Essays on Inventions

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Abstract

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Inventions help individuals and firms to grow, compete, and survive in the marketplace. The context in which inventions are created can shape the nature and purpose of the invention. This dissertation examines how inventions can be created to solve problems and to spark new technological paradigms.

In my first essay, I consider how firms respond to unanticipated performance setbacks and whether their deviation from their routine search, toward either riskier or more conservative problemistic search, is contingent on the societal context in which they are embedded. I find that, when Japanese and South Korean automotive firms experienced involuntary product recalls, they tended to become increasingly conservative in accordance with the general aversion of risk within their societies; subsequent technical solutions in the affected technological space relied less on external technologies than on those derived prior to the recall. In contrast, U.S.

automotive firms deviated relatively little from their routine search patterns in response to product recalls. My post hoc analyses finds that those firms that pursued riskier resolutions to their involuntary recalls by relying increasingly on external technologies were more likely to experience subsequent recalls. Firms that took a more conservative stance by relying on internal technologies, however, prevented subsequent recalls. My analyses suggest that societal norms may influence how effectively firms adapt to performance setbacks.

In my second essay, I pivot my focus from the firm to the individual inventor. Research on knowledge creation produces conflicting conclusions about who creates breakthroughs: are they broadly knowledgeable dabblers, or are they highly specialized experts? I resolve this tension by applying natural language processing to identify and classify breakthrough technologies, parsing the abstracts of 5.5 million U.S. patents between 1969-2017. I make two main contributions. First, I explore the experience of inventors to determine whether broad or focused experience is more conducive to creating breakthroughs. Second, I use topic modelling to isolate these breakthroughs that shift the technological paradigms and establish new vocabularies and cognitive maps.

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1 Introduction

Inventions are vital to the growth and development of societies. Individuals and firms create inventions to serve multiple purposes. Some inventions are developed as technological solutions to unexpected shocks. Other inventions are generated when the existing cognitive frameworks are insufficient; these breakthrough inventions drive change in science, and their very presence signals a shift in technological paradigms. Still other inventions are relatively derivative inventions and are meant to represent steady but incremental progress within a technological domain.

However, the process of invention is costly and uncertain (Arrow, 1962). To reduce this uncertainty, my dissertation aims to shed light on how knowledge is generated and recombined into an invention. In particular, I look at the effect of knowledge diversification on subsequent inventions, comparing riskier search with more conservative search, as well as broad versus focused experience.

In my first essay, I unpack the process of problemistic search through the lens of risk. When faced with an unexpected problem in the form of an involuntary recall, inventors can choose to pursue solutions that vary in their degree of risk (Greve, 2003a). For this study, I assemble recall and invention data for automotive firms at the subsidiary level, then I aggregate to parent firms. I then examine whether social norms influence how firms deviate from routine to problemistic search, by identifying corresponding patents within the same technological area. I supplement this archival data with data from other sources, such as interviews with engineers and managers at automotive firms, to gain firsthand insight of how they view the process of problemistic search.

In my second study, I examine the inventors of breakthrough inventions and derivative inventions, with the goal of understanding whether breakthrough inventors are more likely to be a Jack of all trades or a master of one? I gather data from Google Patent data on individual inventor experience and inventor focus to determine their effect on an inventor's likelihood to create a breakthrough invention. To isolate breakthrough inventions from derivative inventions, I use topic modelling algorithms on patent data from the USPTO. Specifically, I use Latent Dirichlet Allocation (LDA) and Hierarchical Dirichlet Process (HDP) on 5.5 million U.S. patent abstracts between 1969-2017 to determine how breakthrough inventions create new topics through new vocabularies.

2 The influence of societal norms on how firms deviate from routine to problemistic search: The response of automotive firms to involuntary product recalls

2.1 Introduction

Firms often experience unexpected performance setbacks precipitated by external events, such as sudden regulatory decisions or economic shocks (Rerup, 2009; Zollo, 2009). Although organizational routines that guide day-to-day behavior are slow to change (Becker, 2008), abrupt performance setbacks can embolden firms to deviate from these routines (Posen, Keil, Kim, & Meissner, 2018). How firms deviate from their routine behaviors in response to performance setbacks, however, is open to debate.

Unanticipated events such as involuntary product recalls are unequivocal performance failures (Haunschild & Rhee, 2004); these defective products not only slipped past firms' internal quality benchmarks but also failed to meet basic performance standards set by government regulators. Theories of firm behavior suggest that firms respond to such failures in one of two ways (Greve, 2003a). One response is to become increasingly conservative by embracing a crisis mentality (Gilbert, 2005; Staw, Standelands, & Dutton, 1981). The uncertainty created by unexpected performance setbacks triggers those responsible for resolving them to focus on searching for predictable solutions that build on familiar knowledge. By doing so, firms avoid delving into the unknown, which introduces additional risk on the recovery process and exacerbates an already difficult situation (Ref & Shapira, 2017).

Alternatively, performance setbacks can encourage firms to throw caution to the wind by seeking risky solutions that build on relatively unfamiliar external knowledge. As firms recognize the limitations of the status quo that led to their setbacks, they may become more open to exploring the unknown as a means to address their current predicament (Kim, Finkelstein, & Haleblian, 2015; March & Shapira, 1987).

In their literature review on problemistic search processes (i.e., those triggered by setbacks), Posen et al. (2018) present ample evidence that firms that perform below their aspirations do, indeed, deviate from their normal routines (i.e., behavioral patterns that existed prior to setbacks). Nonetheless, strategy scholars still possess a limited understanding of the factors that shape the *direction* in which firms deviate from their routine search to problemistic search (Posen et al., 2018). Thus far, behavioral theories of problemistic search have been applied with little regard for the norms of the societies in which firms are embedded. This is striking, given that risk plays an integral role in the theories that describe how firms rectify such subpar performance (Greve, 2003a; Posen et al., 2018). Societal risk-taking norms may orient firms as to how they *ought* to cope with sudden performance setbacks, in accordance with societal expectations. I consider how firms respond to sudden, unanticipated performance setbacks and whether their deviation toward either riskier or conservative problemistic search (vis-à-vis their routine search processes) is contingent on the societal context in which they are embedded.

Understanding the factors that influence how firms respond to unexpected performance setbacks is an essential first step in identifying the contexts in which firms may be prone to error when adapting to such setbacks. Prescriptive guidance as to how firms *should* respond to performance setbacks to secure positive outcomes, however, is scarce. Does conservative or risky problemistic search lead to better outcomes? If so, might certain societal norms influence how effectively firms adapt to performance setbacks?

To provide insight into these questions, I examine how automotive firms deviate from their inventive search routines in response to unanticipated product recalls initiated by the National Highway Traffic Safety Administration (NHTSA). Inventive search routines vary in their emphasis on exploiting technologies already within the firm as building blocks for solutions, as compared to exploring technologies that are external and, thus, less familiar. I identify 3,700 involuntary product recalls imposed on automotive firms between 1985 and 2006 and meticulously match each recall to its corresponding underlying technology.

I find that how firms deviate from routine to problemistic search in response to product recalls depends on the societal context within which they are embedded. Specifically, I find that, when Japanese and South Korean automotive firms experienced recalls, they tended to become increasingly conservative in accordance with the general aversion of risk within their societies, and subsequent technical solutions in the affected technological space relied less on external technologies than on those derived prior to the recall. In contrast, U.S. automotive firms deviated relatively little from their routine search patterns in response to product recalls in terms of their reliance on external technologies.

Further, my post hoc analyses suggest that those firms in the sample that pursued riskier resolutions to their involuntary recalls by relying more on external technologies had a greater likelihood of experiencing subsequent recalls than did firms that took a more conservative stance. Overall, I find that introducing additional risk into the recovery process for product recalls is counterproductive.

I contribute to the literature in multiple areas. Prior studies that considered how firms respond to performance below their aspirations typically conceptualized aspirations based on median industry financial performance (Shinkle, 2012). As a result, there is often a mismatch between measurement and perceptions of performance setbacks within firms (Posen et al., 2018). I identify firm-specific and *unequivocal* performance failures to examine how firms search for solutions to these specific failures. By doing so, I effectively isolate problemistic search, which is triggered by specific problems, from institutionalized, routine search patterns (Chen & Miller, 2007; Greve, 1998). Further, prior studies in this realm have typically relied on narrow societal contexts that did not lend themselves to insights regarding societal boundary conditions. Consistent with the notion that context influences how firms respond to failure (Kuusela et al., 2017; Posen et al., 2018), I show that firms' responses to setbacks depend on societal risk-taking norms.

Limited work has considered the relationship between how firms respond to subpar performance and the outcomes of such responses. Although these findings should be viewed tentatively, they point to the imprudence of introducing additional risk into the recovery process by relying on external prior art when resolving sudden performance setbacks as well as the potential value in deviating from their routine search by building on familiar knowledge. The entirety of my analyses suggests that firms embedded in societies that are generally accepting of risk may need to take steps to reduce their tendencies to conform to these societal values when pursuing problemistic search.

I begin by describing inventive search routines and how they become malleable in the face of sudden performance setbacks, such as product recalls. I then provide alternative logics for the direction (enhanced risk aversion vs. enhanced risk taking) in which firms are likely to deviate from routine to problemistic search and the role that societal norms play in determining the direction.

2.2 Inventive search routines and their malleability

Organizational routines are patterns of collective behavior that firms use to accomplish tasks (Feldman & Pentland, 2003). Over time, value-chain activities that range from invention to production to distribution become routinized to some degree (Becker, 2004; Levitt & March, 1988). *Inventive* search routines constrain how firms develop technical solutions and can be characterized, in part, by the source from which firms search for insight as they develop solutions. More specifically, inventors can exploit technologies within their firms or explore technologies that are external and less familiar (March, 1991; Miller & Chen, 1994). It is less risky for a firm to develop technical solutions by reformulating technologies that it has previously developed and is familiar with than to do so by integrating relatively unfamiliar technologies that have been developed by others (March, 1991; Kim et al., 2015).

Although routines help firms to contend with normal day-to-day uncertainty, their rigidity can be counterproductive (Abernathy & Clark, 1985; Henderson & Clark, 1990). Managers are often reluctant to pivot from routine behaviors that brought them past success and ignore evidence that supports a need for change (Madsen & Desai, 2010; March & Shapira, 1987).[1] When firms rely on existing routines without challenging the underlying assumptions of existing routines, they can be lulled into complacency and fail to adapt to a gradually changing environment (Teece, Pisano, & Shuen, 1997; Zollo, 2009). Inventive search routines can be particularly enduring. As is apparent from Kodak's downfall (Lucas & Goh 2009), inventors whose firms are gradually deteriorating often escalate their commitment to existing routines rather than modifying them (Brockner, 1992; Staw et al., 1981).

[1] A classic anecdote illustrates this problem: Footage of mounted artillery units in the early days of World War I showed that some of the crew consistently stopped moving for several seconds while firing, a routine that turned out to be a holdover from when soldiers had to hold horses' reins to prevent their bolting at the sound (Morison, 1966).

Sudden performance setbacks, however, can shock employees out of their complacency and spur them to deviate from their routine behaviors (Cyert & March, 1963; Gersick & Hackman, 1990). In contrast to voluntary product recalls, which are pursued by firms when they uncover performance issues on their own, *involuntary* product recalls occur at the behest of government regulators, are relatively rare, and are unexpected by the targeted firms. An engineer at a large automotive firm described to us the gravity of involuntary product recalls:[2]

> If you find an issue during tech development, the cost of fixing it is free. Once you have a product, it costs ten times as much. After you build your first prototype, it costs a hundred times as much. And if you don't discover your mistake until after sales, it's several thousand times as costly.

Due to their serious consequences, involuntary product recalls draw the attention of a wide array of stakeholders. Consumers may shy away from purchasing the firm's products, and dissatisfied investors may weigh down stock prices, triggering takeover bids or bankruptcy. Takata, for example, recently came under fire for producing millions of defective airbags and subsequently filed for bankruptcy (Lienert & Shepardson, 2017).

