firm's propensity for distant search and the three-year moving average of performance feedback. In other words, within this figure, highly persistent feedback determines, with some delay, the current level of distant search.

This more complex model setup also implies that to test our hypotheses, we need to estimate a total of 36 models: three datasets (i.e., industrial machinery, semiconductors, and the two combined) times four different lags between dependent and independent variable (one, two, three, and four years) times three levels of feedback persistency (no persistency, two-year moving average, and three-year moving average). We kept the number of observations per sector constant across all models. While this choice enabled us to compare results, it also meant that we 'lost' observations due to the large minimum quantity of firm observations required. More specifically, we need at least seven years of consecutive company data to have one valid observation—all panels that were shorter or interrupted were removed from our database. Finally, to keep our models parsimonious, we assume that the variable coefficient of performance feedback does not change at some predetermined point (notably when above or below the industry average) (Chen, 2008; Chen and Miller, 2007).

## 4. Results

Table 2 lists the descriptive statistics across all the data. The mean-variance inflation factor (VIF) is 1.54, which is lower than the commonly maintained threshold of three, indicating that multicollinearity did not substantially affect our results.

Given the large number of models needed to test our hypotheses (i.e., 36), we present only a selection of results below.[8] This selection is made post hoc and incorporates the most informative findings concerning our hypotheses. Table 3 shows the selected models' configuration, while Table 4 details the results to highlight our core findings. More specifically, this latter table denotes the results for six models. The first model serves as the base model and does *not* consider sectoral differences to affect the relationship between performance feedback and firm propensity for distant search. More specifically, Model 1 combines the two sectors in one dataset and assumes a one-year lag between performance feedback and firm propensity for distant search. The following two models consider industrial machinery, and they vary in terms of the lag between independent and dependent variables (i.e., there is no variation in terms of feedback persistency). More specifically, Model 2 considers industrial machinery and assumes a one-year lag between performance feedback and firm propensity for distant search. Model 3 also considers industrial machinery but is modeled with a two-year lag between performance feedback and firm propensity for distant search. Finally, the last three models (for semiconductors) only vary in terms of feedback persistency (i.e., there is no variation in the delay between independent and dependent variables). Model 4 considers semiconductors but specifies a four-year lag between performance feedback and firm propensity for distant search. Models 5 and 6 also concern semiconductors but are modeled with a four-year lag between the two-year and three-year moving average of performance feedback, respectively, and firm propensity for distant search.

Our base model (Model 1 in Table 4) reports a positive effect of R&D intensity and a negative effect of GDP growth on a firm's propensity for distant search. Notably, with the aforementioned model specifications, we find no significant effect of performance feedback on a firm's propensity for distant search. This non-finding supports our claim that one needs to consider the innovation pattern separately to assess the effect of performance feedback meaningfully. In-line with this idea, and as expected, the two reported models for industrial machinery (models 2 and 3) paint a different picture. First of all, we observe no significant effect of R&D intensity on firm propensity for distant search. As R&D resources in this sector are typically directed toward local search, this finding is not surprising. We also observe a positive effect of firm growth, a negative effect of GDP growth, and a negative effect of CEO duality on firm propensity for distant search. Performance feedback, however, only has a significant negative effect in the case that a one-year delay is specified between the independent and dependent variables (compare models 2 and 3). The three reported models for semiconductors (models 4, 5, and 6) show results that are different from those we have presented thus far. Here, we find a positive effect of R&D intensity, a negative effect of the current ratio, a negative effect of TMT size, and a negative effect of TMT tenure on a firm's propensity for distant search. Performance feedback, however, has a positive effect on a firm's propensity for distant search that increases in strength as the level of feedback persistency increases.

To compare *all* models in a meaningful manner, Table 5 lists only the effect of performance feedback but does so for all 36 models. In other

[7] Experimentation and data limitations meant that we opted for models with a maximum lag of four years.

[8] The appendix, available upon request, details all output.

