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RESEARCH ARTICLE

Who deviates? Technological opportunities, career concern, and inventor's distant search

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Abstract

Research Summary: Why do inventors facing similar feedback from the technological environment differ in their propensity to search locally or distantly? Problem-driven decision calculus tends not to sufficiently explain such heterogeneity. We instead examine the individual inventor's calculus surrounding career concern. We propose that with reduced technological opportunities in her local domains, the ensuing career concern induces her to search distantly. This response is attenuated when career concern is less salient—she is relatively productive within the firm or is a star—or when opportunity cost of response is higher—she has more firm-specific experience or interdependent knowledge. Data from the US electronic industry support our propositions. Findings help explain differential search in response to common problems and illustrate how personal interest intermingles with problem-driven feedback driving search.

Managerial Summary: A firm relies heavily on its inventors' search for new, distant technologies to stay on technological frontiers. Faced with technological decline, which of its inventors will engage in this distant search? We bring inventors' career concern into consideration and use data from the US electronic industry to show that, counterintuitively, it is the relatively less-productive, nonstar inventors with less firm-specific inventive experience or less interdependence with the rest of the firm's technologies that will more likely engage in distant search. This stresses that managers, in trying to comprehend their inventors' behavior and mindsets, must go beyond understanding how inventors interpret technological problems they are trying to solve, to also consider these inventors' personal concerns which will affect the way they search.

KEYWORDS

career concern, individual inventors, innovation, technological search, technology management

1 | INTRODUCTION

An inventor's search for new technologies plays a crucial role in building a firm's competitive advantage (Almeida & Kogut, 1999; Toh & Polidoro, 2013). While search has largely been studied at the firm-level (Ahuja & Katila, 2004; Eggers & Kaul, 2018), recent researchers are calling for a return to viewing search at the individual-level (Billinger, Srikanth, Stieglitz, & Schumacher, 2021; Lee & Meyer-Doyle, 2017) so as to uncover more fine-grained insights on inventors' search behavior. In this view, per the behavioral theory tradition (Cyert & March, 1963; Levinthal, 1997), the inventor is often seen as searching across a rugged landscape in a boundedly rational way, not knowing beforehand where the globally optimal technological solution resides (Ganco & Hoetker, 2009; Siggelkow, 2002b) and deciding from a given point if she should search locally or distantly (Ahuja, Lampert, & Tandon, 2008; Ethiraj & Levinthal, 2004).

This individual-level view of search could uncover aspects of the inventor's decision calculus not easily gleaned from an aggregate firm-level view. What we have learned thus far, though, about how the inventor searches tends to be confined to her calculus about the *problem* she is trying to solve—true to the spirit of "problemistic search" (Cyert & March, 1963; Posen, Keil, Kim, & Meissner, 2018). A recurring finding is that if search in familiar, local vicinity does not yield satisfactory outcomes, the inventor will be pushed to search distantly (Billinger, Stieglitz, & Schumacher, 2014; Hoeffler, Ariely, & West, 2006). A main reason put forth is that the inventor in this case may interpret the feedback of poor prior outcomes to mean a low chance of finding adequate solutions to the *problem* locally going forward (Gaba & Greve, 2019; Rivkin & Siggelkow, 2003). Even as we learned how this feedback on the problem is conditioned by cognitive representation or the stability of the environment (Gavetti & Levinthal, 2000; Posen & Levinthal, 2012; Stieglitz, Knudsen, & Becker, 2016), the core calculus still surrounds the problem. Without a clear sense of how the inventor interprets the problem differently than the aggregated "firm," the marginal value of imposing an individual-level view on search is limited.

Another limitation is that feedback on the problem alone does not readily address the question: *As local search yields unsatisfactory outcomes, why do some but not all of a firm's inventors facing this problem break out to search distantly?* The real world provides many examples: as the inadequacy of Sony's familiar CRT technologies became evident in the late 1980s (Chang, 2008), only a few inventors within Sony broke away to search in the distant LCD/LED space (see later section for details). Likewise, confronted by the RISC threat in the early 1990s, only a few of Intel's inventors departed from its CISC system to develop RISC chips. What explains this heterogeneity in inventors' responses to a given problem of prior local search? One could assume that all inventors would like to respond similarly, and then see how differential capabilities or resource access make them search differently (Gruber, Harhoff, & Hoisl, 2013; Vinokurova & Kapoor, 2020). But this would skip over a key, often-missed insight—that the inventor's decision calculus on search is not just driven by feedback on the problem; her incentives to respond, given her personal interests, matter as well. This insight has been difficult to surface given the focus in prior research on problem-driven decision calculus.

In a parallel research stream, it is well-accepted that an employee's decisions are guided by her personal interests, such as career concerns (Fama, 1980; Holmstrom, 1999; Sevcenko & Ethiraj, 2017). While not focused specifically on inventor search, this literature has shown that an employee may refrain from drastic actions that risk "rocking the boat" (Hu, Kale, Pagani, & Subramanian, 2011; Kempf, Ruenzi, & Thiele, 2009), but instead make safer albeit inferior investments to safeguard her career (Hellmann, 2007; Zwiebel, 1995). Likewise, when her career prospect within the firm dims, she may pursue tasks that are suboptimal for the firm but increase the odds of her employment elsewhere (Bloom & Michel, 2002; Palomeras & Melero, 2010; Rothaermel & Hess, 2007; Siemsen, 2008). It should follow that an inventor's career concern can be a key decision calculus on her search as well, though little has been done to connect the two. Indeed, level of career concern, being plausibly different across the firm's inventors, could be a ready explanation for their differential responses to feedback from prior, local search.

In this paper, we draw on the career concern literature to bring a different perspective to study individual inventor's decision calculus on search—how her personal interest, specifically her concern about career prospects, influences her response to prior outcomes of local search. We start with a baseline proposition: When the inventor's prior local search does not yield satisfactory outcomes due to reduction in opportunities within her existing technological domains (Ahuja & Katila, 2004), she will be induced to search distantly (H1). This baseline main effect is consistent with prior research (Billinger et al., 2014; Gaba & Greve, 2019) and incorporates both explanations—feedback on low chances of finding solutions and her concern about career prospects should she continue searching locally.

Our key contribution is to then use contingency propositions to flesh out the career concern mechanism. First, we recognize that the inventor's distant search is not just an alternate path to find solutions but can also be viewed as a way to bolster her value on the external job market. The contingencies point to instances where her *career concern is less salient*, or where her *cost of addressing this concern* via *distant search is higher*. We propose that when her career concern is less salient—specifically, when she is relatively more productive in the firm such that her current job is more secure (H2), or when she is a star inventor who can likely secure a job elsewhere (H3)—her inclination toward distant search in response to reduction in opportunities within her existing technologies domains (i.e., H1) is attenuated. Likewise, we propose that when the inventor's cost of addressing her career concern via distant search is higher, due to more firm-specific experience (H4) or greater interdependence within the firm (H5), both of which render her skills less transferable to other employers, the main effect in H1 will be attenuated. We test our propositions empirically with data on inventors within firms in the US electronics industry 1989–2000, focusing on firms in 12 technological domains within the industry that experienced reduction in technological opportunities at some point within the sampling period. Findings largely provide support for our propositions.

This paper makes several noteworthy contributions to the search literature. Specifically, we highlight that there is more to an inventor's search decision calculus than the usual considerations about the problem that search is meant to solve. In our view, the recent call to take a closer look at microfoundations of search at the individual level (Lee & Meyer-Doyle, 2017) is precisely to get at these complex individual-level personal interests and determine how they complicate and add nuances to decision-making in search. Moreover, this focus on how inventors' career concerns affect their search provides a mechanism that more readily explains observed patterns and heterogeneity of search in real life, patterns that are not as clearly driven by inventors' responses to feedback on the problem alone. The mixed empirical findings in the literature on search as response to feedback on problem (Gaba & Greve, 2019; Posen et al., 2018) may not indicate shortfalls in the theorizing of how feedback matters, but rather could be a result of omitting the individual's personal interest in considering how she would respond to the feedback. In this sense, our push to establish career concern as a driver of individual decision calculus could potentially lead to a more potent theory explaining heterogeneity in individual-level search than the traditional approach of focusing on inventors' problem-driven decision calculus. We elaborate on these and other contributions toward the end of the paper.

2 | THEORY AND HYPOTHESES

2.1 | Inventor's decision calculus on search

Classic behavioral search theory depicts the individual as the entity searching for new knowledge or technologies (Cyert & March, 1963). As Simon (1991, p 125) describes "All learning takes place inside individual human heads; an organization learns … by the learning of its members." As the inventor searches, her bounded rationality prevents her from knowing where the "globally optimal" solution is (Ahuja et al., 2008; Siggelkow, 2002b), with the severity of this bound depending on her problem-solving abilities and the problem's structure and complexity (Baumann, Schmidt, & Stieglitz, 2019). Being resource-constrained in her search (Rivkin, 2000), she follows a "satisficing" rule, capturing solutions as long as they satisfy certain preset criteria or aspiration level (Billinger et al., 2021; Nelson & Winter, 1982).

The inventor's search can be characterized as traversing across a rugged landscape containing multiple potential solutions and peaks with varying heights representing solutions' effectiveness (Ethiraj & Levinthal, 2004; Levinthal, 1997). From a point on the landscape, the inventor makes a series of interdependent choices that move her to a location where she can assess if the solution residing therein is superior to what she had before (Katila & Ahuja, 2002; Levinthal, 1997; Toh, 2014).[1] A peak thus represents a choice combination where the solution's effectiveness cannot be improved by changing only one choice. As interdependence across choices is key in determining how she moves across the landscape, past research typically characterizes search with NK models which are useful for capturing such interdependence (Ganco & Hoetker, 2009; Kauffman, 1993; Rivkin & Siggelkow, 2003).

This characterization helps conceptually separate local from distant search (Ahuja & Katila, 2004; Billinger et al., 2021). Local search stays within neighborhoods on the landscape nearby the inventor's current solution. It typically involves changing few choices or aspects of the current solution, staying with scientific principles familiar to her and only refining the

[1]In this view, the solution is seen as having existed already, and the inventor's search is to discover this solution. An example is the element oxygen, which exists in our atmosphere and was discovered by the inventor, Joseph Priestley. A different view of search is that the solution is created via recombining existing and new components found in the landscape, an example being the telephone which had not existed prior to its invention by Alexander Graham Bell. We thank an anonymous reviewer for providing these examples that help clarify these two views.

status quo via incremental tweaks (Billinger et al., 2021). Distant search on the other hand can be considered "long jumps" on the landscape (Siggelkow, 2002a; Rivkin, 2000). It requires the inventor to change her choices along more interdependent dimensions, going beyond her existing capabilities to adapt to solutions with scientific principles that are new to her.