To regain the confidence of consumers and investors, firms must correct their defective products. Doing so, however, is highly disruptive. In this regard, one engineer interviewee stated, "It's definitely a shock to the engineering team's workflow and focus. . . . the magnitude of awareness on this old issue goes from zero to almost the whole team." Ad hoc task forces can further disrupt inertia (MacDuffie, 1997). Another interviewee noted that these task forces often comprise individuals pulled from other teams to supplement the original team that developed the defective product. Routine behaviors that lead up to the defective product are viewed critically, and, thus, employees set aside any bias toward maintaining routine behaviors and are amenable

[2] Structured interviews were conducted with eight product designers, engineers, and managers at four automotive firms, including General Motors, Ford, Chrysler, and Tesla. These interviews lasted from 20 to 60 minutes.

to deviating from them (Gavetti, 2005; Pentland & Feldman, 2005). In sum, sudden performance setbacks, such as involuntary product recalls, provide the impetus for firms to deviate from their routine inventive search patterns. Whether they do so in a manner that decreases or increases risk, however, warrants further attention (Baum et al., 2005; Chen, 2008; Posen et al., 2018; Park, 2007).

2.3 Hypotheses

2.3.1 Alternative Logics for How Firms Respond to Performance Shortfalls

Heightened risk aversion. On the one hand, when facing mounting pressure from sudden performance setbacks, firms can become increasingly conservative (Shimizu, 2007; Sitkin & Pablo, 1992; Staw et al., 1981). In response to crises, managers may avoid risk to minimize further losses (Dutton & Jackson, 1987). Command and control mentalities take hold; as authority accumulates in the hands of fewer individuals, diverging opinions are squelched and experimentation is limited (Gilbert, 2005). Further, due to the psychological stress and anxiety that results from sudden setbacks, employees reduce the amount of information that they process by focusing on what they already understand (Mone, McKinley, & Barker, 1998). This laser focus on what is known enables firms to respond quickly to crises by making small, satisficing adjustments (Janis & Mann, 1977).

There is substantive empirical support for the notion that firms respond to poor performance by becoming increasingly risk averse, by committing either fewer resources to high-risk projects or more to low-risk projects (Klingebiel, 2018). For example, when small Japanese shipbuilding firms performed below expectations, they produced fewer ships and avoided risky factory expansion (Audia & Greve, 2006). Similarly, some manufacturing firms that performed below aspirations were less likely to pursue acquisitions and more likely to pursue lower risk initiatives that focus on cutting costs (Bromiley & Washburn, 2011; Iyer & Miller, 2008).

In accordance with a risk-aversion perspective on problemistic search, when firms experience involuntary product recalls, they will reduce their exploration of external technologies and modestly adjust their existing technologies. Although external technologies can provide firms with valuable insights, assimilating such knowledge can be onerous; it may not be immediately clear how to supplement the firm's existing knowledge by recombining it with external technologies. Relying on internal technology is inherently less risky and more predictable because fellow employees can readily assist in assimilating such knowledge (Gupta, Smith & Shalley 2006; March, 1991). As a result, involuntary product recalls will elicit a decreased reliance on external technologies as compared to what was routinely relied upon.

H1: In response to involuntary product recalls, firms will rely less on external technologies in developing technical solutions than they did before the recall.

Heightened risk seeking. In contrast to the notion that sudden performance setbacks prompt an increasingly conservative search for solutions, there also is logic that suggests that firms become increasingly risk seeking (Capron & Mitchell, 2009; Cyert & March, 1963; Lant & Montgomery, 1987; March & Shapira, 1987). Such setbacks call into question the firm's internal knowledge. Despite the inherent uncertainty in doing so, pursuing solutions that build on unfamiliar external knowledge may be viewed by decision makers as a more logical path toward recovery and a means of maintaining their leadership (Boyle & Shapira, 2012).

There is substantive evidence that suggests that poor performance elicits greater risk taking (Posen et al., 2018). For example, poorly performing U.S. technology firms were more likely to take the risk of joining early-stage R&D consortia than were their better-performing counterparts (Bolton, 1993b). Investment banks that failed to meet their aspirations were likewise more willing to increase their risk exposure (Baum et al., 2005). Relative to their better-performing counterparts, low-performing U.S. firms were shown to be more receptive to the risks of entering new markets (Ref & Shapira, 2017), higher financial volatility (Miller & Chen, 2004), and higher levels of R&D spending (Miller & Bromiley, 1990).

Involuntary product recalls highlight the limitations of a firm's existing technologies and may dissuade a firm from simply advancing such technologies incrementally to resolve these recalls. Indeed, the threat of failure has, in some cases, been found to enhance creativity and "outside the box" thinking when problem solving (Drazin, Glynn, & Kazanjian, 1999; Morris & Moore 2000). Sudden performance setbacks, such as involuntary recalls, underscore the gap between firms' existing knowledge and their requirement to perform satisfactorily. Consequently, firms lose faith in their current knowledge and explore beyond their boundaries to attain unfamiliar, yet potentially valuable, insights into how they might resolve their setbacks (Madsen & Desai, 2010). Consistent with this line of thinking, Posen and Chen (2013) find that U.S. commercial banks tended to search for external knowledge when they performed below their aspirations. In accordance with a risk-seeking perspective on problemistic search, firms will resolve sudden performance setbacks, such as involuntary product recalls, by developing increasingly risky solutions that rely on external technologies more so than prior to the setback.

H2: In response to involuntary product recalls, firms will rely more on external technologies in developing technical solutions than they did before the recall.

2.3.2 The Influence of Societal Risk-Taking Norms on Problemistic Search

As conveyed above, there is logic that suggests that firms generally respond to unexpected performance setbacks by becoming increasingly risk averse as well as logic that suggests they become increasingly risk seeking. Firms, however, are social entities that are embedded within their respective societies and whose behaviors are shaped by societal norms (Hofstede, 2001). Accordingly, societal norms are likely to determine, in part, how germane each of these competing logics is for explaining the direction in which firms deviate from their routine search patterns when pursuing problemistic search.

Societal norms provide guidance on socially acceptable responses to life's challenges. Individuals conform to societal norms by adhering to what they feel society expects of them, often relying on peers and their own experience for cues (Sherif, 1935; Weber, Kopelman, & Messick, 2004). Whereas behaviors that conform to societal norms lead to trust and goodwill, those that diverge from these norms incite scrutiny and punishment (Bradach & Eccles, 1989; Kahneman, Knetsch, & Thaler, 1987). Even when individuals prefer to take actions that differ from societal expectations, they frequently avoid doing so for fear of being rebuffed by those around them. The pressure to conform to the whims of society is so strong that individuals will publicly accept peers' incorrect answers, even when they know these answers to be incorrect (Asch, 1951). The social costs of diverging from societal norms are especially salient when outcomes from the behaviors in question are highly uncertain and have a considerable likelihood of being detrimental (Crutchfield, 1955; Deutsch & Gerrard, 1955).

The impetus to conform to societal expectations is particularly strong when firms try to resolve unexpected performance setbacks. Because they are unforeseen, the path to resolving them is often ambiguous. Recognizing the uncertainty of the situation, and realizing the scrutiny that they are under, the individuals responsible for resolving such setbacks will rely on societal norms for guidance on how to proceed (Deutsch & Gerrard, 1955; Kelman, 1957). If they were to take actions contrary to societal norms and fail, they would likely bear the brunt of the blame for these disappointing outcomes (Brickman, Ryan, & Wortman, 1975; Walster, 1966). If, however, they conform to societal norms and are nonetheless unsuccessful, such outcomes are more likely to be attributed to external contingencies and extenuating circumstances rather than to poor judgment (Brewer, 1977; Brickman et al., 1975).

As described, resolving performance setbacks entails risk, and risk-taking norms vary across societies. East Asian (Japanese, Korean) societies differ markedly from those in the West (Hofstede, 1993). For example, Confucian values underscore gradual, deliberate, and orderly change from within (Milliman, Kim, & Glinow, 1993). Such values permeate institutions in Japan and South Korea, where students are encouraged to follow traditions without question (Weber & Hsee, 2000). Due to an intense respect for hierarchy and ritual, any substantive change requires time-consuming peer buy-in (Hofstede, 1993). As promotions are based on seniority instead of performance, there is little upside in taking risks (Barton, 2016).[3] Moreover, the downside is substantial, as there is a high social cost and stigma attached to failure (Goodman 2009; Lodge & Vogel, 1987). A general tenet within these societies is to avoid failure by shunning risk, sticking to what one knows, and pursuing highly predictable outcomes (Milliman, et al., 1993). The emphasis that collectivist East Asian societies place on long-term relationships highlights their appreciation for the status quo (Nisbett & Miyamoto, 2005; Tiessen, 1997). This preference for stability, however, can limit creativity (Feldman, 1988; Shane, 1992).

[3] As Japanese employees tend to stay with one company for long periods of time, their goal is to get promoted. Promotions are given to those who keep their heads down and avoid errors. Barton (2016) quotes a Japanese employee, stating, “The best way to not make mistakes is to not take risks, and so most employees will just do what their boss says and that’s it.”

In contrast, norms in many Western societies, and in the United States in particular, foster risk taking (Markus & Kitayama, 2003; Twiss, 1980). Creativity that challenges the status quo is respected and rewarded (Weber & Hsee, 2000). Failure is not only tolerated but, in some cases, revered (Goodman, 2009), perhaps based on the general tenet that it is better to try and fail than to not try at all. In individualistic societies, such as the United States, competition within firms is customary, and bearing the risk of searching out external knowledge is one means that employees use to set themselves apart from internal rivals and vie for promotions (Menon & Pfeffer, 2003). Further indicative of a general tolerance of risk and uncertainty within U.S. society is that relationships between firms and between employees and their firms are highly dynamic and change often.

During stable times, societal risk-taking norms influence the *routine* behaviors of member firms. East Asian societies customarily focus on incremental improvements that build on their internal expertise (Bolton, 1993a; Herbig & Palumbo, 1994). U.S. firms, in contrast, generally bear greater risk by routinely exploring external knowledge and disrupting the status quo. Firms' risk preferences, as evidenced through their normal routines, can align with their competitive strategies, and firms can achieve market success by emphasizing either incremental improvements or more highly disruptive innovation (Fleming & Sorenson, 2004; Gavetti & Levinthal, 2000; Taylor & Greve, 2006).

Societal risk-taking norms can shape not only firms' routine behaviors but also the direction in which they *deviate* from their routines, following sudden performance setbacks. Because East Asian societies value predictability, societal expectations for how firms ought to respond to sudden performance setbacks involve firms' becoming increasingly conservative; routine levels of risk taking that might be socially acceptable during stable times will be viewed as irresponsible during times of crisis. Such occasions call for increasingly cautious corrective actions that lead to highly predictable technical outcomes. Those who act contrary to these prevailing societal views by pursuing riskier problemistic search relative to what is routine are subject to the condemnation of their peers, particularly if performance setbacks are not effectively resolved (Herbig & Palumbo, 1994).

Accordingly, Japanese and Korean firms will respond to involuntary product recalls by avoiding the introduction of additional uncertainty into the recovery process. Further, due to the high social cost of failure, any employee responsible for fixing the underlying technologies related to a recall will be reticent to discard faulty internal technologies and to explore solutions based on external technologies. Instead, employees will be inclined to escalate their commitment toward internally developed technologies to reaffirm their value. Overall, as compared to the routine inventive search processes that precede product recalls, the problemistic search behaviors of Japanese and Korean firms will entail developing technical solutions that are less reliant on external technologies.

In contrast, because risk taking is generally accepted in the United States, societal expectations regarding how firms ought to respond to performance setbacks involve their becoming increasingly experimental, based on the notion that times of crisis call for bold, corrective actions. When resolving involuntary product recalls, maintaining routine levels of reliance on external technologies, let alone decreasing such reliance, may be viewed as timid and imprudent.[4] Those who escalate their commitment to the status quo by making relatively small changes will be subject to criticism by their peers, particularly if the product defect is not effectively corrected. Further, because failure is more socially acceptable in the United States,

[4] A sentiment often attributed to Albert Einstein is that the definition of insanity is doing the same thing repeatedly and expecting a different result.

any staff responsible for developing faulty technologies related to a recall is expected to be willing to discard these failing technologies and look externally for insights. Accordingly, U.S. firms will respond to involuntary product recalls by developing solutions that are increasingly reliant on external technologies. Overall, the norms of the society in which firms are embedded will shape the direction in which firms deviate from their routine search to problemistic search and how they respond to involuntary product recalls.