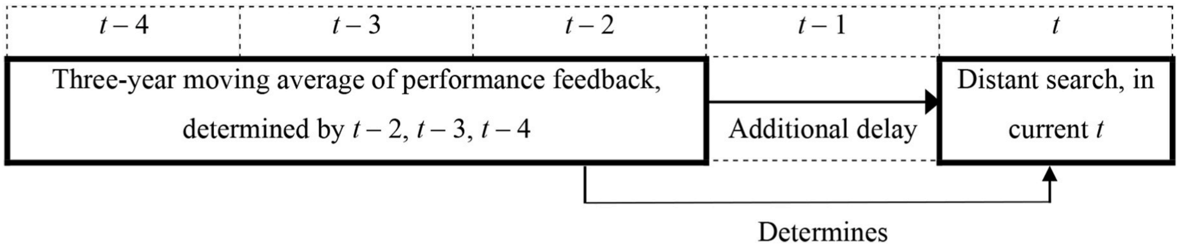


**Fig. 3.** Example of a model with a more complex delay structure.

**Table 2**
Descriptive statistics.

| | Variable | Mean | SD | Min | Max | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Distant search | 0.251 | 0.266 | 0.00 | 1.00 | 1.00 | | | | | | | | | |
| 2 | R&D intensity | 0.106 | 0.127 | 0.00 | 1.10 | −0.01 | 1.00 | | | | | | | | |
| 3 | Performance feedback | 0.050 | 0.300 | −3.52 | 0.73 | −0.05 | −0.18* | 1.00 | | | | | | | |
| 4 | GDP growth | 1.706 | 1.953 | −3.10 | 3.50 | 0.10 | −0.09 | 0.09 | 1.00 | | | | | | |
| 5 | Firm growth | 0.062 | 0.171 | −0.56 | 1.00 | 0.10 | −0.11* | 0.08 | 0.23* | 1.00 | | | | | |
| 6 | Log current ratio | 1.047 | 0.637 | −0.15 | 3.32 | 0.04 | 0.63* | 0.08 | −0.09 | −0.07 | 1.00 | | | | |
| 7 | TMT size | 8.871 | 3.527 | 3.00 | 21.00 | −0.08 | −0.25* | 0.06 | −0.02 | −0.04 | −0.15* | 1.00 | | | |
| 8 | TMT tenure | 5.499 | 2.549 | 0.75 | 15.00 | −0.02 | 0.00 | 0.02 | −0.03 | −0.06 | 0.04 | −0.12* | 1.00 | | |
| 9 | CEO tenure | 13.286 | 10.240 | 0.00 | 39.00 | −0.05 | −0.06 | −0.00 | −0.10 | −0.12* | −0.06 | 0.23* | 0.45* | 1.00 | |
| 10 | CEO duality | 0.521 | 0.500 | 0.00 | 1.00 | −0.03 | −0.37* | 0.01 | 0.06 | −0.03 | −0.36* | 0.19* | 0.19* | 0.34* | 1.00 |

* Significant at the 0.05 level.

**Table 3**
Model configuration.

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| Sector | Industrial machinery and Semiconductors | Industrial machinery | Industrial machinery | Semiconductors | Semiconductors | Semiconductors |
| Innovation pattern | Mixed | Specialized-supplier | Specialized-supplier | Science-based | Science-based | Science-based |
| Lag DV & IV | 1 year | 1 year | 2 years | 4 years | 4 years | 4 years |
| Feedback persistency | None | None | None | None | 2-year moving average | 3-year moving average |

words, Table 5 concentrates on our key variable of interest by listing only its effect on a firm's propensity for distant search (including different levels of persistency and different lag structures). This setup allows us to effectively present the impact of performance feedback and its different operationalizations over different innovation patterns. Consider, for instance, the semiconductor sector (i.e., science-based innovation pattern), where we can observe that the effect of performance feedback on distant search after a four-year delay is .087(0.060) (see Table 4, Model 4). However, the same model estimated with highly persistent performance feedback (i.e., the three-year moving average of feedback) yields a substantially stronger and more significant coefficient of 0.222(0.091) (see Table 4, Model 6).