Polidoro Jr and Toh (2011) illustrate the difference between local and distant search with pharmaceutical drugs. Within a therapeutic area such as hypertension, an inventor starting with diuretics could engage in local search to discover the next improved diuretics antihypertensive drug with the same underlying mechanism of action. Or, she could engage in distant search to find a new beta-blocker antihypertensive drug based on a different underlying mechanism of action. Mirroring the classic exploitation–exploration tradeoff (March, 1991), distant search tends to be more risky than local search, as concurrent changes along multiple interdependent choices make it harder for the inventor to predict search's outcome. But distant search enables her to accumulate new knowledge unfamiliar to her that may prove useful subsequently.

Not all inventors within a firm search in the same way (i.e., locally or distantly). For example, in the early 1990s, Intel was mainly developing microprocessor-chips with the CISC architecture, and its inventors' search mostly lay within CISC technologies. However, with rising threat from the RISC architecture backed by Motorola, some of Intel's inventors had secretly veered off to search in the RISC space and develop RISC-based chips using Intel resources while masking them as auxiliary CISC chips. Likewise, Sony's inventors in the late 1980s were mostly continuing their investments and search in the familiar cathode-ray tube (CRT) technologies (Brooke & Hansell, 2005; Chang, 2008). But a closer look would reveal that some of its inventors were actually searching in more distant and new liquid crystal display/light-emitting diode (LCD/LED) technologies championed by Sharp.[2] This calls for the need to understand the inventor's decision calculus in her choice to search either locally or distantly in a particular situation.

Prior studies examining an inventor's decision calculus to search locally or distantly tend to focus on her assessment of the problem she is trying to solve. Per "problemistic search" (Cyert & March, 1963; Posen et al., 2018), search is triggered when she faces a problem, and her choice of local or distant search depends on which is more likely to uncover a satisfactory solution. Absent perfect information on global peak, or information or vicarious learning about possible solutions, she relies on feedback from prior search, especially recent ones (Laureiro-Martínez, Brusoni, Canessa, & Zollo, 2015), to form an aspiration level or criterion for deciding what is a satisfactory solution (Billinger et al., 2021; Hu, Blettner, & Bettis, 2011).

[2]To substantiate this example, we examined Sony's patenting behavior in the late 1980s and 1990s. We found that subsequent to Sharp's watershed launch of the 14″ LCD/LED TV in 1988 and the corresponding industry shift towards LCD/LED (Kawamoto, 2002), there were 18 inventors within Sony that created new LCD/LED technologies as reflected in eight patents in the following 10 years, even while most of Sony's inventors remained focused on CRT technologies. We traced Sony's inventors patenting in LCD/LED technologies in the following way. First, we manually identified all technology subclasses, within the main class 348 (Television) in the USPTO class schedule, which had the words "liquid crystal display" or "light emitting diode" in the descriptions. We further identified all subclasses which were indented within/under the ones which had these words in the descriptions. This resulted in the following list of subclasses: 751, 761, 766, 790, 791, 792, 793, 794, 801, and 802. We then trace all Sony's patents in these subclasses. We find that between 1988 and 1998, Sony filed for eight patents in these LCD/LED subclasses, involving 18 inventors. For comparison, we also trace Sony's patents in CRT, identifying subclasses (within the main class of 348) related to "cathode-ray" with a similar procedure. Between 1988 and 1998, Sony filed for a total of 65 patents related to CRT.

Past research consistently finds that an inventor searches locally till prior search yields solutions below an aspirational or satisfactory level, which pushes her to search distantly instead (Billinger et al., 2014; Hoeffler et al., 2006). This finding is echoed in firm-level studies as well (Eggers & Kaul, 2018; Gaba & Greve, 2019; Posen et al., 2018). The core explanation given is that effective solutions to problems tend to cluster together. Successful prior searches function as feedback indicating a promising neighborhood on the landscape where satisfactory solutions can be found, thus prompting further local search. Failed prior search signals decreased chances of yield in local vicinity, prompting the inventor to venture to search in more distant areas relative to status quo.

This problem-driven decision calculus does not fully explain why some inventors search distantly while others facing a similar problem search locally. One approach to address this shortfall is to assume that all inventors within a firm share the same decision calculus, for example, they all would like to search distantly, but that some of them lack the abilities to do so. Heterogeneous abilities across inventors may stem from differences in their positions in the knowledge network, boundary-spanning capabilities, vantage points to identify particular types of opportunities, breadth and diversity of knowledge sets they can access for recombination, and so on (Dahlander, O'Mahony, & Gann, 2016; Galunic & Rodan, 1998; Gruber et al., 2013; Marrone, Tesluk, & Carson, 2007; Paruchuri & Awate, 2017; Rivkin, 2000). Alternatively, the inventors may have similar inclination to search but different access to commercialization resources to implement the solutions (Vinokurova & Kapoor, 2020). However, this approach implicitly holds constant the search decision calculus across inventors, ignoring the possibility that the inventor, in deciding whether to search locally or distantly, may have other calculations based on her personal interest outside of the likelihood of solving the problem.

2.2 | Career concern in the inventor's decision calculus

We bring the focus back to the inventor's decision calculus on search and examine how her calculations, besides relating to feedback on the problem, can be driven by personal interest, specifically, career concern, that is, concern about career advancement. This focus on career concern has the merit of explaining heterogeneity in inventor search not readily accountable by the traditional focus on problem-related feedback. Even though the career concern literature has tended not to study inventor search as an outcome, either local-distant or other search dimensions, it has clearly made the case that career concern guides an individual employee's decisions along various activities in the firm (Fama, 1980; Holmström, 1999). Below, we lay out the core principles in this literature before drawing on them to show how career concern influences the inventor's decision calculus on search.

When the prospects of internal reward and career advancement within the firm remain favorable to the individual employee, for example, the inventor, she tends to refrain from more drastic actions that would otherwise "rock the boat." For example, studies have shown that she refrains from taking excessive risk (Hu, Kale et al., 2011; Kempf et al., 2009), and would choose to adopt technologies where benchmarks are safer, even if these technologies are inferior (Zwiebel, 1995). Moreover, she would also have the implicit incentives to exert effort at a level required by the firm even in the absence of formal incentive-based contracts (Fama, 1980), especially if the firm is uncertain about her skill level and relies on her providing signals (Holmstrom, 1999). The prospect of compensation guides her focus and choice of tasks (Hellmann, 2007).

However, when the prospects of career advancement within the firm dims, external job market considerations become more salient in her calculus, and she is more likely to deviate from her current trajectory. For instance, she may begin to pick moderately difficult tasks that have low odds of success for the firm to showcase her skills externally (Siemsen, 2008). She may push for more novel ideas or higher-quality work, not necessarily in ways optimal for the firm, but so she can increase her chances of being employed elsewhere with higher pay (Palomeras & Melero, 2010; Rothaermel & Hess, 2007). Likewise, if she perceives unfairness in the rewards received from the firm, she may be pushed to actively seek other jobs (Bloom & Michel, 2002; Yanadori & Cui, 2013). This behavioral pattern described in prior research provides the basis for our proposed effect of career concern on the inventor's distant search, as we describe below.

2.3 | Reduction of technological opportunities as trigger of career concern and search

We examine the reduction of technological opportunities (Ahuja & Katila, 2004) as a trigger of career concern driving the inventor to engage in distant search. Technological opportunities usually reduce in ways external to the individual inventor. Competitors' intensive search depletes "low-hanging" opportunities (Clarkson & Toh, 2010). Progression in science radically changes underlying paradigms, causing rapid loss of opportunities along local trajectories (Tushman & Anderson, 1986). The inventor is more often pressured to adapt to exogenous changes (Okhuysen & Eisenhardt, 2002) than has the luxury to endogenously determine the rate at which she herself exhausts local opportunities with her own search.[3]

Reduction in technological opportunities in an inventor's existing domain lowers her expected inventive outputs. If she persists in local search, she will have to dwell deeper into nuanced problems (Katila & Ahuja, 2002), since ready opportunities have already been captured. She may be left with suboptimal solutions that no longer satisfice pre-set search criteria (Levinthal, 1997; Nelson & Winter, 1982). Fewer remaining opportunities means that more costly efforts and specialization are required to find them (Jones, 2009). The cumulative nature of discovery calls for each further step to have more trials and experiments with increasing complexity in order to affirm existing principles and test new ones (Scotchmer, 1991). The worsening web of interdependence between principles adds to causal ambiguity, making it harder to determine where problems in experimentations arise (Rivkin, 2000).

Having fewer inventive outputs fuels an inventor's career concerns (Siemsen, 2008; Zwiebel, 1995). When her job centers on capturing technological opportunities with inventions, her internal career advancement is inherently tied to these inventions (Fama, 1980; Holmstrom, 1999). Reduction of inventive opportunities puts her job internally at jeopardy. In addition, as reduced opportunities constitute a problem spanning beyond her current firm, her reduced

[3]Hypothetically, it is possible that the inventor's own prior search contributes to depleting the remaining opportunities within the local domain in the long run. This endogenously driven exhaustion could create selection issues in our empirical analysis. However, we think this is unlikely, given that the single inventor usually does not play such a dominant role in competitive high-tech settings. Moreover, if exhaustion is endogenously driven by the inventor, then we should not see our contingency predictions (H2–H5) playing out as we explain in a later section. The inventor who is capable of exhausting opportunities in her local domain is also likely to be a relatively productive inventor (H2) or a star (H3) with substantial experience inventing for her firm (H4) and building up interdependence within the firm (H5). If she is exhausting local opportunities, thereafter accordingly moving to distant domains in search of new opportunities, then we should be having opposite predictions than H2–H5.

ability to create satisfactory inventions in the local domain will also curtail her external market value (Palomeras & Melero, 2010) and fuel her concern about finding a job elsewhere.

This heightened career concern induces the inventor to search distantly. Distant search, on the one hand, can be viewed as an alternative path (to local search) to find solutions to problems on the landscape (Billinger et al., 2014). On the other hand, distant search can also be seen as a way to bolster the inventor's job market value, especially in times where her existing local domain is not yielding adequate solutions. Distant search, relative to continued search in local domains, enables the inventor to acquire new knowledge and adapt to new scientific principles (Ahuja & Katila, 2004; Polidoro Jr & Toh, 2011). It enlarges her knowledge set and increases components available for future recombination (Galunic & Rodan, 1998; Gruber et al., 2013), making her more valuable to other firms, especially those operating in related but different technological areas. Thus, when her local domains experience reduced opportunities fueling her career concern, she engages in distant search to increase her value on the market as a hedge against potentially losing her current job. This aligns with established wisdom that when internal career prospects flounder, the inventor would try to bolster her external market value and opportunities (Siemsen, 2008; Yanadori & Cui, 2013). Based on the above arguments, we arrive at the baseline hypothesis.