H3: Following an involuntary product recall, Japanese and Korean firms will rely less on external prior art in developing technical solutions than they did before the recall; U.S. firms will rely more on external prior art in developing technical solutions than they did before the recall.

2.4 Methods

2.4.1 Sample and Data

To test my hypotheses, I merged data on automotive product recalls and automotive firm invention. The automotive industry is an ideal context for my study for two reasons. First, automotive manufacturers are subject to product recalls initiated by NHTSA. NHTSA was created in 1966 by the U.S. Congress to enforce minimum standards for automobiles and to protect drivers and passengers. These standards apply to all automobiles sold or certified for use in the United States. Any violation by an automotive manufacturer results in NHTSA's imposing an involuntary product recall. Second, to protect their intellectual property, automotive firms rely heavily on patents (Cohen, Nelson, & Walsh, 2000), which we use to assess routine and problemistic inventive search routines.

From NHTSA reports, I compiled all 38,248 vehicular product recalls (voluntary and involuntary) experienced by automotive manufacturers between 1985 and 2006 and processed by either of two offices within NHTSA: the Office of Defects Investigations (ODI) or the Office of Vehicle Safety Compliance (OVSC). Of these 38,248 product recalls, 26,096 were voluntary and 12,152 were involuntary.[5]

NHTSA vehicular product recalls are specific to particular parts of a vehicle. For example, NHTSA's 1996 involuntary recall of several Ford models concerned their ignition switches. NHTSA describes each recall with a two- to five- sentence narrative and identifies the offending firm. I used a multi-step process to meticulously match each NHTSA recall narrative to the underlying technology associated with the respective recalled part. To do so, I relied on the United States Patent and Trademark (USPTO) technology categorization. USPTO categorizes patented inventions into specific technology classes and describes them using narratives. For example, Patent Class 296 describes the technologies associated with "Land Vehicles: Bodies and Tops." These classes are further differentiated into subclasses. For example, Patent Class 296 is broken into more than 250 subclasses, such as "Subclass 1.01–Bodies" and "Subclass 225–Tops," each with its own narrative.

Of the over 110,000 technology subclasses, I identified 20,135 automotive technology subclasses associated with 113 primary classes by hand-verifying that they were relevant to passenger vehicles based on their narratives that contained keywords such as "automobile," "car," "vehicle," or "automotive." I then created a matrix in which the 20,135 subclasses comprised the rows of the matrix, and the 38,248 NHTSA vehicular product recalls comprised the columns. I used a keyword-matching algorithm to compare each recall narrative with each USPTO technology subclass narrative, counting keywords common to both the subclass and

[5] According to NHTSA, a recall is issued when a manufacturer or NHTSA determines that an unreasonable safety risk is present or that the vehicle fails to meet minimum safety standards. Most decisions to conduct a recall are made voluntarily by manufacturers prior to involvement by NHTSA.

recall narratives (and excluding common words, such as "and," "of," and "the"). For each cell, I then created a ratio to measure how similar each NHTSA product recall is to each patent subclass. This can be conceptualized as a Venn diagram, in which one circle represents the count of keywords in the recall, and the other circle represents the count of keywords in the subclass description. I calculated the *intersection* of keywords, normalized by the total number of words in both descriptions.

Using this method, however, I found that product recalls tended to be indistinguishably linked to multiple subclasses within a given class. Consequently, I assigned each recall to a unique patent class based on the subclasses for which it had the highest similarity. I retained NHTSA product recalls that were linked to one of the 113 unique patent classes that were hand-verified to be relevant to passenger vehicles.

I limited the sample of firms at risk of NHTSA involuntary vehicular product recalls to those that are members of either primary SIC codes 3711 (Motor Vehicles and Passenger Car Bodies) or 3714 (Motor Vehicle Parts and Accessories) and were R&D active (as evidenced through patenting), publicly traded, and incorporated in the United States, Japan, or South Korea. I used the Corporate Affiliations and SDC Platinum databases to connect all relevant subsidiaries to their parent firms on a yearly basis. Table 2.1 provides a list of the 16 firms and their nationalities. There were 3,700 involuntary recalls and 9,720 voluntary recalls associated with the sample of firms. Using the National Bureau of Economic Research (NBER) patent database, I collected those patents applied for and subsequently granted in the 113 patent classes identified, for each firm in each year between 1985 and 2006.

Table 2.1. Parent Firm and Country

Parent Firm	**Parent Country**
Chrysler	United States
Ford Motor Company	United States
Fuji Heavy Industries, Ltd.	Japan
General Motors Company	United States
Honda Motor Co., Ltd.	Japan
Hyundai Motor Company	South Korea
Mazda Motor Corporation	Japan
Mitsubishi Motors Corporation	Japan
Navistar International Corporation	United States
Nissan Motor Co., Ltd.	Japan
Oshkosh Corporation	United States
PACCAR, Inc.	United States
Spartan Motors, Inc.	United States
Suzuki Motor Corporation	Japan
The Furukawa Electric Co., Ltd.	Japan
Toyota Boshoku Corporation	Japan

2.4.2 Research Design

To assess how my sample of automotive firms responded to involuntary product recalls (Hypotheses 1–3), I created a panel of data composed of firm-class observations across year. Our final panel includes 183,738 firm-class-year observations between the years of 1985 and 2006. During this period, 454 observations had involuntary recalls, of which 157 were associated with either Japanese or Korean firms and 297, with U.S. firms.

Three considerations influenced our empirical specification and variable construction. First, to adequately gauge problemistic search patterns (i.e., search triggered by a focal problem), these search patterns need to be disentangled from routine search patterns that occur absent triggers (Greve, 2003b; Posen et al., 2018). Thus, I use dynamic panel data analyses to assess the *change* that occurs in my dependent variable (i.e., *reliance on external technologies*) that results from involuntary recalls by controlling for the lagged value of my dependent variable. Doing so also accounts for extensive unobserved heterogeneity. In essence, a lagged dependent variable can be viewed as a summary control measure that encapsulates the influence of all lagged values of unobserved variables related to the lagged dependent variable (Tan & Rider, 2017). Further, these models use deeper lags of the independent variables as instruments, thereby rendering them exogenous. Consequently, including a host of additional measured variable in these models to protect against omitted variable bias is not as essential as it would be for other econometric specifications that are not dynamic.

Second, there is compelling evidence that empirical analyses, using ratio variables, are susceptible to inaccurate parameter estimates and spurious relationships (Certo et al., 2018; Kronmal, 1993; Wiseman, 2009). The prevailing recommended approach is to estimate unscaled variables and to normalize these variables by separately controlling for scale (Certo et al., 2018).

Third, I desired a temporal structure that accurately and conservatively reflected the likely lag between the occurrence of recalls and the response to those recalls and that clearly distinguishes a routine inventive search pattern that precedes such recalls from a problemistic inventive search that occurs subsequent to the recalls. Thus, I measure involuntary recalls in year t, problemistic inventive search behaviors that follow the occurrence of recalls in year $t+1$, and routine inventive search behaviors that precede the occurrence of recalls, using a time window from years *t-1* to *t-3*.

2.4.3 Dependent Variable

A firm's reliance on external technologies when developing technical solutions can be assessed based on its patent citations to prior art developed by other firms (Hall, Jaffe, & Trajtenberg, 2001). I measured a firm's *reliance on external technologies*$_{(ij,t+1)}$ by counting the number of backward citations of patents (i.e., prior art) developed by other firms that are made by patents applied for (and subsequently granted) by focal firm *i*, in technology class *j*, in year *t+1*.

2.4.4 Independent Variables

Involuntary recalls$_{ij,t}$. I aggregated all involuntary product recalls that occurred for focal firm *i*, for technology class *j*, in year *t*. Involuntary product recalls are rare events. Nonetheless, multiple recalls can occur for the same defect for any firm in a given year and class across its various vehicle models. For each firm-class-year observation, I counted the total number of involuntary vehicular product recalls. Although a greater number of recalls for a focal firm, focal class, and focal year is likely to have greater influence on our proposed outcomes, the marginal effect of each additional recall is likely to diminish. Thus, I transformed this count by computing its natural log.[6]

United States vs. Japan/Korea$_i$. I distinguished the home region of my sample firms using a dichotomous variable. Firm *i* was assigned a value of 1 if the home country of the parent firm

[6] 1 was added to all values prior to taking a natural log transformation.

was in the United States and assigned the value of 0 if its home country was Japan or South Korea.

2.4.5 Control Variables

Backward citations$_{ij,t+1}$. I controlled for the total number of backward citations to prior art (regardless of external or internal) made by patents applied for (and subsequently granted) by focal firm *i*, in technology class *j*, in year *t+1*. Doing so enabled me to assess the reliance on external technologies *relative* to reliance on internal prior art.

Reliance on external technologies$_{ij,t-1 \text{ to } t-3}$. To assess routine inventive search behavior and model the change in our dependent variable, I controlled for its value prior to the potential occurrence of involuntary recalls in year *t*. To enhance reliability, I used a three-year window to measure this lag. Consequently, I controlled for the number of backward citations of patents developed by other firms that are made by patents applied for (and subsequently granted) by focal firm *i*, in technology class *j*, in years *t-1* to *t-3*.

Voluntary recalls$_{ij,t}$. Voluntary recalls initiated by firms have been previously found to influence their learning (Haunschild & Rhee, 2004). I therefore controlled for the number of voluntary recalls for firm *i*, technology class *j*, and year *t*. As with *involuntary recalls*, I transformed this count by computing its natural log.[7] I also controlled for year fixed effects to account for unobserved heterogeneity across specific years.

2.4.6 Empirical Models

To analyze the data, I utilized Arellano-Bond (AB) estimation based on generalized methods of moments (GMM). Such estimation is ideal when (1) the data-generation process is

[7] Ibid.

dynamic, whereby current values of the dependent variable are likely influenced by past values; (2) the number of time periods is small relative to the number of unique entities (i.e., firm-class); (3) there are likely to be fixed effects (i.e., time-invariant factors associated with firm-class); (4) some regressors are endogenous; and (5) idiosyncratic errors may be heteroskedastic or serially correlated (Roodman, 2009). A critical advantage of AB estimation is that the instruments for an endogenous regressor are generated internally based on lagged values of the regressor. A general disadvantage of dynamic panel analyses is that lagged dependent variables tend to suppress the explanatory power of other independent variables (Achen, 2000). Consequently, results from models that include lagged dependent variables are often deemed to be conservative (Tan & Rider, 2017).

I use *system* GMM to estimate our models. System GMM estimation is more efficient than earlier-developed *difference* GMM specifications, whereby fixed effects are expunged by differencing all regressors (Roodman, 2009). Similar to difference GMM, system GMM relies on deeper lags to instrument endogenous regressors but differences in these instruments to render them exogenous to the fixed effects. Thus, system GMM assumes that the lagged instruments are uncorrelated with any fixed effects. For my empirical models, all regressors except *firm age* and *United States vs. Japan/Korea*$_i$ are instrumented using all possible lags. Tests of serial correlation indicate the absence of higher-order serial correlation and suggest that the instruments are statistically valid. Standard errors are clustered by firm-class. Although the number of observations in my panel is quite large, the power of any statistical test is limited by the number of observations with firm-class-year involuntary recalls (454).

Table 2.2 provides summary statistics and correlations.

Table 2.2. Descriptive Statistics and Correlations

Variable	Mean	Std. Dev.	1	2	3	4	5	6	
1. Reliance on external technologies$_{t+1}$	1.00	12.07	1.00						
2. Ln (Involuntary recalls$_{ij,t}$)	0.00	0.10	0.04	1.00					
3. U.S. vs. Japan/Korea$_{i}$	0.43	0.49	-0.01	0.03	1.00				
4. Backward citations$_{ij,t+1}$	1.48	16.73	0.69	0.05	-0.01	1.00			
5. Reliance on external technologies$_{ij,t-1 \text{ to } t-3}$	2.99	32.53	0.68	0.05	-0.01	0.91	1.00		
6. Ln (Voluntary recalls$_{ij,t}$)	0.01	0.15	0.07	0.28	0.05	0.09	0.09	1.00	
7. Firm age$_{ij,t}$	60.62	30.86	0.03	0.04	0.02	0.04	0.04	0.07	1.