The results for both sectors combined (see 'Overall' in Table 5) are inconclusive in terms of the effect of performance feedback on firm propensity for distant search. We find a non-significant *negative* short-term effect (one-year lag), yet a significant *positive* long-term effect (four-year lag). As we mentioned, this non-finding is in-line with our expectation that lumping highly heterogeneous innovation patterns together will not help us to understand the effects of performance feedback. When we explicitly take the sectoral context into account and distinguish between semiconductors and industrial machinery, the findings become much more insightful. For industrial machinery (i.e., specialized-supplier innovation pattern), a firm's propensity for distant search *decreases* (or increases) as its performance feedback increases (or decreases), in-line with the established idea's underlying feedback theory. For semiconductors (i.e., science-based innovation pattern), however, our results indicate that firms' propensity for distant search *increases* (or decreases) as their performance feedback increases (or decreases), but only after a substantial delay—which is indicative of longer deliberation and incubation processes at the managerial level.

Furthermore, we observe that, for both sectors, more persistent performance feedback better explains a firm's propensity for distant search—signaling that more persistent feedback has a stronger influence on managerial cognition and decision-making processes. In other words, for managers, more persistent performance feedback serves as an important signal to adjust firm search behavior in terms of distant search. Furthermore, we observe a shorter 'response' time, with respect to redirecting attention to (or from) distant search, of firms operating within industrial machinery compared to those active within semiconductors. This latter finding can be attributed to a fundamental

**Table 4**
Core findings.

| DV: Firm propensity for distant search | Model 1 | | Model 2 | | Model 3 | | Model 4 | | Model 5 | | Model 6 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coef. | Std. err. | Coef. | Std. err. | Coef. | Std. err. | Coef. | Std. err. | Coef. | Std. err. | Coef. | Std. err. |
| R&D intensity | .210 | (.140)+ | .493 | (.502) | .374 | (.943) | .184 | (.207) | .320 | (.208)+ | .336 | (.216)+ |
| **Performance feedback** | **−.019** | **(.041)** | **−.912** | **(.360)**** | **−.247** | **(.340)** | **.087** | **(.060)+** | **.189** | **(.071)**** | **.222** | **(.091)**** |
| GDP growth | −.338 | (.120)** | −.378 | (.187)* | −.081 | (.095) | .035 | (.120) | .014 | (.126) | .087 | (.123) |
| Firm growth | .010 | (.076) | .101 | (.071)+ | .084 | (.053)+ | −.009 | (.145) | .003 | (.139) | −.008 | (.141) |
| Log current ratio | .013 | (.028) | .011 | (.038) | −.019 | (.052) | −.115 | (.059)* | −.128 | (.059)* | −.132 | (.060)* |
| TMT size | −.003 | (.005) | .003 | (.005) | .001 | (.006) | −.010 | (.008) | −.010 | (.008)+ | −.011 | (.008)+ |
| TMT tenure | −.003 | (.005) | .000 | (.004) | −.004 | (.008) | −.022 | (.015)+ | −.023 | (.015)+ | −.023 | (.014)+ |
| CEO tenure | .000 | (.001) | .001 | (.001) | .003 | (.003) | .007 | (.006) | .007 | (.006) | .007 | (.006) |
| CEO duality | .010 | (.031) | −.069 | (.035)* | −.055 | (.069) | −.076 | (.068) | −.076 | (.069) | −.081 | (.071) |
| Serial-correlation | .397 | (.048)*** | .502 | (.053)*** | .272 | (.088)** | .156 | (.078)* | .170 | (.071)** | .168 | (.070)** |
| SIC-35 dummy | .067 | (.031)* | – | – | – | – | – | – | – | – | – | – |
| Constant | .838 | (.253)*** | .954 | (.417)* | .477 | (.500)* | .439 | (.275)+ | .466 | (.285)+ | .332 | (.274) |