> **H1.** *Career concern brought on by reduced technological opportunities within an inventor's existing domains will induce the inventor to subsequently search distantly*.

2.3.1 | Contingencies: Salience of career concern

While the baseline H1 is explained with career concern as the theoretical mechanism, it can also reflect received wisdom from extant literature—reduced technological opportunities act as feedback indicating the inadequacy of further search in local domains, prompting the inventor to search distantly (Billinger et al., 2014). But the problem of reduced opportunities is not specific to the individual inventor; a theory focused on problem-driven decision calculus tends not to readily explain heterogeneity in response to this problem across individuals. Below, we use contingency predictions to more closely demonstrate the career concern mechanism and explain the individual-level heterogeneity. In the first set of contingencies, we focus on instances where the particular inventor's career concern is less salient and hence H1 is attenuated. Specifically, we examine *for which inventor is there greater job security*, such that the prospect of having fewer inventive outputs in her local domain triggers less concern about her career (Siemsen, 2008; Zwiebel, 1995) and thus her need to react.

First, we propose that the inventor's job at the firm is more secure when she is relatively more productive at generating inventions compared to other inventors in the firm. In this scenario, she has a greater "buffer" of other inventors within the firm with lower productivity. If reduction of opportunities leads to the firm retrenching its inventors, for cost-cutting or other reasons, it will likely start with the less productive ones. Moreover, being more productive, she will tend to have greater control over resources and setting the firm's research agenda (Kehoe & Tzabbar, 2015; Paruchuri, 2009), such that she knows it will be more disruptive to the firm if she is let go. Thus, she faces less severe selection pressure within the firm, meaning her current job is more secured, and accordingly she has less concern about her career even with reduced technologies opportunities in her existing domains.

> **H2.** *The relatively more productive the inventor is within the firm, the less the career concern brought on by reduced technological opportunities within an inventor's existing domains will induce the inventor to subsequently search distantly.*

Second, we propose that the star inventor, relative to nonstars, has greater job security and thus less career concerns even when her existing domains experience reduced technological opportunities. The prominence of star inventors has been extensively studied in human capital research (Campbell, Ganco, Franco, & Agarwal, 2012; Zucker, Darby, & Torero, 2002). Stars are more likely to create path-breaking inventions boosting firm performance (Zucker & Darby, 1996). They exert disproportionate influence over firms' research programs, and their areas of expertise determine firms' directions of commercialization efforts (Zucker, Darby, & Brewer, 1998). They generate knowledge spillovers to other inventors in the firm, and nonstars' collaboration with them increases nonstars' productivity and success (Kehoe & Tzabbar, 2015).

With such prominence, the star has greater external job market value (Groysberg, Lee, & Nanda, 2008) so much so that even if the security of her current job is threatened, she has less career concern than a nonstar inventor. Research shows that the star tends to possess inherent traits that are valuable to other firms (Campbell et al., 2012; Hurtz & Donovan, 2000). To the extent that some of her skills are not firm-specific and can be transferred to other firms (Lazear, 2009), she is relatively assured of securing a job elsewhere if needed. In fact, past research has argued that these generic, transferable skills even enable the star inventor to bargain for a greater share of value with her current firm (Coff, 1997). Thus, even when she experiences reduced technological opportunities in her existing domains, the level of career concern triggered inducing her to react will likely be less relatively to nonstars.

> **H3.** *When the inventor is a star (relative to a nonstar), career concern brought on by reduced technological opportunities within an inventor's existing domains will induce the inventor to subsequently search distantly to a lesser extent.*

2.3.2 | Contingencies: Cost of addressing career concern

For the second set of contingencies, we focus on instances where the cost of addressing career concern is greater for a particular inventor, thereby attenuating H1. Specifically, we examine *for which inventor is there greater opportunity cost of switching to another firm*, such that even when reduced opportunities in her existing domain threatens the security of her current job, she is less inclined to react per H1.

We propose that the inventor with greater firm-specific experience in creating new technologies, that is, inventive experience within the current firm, has a higher opportunity cost of switching to another firm. As she invents within the firm, she tends to build up firm-specific knowledge over time (Kogut & Zander, 1992; Lazear, 2009) that goes beyond enabling her to create technically superior inventions. This experience familiarizes her with the firm's routines, constraints, and usage of the firm's complementary assets such as labs, equipment, procedures, existing knowledge, relationships, and ties to other complementors (Campbell et al., 2012). In doing so, she becomes more capable of creating specific technologies that can be utilized by the firm. While such firm-specific experience generates greater value for the firm (Grant, 1996), it is less transferable across firms (Coff, 1997; Lazear, 2009). In other words, the greater the firm-specificity of her experience and knowledge, the greater the marginal product of applying it within the firm, and thus the greater the loss (opportunity cost) if she switches to another firm and tries to apply her experience and knowledge there. As such, even as the reduction in technological opportunities in her existing domains threatens her internal job security and triggers her career concern (per H1), it is costlier and thus less worthwhile for her to try to react by bolstering her external market value via distant search.

H4. *The more firm-specific inventive experiences the inventor has, the less the career concern brought on by reduced technological opportunities within an inventor's existing domains will induce the inventor to subsequently search distantly.*

Next, we propose that the inventor whose knowledge exhibits greater interdependence with the firm will have higher opportunity cost of switching to another firm. Knowledge that an inventor possesses can be more modular and generic (Ethiraj & Levinthal, 2004), such that it is applicable on a "standalone" basis across settings and firms. Or, it can be interdependent with other knowledge components within the firm's portfolio, such that its application requires joint utilization with them for it to be useful (Thompson, 1967; Yayavaram & Ahuja, 2008). Such interdependence tends to originate during the creation phase of the knowledge itself, as the inventor draws on basic principles from these other components, builds on and advances them, or explicitly constructs the knowledge to complement them.

Past research has shown that interdependence increases the value-add of the inventor's knowledge within the firm (Ethiraj & Garg, 2012). Closer connections between her knowledge and other components make imitation more costly by complicating causal links, making it difficult for others to figure out how the knowledge portfolio as a whole operates (Ethiraj, Levinthal, & Roy, 2008; Rivkin, 2000). Alcácer and Zhao (2012) shows that this benefit even extends across national borders, allowing the firm to ward off imitations of its IP. Beside value appropriation, interdependence also enhances value creation by generating better "fit" in superior end-products, raising the marginal value for its users (Ethiraj & Garg, 2012; Siggelkow, 2002a). However, this value-add by the inventor's knowledge cannot occur without the firm's other components with which it is interdependent. Per earlier, this means that the marginal product of the inventor's knowledge is highest when applied within the firm, and the loss is greater if she applies it elsewhere. This is in line with past research showing that interdependence or complementarities of the inventor with other parts of the firm hinders her mobility (Campbell et al., 2012; Ganco, 2013). Thus, even with reduced technological opportunities in her local domain triggering career concern (H1), she is less inclined to react by trying to bolster her external market value with distant search.

H5. *The greater the interdependence between the inventor's and the firm's knowledge, the less the career concern brought on by reduced technological opportunities within an inventor's existing domains will induce the inventor to subsequently search distantly.*

3 | DATA AND METHODS

3.1 | Sample

Empirically examining an inventor's search in response to reduced technological opportunities requires research settings characterized by fast-paced changes. Technology-intensive settings are particularly appropriate, given the frequent changes in terms of growth and decline of fields of knowledge. Also, with inventions being common and important in these settings, there is considerable longitudinal data available for us to trace inventors' activities. The electronic industry is one such setting.

We use patents in the US electronics industry from 1989 to 2000 to identify an inventor's technological domain and search trajectory. The US Patent and Trademark Office (USPTO) assigns patent subclass references to a patent to categorize the nature and application of the underlying invention (Fleming & Sorenson, 2004). It is not uncommon for an inventor in a given year to be working on more than one subclass or associated with multiple patents filed. Tracing these subclasses allows researchers to examine various aspects of the inventor's technological search (Fleming, Mingo, & Chen, 2007; Ganco, 2013). Following prior literature, we use subclasses that the inventors' patents are assigned to as indications of the inventors' technological domains (see elaborations later).

The electronics industry is well-suited for this examination, as patenting is a common tool used in this industry to protect intellectual property (IP). Individual inventors in this industry also have strong incentives to file for patents, so as to use them as ownership claims over crucial IP, as indictors of their personal success, and also as signals of their value to the external market (Lemelson-MIT, 2004). Thus, patent data provides relatively reliable indications of inventive activities in this industry and is indeed one of the most comprehensive available longitudinal sample of inventions. By limiting our study to a single industry, we reduce potential selection problems arising from differential patenting propensities across industries.

To better capture reductions in system-wide technological opportunities that occur externally and exogenously to the focal inventor, we restrict our sample to only firms with patents in technological domains which exhibited clear overall signs of reduction in opportunities (decline in total patenting) at some point. First, we use the SIC-patent class concordance data provided by USPTO to list all the patent classes that correspond to the electronic industry. From these patent classes, we identified 12 classes which showed clear signs of decline in overall patenting at some point within our sampling period. These 12 classes and their respective number of patents over time are illustrated in Figure 2. Next, we use the National Bureau of Economic Research patent data to identify all public firms that had at least one patent in any of these 12 classes during the sampling period. For each of these firms, we restrict our sampling to only patents in classes relevant to the electronics industry, as indicated by industry-technology class matching with the concordance data. From these patents, we identified inventors in these firms with one or more patents in the current and three previous years. We used the data provided by Lai, D'Amour, Yu, Ye, and Fleming (2011) to match patents to inventors and obtain the USPTO classes and subclasses associated with the patents. We obtained data on R&D expenses, sales, and other financial variables from COMPUSTAT.

3.2 | Variables

As most of our main variables are related to the inventor's technological domains, we first define these domains. An inventor's technological domains refer to the set of subclasses to which the inventor's patents are assigned in the 3 years preceding the focal year t, that is, the domain period is represented by the window encompassing $t-1$, $t-2$, and $t-3$. Thus, this definition of the inventor's domains does not include the focal year t.