N = 183,738

Table 2.3 provides the results of our AB estimation. Model 1 includes control variables and the main effects of *involuntary recalls*$_{ij,t}$ for predicting *reliance on external technologies*$_{ij,t+1}$. In Model 2, I subsequently added the interaction term *United States vs. Japan/Korea*$_{i}$ *X Involuntary recalls*$_{ij,t}$.

Hypothesis 1 predicted that, in response to involuntary product recalls, firms will rely less on external technologies in developing technical solutions than they did before the recall. Alternatively, Hypothesis 2 proposed that firms will rely more on external technologies in developing technical solutions than they did before the recall. Based on Model 1 of Table 3, *Involuntary recalls*$_{ij,t}$ is insignificant. Neither Hypothesis 1 nor 2 is supported.

Table 2.3. Response to Involuntary Recalls

	Reliance on external technologies$_{(t+1)}$	
Variable	Model 1	Model 2
U.S. vs. Japan/Korea$_i$ X Ln (Involuntary recalls$_{ij,t}$)		1.018**
		(0.369)
Ln (Involuntary recalls$_{ij,t}$)	-0.065	-0.855**
	(0.169)	(0.316)
U.S. vs. Japan/Korea$_i$	-0.077**	-0.080**
	(0.030)	(0.030)
Backward citations$_{ij,t+1}$	0.278***	0.278***
	(0.002)	(0.002)
Reliance on external technologies$_{ij,t-1\ to\ t-3}$	0.116***	0.116***
	(0.001)	(0.001)
Ln (Voluntary recalls$_{ij,t}$)	0.416***	0.422***
	(0.118)	(0.117)
Constant	0.510***	0.278***
	(0.065)	(0.002)
Observations	183,738	183,738
Number of parent-class groups	11,978	11,978
Wald X^2	283,462.79	284,162.26
Change in X^2		699.45

Note. Standard errors in parentheses; one-tailed tests for hypothesized effects; year dummies were included but not reported.

†$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

In Hypothesis 3, I provided further refinement of these predictions: Following an involuntary product recall, Japanese and Korean firms will rely less on external technologies in developing technical solutions than they did before the recall, whereas U.S. firms will rely more on external technologies in developing technical solutions than they did before the recall. The interaction term *United States vs. Japan/Korea*$_i$ *X Involuntary recalls*$_{ij,t}$ is included in Model 2 of Table 3 and is significant (β = 1.018; $p < 0.001$). The pattern of results suggests that, for Japanese and South Korean firms, as *involuntary recalls*$_{ij,t}$ increases, *reliance on external technologies*$_{ij,t+1}$ decreases precipitously, as reflected by the negative and significant coefficient on *involuntary recalls*$_{ij,t}$ (β = -0.855; $p < 0.001$). In contrast, for U.S. firms, an increase in *involuntary recalls*$_{ij,t}$ has relatively little influence on *reliance on external technologies*$_{ij,t+1}$, as reflected by the modest sum of the coefficients on *involuntary recalls*$_{ij,t}$ and the interaction term *United States vs. Japan/Korea*$_i$ *X Involuntary recalls*$_{ij,t}$ (i.e., 0.163).

Further, I used Model 2 and the mean value of *involuntary recalls*$_{ij,t}$ for all observations for which there were involuntary recalls to compute the predicted margins for Japanese/Korean firms and U.S. firms. This analysis indicates that, when there are no recalls, the reliance of Japanese/Korean firms on external technologies is significantly greater than zero. At the mean level of recalls, however, Japanese/Korean firms rely on external technologies significantly less than when there are no recalls and at a level that is not significantly different than zero. Similar to Japanese/Korean firms, when there are no recalls, the reliance of U.S. firms on external technologies is significantly greater than zero. In contrast, at the mean level of recalls, the reliance of U.S. firms on external technologies is not significantly different than when there are no recalls.

2.4.7 Post Hoc Analysis: Problemistic Search and the Resolution of Performance Shortfalls

Routine inventive search behaviors that are either risk seeking (i.e., more reliant on external technologies) or risk averse (less reliant on external technologies) support opposing, yet viable, competitive strategies (Ahuja & Lampert, 2001; March, 1991). It is not clear, however, whether particularly risky or risk-averse *problemistic* search behaviors are more beneficial in resolving performance setbacks.

There is some wisdom that suggests that firms should respond to innovation failure with radical change to avoid doubling down on failed technology (Maslach, 2016). Nonetheless, doing so is risky and may be prone to failure. We explore how problemistic search in terms of relying on external technologies influences the resolution of performance shortfalls.

Research Design

One indication that firms have learned from and responded effectively to their product recalls is that they are able to avoid similar subsequent recalls (Haunschild & Rhee, 2004). Keeping government regulators at bay is a minimal but essential performance aspiration. Recurring involuntary recalls in the same technological space indicate that the firm responded ineffectively to previous recalls. I created an observation for each firm-class-year where involuntary recalls occurred. Of the 454 firm-class-year observations of involuntary recalls, 417 occurred before the last year of the panel and are viable for event history analysis. For 235 of these observations, a subsequent recall occurred prior to the end of our study. For the remainder of these observations, the focal firm did not experience a subsequent involuntary product recall associated with the focal technology class. Consequently, these observations were right censored.

Variables

Time until subsequent recall$_{ijt}$. I measured the passage of time in years between the year *t* that firm *i* experienced an involuntary recall in focal technology class *j* and the next occurring involuntary recall experienced by firm *i* in focal technology class *j*.

Reliance on external technologies$_{ij,t+1}$. For each observation, I measured the level of reliance on external technologies in responding to involuntary product recalls that occurred in year *t* by counting the number of backward citations to patents developed by other firms in patents applied for (and subsequently granted) by focal firm *i*, in technology class *j*, in year *t+1*. To enhance normality, this count was transformed using a natural log.

Reliance on internal technologies$_{ij,t+1}$. For each observation, I measured the level of reliance on internal technologies in responding to involuntary product recalls that occurred in year *t* by counting the number of backward citations to patents developed by the focal firm in patents applied for (and subsequently granted) by focal firm *i*, in technology class *j*, in year *t+1*. To enhance normality, this count was transformed using a natural log.

Prior recalls$_{ij,t}$. Having experienced prior involuntary recalls may increase firms' abilities to learn. Consequently, I controlled for the number of prior class-years that firm *i* experienced involuntary recalls. I also included firm and year fixed effects to control for any unobserved heterogeneity across firms and across years.

Empirical Model

I used a Cox regression model to assess the effect of the regressors on the hazard rate of a subsequent involuntary recall that occurred for a focal firm in a specific technology class. Table 2.4 provides summary statistics and correlations, and Table 2.5 provides the results of this analysis.

Table 2.4. Descriptive Statistics and Correlations

Variable	Mean	Std. Dev.	1	2	3	4
1. Years until next recall$_{ijt}$	4.72	4.65	1.00			
2. Ln (Reliance on external technologies$_{ij,t+1}$)	0.67	1.37	0.03	1.00		
3. Ln (Reliance on internal technologies$_{ij,t+1}$)	0.23	0.72	0.01	0.78**	1.00	
4. Ln (Prior recalls$_{ijt}$)	3.26	1.09	-0.47**	0.19**	0.16**	1.00

** Correlation is significant at the 0.01 level (2-tailed).
N = 474

In Table 5, the coefficient associated with *reliance on external technologies*$_{ij,t+1}$ is positive (β = 0.14) and significant ($p < 0.05$) based on a relatively conservative two-tailed test. A positive coefficient suggests an increased probability of a subsequent recall. Based on the exponentiated coefficient ($e^{0.14} = 1.15$), a one-unit increase in *reliance on external technologies*$_{ij,t+1}$ increases the hazard of a subsequent recall by 15 percent. In contrast, the coefficient associated with *reliance on internal technologies*$_{ij,t+1}$ is negative (β = -0.22, $p < 0.1$). Based on the exponentiated coefficient ($e^{-0.22} = 0.80$), a one-unit increase in *reliance on internal technologies*$_{ij,t+1}$ decreases the hazard of a subsequent recall by 20 percent.

Table 2.5. Hazard of Subsequent Involuntary Recalls

Variable	Model
(Ln) Reliance on external prior art$_{ij,t+1}$	0.14* (0.07)
(Ln) Reliance on internal prior art$_{ij,t+1}$	-0.22^{+} (0.12)
Prior recalls$_{ij,t}$	0.27 (0.35)
Firm fixed effects	Yes
Year fixed effects	Yes
Observations	471
-2 Log likelihood	2,498.97
X^2	78.65***

Note. Standard errors in parentheses.
†$p < 0.10$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

2.5 Discussion

How firms adapt in response to performance setbacks is a fundamental question that has elicited considerable research. The preponderance of evidence suggests that firms that perform below their aspirations deviate from their normal routines to resolve their performance setbacks (Posen et al., 2018). I explore how the norms of the societies in which firms are embedded influence the direction by which they deviate from routine to problemistic search in terms of risk taking. My analyses suggest that, when Japanese and South Korean automotive firms experience involuntary product recalls, they tend to become increasingly conservative, in accordance with the general aversion of risk within their societies. Technical solutions in the affected technological space relied less on external technologies than did those derived prior to the recall. In contrast, my analyses suggest that U.S. automotive firms deviated relatively little from their routine search patterns in response to product recalls in terms of their reliance on external technologies.

I also find that the firms that pursued riskier problemistic search in response to their involuntary recalls by relying on external technologies had a greater likelihood of experiencing subsequent recalls than did firms that took a more conservative stance. Indeed, I find some evidence that relying on internal technologies prevents subsequent recalls. Overall, my results suggest that introducing risk into the recovery process for product recalls is ultimately counterproductive.

My study contributes to theory in several areas. Whether firms' problemistic search tends to be more or less risk seeking than their routine search is unclear. Past research indicates that both directions are viable. Further, contingencies that may influence this direction has been called out for further exploration (Posen et al. 2018). I initiated a path toward understanding possible contingencies by considering relatively macro-level differences across firms. Although it stands to reason that the cultural norms of the societies in which firms are embedded influence their risk taking in general, my study shows that these cultural tendencies also influence how they adjust their search behaviors in response to performance setbacks. Future studies also might consider increasingly micro indications of a firm's risk propensity, such as ownership structure or slack resources. One might imagine a tipping point along a distribution of firms with varying risk propensities; those with generally conservative risk profiles may become increasingly conservative vis-à-vis their routine behaviors in response to sudden performance setbacks, whereas those with less conservative profiles may become increasingly risk seeking in response.

Indeed, there may be firms with risk profiles that enable them to be particularly even keeled in response to sudden setbacks such that they deviate little from routine to problemistic search.

The importance of understanding factors that influence the direction by which firms deviate from routine to problemistic search is predicated to some degree on our understanding of whether risk taking in response to performance setbacks is harmful or beneficial. I find that risky resolutions to sudden performance setbacks led to worse firm outcomes than when firms utilized what they already knew. These results should be viewed tentatively, given the narrow context, and future research should explore the relative outcomes of more or less risky problemistic search in other contexts. Nonetheless, my research highlights the potential for firms to introduce too much risk into their resolutions of performance setbacks. Such errors may be more prevalent in some societies than in others. Indeed, some societal norms may inoculate firms from overreacting to performance setbacks in terms of taking on too much risk.

2.5.1 Limitations and Future Research

A key limitation of my work is the limited context in which performance setbacks were empirically measured. Other work that has explored problemistic search has typically conceptualized performance setbacks in terms of somewhat subjective and broad financial aspirations (Shinkle, 2012). Nonetheless, by relying on narrowly defined and unequivocal performance setbacks and responses to those setbacks, we were able to deploy a relatively precise research design.

My analysis focused on how individual firms responded to their own setbacks. Notably, unanticipated setbacks may have an impact on not only the firm directly affected but also others that are competing in the same space (Borah & Tellis, 2016; Desai, 2011). Additional research into how one firm's sudden performance setback influences the behavior of its competitors would be insightful. Such influence may depend on severity, country of origin, or geographic distance.

I used patent citation measures to assess firms' reliance on external and internal technologies to create subsequent patented inventions. My data do not account for the extent to which these inventions are integrated into the redesign of products. Further, it would be valuable to explore whether competitors are inclined to adopt technological advances that arise from product recalls or if such advances are avoided by others due to a stigma attached to firms that are subjected to product recalls.