+ $p < .1$; *$p < .05$; **$p < .01$; ***$p < .001$; time dummy variables were included in all models but are omitted from these results. One-tailed significance levels are reported. For Model 1, which combines all data, we included a dummy variable ("SIC-35 dummy"), which is coded 1 for industrial machinery.

difference in innovation process length, which is arguably (much) shorter in industrial machinery (i.e., innovation is 'purchased') compared to semiconductors (i.e., innovation is developed).[9]

## 5. Discussion and conclusions

Whereas local search forms the default for many firms, distant search entails the exploration of novel and unfamiliar domains. This makes distant search an inherently riskier activity, but also a superior one when it comes to generating new insights and knowledge that may contribute to the development of innovations and, by doing so, supports the anticipation and adaptation to future environments. Despite its strategic importance, we still have a limited understanding of when firms engage in distant search, mainly because foresight and anticipation of the future are largely missing from BTF (Gavetti et al., 2012). According to the default prediction of BTF, poor performance will lead to lower confidence in current routines and ways of operating, which pushes a firm to engage in a higher degree of risk-taking. On the other hand, good performance will strengthen firm confidence in the value of its current strategy and operations, which attenuates its risk-taking propensity. For distant search, a higher risk-taking propensity leads to its increase, whereas a lower risk-taking propensity leads to its decrease. However, standing in contrast to BTF is an emerging capability cue perspective (Chatterjee and Hambrick, 2011). This perspective suggests that good performance may be interpreted as a positive cue that will make firms more tolerant of risks, leading to an increase in distant search. Unsatisfactory performance instead makes them more risk-averse, leading to a decrease in distant search.

To make sense of these conflicting predictions between BTF and a capability cue perspective, we have started from the idea that managers are boundedly rational (Simon, 1955) and that their decisions to increase or decrease distant search activities, in response to past performance, are subject to interpretations of that performance. Drawing on Gavetti and Levinthal (2000), we argue that the interpretation of past performance follows from managers' dominant cognition, which differs across different sectoral contexts. In this way, we recognize the profound impact that context can have on organizational behavior, which is often not appreciated by organization scholars (Johns, 2006).

To address this key issue of the role of context and associated mental models, we followed the literature on sectoral innovation patterns (Pavitt, 1984, 1990; Marsili, 2001; Malerba, 2002; Bogliacino and Pianta, 2016) and argued that different sectoral innovation patterns shape different cognitions on how managers see distant search and its risks. We distinguished between a science-based innovation pattern and a specialized-supplier innovation pattern (Pavitt, 1984, 1995; Bogliacino and Pianta, 2016). These patterns differ profoundly in the dominant cognition on the risks of distant search and the meaning attached to past performance. Utilizing generalized estimating equations on a panel database that is comprised of 68 firms and 334 observations we draw conclusions.

First, we found that when a firm operates in a science-based innovation pattern, such as in the semiconductor industry, its propensity for distant search will increase to the extent that its performance increases. In this innovation pattern, innovations are mostly endogenously generated, that is, by firms themselves. This shapes a dominant cognition that distant search is generally seen as a 'game of skill' and that its risks are manageable to the extent one is skilled. This also colors the interpretation of past performance. Positive performance is seen as that one is skilled, which bolsters confidence and leads to an increase in distant search. Negative performance is seen as that one is not skilled enough, which induces timidity and decreases the propensity for distant search. This is in-line with the capability cue perspective (Chatterjee and Hambrick, 2011).