3.2.1 | Dependent variable

We operationalize *Distant Search* as the number of "new" subclasses in which the inventor filed her patents in the current year t, where "new" subclasses are ones that are not included in the inventor's domain, that is, subclasses in which the inventor had not previously patented an invention during the previous 3 years, that is, $t-1$, $t-2$, and $t-3$. We subsequently conducted robustness tests using the alternative window of previous 5 years to define subclasses "new" to the inventor and obtained substantively similar results.

3.2.2 | Independent variables

The main independent variable is *Change in Technological Opportunities*, which is measured as the change in the total number of patents in the inventor's domain during the domain period, that is, from $t-3$ to $t-1$. Specifically, we subtract the total number of patents filed in subclasses included in the focal inventor's domain in year $t-3$ from that in year $t-1$. This effectively lags the independent variable by 1 year (since the variable does not include the current year t). Past research has shown that it is reasonable to expect the lag between investments and patenting to be slightly less than a year in the electronics industry (Hall, Griliches, & Hausman, 1986; Pakes & Schankerman, 1984). In subsequent robustness checks, we also used an alternate lag structure which we detail in a later section. Recall from H1 that we predict a reduction in opportunities to induce the inventor to search distantly, meaning that we expect the coefficient of this variable to be negative in our analyses. We conduct robustness analyses using alternate measure based on change in number of inventors who patented in the focal inventor's domain and obtained substantively similar results.

We use the variable *Relative Productivity* to capture the extent to which the inventor has been productive in generating new technologies relative to other inventors within the firm. We first calculate the number of patents filed by each of the firm's inventors for the firm across all classes during the domain period, that is, in years $t-1$, $t-2$, and $t-3$ cumulatively. We then count the number of inventors in the firm who are less productive (have fewer patents) over this 3-year window period than the focal inventor. Again, this effectively lags the variable by 1 year (as it does not include year t), per the previous main independent variable.

We followed prior research (Kehoe & Tzabbar, 2015; Zucker et al., 1998) to identify star inventors by the quantity and quality of their cumulative inventive output. We first calculated the average number of patents produced by the focal inventor throughout her career till $t-1$. We then multiplied this by the average quality of the patents, specifically the average number of citations received by these patents within 5 years of the patents' filing year. Counting citations within 5 years of filing accounts for the vintage effect of the patents (newer patents may not get similar time to gather citations regardless of quality). Finally, we compare the score generated for each inventor with the average across all inventors in the industry to identify stars. Inventors who score at least more than two standard deviations above the mean across all inventors are defined to be stars; the *Star* variable is one for the identified stars, and zero otherwise.

The variable, *Firm-Specific Experience*, captures the number of years the focal inventor has been active in patenting for the focal firm. This variable measures the number of years from the first year the inventor was present in the firm to $t-1$. To be consistent with the one-year lag between R&D investment and patent filing used earlier, we assume that the inventor was present in the firm 1 year before the filing of her first patent for the focal firm. While this measure may not always precisely capture the length of time the inventor has spent in the firm (e.g., her first invention may not have been patented), it is adequate for our purpose, as inventors with more experience in creating new technologies for the firm are likely to have filed their first patents for the firm earlier than less experienced inventors.[4]

For the contingency variable, *Interdependenc*e, we adapt measures from prior research (Zhao, 2006) to compute the dependence of an inventor's inventiveness on the focal firm. We compute *Interdependence* as number of citations made in the focal inventor's patents (till $t-1$) to the firm's patents (i.e., the number of cumulative backward citations to the firm's patents).[5]

3.2.3 | Control variables

Firm-level attributes can potentially drive inventors' search. Changes in a domain can alter a firm's interest in it and influence its inventors' search. We account for such firm's influence by controlling for the firm's strategic thrust in terms of its overall tendency to increase/decrease investments in the inventor's technological domain. For this, we construct a variable, *Firm's investment in domain*, as the change in the proportion of the firm's patents in the inventor's domain during the domain period, that is, years $t-3$ to $t-1$, to account for the extent to which the firm's attention to these technologies is increasing or decreasing, and include it in all specifications. We also control for the *Firm's number of inventors*, the total number of inventors (measured in thousands) in the firm during the domain period ($t-1$, $t-2$, and $t-3$). We account for firm size by adding the 1 year lagged value of the firm's *Total Assets*, and control for the 1 year lagged *R&D Expense* (both measured in billions). We control for *Firm specialization*, as the firm's diversity of search can impact the diversity of knowledge available to the focal inventor and thereby her search. We do this by including the Herfindahl index of the distribution of the firm's patents in different technological subclasses in the period corresponding with the inventor's domain period, that is, $t-1$, $t-2$, and $t-3$.

We also include *Number of patents in domain*—the number of inventor's patents in her domain. Since the number of new subclasses by an inventor can be influenced by the scale her research activity, we include the *Number of patents by inventor in the focal year*—the count of the patents filed by the inventor in the focal year for the firm to control for the scale of research activity of the inventor. An inventor's distant search proclivity could be affected by the extent to which the search builds on prior technologies. To control for this, we include a variable, *Backward Citations*, measured as the total number of citations made by the inventor's patents to other patents. An inventor's distant search behavior can also be affected by the extent she relies on same team for her

[4]A potential concern is that the "Firm-Specific Experience" measure could be too highly correlated with the "Relative Productivity" measure. We conducted the following checks. The pairwise correlation between the two contingency variables is 0.28. See Table 1. Thus, it seems like the two measures are indeed picking up different concepts that are not too highly correlated. Furthermore, we trace whether the inventors with the most firm-specific experiences are also the most productive in the firm. We first define "the most firm-specific experiences" as those where the variable value is greater than 90th percentile. We similarly define the most productive as those where the *Relative Productivity* variable value is greater than 90th percentile. We then calculate the percentage of instances where the inventor is both most experienced as well as most productive, as a percentage of the total number of instances where the inventor is either most experienced or most productive. The percentage comes to 13%. Thus, it seems that the most experienced and the most productive do not tend to intersect.

[5]Note that we separately control for the total number of backwards citations the inventor makes in her patents (see section on control variables below), instead of scaling *Interdependence* and measuring it as a ratio.

inventions. We use the variable *Collaborators* to capture the extent to which the inventor has repeat collaborative ties with the same set of inventors within the firm. We trace the inventor's collaborators as listed in her patents over the domain period, that is, years $t-1$, $t-2$, and $t-3$, and count the number of unique collaborators during this period whom the inventor has collaborated with more than once. This effectively lags the variable by a year. The inventor's inherent quality, intrinsic motivations, and other unobserved factors specific to the firm-inventor relationship (e.g., job design, other facets of the employment relationship, etc.) and not otherwise captured by the control variables could also influence her search decision. We employ firm–inventor pair fixed effect specifications to control for this unobserved heterogeneity. Finally, we control for time period effects by including period dummies variables.[6]

3.3 | Model specification

Since the dependent variable is a count, we use Poisson regressions with robust standard errors in our tests. We chose Poisson over Negative Binomial specifications as Poisson models are less sensitive to distributional assumption (Cameron & Trivedi, 2013), and the robust standard errors account for potential over dispersion in the data.[7] We use standardized values of the independent and moderator variables (calculated by subtracting the mean from the variable and dividing by the standard deviation) to ensure comparability of effects across the moderators and ease of interpretation. As mentioned earlier, to control for other unobserved heterogeneity in the firm-individual employment relationship, we use the firm–inventor pair fixed effects model. Fixed-effects models are more appropriate than random-effects models as the unobserved heterogeneity (e.g., inventor's intrinsic motivation, inventor–firm employment relationship) likely correlates with other independent variables as well as the dependent variable, which could result in biased estimates in random-effects models.

4 | FINDINGS

4.1 | Heterogeneity in inventor search

Before presenting our main findings, we first document evidence of within-firm heterogeneity in inventor search across the 12 technological domains that experienced declining opportunities in our sample. For each of these 12 classes, we identify a 5-year window that best capture the decline in patenting, as reflected in Figure 2.[8] Next, within each class, we want to find firms that had remained invested in the class, despite signs of decline. We trace the firms whose proportion of patents in this class (relative to its patents in all classes) either remained the same or increased from the start to the end of the identified 5-year window. Following that, we examine whether, within these firms, some inventors had searched and patented minimally in "new" domains

[6]Time period dummies capture 1993–1994; 1995–1997; and 1998–2000, with 1992 as the omitted year.

[7]Note that in a later section, we also test for robustness of findings with negative binomial regressions.

[8]The following lists the 12 technology class number, followed by the years representing the start and end of the window: "83": 1997–2002, "148":1995–2000, "206": 1997–2002, "241":1993–1998, "264":2001–2006, "329":1997–2002, "332":1997–2002, "338":1997–2002, "346":1991–1996, "367":1990–1995, "377":1991–1996, "505":1991–1996.

despite the firm remaining invested in the class experiencing decline. We trace the number of classes where the firms had not patented in at the start of the 5-year window but had patented in by the end of the 5-year window, and restrict this count to new classes where the firm has two or fewer patents (to indicate few inventors searching in this distant domain).

We find that out of the 127 firms that had remained invested in these classes experiencing decline during the 5-year window, inventors within 108 firms (85%) had actually patented in at least one new technology class during this period. On average, across all 127 firms over their respective 5-year windows, inventors in a firm patented in 11 new technological classes over this decline period. Next, we alternatively define a "new" class more stringently as one where the firm only has one patent (instead of 2) over the 5-year window. The corresponding statistics show that 105 firms (83%) had patented in at least 1 new technology class over the 5-year window, and on average, inventors in a firm patented in nine new technological classes over this decline period. The above evidence suggests that there is indeed heterogeneity in inventor search within the firm, such that not all inventors within the firm necessarily stayed within local domains even when the firm appeared to do so.

4.2 | Main results

Table 1 presents descriptive statistics and correlations of variables (prior to being standardized). Table 2 reports the results of the Poisson regressions with robust standard errors. Model 1 includes only the controls. Model 2 adds the main variable *Change in Technological Opportunities*. Models 3, 4, 5, and 6 include one interaction at a time, and Model 7 is the full model. The coefficients on the hypothesized variables remain stable across the specifications. We report *p* values of the estimated coefficients based on two-tailed tests.

To facilitate the discussion of our findings, we summarize our theoretical framework and the predicted directions of the coefficients in Figure 1. H1 predicts that a reduction in technological opportunities in the inventor's domains is associated with greater subsequent search beyond these domains; in other words, it predicts a negative coefficient of *Change in Technological Opportunities*. H2, H3, H4, and H5 predict that the negative main effect laid out in H1 is attenuated (less negative) when the moderators have higher value, that is, the coefficients of the interaction terms should be positive.