3 Jack of All Trades or Master of One? How Inventor Experience and Breadth Influences the Development of Breakthrough Inventions

3.1 Introduction

"Fortune favors the prepared mind," Louis Pasteur.

Inventions are critically important for economic progress, and as such, they have been widely studied (e.g., Abernathy & Utterback, 1978; Foster, 1985). However, inventions are not created equal. The vast majority are relatively mundane, in the sense that they preserve the underlying technologies and reinforce how they are used in practice (Abernathy and Clark, 1985; Henderson & Clark, 1990). Few inventions are truly cognitive breakthroughs, which change how technologies can be developed or applied to other contexts (Kaplan & Vakili, 2015). In other words, such inventions represent the origination of new domains of knowledge. Because these breakthroughs drive change in science, understanding how to allocate resources to create and subsequently derive value from them is essential (Arrow, 1972; Von Hippel, 1988). Yet, how these breakthroughs arise is still unclear.

Who is prepared to create breakthroughs? There are two schools of thought. On the one hand, sociologists have long glorified the idea of the marginal man (Park, 1928; Stonequist, 1937): those on the margins of a profession or art, and who are not indoctrinated to the "rituals of the calling" (Morison, 1966: 128-129). These individuals have less experience in any one field and thus are unrestricted by common practices and incentives within that field. As a result, they are free to choose an interdisciplinary approach, combining key concepts across multiple fields with a broad array of knowledge (Tushman & Anderson, 1986; Hargadon & Sutton, 1997). But are these dabblers inherently more creative than experts? Or instead, are those who avoid dabbling in different areas – who develop deep expertise in a limited number of domains – the creative ones who develop breakthrough inventions? Compared to dabblers, these experienced individuals may be more likely to understand the nuances and gaps within the existing technology with enough depth to ultimately overcome them (Levinthal & March, 1993; Ahuja & Lampert, 2001).

To resolve this tension, I examine how inventor experience influences whether a breakthrough invention or an otherwise similar derivative invention is created. To identify breakthroughs, I use natural language processing via topic modelling algorithms to assess utility patent abstracts granted by the United States Patent and Trademark Office (USPTO) and identify breakthroughs. I match 1271 breakthroughs created by individual inventors with 6355 derivative inventions. Ultimately, I compare the experience and breadth of inventors of breakthroughs to that of inventors of derivative inventions.

I contribute to theory on inventions by studying inventor experience and focus. Specifically, I seek to understand whether depth or breadth of experience is more suitable for creating breakthrough inventions. Much research has looked at how firms search for knowledge to create novel inventions. Understanding the nature of cognitive breakthroughs, and the individuals responsible for them, is important to understand how to best allocate resources. Additionally, I contribute to methods within the field of strategy, using LDA and HDP to create topic models of patent data with natural language processing, as an extension of recent work by Kaplan and Vakili (2015). In capturing the shift in language that is used to discuss these breakthroughs, this methodology captures the shift in how people understand the underlying technologies.

3.2 What are and are not breakthrough inventions

Scientists create inventions to provide sustainable competitive advantages (Barney, 1991) and to improve their society (Schumpeter, 1975). As inventors build upon prior knowledge to create more inventions, they rely on shared vocabularies, heuristics, and frameworks to form a technological trajectory and develop derivative inventions within a trajectory.

Occasionally, existing trajectories are disrupted by breakthrough inventions. Fundamentally, breakthroughs require unusually high creativity. The creation of these uniquely disruptive inventions involves the development of creative and original ideas, requiring a shift in cognitive framing (Kaplan & Vakili, 2015). Individuals who think particularly creatively are able to deviate from widely held norms or to explore entirely new fields of thought. The result of these creative processes, breakthrough inventions, transform how technologies are developed or applied, establishing fresh vocabularies and cognitive maps (Kuhn, 1962; Dosi, 1982). Because breakthrough inventions challenge the current heuristics, frameworks, and assumptions associated with the prevailing trajectory, prevailing paradigms may shift, branch into another trajectory, or be discontinued entirely (Dosi, 1982). Crucially, this shift causes changes in a substantively different way than what had previously been developed.

In contrast with derivative inventions, breakthroughs either (1) replace existing technologies or their production methods, or (2) create new links between a technology's components and/or their applications. For example, electric engines in cars negated the need for a mechanical transmission system. However, the underlying applications of engines and cars did not change. On the other hand, Fujifilm's development of skincare products from their expertise in photographic film was anchored in the same underlying technologies. In this case, researchers applied familiar concepts to new domains, representing a technology transfer from an old domain to a new one. Finally, still other breakthroughs transform both the inherent technologies and their applications: for example, the creation of personal computers unlocked new technologies and applications that had previously been inaccessible to most people.

The designation of being a breakthrough invention is distinct from other invention characteristics. For example, while *highly cited* inventions have been widely studied (Fleming, 2001), breakthroughs are not necessarily the inventions with the highest number of citations; niche breakthroughs, such as in medical advances in artificial hearts, may have relatively few citations, but nonetheless be a cognitive shift that replaces current technologies or creates new links between components and applications. Moreover, breakthroughs may not be entirely *novel* inventions; a breakthrough can reconfigure and build extensively on existing knowledge, as long as it changes the trajectory of the technological paradigm. For example, hydraulic fracking revolutionized the oil industry but built on foundational knowledge dating back to 1885. On the other hand, derivative inventions can be highly cited as well as novel. Highly cited derivative inventions progress along established technological trajectories and can be readily combined with existing technical applications. Unlike breakthrough inventions, derivative inventions do not alter the vocabularies, heuristics, or frameworks of existing trajectories.

3.3 Hypotheses

3.3.1 Inventor experience and the development of breakthroughs

Invention is a deliberate skill that inventors hone through practice (Weisberg, 1999). With time and experience, inventors become familiar with the nuances of whether specific prior art can or should be recombined. They get better at the trial and error process of recombination. These skills are essential for creating new inventions. Furthermore, the process of invention is a creative one. Much effort has been spent devising training programs that enhance creativity at schools and in the workplace through curated programs and exercises (Bull, Montgomery, & Baloche 1995; Smith, 1998). Individuals who train their creativity over time improve their creative abilities (Weisberg, 1999; Scott, Leritz, & Mumford, 2004). Thus, the more individuals invent, the more creative they will ultimately be. This is especially vital for breakthrough inventions, which shift the cognitive frames used to understand existing technologies, and which ultimately change the underlying technology, how it is produced, or how it can be applied in practice.

Therefore, experience should help an inventor to create such breakthrough inventions: Suppose there are two inventors, but one is a novice inventor, and the other is a highly experienced inventor. In contrast to the novice, the experienced inventor has clearly understood how to generate and recontextualize unique knowledge elements that are necessary to create inventions (Arrow, 1972). In turn, the experienced inventor is comparatively more likely than the novice to apply that knowledge to novel contexts in a useful manner, due to their familiarity with the creative inventive process. This experience of working with and experimenting on existing prior art, as well as the heuristics with which to apply such experience across different environments, is lacked by a novice inventor. Ultimately, the experienced inventor is better positioned to create new cognitive frames of existing technologies.

The conclusions from this thought experiment seems to have support from existing research. To create derivative inventions, inventors need only to understand the relevant technologies and add a novel dimension to complex technical knowledge. Learning and integrating knowledge occurs through well-identified mechanisms of search (Schumpeter, 1939; March & Simon, 1958; Nelson & Winter, 1982). However, to create breakthroughs, inventors must not only understand the relevant technologies, but also decipher the current limitations and surpass them in a way that is distinct from the existing linkages. The benchmark of establishing fresh vocabularies and cognitive maps may be especially difficult, given that not all knowledge elements are easily accessible to an inventor (Teece 1977).[8]

General experience with the inventive process is indeed invaluable and non-substitutable. Many knowledge elements are tightly interconnected with other knowledge elements, and thus difficult to understand without experience (Fleming, 2001). Even when this knowledge is freely shared, novice inventors may fail to fully internalize it, lacking the relevant experience to do so. For instance, research in knowledge transfer has pointed to causal ambiguity (Lippman & Rumelt, 1982; Reed & DeFillippi, 1990), a lack of necessary tacit knowledge (Polanyi, 1966; von Hippel, 1988), and even the difficulty of codifying knowledge (Zander & Kogut, 1995). With experience, inventors gain the tacit knowledge and increased familiarity with how to process such knowledge; as a result, they are able to recombine prior knowledge in a more creative fashion than inventors without experience.

Knowledge and creativity, which a novice inventor may not yet possess, are necessary to create a cognitive breakthrough invention and to discover a new cognitive framing of possible knowledge combinations. Those inventors who have experience that can be effectively leveraged are more likely to have both the creativity needed to think outside the box, as well as the foundational knowledge on which to build. As a result, they are able to create breakthroughs that disrupt underlying technologies or their production methods, and potentially open future avenues for application.

[8] This process is far from trivial: in a study on 26 international technology transfer projects, Teece (1977) found that transmitting and adapting to technical know-how accounted for 19% of project costs on average, with one case running as high as 59%. It has been concluded that even with perfect access to complex knowledge, inventors should perceive "the act of receiving and building on knowledge not as the acceptance of a complete, well-packaged gift, but rather as the beginning of a trial-and-error process" (Sorensen et al., 2006, p996-997).

Therefore, while the experienced inventor will be more likely to create breakthrough inventions, the novice is more likely to create derivative inventions.

H1. Inventors who create breakthrough inventions will have greater prior experience with the invention process than will inventors who create otherwise comparable derivative inventions.

3.3.2 Jack of all trades

Not all experience with the inventive process is equal. While some inventors may choose to focus deeply on a narrow set of technologies, others may search broadly among multiple knowledge domains. The broadly experienced inventor is exposed to existing knowledge and heuristics across a wide body of technical domains (Hargadon & Sutton, 1997; Fleming, Mingo, & Chen 2007). These diverse experiences allow such inventors to be particularly open-minded and creative (Teodoris, Bikard, & Vakili 2019). In 2013, a display-refrigerator specialist recognized that aero foils used in Formula One racecar technologies could be broadly applied to save up to 41% of the total energy used by grocery stores (Wood 2015). This creative solution combined relatively mature technologies across different fields; the inventor did not need to possess extremely specialized experience. Not only does broad experience across multiple knowledge domains help such generalist inventors to be creative, the lack of such experience may hinder creativity.

Indeed, an inventor with too much experience within only one narrow domain can be hampered from thinking outside the box: Cognitive biases and heuristics often constrain individuals' attention to what they already know (Arthur 1989; March & Simon 1958), limiting their search for knowledge (Tversky & Kahneman 1973; Prahalad & Bettis 1986). Likewise, conformity to existing pressures can reduce autonomy that leads to creativity (Amabile 1996, Perry-Smith 2006). Occasionally, those who are narrowly confined to one condition may have no advantage, or even worse, a disadvantage, by those who lack such focused experience (Chase & Simon, 1973; Voss, Vesonder, and Spilich 1980; Wiley 1998). When seeking to discover a new cognitive frame, narrow expertise may be counterproductive. Indeed, a focus on standard, routinized behaviors may lead experts to fail to adjust even when the situation calls for a more flexible point of view (Hecht & Proffitt, 1995; Wiley 1998). Inventors who are deeply entrenched within one technological domain may find it difficult to pivot to new cognitive frameworks or to reason through intermediate steps to solve problems. Fundamentally, expertise is highly specific. When expertise within a domain is stretched to apply to a different domain through creative solving, these narrowly focused experts can find themselves disadvantaged (Amabile 1993; Wiley 1998).

Broad experience, as opposed to a narrow focus on one domain, has been shown to lead to greater innovation success for firms (Rosenkopf & Nerkar 2001; Ahuja & Katila 2004; Leiponen & Helfat 2010). For individual inventors, because innovation often results from knowledge recombination (Kogut and Zander, 1992; Schumpeter, 1939), having more complementary sources of knowledge helps create new vocabularies and cognitive maps. Inventors who are skilled at spanning multiple knowledge domains use a broader repertoire of perspectives and heuristics in their work, and thus are more flexible and creative in approaching problems (Dunbar, 1995; Scott, Leritz, & Mumford 2004). Knowledge workers who access atypical knowledge sources tend to be more creative (Reagans & Zuckerman, 2001; Schilling & Green, 2011). Unique, nonredundant information helps individuals understand the nuances of potential solutions to create unusual connections during knowledge recombination, which may enhance creativity (Mumford & Gustafson, 1988; Simonton, 1999). For example, individuals with heterogeneous social weak ties amass different approaches and perspectives that enhance important creativity-related cognitive processes, such as divergent and flexible thinking (Coser, 1975; Granovetter, 1982). As breakthrough inventions require new cognitive frames to disrupt existing technological paradigms, it is breadth of experience, not depth, that is conducive to the invention of breakthroughs.