Second, we found that when a firm operates in a specialized-supplier innovation pattern, such as found in general industrial machinery & equipment, special industry machinery, and farm machinery & equipment, its propensity for distant search will decrease to the extent that its performance increases. In this innovation pattern, innovations are

[9] We also collected data on an information-intensive pattern, specifically the software industry (SIC 7372). Studying the software industry (SIC 7372) is in-line with previous work on BTF, notably Chatterjee and Hambrick (2011), who relied on an empirical setting that comprises the computer hardware and software industries. This pattern is highly interesting because it presents an 'in-between' case. More specifically, the software industry can be considered an industry that combines elements of a science-based pattern—high discretion for innovation—and a specialized-supplier pattern—low discretion for innovation. That is, the software industry is both developing path-breaking technology (e.g., artificial intelligence, cloud solutions, platform technology, new forms of encryption, etc.) while also adopting it (e.g., chip tech, quantum, photonics), which in turn enables this sector to further innovate (Autio et al., 2018; Elia et al., 2020; Nambisan et al., 2017). Mainly because of the limited patenting activity in this sector, our final 'software' subset is composed of 14 companies (63 observations). The results of our analyses of this sector, which are listed in the appendix, available upon request, indicate a clear 'in-between' pattern. On the one hand, it shows significant medium-term (two to three years) positive effect of performance feedback on firms' propensity for distant search. As such, our findings for this sector point to a response, in terms of direction, similar to the science-based pattern (following capability cue). Yet, on the other hand, our results also indicate that the 'response time' is in-between the other two considered patterns—slower than science-based, yet faster than a specialized-supplier pattern. Once more, we find that more persistent performance feedback better explains distant search—which is in-line with the other two patterns. Overall, these findings provide further support for the idea that the context influences firms' interpretation processes and thereby effects the manner (i.e., direction and speed) in which firms respond to feedback.

**Table 5**
Effect of performance feedback on distant search (composed of 36 models).

| DV: Firm propensity for distant search | | Modeled lag, in years, between performance feedback and distant search | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | one year | | two years | | three years | | four years | |
| | | Coef. | Std. err. | Coef. | Std. err. | Coef. | Std. err. | Coef. | Std. err. |
| Overall | Performance feedback | −.019 | (.041) | −.067 | (.059) | .023 | (.046) | .072 | (.049)+ |
| Mixed innovation patterns | Performance feedback (2-year moving average) | −.042 | (.053) | −.093 | (.066) | .077 | (.066) | .135 | (.066)* |
| | Performance feedback (3-year moving average) | −.057 | (.058) | −.090 | (.076) | .099 | (.085) | .161 | (.096)* |
| Semiconductor | Performance feedback | .031 | (.031) | −.022 | (.050) | .042 | (.047) | .087 | (.060)+ |
| Science-based innovation pattern | Performance feedback (2-year moving average) | .029 | (.043) | −.043 | (.064) | .105 | (.072)+ | .189 | (.071)** |
| | Performance feedback (3-year moving average) | .032 | (.048) | −.045 | (.084) | .192 | (.082)** | .222 | (.091)** |
| Industrial machinery | Performance feedback | −.912 | (.360)** | −.247 | (.340) | −.294 | (.438) | .108 | (.453) |
| Specialized-supplier innovation pattern | Performance feedback (2-year moving average) | −.869 | (.416)* | −.878 | (.394)* | −.422 | (.490) | −.289 | (.543) |
| | Performance feedback (3-year moving average) | −1.146 | (.428)** | −.881 | (.445)* | −.575 | (.561) | −.136 | (.624) |

+ $p < .1$; *$p < .05$; **$p < .01$; ***$p < .001$; One-tailed significance levels are reported.

mostly exogenously generated, that is, by external users and others beyond the industry, meaning that firms operating within the specialized-supplier pattern need to search for and discover these opportunities. This shapes a dominant cognition where distant search is seen as a 'game of luck' and that its risks are largely uncontrollable; and colors the interpretation of past performance in that positive performance is seen as to stay course, which breeds inertia and decreases the propensity for distant search. Negative performance, on the other hand, serves as a switch to break with this inertial behavior and to increase distant search activities instead.