As Table 2 shows, the coefficient of the main variable *Change in Technological Opportunities* is negative in the full model (Model 7). The z-statistic of the coefficient is −5.97 and the *p* value is less than .001. This provides support for Hypothesis 1: as technological opportunities in the inventor's domains reduces, her search beyond these domains increases. We calculate the marginal effect by keeping all the covariates at their means and using the STATA margins routine to compute the marginal impact (semi-elasticity) with respect to a one unit change in *Change in Technological Opportunities*. We find that a decrease in *Change in Technological Opportunities* by one standard deviation is associated with a 6.3% increase in her search beyond these domains. For an inventor whose distant search was at mean, this would translate to an increase from 5.54 subclasses to 5.89 subclasses.

Hypothesis 2 predicts that the more productive the inventor is relative to others in the firm, the less she will react to reduction of opportunities in her domain by searching beyond these domains, that is, the less negative will be the main effect laid out in H1. As Model 6 shows, the coefficient of this interaction term is positive. The *p* value is .007 in the full model. In Model 3, the coefficient remains positive with a *p* value less than .001.

Next, to evaluate the magnitude of the moderation effect of *Relative Productivity*, we compute the marginal impact (semi-elasticities) of a decrease in *Change in Technological Opportunities* at different levels of *Relative Productivity*.[9] We compare this marginal impact when *Relative Productivity* is one standard deviation below the mean, to the corresponding marginal impact when *Relative Productivity* is one standard deviation above the mean, keeping all other covariates at their means. We find that at one standard deviation below the mean of *Relative Productivity*, one unit decrease in *Change in Technological Opportunities* is associated with an increase of 7.95% of subclasses in *Distant Search*. When we set *Relative Productivity* to one standard deviation above the mean, the corresponding effect (semi-elasticity) of *Change in Technological Opportunities* changes, specifically, becomes less in magnitude, to 4.66%, a drop of 41.3% in the effect. For an inventor at mean values of distant search, this would translate to a change in distant search from an increase of 0.44 subclasses to an increase of 0.26 subclasses. Thus, the inventor responds more to decline in opportunities in her domains when she is a relatively less productive inventor within the firm, in line with H2.[10]

Hypothesis 3 lays out the moderating effect of stardom on H1, predicting that stars compared to nonstars will react less to a reduction of opportunities in her domain by searching beyond these domains, that is, less negative H1. As Model 7 shows, the coefficient of this interaction term is positive. The p value is .054 in the full model. In model 4, the coefficient remains positive with a p value of .013.

To evaluate the magnitude of this moderation effect, we compute the marginal impact (semi-elasticities) of a decrease in *Change in Technological Opportunities* for stars v. nonstars, using the contrast operator in the STATA margins command for the comparison. We find that for nonstars, one unit decrease in *Change in Technological Opportunities* is associated with an increase of 6.3% of subclasses in *Distant Search* whereas for stars this reduces to 1.65%. Thus, the effect drops by 4.65 percentage points, which represents a 73% drop from the semi-elasticity for nonstars. For an inventor at mean values of distant search, this translates to a change in distant search from an increase of 0.35 subclasses for nonstars to an increase of 0.10 subclasses. Thus, the nonstar inventor responds more to technological decline than a star inventor.

Hypothesis 4 similarly lays out the moderating influence of the inventor's experience within the firm on main effect H1. It predicts that with more *Firm-Specific Experience*, the inventor will respond less strongly to reduction of opportunities in her domains. Put differently, we expect *Firm-Specific Experience* to attenuate (make less negative) the main negative effect in H1, that is, the co-efficient of interaction of *Change in Technological Opportunities* with *Firm-Specific Experience* to be positive. As Table 2 shows, the coefficient of this interaction term is positive. The p value based on two-tailed tests is .089 in the full model. In Model 5, the coefficient remains positive with a p-value of less than .001.

Per earlier, to calculate the magnitude of the effect, we keep all other covariates at their mean values and compare the marginal impact of *Change in Technological Opportunities* on *Distant Search* when *Firm-Specific Experience* is one standard deviation below the mean to that when *Firm-Specific Experience* is one standard deviation above the mean. At one standard deviation below mean of *Firm-Specific Experience*, one unit drop in *Change in Technological Opportunities* is associated with an increase of 7.64% in *Distant Search*. When *Firm-Specific Experience* is at the higher

[9]The Poisson model is of the following functional form: $E[Y] = e^{\beta X}$. This is a log-linear form, such that taking logs on both sides yields $\log(Y) = \beta X$. Thus, the equation becomes linear in X, and the coefficients can be interpreted as semi-elasticities. In differentiating the equation, we see that $\beta = \frac{dY/Y}{dX}$. This allows us to interpret the coefficients of interactions simply as moderators of semi-elasticities (Cameron & Trivedi, 2013, p. 95). For example, consider the equation of the form $\log(Y) = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2$. In this case, $\frac{dY/Y}{dX_1} = \beta_1 + \beta_3 X_2$. Thus, β_3 directly represents how X_2 moderates the semi-elasticity with respect to X_1. The problem of nonlinearity of the models is addressed by interpreting the interactions as moderators of semi-elasticities.

[10]We also test for robustness with an alternate measure of *Relative Productivity*—the proportion of firm's patents in previous 3 years invented by the focal inventor. The results were substantively similar.

TABLE 1 Correlations and descriptive statistics

	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Distant search	5.537	7.171	1													
(2) Change in technological opportunities	103.862	171.626	0.33	1												
(3) Relative productivity	1324.891	1452.975	0.066	0.217	1											
(4) Star	0.042	0.201	0.142	0.275	0.007	1										
(5) Firm-specific experience	5.536	4.824	0.006	0.025	0.28	−0.09	1									
(6) Interdependence	6.87	12.224	0.153	0.29	0.263	0.177	0.375	1								
(7) Number of patents in domain	4.612	6.246	0.266	0.569	0.243	0.329	0.136	0.556	1							
(8) Number of patents by inventor in focal year	2.176	2.604	0.739	0.343	0.101	0.235	0.04	0.317	0.484	1						
(9) Backward citations	56.071	73.484	0.214	0.483	0.205	0.234	0.348	0.686	0.78	0.376	1					
(10) Collaborators	2.947	4.657	0.116	0.302	0.458	0.119	0.291	0.466	0.442	0.238	0.426	1				
(11) Firm specialization	0.004	0.016	-0.058	−0.055	−0.174	0.005	−0.055	−0.019	−0.021	−0.015	0.011	−0.035	1			
(12) Firm's investment in domain	0.004	0.07	0.029	0.054	−0.022	0.038	−0.045	−0.014	0.017	0.037	−0.004	−0.013	0.035	1		
(13) Firm's number of researchers	2.264	1.666	0.009	0.051	0.696	−0.077	0.22	0.09	0.001	−0.026	0.011	0.225	−0.258	−0.043	1	
(14) R&D expense	2.351	1.655	−0.019	−0.002	0.559	−0.079	0.172	−0.023	−0.05	−0.062	−0.053	0.142	−0.253	−0.039	0.821	1
(15) Assets	43.756	43.093	−0.033	−0.054	0.34	−0.069	0.207	0.048	−0.043	−0.049	−0.017	0.118	−0.175	−0.024	0.505	0.657

TABLE 2 Main specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Change in technological opportunities		−0.028 (0.001)	−0.042 (0.000)	−0.043 (0.000)	−0.036 (0.000)	−0.042 (0.000)	−0.063 (0.000)
Tech opportunities × relative productivity			0.021 (0.000)				0.016 (0.007)
Tech opportunities × star				0.063 (0.013)			0.047 (0.054)
Tech opportunities × firm-specific experience					0.027 (0.000)		0.013 (0.089)
Tech opportunities × interdependence						0.013 (0.017)	0.009 (0.072)
Relative productivity	−0.087 (0.000)	−0.083 (0.000)	−0.085 (0.000)	−0.076 (0.000)	−0.080 (0.000)	−0.072 (0.000)	−0.070 (0.000)
Star	−0.064 (0.227)	−0.059 (0.259)	−0.063 (0.224)	−0.151 (0.005)	−0.046 (0.372)	−0.030 (0.526)	−0.103 (0.007)
Firm-specific experience	0.020 (0.509)	0.008 (0.792)	0.030 (0.310)	0.022 (0.495)	0.022 (0.466)	0.083 (0.021)	0.098 (0.004)
Interdependence	0.016 (0.320)	0.012 (0.454)	0.006 (0.714)	0.006 (0.717)	0.011 (0.501)	−0.025 (0.187)	−0.026 (0.136)
Number of patents in domain	−0.007 (0.164)	−0.006 (0.222)	−0.005 (0.341)	−0.007 (0.156)	−0.005 (0.346)	−0.007 (0.102)	−0.006 (0.197)
Number of patents by inventor in focal year	0.118 (0.000)	0.118 (0.000)	0.118 (0.000)	0.118 (0.000)	0.118 (0.000)	0.118 (0.000)	0.118 (0.000)
Backward citations	−0.002 (0.000)	−0.001 (0.000)	−0.001 (0.000)	−0.002 (0.000)	−0.002 (0.000)	−0.002 (0.000)	−0.002 (0.000)
Collaborators	−0.013 (0.000)	−0.013 (0.000)	−0.014 (0.000)	−0.012 (0.000)	−0.013 (0.000)	−0.011 (0.000)	−0.013 (0.000)
Firm specialization	2.067 (0.000)	2.061 (0.000)	1.978 (0.000)	1.995 (0.000)	1.929 (0.001)	1.885 (0.001)	1.758 (0.001)

TABLE 2 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Firm's investment in domain	−0.089 (0.242)	−0.057 (0.431)	−0.043 (0.552)	−0.048 (0.506)	−0.039 (0.579)	−0.037 (0.590)	−0.016 (0.814)
Firm's number of inventors	0.127 (0.000)	0.129 (0.000)	0.102 (0.000)	0.130 (0.000)	0.122 (0.000)	0.123 (0.000)	0.100 (0.000)
R&D expense	−0.027 (0.002)	−0.028 (0.001)	−0.023 (0.007)	−0.029 (0.001)	−0.025 (0.003)	−0.027 (0.001)	−0.022 (0.011)
Assets	0.0003 (0.348)	0.0003 (0.353)	0.0002 (0.514)	0.0003 (0.326)	0.0003 (0.413)	0.0004 (0.257)	0.0003 (0.403)
<Inventor-firm> fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	104,448	104,448	104,448	104,448	104,448	104,448	104,448
Log likelihood	−186,953	−186,852	−186,694	−186,671	−186,711	−186,387	−186,178

Note: Robust p values in parentheses; two-tailed tests.