H2. The experience of inventors who create breakthrough inventions will be more broadly focused as compared to the experience of inventors who create comparable derivative inventions.

3.3.3 Master of one

On the other hand, deep, focused experience may be necessary to create breakthroughs. Knowledge is considered the "raw material" of the creative process (Amabile, 1988). Furthermore, creativity requires deeply understanding a knowledge domain to successfully push its boundaries (Sternberg & O'Hara, 2000) and identify linkages that have the potential to be novel and useful (Taylor & Greve, 2006). For example, scientists at the Fujifilm Advanced Research Laboratories used Fujifilm's decades of scientific knowledge and experimentation with chemical knowledge in photography to develop breakthrough products that captured and reflected light on skin in a flattering manner (Bifue, 2013; Fujifilm, 2018). The resulting invention required deep understanding of the relatively nascent underlying chemical technologies, which could only be used by inventors who contributed enormous efforts to appreciate them and leverage them for a new technological trajectory.

An inventor who is deeply focused within one technological domain has the familiarity with the existing body of knowledge that is required to break through the barriers of entry and to surpass the existing scientific or practical limitations. These niche inventors possess specific skills needed to absorb and build upon existing knowledge (Cohen & Levinthal, 1990), at the expense of broader search (Gupta, Smith, & Shalley, 2006; Audia & Goncalo, 2007). Such specialized inventors are more likely to be creative: They are best able to identify and understand gaps in their domains, due to their nuanced understanding of each component in their domain and its relation to other knowledge components (Dane, 2010). This allows the specialist to not only understand the potential gaps in the current understanding of the technology, but to bridge these gaps using hitherto unknown cognitive frames. In addition, deeply focused inventors tend to have better problem-solving and memory skills compared to non-specialists within their domains (Chase & Simon, 1973; Dane, 2010). As a result, inventors who specialize are often more productive and successful at creating more novel inventions (Conti, Gambardella, & Mariani, 2013; Kaplan & Vakili, 2015). This highly specialized experience allows inventors to start new technological trajectories using fresh vocabularies.

A broad base of knowledge may be difficult to recombine due to knowledge variety and complexity (Fleming & Sorenson, 2001). As inventors refine and extend existing competencies and technologies, learning and knowledge creation generates predictable and proximate returns to firms (March, 1991). For such inventors, fully integrating the knowledge already captured these diverse domains is inherently challenging. Creating entirely new cognitive frames to disrupt existing technological paradigms may be out of the question. Moreover, individual inventors are likely to be guided by a firm’s core competency. Inventors who create new discoveries by exploiting some of their previous knowledge often continue to search for new knowledge through exploitation (Gupta, Smith, & Shalley, 2006). The default, then, is to incrementally improve on what is already known and familiar. Thus, too much breadth of knowledge may hinder inventors from creating breakthroughs. As a result, inventors are likely to focus on a specific domain of knowledge to disrupt existing technological trajectories and paradigms.

H3. The experience of inventors who create breakthrough inventions will be less broadly focused as compared to the experience of inventors who create comparable derivative inventions.

3.4 Methods

3.4.1 Model

To identify breakthrough inventions, I deployed topic modeling techniques on the abstracts of patented inventions. Because scientific ideas are described using language, shifts in ideas can be captured via corresponding shifts in language (Kuhn, 1962; Kuhn, 1996). As new topics are described using patents, the language that shapes these topics become entrenched over time. Similarly, new language introduces new ways of thinking about ideas. Patents are widely used as measures of invention, and to be accepted in the first place, they must be novel and non-obvious, contributing to the body of accepted scientific knowledge. Their abstracts are clear and concise summaries of the claims to intellectual property and are vetted by both the patent applicant and USPTO patent examiner. As such, patent abstracts contain rich textual data that can be used to understand the development of knowledge over time.

Topic modeling has been used increasingly to analyze text across many different contexts. More recently, it has been applied to patent abstracts to identify distinct topics across all patents granted by the USPTO. (Kaplan & Vakili, 2015; Arts, Cassiman, & Gomez, 2018). Use of such topic modeling algorithms, including Latent Dirichlet Allocation (LDA) and Hierarchical Dirichlet Process (HDP), assumes that 1) there are common topics across a collection of patent abstracts, and 2) that the language within each abstract is based on these topics (Blei, 2012; Wilkerson & Casas, 2017). Ultimately, it recursively identifies distinct topics from words that frequently appear within the same abstract, and then determines which topic or combination of topics best describes each abstract. In such a way, LDA finds many factors that are often related, but hidden, in the patent abstract text and offers a richer explanation of the variance than simpler models.[9]

In conjunction with a fellow graduate student, I compiled the 5.5 million patent abstracts associated with every patent granted by the USPTO between 1969 and 2017. Prior to 1969, granted patents did not systematically include abstracts. It was important to do this process on the entire database as opposed to a predefined subsection, as creativity is determined only within the predetermined space. Models are likely to incorrectly flag patents as breakthroughs when they were actually derivative inventions transposed from a different space. To reduce the likelihood of capturing such false positive breakthroughs, we analyze the entire population of patent abstracts.

However, given the large number of abstracts, content analysis using LDA has two main limitations. First, the model requires that the number of total topics are to be specified prior to analysis. While existing diagnostics can be used to compare the quality of models with differing numbers of topics, these choices – including relative entropy (Arun, 2010), coherence (Mimno et

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[9] Generative models make assumptions about how a text was created. Simple generative models attempt to understand the structure of text. For instance, in a Hidden Markov model, the next word in a sentence or document is a function of the previous words in that document (i.e., when autocomplete proposes future text). Of interest to scholars are more complex generative models that include unobserved factors. This is akin to a structural equation model, where unobservable factors influence the generation of data and are inferred from patterns in the data.

LDA assumes that, underlying any pool of documents, there is a set of latent, unobserved 'topics' with unique vocabularies. When creating a document, an author selects from the relevant vocabulary. For example, a document about cars will use words like 'engine' or 'speed', while a document about food may use 'recipe' or 'taste'. Each document has a set of words that are assumed to have been chosen from one or more of the unobserved topic vocabularies. LDA first models each document as an observation of a distribution of topics over documents, then as an observation of words over those topics. This model assumes that documents generally cover one topic -- a document may be about 'cars' or 'food' but is unlikely to be about both -- which is represented in the shape of the distribution of topics over documents. Put together, this 'distribution of distributions' describes the data through matrix factorization, based on the document-topic and topic-vocabulary relationships (Blei et al. 2003; Blei 2012).

al., 2011), and density (Cao, 2009) – are somewhat subjective. Second, the computational costs go up very quickly as topics are added. Topic models with more than 200 topics tend to be difficult to compute, in terms of time for the models to converge, as well as stability to random noise.

To avoid these limitations, both Latent Dirichlet Allocation (LDA) and Hierarchical Dirichlet Process (HDP) models were used. LDA is a supervised[10] algorithm that identifies common characteristics of a specified number of topics, then categorizes individual patent abstracts as a combination of those topics. It assumes that all documents comprise several topics that may not be hierarchically organized. In contrast to LDA, HDP is an unsupervised[11] algorithm that predicts both the number of topics and the themes within each topic [12] (Wang, Paisley, & Blei, 2011). HDP is used when data is assumed to be hierarchical, with topics within categories (and subcategories, and so forth). We used these models to organically discover the topics within patent abstracts.

We first collected 5,488,194 USPTO patent data from Google's patent database between 1969-2017. To use topic analysis, we first normalized[13] and tokenized[14] every patent abstract as a

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[10] A supervised model fits each predictor observation with an associated response measurement. Such a model helps researchers make predictions (predicting the response for future observations) and inferences (understanding the relationship between predictors and their responses).

[11] Unsupervised learning occurs if the predictors are known but their predicted responses are unknown. These models are useful to understand the relationships between observations. A common example is cluster analysis, where observations may fall into distinct groups based on observable traits. Identifying clusters may be important if each group has distinct properties of interest.

[12] The HDP model prioritizes large topics that describe as much of the corpus as possible, then adds topics to get maximum fit. In other words, if there are two distinct topics, HDP will perform similarly to LDA in saying there are two distinct topics. However, two topics have much overlap, HDP will conclude that there is one big topic with the best fit, and a bit of additional variance that comes from a second latent topic.

[13] Normalization is how differences in punctuation are eliminated; for example, removing capitalization. I used existing dictionaries to handle punctuation within words.

Compound words were checked against single words (ie, 'anti biotic', 'anti-biotic', and 'antibiotic' would all become "anti" and "biotic" as separate tokens).

[14] Tokenization is the process by which text is parsed into meaningful tokens. In my data, spaces were used to distinguish words and numbers as tokens. While single numbers were removed, I kept scientific numbers related to crystallization, chemical compounds, and units (e.g., '20m/s' became '20' and 'm/2'). Abbreviations were first unabbreviated, then normalized and tokenized.

separate document. Then, we removed text that was not specific and meaningful to the patent technology itself.[15] To conservatively capture topics, we stemmed words into their most basic form.[16] We culled extreme values, defined as words that appeared less than five times across all abstracts. This process resulted in approximately 96,000 unique tokens. We separately validated each step of these processes and outputs, then cross-validated results before proceeding with the algorithms for topic modelling.[17] Once data has been collected, cleaning it is necessary before it can be analyzed.

While a topic model will tease out latent factors responsible for variance in the data, without proper cleaning, the algorithm may latch onto factors irrelevant to the research design, such as nuances in an author's vocabulary or tone.[18] We triangulated the number of highest level of topics using the LDA and HDP models. Consistency between those approaches led us to conservatively choose 21 broad categories.

These 21 broad categories are listed in Table 3.1.

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[15] This includes legal language, as well as language referring to how the patent itself is organized.

In addition, I built a list of stopwords, which are words too common to provide descriptive value. I used generic stopwords as identified using established dictionaries, in addition to a second set of dictionaries specific to patents. Examples of stopwords include: form, on, method, device, second, pre, and use.

[16] Using the Porter2 algorithm, we reduced all words to their roots, then combined different forms of the same word (for example, manufactured = manufacturer = manufacturing = manufacture). This process is referred to as stemming.

Unlike other contexts, overstemming is not a serious concern in the context of patent abstracts. For example, both "positive" and "position" will stem to "posit" – however, the patents that discuss "position" (mechanics) are unlikely to use "positive" (electronics) as well, so complementary vocabulary would help the algorithm distinguish the meanings.

[17] We kept acronyms and initialisms, as the context is more important than the word itself. This NLP approach considers the meaning of (and relationships between) words, in contrast to a Bag of Words approach that treats words as features in isolation.

[18] While more personable writing often uses common active words with unusual grammatical forms (e.g., run vs ran), social media scholars preserve punctuation and parse shorthand (Tirunillai & Tellis, 2014). Technical documents must be cleaned so that researchers can interpret numbers and units consistently.

Regardless of the original context of the documents, the objective of the researcher is to remove characters and words that do not improve model fit.