Our study's two key findings align with the two general 'strategies' on how firms manage risks (Kahneman and Tversky, 2013), one option is to avoid the risk, if possible, which is uncertainty avoidance and in-line with BTF. The other option is to accept the risk while managing the uncertainty that comes with it. That is, risk can be managed (March and Shapira, 1987: Kahneman and Tversky, 2013). Here, our paper argues and shows that both strategies can be associated with different cognitions, shaped by different environmental contexts. Either the odds are considered to be mostly exogenously determined and largely uncontrollable, and distant search subject to gambling and luck. Hence, the typical managerial response is to avoid it, if possible. Or the odds are considered to be manageable as uncertainty can be reduced, if one is skilled enough.

The important implication that follows from our study is that a dominant cognition in a certain sectoral innovation context deeply colors what past performance actually means. When the dominant belief is that distant search is a 'game of luck' and risks are largely uncontrollable, past performance is interpreted in terms of risk avoidance. Yet, when the dominant belief is that distant search is a 'game of skill' and its risks can be managed, past performance is not so much being interpreted in terms of risk avoidance but in terms of being skilled or unskilled. This means that different cognitions do not affect interpretations of past performance simply in a matter of degree but in a more profound way, namely representing different kinds. In a science-based pattern, the dominant cognition sees past performance as a measure for sufficient skills, whereas in a specialized-supplier pattern, the dominant cognition sees past performance as a justification for avoiding risks. These represent two entirely different meanings of past performance with opposite implications for what it means for a risk-taking activity such as distant search.

### 5.1. *Theoretical contributions*

These findings and conclusions contribute to different bodies of literature. First, we contribute to the literature on BTF by demonstrating that whether firms increase or decrease their distant search activities is not uniform but instead differs with the sectoral context, such as the dominant sectoral innovation pattern. This conclusion challenges the implicit assumption that feedback effects are invariant across different industries, reflecting Greve's claim that the theory holds across a wide range of industries (2003a), at least in relation to distant search. Whereas the micro-level focus of BTF has evident merits, it comes at the price of a general abstraction from the larger, macro-level context in which firms operate (Johns, 2006). By distinguishing between two different sectoral innovation patterns, we respond to Gavetti and Levinthal's (2000) call for attention to cognition in BTF, in the sense that we are appreciative of the profound effect that a sectoral context can have on the dominant belief on distant search and whether its risks are manageable or uncontrollable. This difference in beliefs carries attendant implications for the meaning attached to performance feedback: Does positive performance signal skills (in distant search) or does it signal to avoid risks?

We also contribute to the literature on innovation and corporate entrepreneurship. Here, the dominant approach until now has been to deploy a more normative perspective that considers what capabilities firms *should* develop to boost their innovation performance through their conducting different distant search activities such as searching for novel, emerging, or pioneering technologies (e.g., Ahuja and Lampert, 2001); through crossing technological, organizational, or national-institutional boundaries (e.g., Rosenkopf and Nerkar, 2001; Phene et al., 2006); through turning to different search mechanisms such as inventor mobility, alliances, or crowdsourcing (Rosenkopf and Almeida, 2003; Gilsing et al., 2008; Phelps, 2010; Srivastava and Gnyawali, 2011; Afuah and Tucci, 2012), or through different configurations of teams of inventors (e.g., Vakili and Kaplan, 2020). Notwithstanding the positive effects of different activities and mechanisms for distant search on a firm's innovation performance, the implicit assumption here is that firms are equally motivated to engage in distant search in the first place (Laursen, 2012). However, this assumption conflicts with the large degree of interfirm heterogeneity in their intensity of search activities (Ahuja et al., 2008) and one of the core premises of BTF, namely that local search forms the default for the vast majority of firms. Although some firms will, in fact, engage in distant search persistently, others will procrastinate or avoid it altogether. Hence, we contribute to this more normative literature by adding a behavioral perspective showing firms are differentially motivated to increase or decrease their distant search activities as a function of their interpretation of past performance, rooted in deeper cognitions that vary across sectoral innovation patterns.