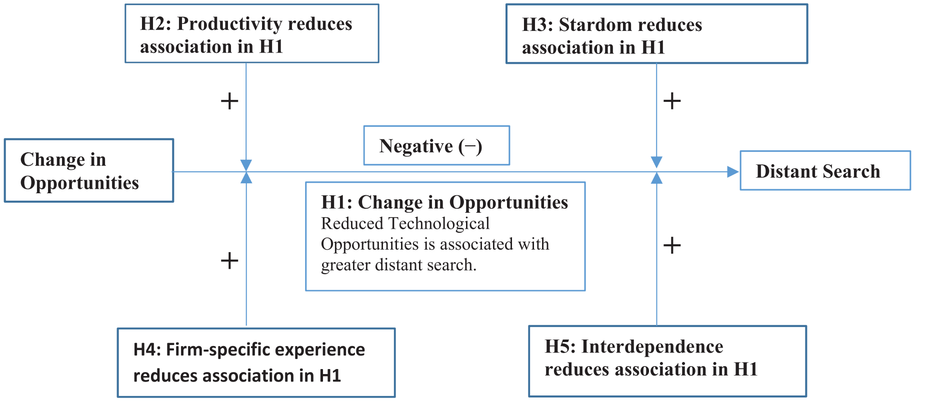

FIGURE 1 Theoretical framework

level, the marginal impact of *Change in Technological Opportunities* decreases to 4.97%, an overall decrease of 35%. For an inventor at mean values of distant search, this would translate to a change in distant search from an increase of 0.42 subclasses for inventors with low firm-specific experience to an increase of 0.275 subclasses for inventors with high firm-specific experience. Thus, with higher firm-specific experience, the inventor reacts in a less pronounced way to reduction in opportunities in her domain, in terms of distant search, as in line with H4.

Hypothesis 5 posits the moderating effect of the inventor's *Interdependence* with the firm on the main effect represented in H1. It predicts that as interdependence increases, the inventor reacts less strongly to reduction of opportunities in her domain in her distant search, that is, the co-efficient of the interaction term between *Change in Technological Opportunities* with *Interdependence* is positive. As Table 2 shows, this coefficient is positive with *p* value of .072 in the full model. In Model 6, the coefficient remains positive with a *p* value of .017.

Again, we compare the marginal impact at different values of *Interdependence*. As before, we keep all other covariates at their respective mean levels and then compare the marginal impact of *Change in Technological Opportunities* when interdependence is one standard deviation below the mean, versus that when interdependence is one standard deviation above the mean. When interdependence is at the lower level, a unit drop in *Change in Technological Opportunities* is associated with an increase of 7.23% in *Distant Search*. At higher level of interdependence, the corresponding marginal impact decreases from 7.23% to 5.37%, a decrease of 25.7%. For an inventor at mean values of distant search, this would translate to a change in distant search from an increase of 0.40 subclasses for inventors with low interdependence to an increase of 0.297 subclasses for inventors with high interdependence. Thus, with greater *Interdependence*, the inventor reacts less strongly to reduction of opportunities in her domains, which is in line with H5.[11]

[11]Despite having controlled for the firm's investments in the focal inventor's domains, it is possible that the above findings for the main effect (H1) may be confounded by other firm-level influences, for example, a firm's interests not reflected in its investments could partially direct the inventor's technological search. However, the findings for the moderation effects presented here do raise the hurdle for such unobserved firm-level influences to fully account for all results. For instance, if the inventor's search is fully directed by firm, one would expect that, faced with reduced opportunities in the existing domains, the firm would direct its more experienced lead inventors or stars to search in new directions. Similarly, one would expect the central players (the more productive lead inventors) to be more in line with the firm's directive to expand search. This is contrary to our findings for H2, H3, and H4. Thus, we are relatively confident that earlier findings for H1 do not merely reflect firm-directed inventor search.

4.3 | Additional analyses and robustness checks

4.3.1 | Difference-in-difference

Despite narrowing our sample to only firms that are active within the 12 classes exhibiting signs of system-wide decline and the use of firm-inventor fixed effects and other controls, there could still be unobserved heterogeneity (e.g., time-varying) driving both the observed technological decline in the inventor's domains and her subsequent distant search. To further minimize this concern, we perform a difference-in-difference (DID) analysis for the main effect.

First, we define a treatment period where (some) inventors faced a decline in technological opportunities in their domains. Of the 12 classes that experienced decline in our sample (see Figure 2), 5 had experienced a pronounced decline during the period 1997–2000.[12] We select this period as the treatment period, setting the dummy variable, "Treatment," to one in this time period, and zero otherwise. Next, we define the cases in which inventors were exposed to this treatment period. We identify observations where at least one of these five "treatment" classes falls within the inventor's domain, that is, the inventor had patented in at least one of these five classes in years $t-1$, $t-2$, or $t-3$ (as consistent with our definition of "domain period" explained earlier). The dummy "Treated" is set to one for these observations, and zero otherwise. Note that there are 3 other classes out of the 12 that had periods of decline that partially overlapped with the 5 selected in the "Treatment" variable.[13] To ensure that the analysis is not contaminated by instances where the inventor may have patented in these other three classes facing decline during the "*Treatment"* period, we drop all observations where the inventor also patented in any of these three partially overlapping classes.

We then interact these two dummy variables. The coefficient of interaction term serves as a test for our main effect. Specifically, it indicates the size of the increase in distant search during periods of decline compared to periods of no-decline (*Treatment*) for the inventors who are exposed to this decline (*Treated*), relative to the size of the same increase (in distant search during periods of decline compared to periods of no-decline) but for the inventors who are not exposed to this decline. This DID approach thus accounts for other confounding factors that may be affecting both the treated and nontreated inventors during the decline period. A positive coefficient of this interaction term would indicate that the treated inventor exposed to the decline increases her distant search to a greater degree than another nontreated inventor who was not exposed to decline during this period.

Table 3 reports results of this DID analysis. All models have year fixed effects. Models 1–4 use Poisson regressions, whereas model 5 uses negative binomial regression. Model 1 consists of controls and model 2 introduces the two dummies. All models include fixed effects as in main models. Model 3 includes the interaction term. It is the full (Poisson) model with firm-inventor fixed effect. Model 4 tests for robustness with random effects whereas model 5 is the negative binomial model. Across all models we find positive coefficients of the interaction term, with p values less than .03 (except for Model 5, where p value is .081). Hence, the results in these DID tests strengthen our confidence that earlier main findings are likely not confounded by unobserved heterogeneity.

[12]The following are the list of five classes that declined in the period: 1997–2000: "83," "206," "329," "332,"and "338."
[13]These three classes are as follows: "148," "241," and "264."

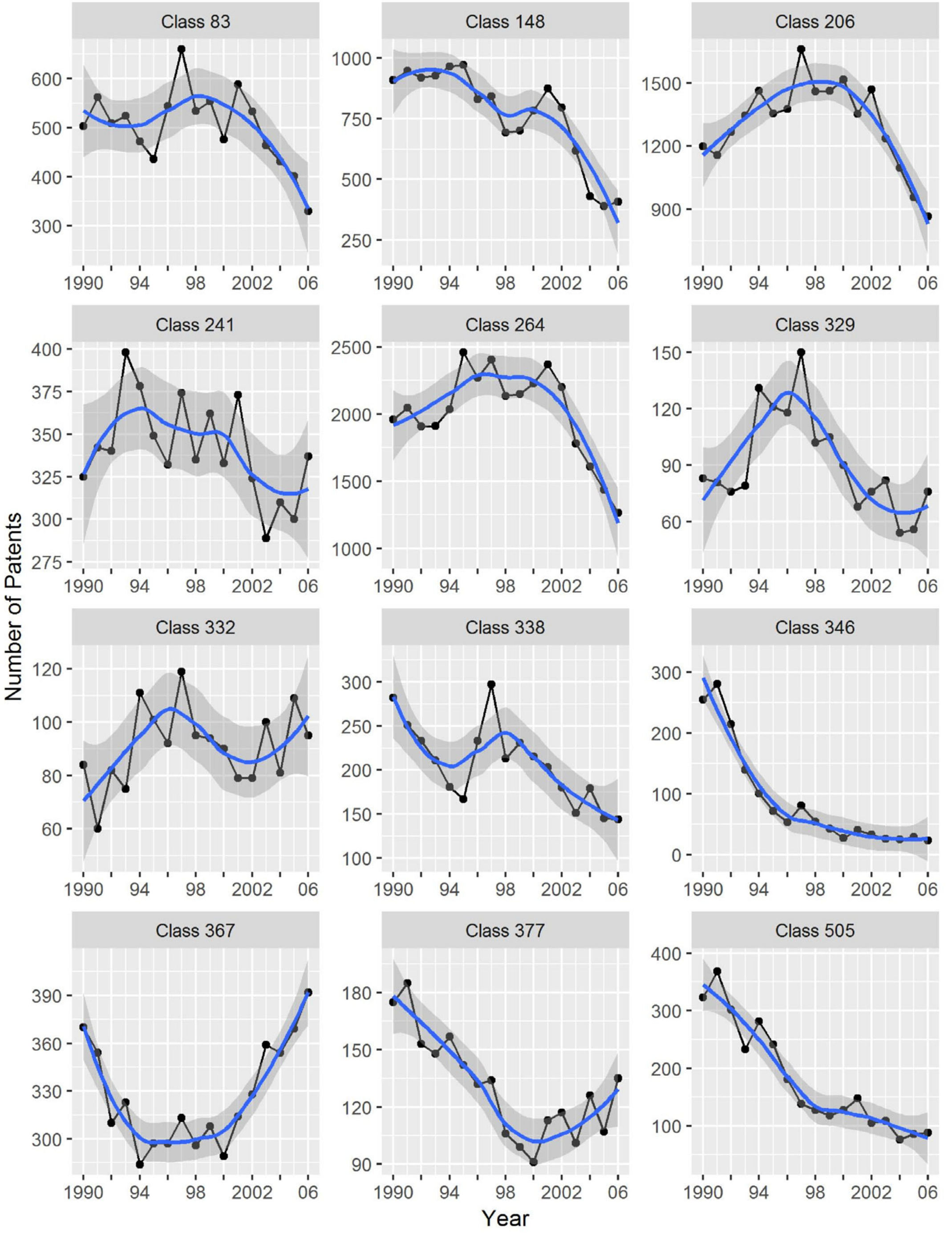

FIGURE 2 Number of patents over time (12 classes)

4.3.2 | Alternative measure of change in technological opportunities

The measure of *Change in Technological Opportunities* is based on the change in number of patents within the relevant technology subclasses. A potential issue could be that this change in number of patents reflects a change in patenting behavior, rather than change in the underlying inventive behavior per se. We check for robustness of earlier findings with an alternate measure based on the growth in the number of inventors patenting in domain during the period that defines the domain, that is, $t-1$, $t-2$, and $t-3$. Column 1 of Table 4 reports this finding. The main results for all propositions remain robust with this new measure and the statistical significances increase.