Table 3.1. Categories Derived From Topic Modeling

Category	Number of Patents
Digital Data	752107
Transponders	427197
Pharmaceuticals	354498
Mechanical Tools	350235
Photonics	344345
Semiconductors	330224
Structural Components	323409
Power Supplies	296306
Rotators	289005
Polymers & Ceramics	283305
Liquid Chemicals	206373
Medical Devices	205897
Electric Circuits	197579
Hydraulics	192978
Mechanical Structures	189421
Metallurgy	186706
Heating & Ventilation	151513
Organic Chemicals	134055
Vehicles	132695
Physical Media	71563
Plants & Animals	68768

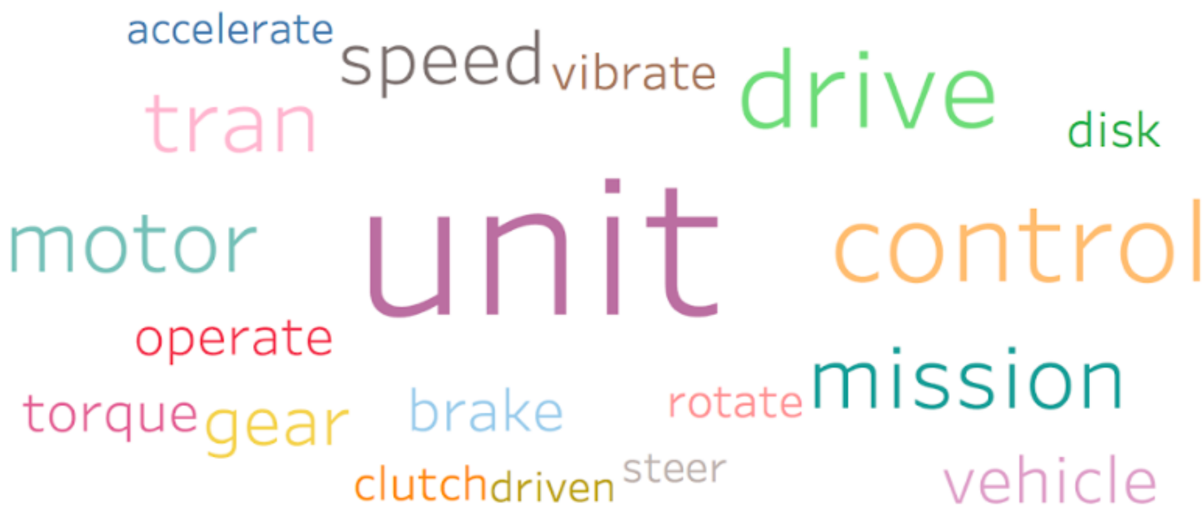
We validated these categories by checking for a "core" category, where patents cited one another or were related to the same category.[19] This system was independently validated using a team of RAs. They hand-checked these categories to verify that the process we used was able to correctly produce categories with both internal cohesion and external distinctiveness.

Results from this process can be seen in Figure 3.1. These words clouds show the vocabularies that are best associated with a given category.

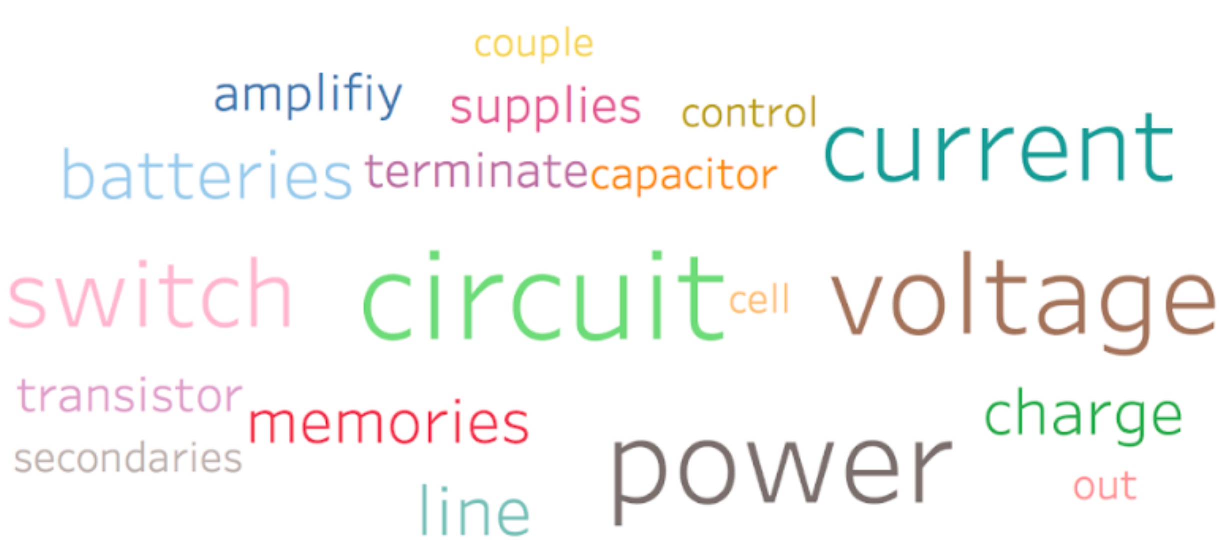
[19] In addition to the authors, six undergraduate students were recruited to validate that patents and keywords were accurately sorted into generic topics that were neither too narrow nor too abstruse. These RAs were undergraduate students pursuing degrees in economics, statistics, and information systems, and in addition to looking within the data, they also used external resources, including: Google searches, Wikipedia articles, interviews, etc.

Figure 3.1. Word Clouds of Highest-Level Categories

1a – Vehicles



1b – Electric Circuits



From these 21 categories, each patent was assigned to a category corresponding with the topic from which it drew its largest proportion of text (Kaplan and Vakili, 2015).[20] Each category was categorized then further analyzed using an HDP model to identify sub-categories within that category.[21] This methodology was applied recursively to each category, and then again to each sub-category, resulting in 682 sub-sub-categories.

To verify that these sub-categories were parsimonious, we used HDP and discovered only one substantial topic within each sub-category. Additionally, we examined the keywords and representative patents of each sub-category, finding that each sub-category consisted of patents that used generally similar language within a similar domain of knowledge.

Finally, from this lowest sub-subcategory level, we ran an HDP to figure out the distribution of the weights of the topics. We find the fit of the number of topics for each sub-subcategory using cosine dissimilarity (Cao et al., 2009). Graphs of cosine similarities were distributed separately to RAs, who manually selected the most conservative point of best fit.[22] Our selections agreed around 95% of the time. We further reduced our sample to those topics addressing a clear theme. Topics without a sustained trajectory (i.e., with fewer than ten patents primarily on that topic) were discarded.

Figure 3.2 contains graphs portraying several cosine similarities for sub-subcategories within the 'Vehicles' category.

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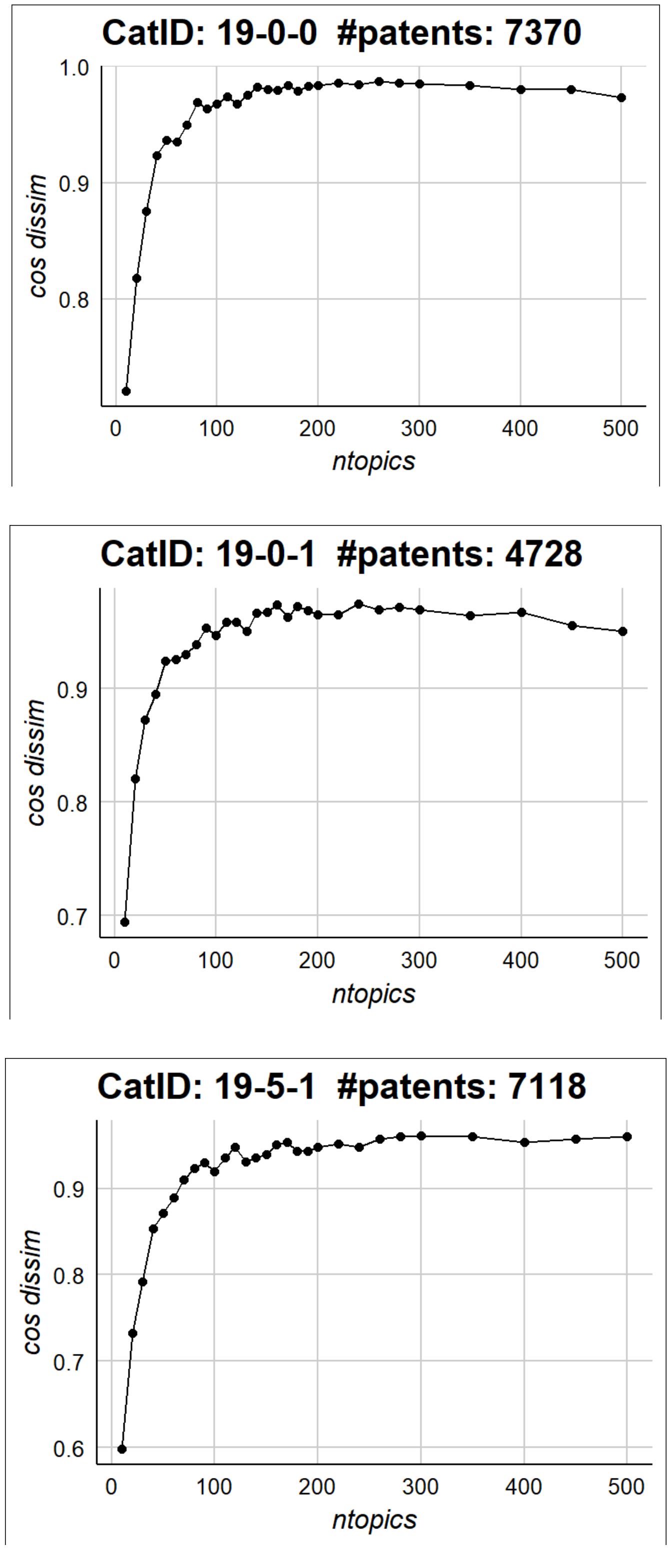
[20] The results of our analysis are not sensitive to the initial categorization of different clusters of multi-disciplinary patents in the first stage model due to the multiple recursive stages of categorization that were undertaken.
[21] For example, from the category of vehicle patents, the first six topics identified by the HDP model corresponded to distinct sets of patents that did not substantially overlap with each other, such as automobile transmission patents versus engine patents. However, the seventh topic overlapped almost entirely with the first topic; we concluded that this category contained patents on six major topics. The results from the HDP helped inform the nuisance parameter (how many topics exist) in LDA; in this case, six topics were pre-specified.
[22] Other measures of fit were considered: however, patents are specifically written to capture novelty and are not necessarily to be related to one another. Coherence would lump multiple ill-fitting patents into topics they may not fit into. Using a large number of topics will preserve the clustering of topics and absorb variance; very small topics may only have one or two patents and can be discarded.

Figure 3.2. Cosine Similarity Charts For ‘Vehicles’ Category



We then reduced our sample to those patents that strongly fit our model. Short patents with low information content in their abstracts (less than one standard deviation below the mean in their category) were discarded.[23] A clear and precise vocabulary (low entropy) was found to be strongly associated with a clear trajectory; on the other hand, topics with large vocabularies were more likely to capture idiosyncratic elements that were not related to the technology discussed in the abstract itself. Conservatively, patents that did not have at least a 30% fit with a single topic were discarded. These patents could be safely be eliminated as a breakthrough, as they did not fit with the major streams of knowledge. Altogether, the resulting topics were coherent, compact, and depicted a clear trajectory.

From these topics, the first patented invention was deemed to be a breakthrough. To reduce the likelihood of false positives (i.e., derivative inventions wrongly identified as breakthroughs), we further restricted our sample. As patent abstracts only became required in 1974, we allowed only topics where the first patent was applied for after 1988. This 15-year window ensured that we would not accidentally categorize a derivative patent as a breakthrough. With this final restriction, 3569 breakthroughs and topics were identified. At the end of this process, we checked the results from these algorithms to ensure that we were truly capturing breakthroughs. For example, the first hybrid engine ever produced was categorized by my algorithm as a breakthrough. Interestingly, this patent was invented decades before the Toyota Prius became popular in the late 1990s.

This entire process is captured in Figure 3.3.