We also make an important methodological contribution by modeling persistence and delay in firms' responses to feedback. Our analysis brings the degree of feedback persistence to the fore, as the explanatory power of feedback rises as persistence increases, signaling that more persistent feedback has a stronger influence on managerial interpretation and decision-making processes. Moreover, by including various levels of delay, our analyses effectively allow for variation in terms of innovation process length between sectors. In this respect, our findings demonstrate that it is important to consider temporal aspects to continue developing a more in-depth understanding of performance feedback (also see Ye et al., 2021 for another take on feedback persistency).

### 5.2. Practical implications

First of all, our findings point toward the existence of dominant sectoral logics—action-outcome relationships that influence how senior management interprets and responds to performance feedback. Our results imply that TMTs, active in a specialized-supplier innovation pattern (Pavitt, 1984; Bogliacino and Pianta, 2016), need to be careful how to respond to positive performance feedback. That is, their 'natural' response to such feedback is to decrease innovation and distant search activities, which can trigger a vicious feedback loop where a limited innovation budget actually brings down organizational performance, which potentially hampers the firm's ability to innovate, ultimately resulting in the organization's demise (also see Walrave et al., 2011, for a rich description of such an innovation suppression process). For TMTs in a science-based innovation pattern, our results indicate rather slow, or delayed, response times to performance feedback. While a more persistent approach to innovation is often considered to be beneficial for the adaptive performance of a firm, it may come at the cost of their reactive ability—that is, the ability to quickly response to disruptions. In this respect, it seems especially important for TMTs active in a science-based pattern to carefully balance innovation persistency and their firm's ability to quickly respond to changes in their environment.

Moreover, our findings are potentially interesting to investors. We detail how firms vary in their responses to performance feedback across three innovation patterns and how such responses implicate a firm's distant search activities. A better understanding of how and why firms invest in innovation and distant search, which influences their future viability, is valuable information for investors to make better informed investment and divestment decisions.

### 5.3. Limitations and future research

Of course, this study has a number of limitations. First, we distinguish between two types of sectoral innovation patterns: a science-based and a specialized-supplier one. Although these two patterns exhibit sharp contrasts in their defining characteristics, we have not considered any other patterns. This limitation narrows the extent to which we can apply our findings to these different patterns, namely scale-intensive, user-led, and supplier-dependent ones. A second limitation is that we only considered one (science-based) or a few (specialized-supplier) type(s) of industry per pattern when there might also be some variation between industries within each pattern. For example, pharmaceutical biotechnology also qualifies as a science-based pattern, while construction may also qualify as a specialized-supplier innovation pattern. An interesting direction for future research may be to test our hypotheses within these and other related industries. Third, we constrained our models to a single variable coefficient for performance feedback. However, this coefficient might differ (slightly) for performance below or above a firm's aspirations (cf. Greve, 2003b). We decided to keep our already complicated analyses and models as parsimonious as possible (Chen, 2008; Chen and Miller, 2007). However, building on our insights, future work may relax this approach—for instance, by employing a spline function (e.g., Greve, 2003b; Rhee et al., 2019)—to further investigate any potential non-linear effects that may exist and how these may differ across different sectoral innovation patterns.

From our theory and empirical findings, we can conclude that sectoral differences matter when it comes to performance feedback. With an exception formed by Joseph et al. (2016), who considered mobile phones, most studies in this field have taken more traditional industries—such as shipbuilding (Greve, 2003a, 2007), investment banking (Baum et al., 2005), public transport (Baum and Dahlin, 2007), education (Labianca et al., 2009), or manufacturing (Chen, 2008)—as their empirical settings. It would be interesting and useful to see to what extent the arguments and findings of these studies are similar or different in cases where the empirical setting is formed by an industry that can be characterized as a highly science-based context. Following our distinction between different sectoral innovation patterns, the findings of these studies—or at least some of these findings—may change within an (entirely) different sectoral context, either in degree or, as in our study, in kind.

## Data availability

The authors do not have permission to share data.

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