4.3.3 | Alternative periods for defining inventor's domain

Thus far, the inventor's domain has been defined by the subclasses of which the focal inventor's patents are assigned to in years $t-1$, $t-2$, and $t-3$. We check for robustness of findings to this specification of the 3-years window, by using an alternative window of five preceding years ($t-5$ to $t-1$). Findings for all propositions remain consistent with this alternative window definition.

4.3.4 | Lag structure

In all the above tests, all main independent variables and most control variables (where relevant) are constructed assuming a lag of 1 year between R&D and patent filing. We selected the 1-year lag to be consistent with prior research on this setting (Hall et al., 1986; Pakes & Schankerman, 1984). However, a potential concern is that some R&D investments could take longer than 1 year to materialize as patents, even in a fast moving industry such as the electronics sector. To capture and include these R&D investments with longer lags, we construct all independent variables and the relevant control variables assuming a 2-year lag, and then take the average across the 1- and 2-year lagged values for each variable. We report the results in Column 3 of Table 4. Findings for all propositions remain robust with this lag specification except for the interaction with the star, where the p value dropped slightly to .099.

4.3.5 | Alternate dependent variables

We also tested the robustness of these results to another alternate dependent variable based on citations; specifically, we look at the number of "new" subclasses in the backwards citation made within the inventor's patents in year t. To construct this measure, we compile all patents cited by the inventor's patents in year t, trace the subclasses of these cited patents, and then count the number of subclasses that are "new." We defined a subclass as "new" if it had not been cited by the inventor's patents in the previous 3 years. The core idea of this measure is to trace the extent to which the inventor has used new types of knowledge in her recombination to create new inventions. Findings with this new measure remain consistent (see Table 4, Column 4).

4.3.6 | Alternate model

We also tested our hypotheses using a negative binomial model. The findings remain consistent (Table 4, Column 5).

TABLE 3 Differences-in-differences tests

	(1) Poisson Controls	(2) Poisson Main effects	(3) Poisson Diff-n-diff	(4) Poisson Random effects	(5) Negative binomial
Treated		−0.021 (0.449)	−0.081 (0.015)	−0.047 (0.008)	−0.056 (0.054)
Treatment		0.003 (0.805)	0.000 (0.988)	−0.000 (0.940)	0.004 (0.683)
Treated × treatment			0.101 (0.028)	0.074 (0.001)	0.062 (0.081)
Number of patents in domain	−0.028 (0.000)	−0.028 (0.000)	−0.028 (0.000)	−0.029 (0.000)	−0.041 (0.000)
Number of patents by inventor in focal year	0.166 (0.000)	0.166 (0.000)	0.166 (0.000)	0.175 (0.000)	0.146 (0.000)
Backward citations	−0.001 (0.001)	−0.001 (0.001)	−0.001 (0.001)	−0.000 (0.000)	−0.001 (0.000)
Collaborators	−0.010 (0.000)	−0.010 (0.000)	−0.010 (0.000)	−0.009 (0.000)	−0.008 (0.000)
Firm specialization	1.290 (0.037)	1.294 (0.036)	1.288 (0.037)	−4.594 (0.000)	0.495 (0.338)
Firm's investment in domain	−0.024 (0.643)	−0.024 (0.644)	−0.025 (0.637)	0.005 (0.850)	−0.071 (0.090)
Firm's number of inventors	0.051 (0.000)	0.050 (0.000)	0.049 (0.000)	0.030 (0.000)	0.034 (0.000)
R&D expense	−0.015 (0.061)	−0.014 (0.081)	−0.015 (0.073)	0.001 (0.696)	−0.004 (0.496)
Assets	0.0002 (0.508)	0.0002 (0.509)	0.0002 (0.518)	−0.0008 (0.000)	0.0001 (0.688)
<Inventor-firm> panel effects	Fixed	Fixed	Fixed	Random	Fixed
Period dummies	Yes	Yes	Yes	Yes	Yes
Observations	99,358	99,358	99,358	99,903	99,358
Log likelihood	−162,938	−162,937	−162,927	−271,131	−145,225

Note: Robust p values in parentheses; Two-tailed tests.

TABLE 4 Additional analyses

	(1) Growth of inventors	(2) Domain period: 5 years	(3) Average lag of 1 and 2 years	(4) New subclass cited	(5) Negative binomial
Change in technological opportunities	−0.072 (0.000)	−0.064 (0.000)	−0.084 (0.000)	−0.063 (0.000)	−0.076 (0.000)
Tech opportunities × relative productivity	0.021 (0.000)	0.016 (0.008)	0.019 (0.002)	0.021 (0.002)	0.020 (0.000)
Tech opportunities × star	0.057 (0.018)	0.044 (0.072)	0.037 (0.099)	0.066 (0.004)	0.037 (0.000)
Tech opportunities × firm-specific experience	0.017 (0.007)	0.015 (0.079)	0.012 (0.080)	0.029 (0.001)	0.017 (0.000)
Tech opportunities × interdependence	0.014 (0.003)	0.011 (0.045)	0.009 (0.012)	0.021 (0.000)	0.014 (0.000)
Relative productivity	−0.066 (0.000)	−0.067 (0.000)	−0.078 (0.000)	−0.101 (0.000)	−0.067 (0.000)
Star	−0.108 (0.009)	−0.102 (0.007)	−0.104 (0.007)	−0.045 (0.245)	−0.123 (0.000)
Firm-specific experience	0.132 (0.000)	0.066 (0.047)	0.144 (0.000)	0.479 (0.000)	0.074 (0.000)
Interdependence	−0.038 (0.024)	−0.020 (0.280)	−0.044 (0.016)	0.002 (0.918)	−0.021 (0.003)
Number of patents in domain	−0.005 (0.284)	−0.002 (0.482)	−0.008 (0.107)	0.002 (0.563)	−0.011 (0.000)
Number of patents by inventor in focal year	0.118 (0.000)	0.118 (0.000)	0.115 (0.000)	0.124 (0.000)	0.084 (0.000)
Backward citations	−0.002 (0.000)	−0.002 (0.000)	−0.002 (0.000)	−0.006 (0.000)	−0.002 (0.000)
Collaborators	−0.013 (0.000)	−0.014 (0.000)	−0.011 (0.000)	−0.009 (0.000)	−0.014 (0.000)
Firm specialization	1.610 (0.003)	1.578 (0.018)	2.098 (0.032)	0.479 (0.643)	0.871 (0.080)
Firm's investment in domain	−0.020 (0.771)	0.023 (0.741)	−0.233 (0.042)	−0.162 (0.024)	−0.120 (0.004)
Firm's number of researchers	0.091 (0.000)	0.109 (0.000)	0.121 (0.000)	0.055 (0.003)	0.066 (0.000)
R&D expense	−0.019 (0.026)	−0.023 (0.007)	−0.036 (0.002)	0.003 (0.793)	−0.005 (0.371)
Assets	0.0003 (0.412)	0.0003 (0.443)	0.0007 (0.105)	0.0003 (0.498)	−0.0002 (0.264)
<inventor-firm> fixed effects	Yes	Yes	Yes	Yes	Yes
Period dummies	Yes	Yes	Yes	Yes	Yes
Observations	104,448	104,341	99,555	104,147	104,448
Log likelihood	−185,981	−184,599	−178,216	−719,119	−161,133

Note: Robust p values in parentheses; two-tailed tests.

4.3.7 | New to inventor/new to firm

Distant Search has thus far been defined as what is new to the inventor. An interesting extension could be to examine which type of inventor deviates not just from her own previous search path but also the firm's previous search path. In other words, we want to see if the attributes of the inventor characterized in the four contingencies (H2, H3, H4, and H5) matter toward her tendency to search in domains that are not just new to herself but also new to the firm. While, strictly speaking, our core focus in this paper is simply to determine which inventor deviates in her own search path in response to career concern, it could also generate worthwhile implication to firm managers to see when and which inventor deviates from the firm's search and create new technologies for the firm.

First, as we mean to see inventors' reactions in times of decline in technological opportunities, we focus on the subsample with lower than median value of *Change in Technological Opportunities*. For each inventor-year observation, we create two columns, respectively capturing: (i) if the inventor patented in at least one subclass that is new to the inventor as well as new to the firm, and (ii) if the inventor patented in at least one subclass that is new to the inventor but not new to the firm. Note that, per before, "new" is defined relative to years $t-1$, $t-2$, and $t-3$. We then calculate the average value of the contingencies—Relative Productivity, Firm-Specific Experience, and Interdependence—across observations that fall into each of the two columns, so that we can then see if inventor attributes differ significantly across the two columns. For stars, we compute the percentage of stars in each of the two columns. Findings are reported in panel A of Table 5.

As shown across the two columns in panel A of Table 5, the inventor who searched in domains that are new to herself and to the firm (Column 1) on average has lower relative productivity within the firm, has less firm-specific inventive experience, and exhibits less interdependence than the inventor who searched in domains that are new to herself but not to the firm. *T*-tests of difference for all three contingencies show that such differences are statistically significant. This suggests that the inventor who deviates in search from her and the firm's previous search paths (new to herself and new to the firm) tends to be the one who faces greater selection pressures and career concern (per the three contingencies) than the inventor who deviates from her own but not from the firm's search path (new to herself but not new to firm). The percentage of stars in each of the groups—those that searched in domains that are new to both the inventor and the firm, and those that searched in domains new only to themselves—do not seem to differ from each other (the t-stat of the difference is much below the conventional levels). The stars have a global market appeal, and their employability is likely independent of the employer. Hence, the nature of their distant search does not differ with regard to whether it falls in domains that are new to the firm. In other words, stars seem to operate as "free agents" in that their search decisions do not appear to be influenced by firm-specific factors. Investigating this observation more deeply would be outside the scope of this study; we defer to future studies for deeper examination of this issue.

We then increase the stringency of the test by varying the definition of when the inventor has searched distantly as follows: instead of patenting in "at least one subclass that is new" (to herself and the firm, or to herself but not to firm), we now measure whether the inventor has patented in the median or more number of subclasses that is new to herself and new to the firm (first column), or new to herself but not to the firm (second column). Results reported in panel B of Table 5 remains robust. Going further, in panel C of Table 5, we measure if the inventor patented in the 90th percentile or more subclasses that are new to the firm

TABLE 5 New-to-firm analyses

	(A) Expanded into at least one class		(B) Median or greater level of expansion		(C) 90th percentile or greater level of expansion	
	(1) New to the inventor and to the firm	(2) New to the inventor but not to the firm	(1) New to the inventor and to the firm	(2) New to the inventor but not to the firm	(1) New to the inventor and to the firm	(2) New to the inventor but not to the firm
Relative productivity	869.77	1,018.65	869.77	1,057.03	761.39	1,183.32
	Difference (2–1): 149;		Difference (2–1): 187;		Difference (2–1): 422;	
	t-stat of difference: 15.76		*t*-stat of difference: 17.76		*t*-stat of difference: 19.33	
Star	1.74%	1.62%	1.74%	1.65%	1.80%	1.76%
	Difference (2–1): −0.12%;		Difference (2–1): −0.09%;		Difference (2–1): −0.04%;	
	t-stat of difference: −1.31		*t*-stat of difference: −0.87		*t*-stat of difference: −0.16	
Firm-specific experience	5.37	5.48	5.37	5.51	5.26	5.66
	Difference (2–1): 0.11;		Difference (2–1): 0.14;		Difference (2–1): 0.40;	
	t-stat of difference: 2.99		*t*-stat of difference: 3.57		*t*-stat of difference: 4.79	
Interdependence	4.5	5.33	4.5	5.45	4.16	6.24
	Difference (2–1): 0.83;		Difference (2–1): 0.95;		Difference (2–1): 2.08;	
	t-stat of difference: 11.98		*t*-stat of difference: 12.18		*t*-stat of difference: 11.87	

(first column), or new to herself but not to the firm (second column). In these more stringent tests, results remain robust. Overall, our predictions surrounding the contingencies—relative productivity within the firm, firm-specific inventive experience, and firm-specific interdependence—appear to extend to the inventor deviation in search not just from her own but also from the firm's previous search path as well.

4.3.8 | Push versus pull factors of distant search

Another potential issue is that when we observed distant search by the inventor, instead of being driven by a "push" factor as we proposed (decline in technological opportunities in existing domains), it could alternatively be drive by a "pull" factor such as attractiveness of opportunities arising in a new domain. If it is indeed a pull factor at work, then we should see inventors or firms converging toward similar new domains as they search distantly. In other words, a large overlap in the "new domains that inventors shifted to would indicate a possibility of a 'pull' factor."

To assess this possibility, we examine if inventors within a firm who searched distantly are searching in the same new domains. We count the number of different unique subclasses that all the inventors of a firm collectively expanded into every year. We then calculated what percentage of these subclasses on average were common among all the inventors in the firm. This indicates the overlap between the inventors' new domains that they searched in. We find that this percentage was less than 1% (0.78%) in our sample. This suggests that the pull effect appears to be minimal within our sample. Next, we conduct similar analyses at the firm level. We check whether all firms in the industry moved toward common domains in a given year. We find zero instances of such common domain across our sampling period. Again, there is no indication of a pull factor at work. Then, we trace the pairwise overlap of subclasses between two firms. For each pair of firms in our sample, we calculate the overlap of new subclasses they searched in during the year and then take the average across the possible pairs in each year. This tells us how much on an average any two firms of the industry searched distant in the same new subclasses. We find that this average is about two subclasses per pair of firms. This appears to be low, given that inventors in a firm on average collectively search in about 110 unique subclasses that are new to them in a year. Overall, we do not find evidence suggesting that there is a pull factor at work here.

4.3.9 | Inventor mobility

The contingency hypotheses (H2–H5) anchors on the theoretical mechanism that certain inventors—relatively more productive, or stars, or those with more firm-specific experience, or with more interdependence with the firm's technologies—experience less career concern when faced with declining technological opportunities. A logical extension could be that such inventors are also less likely to subsequently depart from the focal firm. We further check to see whether we observe this extension in our data.

To define subsequent mobility of an inventor, we took a conservative approach, and determined subsequent mobility as cases when the inventor is found to innovate in other firms and not in her current firm in years $t + 3$, $t + 4$ and $t + 5$. We then split the sample into low and high values of each contingency (low corresponds to less than the 25th percentile, and high to more than 75th percentile; for stars the sample was split into nonstars and stars) and compared the occurrence of mobility across the two subsamples. To compare across the subsamples, we adapt the DID regressions we described earlier. In these regressions, the dependent variable is whether the inventor moved, that is, invented in another firm in subsequent period, the model used was logit with firm-inventor random effects.[14] We found that for inventors with higher values of productivity, the coefficient of interaction was negative and significant at 5% level (−1.266, $p = .014$), whereas in the sample of lower values of productivity, the coefficient was smaller and not significant at conventional levels (−0.186, $p = .713$).[15] This suggests that the proportional change in odds of mobility due to technological decline is likely less for inventors at higher level of relative productivity compared to less productive inventors. For firm-specific experience, the coefficient for high value subsample was negative and significant at 10% (−0.849, $p = .077$) whereas the coefficient for low value subsample was positive and not significant at conventional levels (0.201, $p = .844$). For *Interdependence*, the coefficient of interaction for higher levels is negative and significant at 5% level (−0.953, $p = .035$), whereas the coefficient is positive and not significant at conventional levels (0.049, $p = .930$) for the subsample with low values. Thus, consistent with the extended idea described above, inventors who are more productive, have more firm-specific experience, or more interdependence with the firm seem to face lesser career concern and thus their odds of moving to a new firm decline.

This pattern was however not observed for the star contingency. The coefficients of interaction in the DID estimates for stars and nonstars were positive (0.881, $p = .345$) and negative (−0.26, $p = .265$), respectively, though both were not sufficiently significant to warrant a conclusive interpretation. Thus, stardom by itself does not appear to affect the mobility of inventors in face of technological decline. Given that mobility is not the main focus in this study, we defer to future research to dig deeper into this finding. Also, we stress that despite numerous tests employed here, we treat the above examination on mobility simply as exploratory, and findings here should be treated as suggestive rather than conclusive.

5 | CONCLUSION

This paper stresses that career concern is a key part of an inventor's decision calculus driving her search behavior. Departing from the typical view of distant search as a path to find solutions, we instead view it as a way to bolster the inventor's external job market value. We propose that a reduction in technological opportunities in her local domains triggers career concerns and induces her to subsequently search distantly (H1). To further highlight the career concern mechanism, we propose that this main effect is attenuated when her career concern is less salient, specifically, when she experiences greater job security as she is relatively more productive within the firm (H2) or as she is a star inventor (H3). We also propose that the main effect is attenuated when the opportunity cost of her addressing this career concern is higher, specifically, the loss in value is higher if she moves to another firm as she has more firm-specific

[14]There was insufficient variance in some of the interaction terms for fixed effect models to converge.

[15]Since the logistic model assumes that the natural log of the odds of moving (i.e., $\log(p/1-p)$) where p is probability of move) is a linear function of the regressors, we can treat the difference in coefficients across the subsamples as suggestive evidence that technological decline has differential impact on the odds of mobility across the two subsamples.

experiences (H4) or as her knowledge exhibits greater interdependence with the firm (H5). Data from the US electronics industry shows results consistent with our propositions.

By shifting the focus in examining an inventor's decision calculus away from calculations about the problem (Billinger et al., 2014; Hoeffler et al., 2006) to that about her personal career concern, we introduce the argument that there is more to an inventor's decision on search than the usual considerations about the problem such as where satisfactory solutions to the problem likely reside, how to go about searching for them, how likely is search going to successful in uncovering them, and so on. Decision calculus for an individual is arguably more complex than that for a firm. While one may assume that in firm-level studies of search, it is safe to put aside the more-complex human elements in decision-making and imagine that calculus about the problem is the main driver of search, this assumption may not be sound when we study search at an individual inventor-level. Personal interest such as worry about career prospect kicks in (Fama, 1980; Holmström, 1999), intermingles with her interpretation of signals about the problem, adding nuances and complexity to decision calculus on search. The call for closer examination of microfoundations of search at individual level (Lee & Meyer-Doyle, 2017) is precisely to get at these complex personal interests and how they complicate decision-making in search.

Bringing in the notion of the inventor's search as a response to her career concern also introduces a mechanism that more readily explains observed patterns and heterogeneity of search in real life. While the problem that a firm faces likely exerts a common influence on all its inventors regarding how they search, not all of the firm's inventors in that instance end up searching equivalently (i.e., locally vs. distantly). Some appear to succumb to inertia of continued local search (Tushman & Anderson, 1986) while others do not but instead venture into distant space. Unless we start theorizing that somehow each individual interprets signals of prior local search's inadequacy differently, or that each has different abilities to react to this signal, the calculus about the problem by itself will not fully explain what is driving each inventor's search decision. In that sense, an alternative theory of decision calculus based on career concern, as we proposed here, could serve as a more potent one in explaining heterogeneity across inventor search in response to a given problem. Also, we have highlighted but one aspect of personal interest—career concern—that could shape an inventor's search. There are likely more such factors that future research can and should uncover.

We hope this paper also contributes to the literature on employees' career concern, human capital and mobility (Campbell et al., 2012; Ganco, 2013; Siemsen, 2008). We learn from this literature that when an employee faces internal career concern within the firm, that is, when prospect of career advancement within the firm wanes, she starts to react to external market in search of future job opportunities elsewhere (Bloom & Michel, 2002; Yanadori & Cui, 2013). A key insight offered was that the employee with superior ability or knowledge is better positioned to do so (Palomeras & Melero, 2010). But where does this individuals' ability or knowledge come from? Meanwhile, we learn from the search literature that employees' searches add to their ability and knowledge. Thus, by studying search as an outcome of an employee's career concern, we are essentially examining the preceding step that leads her to possess the observed level of ability or knowledge. The ability that allows her to be mobile could itself be endogenous. Furthermore, our contingency hypotheses raise a crucial conceptual tension: Even if the more-abled employee is better positioned to move to another firm, does she have the incentive to do so? Our findings hint that perhaps the more abled-employee (inventor), in terms of her productivity, firm-specific experience and collaborative ties, may systematically have less incentive to move. At a minimum, this calls for caution in interpreting empirical findings on the mobility of abled-inventors, specifically that they may underestimate the mobility effect of the employee's ability. Beyond empirics, the tension between ability and incentive merits theoretical pursuit in future research.

DATA AVAILABILITY STATEMENT

Research data are not shared.

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