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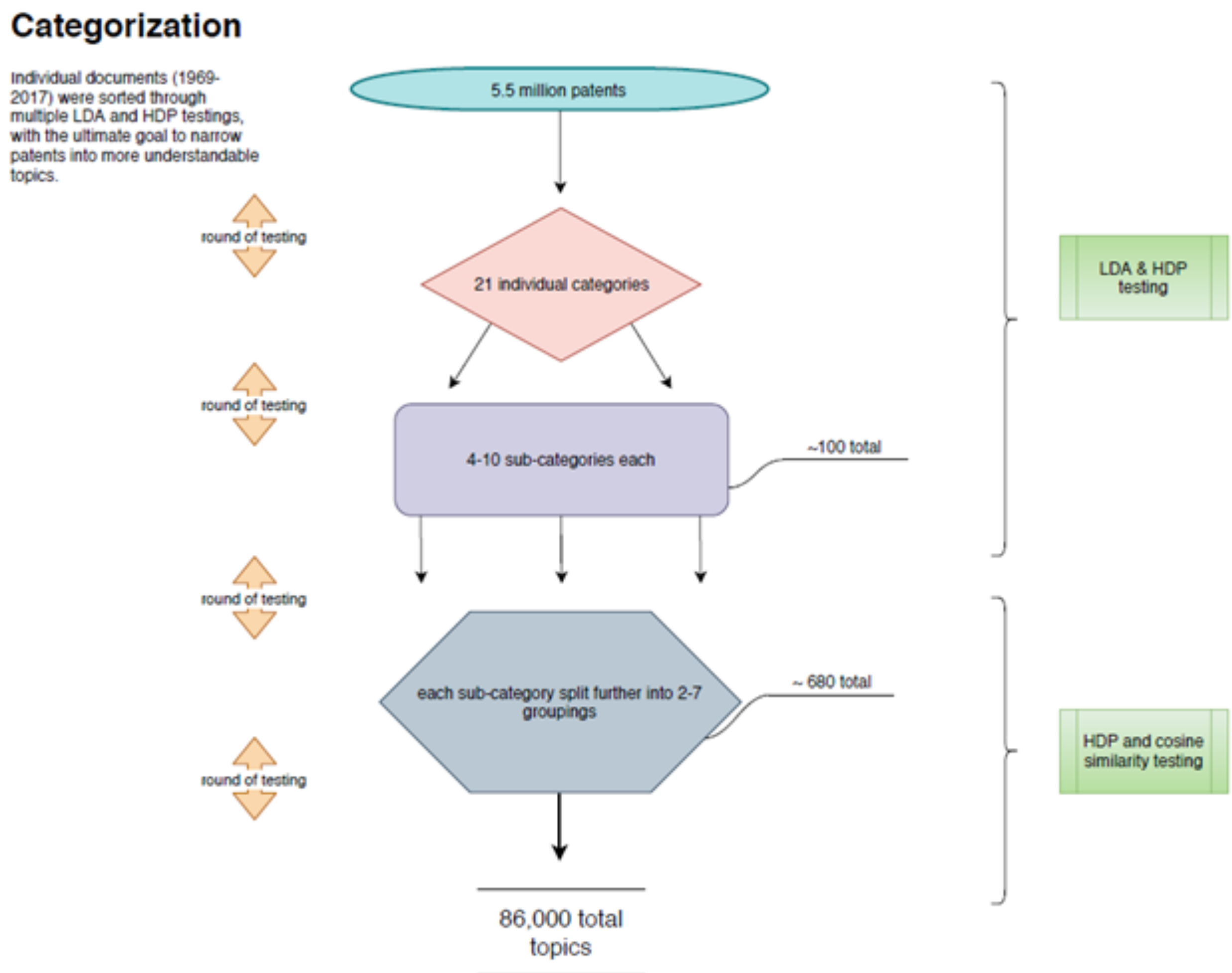
[23] Low-information abstracts may only contain a few distinct words or may have words that are relatively common. Additional analysis revealed that such patents tended to have low value and impact.

Figure 3.3: Flowchart to Categorize Topics from Patents



While the algorithm found 3569 distinct breakthroughs, 1271 were authored by single individuals. To find a conservative set of matches for the breakthrough patents, we identified those derivative patents with the most similar patent class combinations to the focal patent, filed within the same year of the patent application date of the breakthrough invention. These control patents were also authored by single individuals. For each breakthrough patented invention, five control matches were found in order to reduce error. We thus matched each breakthrough patent with a set of derivative patents by selecting on USPTO technology patent class and the year of patent application. This matched sample controls for unobserved heterogeneity between individuals, as well as between technological domains that may vary in their likelihood of generating citations from subsequent inventions. This resulted in a total of 7623 patents.

3.5 Data

3.5.1 Dependent Variable

Breakthroughs. I created a dummy variable indicating whether a sample patented invention is designated as a breakthrough invention or is part of the control set. This dummy variable has a value of 1 for a breakthrough and a value of 0 for a control.

3.5.2 Independent Variables

I used Google patent data[24] to collect *inventor experience*. To calculate this measure, I counted the number of prior patents created by the inventor before the focal patent, regardless of whether it is a breakthrough or a derivative patent. Inventors who have created many prior patents can be said to be highly experienced.

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[24] This data was collected in August 2018.

I also calculated *inventor breadth*, based on the number of technological classes that an inventor has experience with, prior to the application of the focal patent. For each inventor, I looked at their portfolio to count the different technology classes assigned to the inventor's past patents, which is defined by the USPTO to more easily classify knowledge. Inventors who create patents across many technology classes have much broader focus than those who create patents in only a few classes. Given that some patents are assigned to multiple patent classes, I count the unique number of classes that appear in the inventor's portfolio.

3.5.3 Control Variables

To ensure that the models are not affected by omitted variables, I first use the small entity flag as recorded by Google to determine whether the application was applied for is a *Small Entity*. Google maintains a Patent Maintenance Fees file associated with each patent application. Independent inventors, small firms, universities, or non-profit scientific or educational organizations are eligible for a reduced fee[25]. This data has been used to compare citation rates between small and large firms (Alcácer, Gittelman, & Sampat 2009).

I also control for whether the patent assignee is located in the United States. This is a dummy variable, where *Assignee is in US* is equal to 1 if the assignee is indeed located in the United States, and 0 otherwise.

[25] http://www.google.com/googlebooks/uspto-patents-maintenance-fees.html

3.6 Analysis and results

I use a logistic model to estimate how inventor experience and inventor breadth affect the likelihood of creating a breakthrough. Below, Table 3.2 provides summary statistics and correlations.

Table 3.2 Descriptive Statistics and Correlations

	Mean	Std Dev	(1)	(2)	(3)	(4)	(5)
(1) Breakthrough Dummy	0.17	0.37	1				
(2) Is Small Entity	0.23	0.42	-0.01	1			
(3) Assignee is in US	0.45	0.50	0.05	-0.09	1		
(4) Inventor Experience	6.15	21.16	0.03	-0.06	-0.03	1	
(5) Inventor Breadth	3.91	8.41	0.05	-0.06	-0.07	0.76	1

I examine my hypotheses using two successive models. The first model includes the control conditions and the two independent variables to establish the context of our study. In particular, the *inventor experience* has a positive coefficient ($p<0.05$). This finding suggests support for H1: inventors of breakthrough inventions will have greater prior experience with the invention process than will inventors of otherwise comparable derivative inventions.

Table 3.3: Likelihood of Creating Breakthrough Invention

	Model 1	Model 2
Is Small Entity	0.003	0.010
	(0.074)	(0.074)
Assignee is in US	0.257***	0.252***
	(0.062)	(0.062)
Inventor Experience	0.006**	0.010***
	(0.002)	(0.004)
Inventor Breadth	-0.004	-0.002
	(0.005)	(0.005)
Inventor Experience X Breadth		-6.55e-05*
		(3.15e-05)
Constant	-1.756***	-1.778***
	(0.051)	(0.052)
Observations	7,623	7,623

Standard errors listed in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

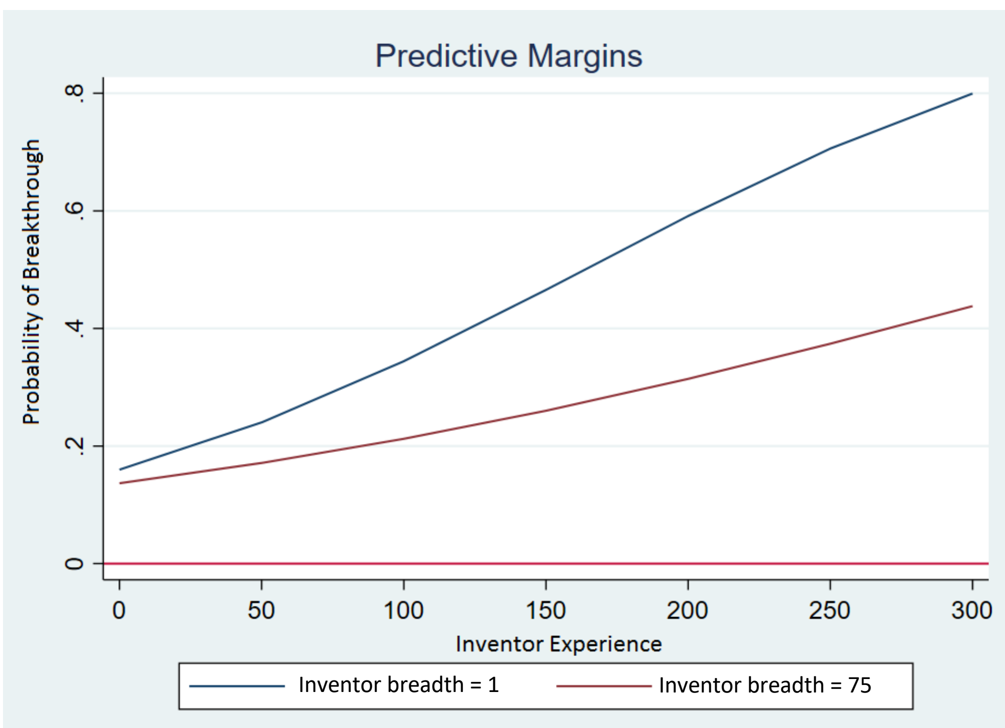
The second model directly tests H2 (jack of all trades) and H3 (master of one). The control variables are included. The interaction of the *inventor experience* and the *inventor breadth* (Patent X Breadth) has a coefficient that is negative ($p < 0.05$). This suggests that breakthroughs are created by inventors who have extensive experience in a narrow range of technological classes. This supports H3, which suggests that being a master of one is more conducive to developing breakthrough technologies. In contrast, an inventor who is a jack of all trades is less likely to create breakthroughs. In the context of the well-known idiom[26], then, it

[26] The full idiom is often written as "A jack of all trades is a master of none, but oftentimes better than a master of one."

seems that jacks of all trades perform *worse* than masters of one in terms of creating breakthrough inventions.

Figure 3.4 is useful for understanding the effect of the interaction between the *inventor experience* and the *inventor breadth*. I graph the probability of a breakthrough, given prior inventor experience and focus. When the inventor breadth is narrow (i.e., there are very few patent technology classes represented in inventor's portfolio prior to the focal patent application), experienced inventors are consistently more likely to create breakthroughs than when the number of technological classes is high.

Figure 3.4: The Probability of Breakthrough Given Prior Inventor Experience



As part of my post-hoc analysis, I create an additional variable called *patent breadth*. This is measured by computing the number of classes that is assigned to the focal patent by the USPTO. Patents with narrow focus should be assigned to fewer technology classes, which patents with broader focus should be assigned to a greater number of technology classes. This measure of patent breadth can then be used to shed more light on the distinctions between breakthrough inventions and derivative inventions.

Using a simple ANOVA, I find that *patent breadth* for breakthrough inventions (mean = 1.829) is indeed statistically different ($p < 0.001$) from the *patent breadth* for derivative inventions (mean = 2.075). This analysis suggests that breakthrough inventions are more narrowly focused than are derivative inventions.

The previous results from my hypotheses have suggested that inventor focus should be narrow to create breakthroughs. The correlation between *patent breadth* and *inventor breadth* may be sensibly pre-supposed to be high. However, the correlation between these two variables is only 0.015, suggesting that it is useful to add *patent breadth* as a new control variable.

Results are shown in Table 3.4. As before, the first model includes the control conditions and the two independent variables to establish the context of our study, with *patent breadth* as an additional control variable. The second model includes these variables and the interaction of Inventor Experience X Focus to directly tests H2 (jack of all trades) and H3 (master of one). While *patent breadth* is highly significant in these models, it does not affect the overall conclusion that can be drawn. Masters of one are still better than jacks of all trades in creating breakthrough inventions.

Table 3.4. Likelihood of Creating Breakthrough Invention with Patent Focus

	Model 1	Model 2
Is Small Entity	0.009	0.016
	(0.074)	(0.074)
Assignee is in US	0.281***	0.277***
	(0.062)	(0.063)
Patent Breadth	-0.250***	-0.249***
	(0.033)	(0.033)
Inventor Experience	0.006**	0.010***
	(0.002)	(0.003)
Inventor Breadth	-0.002	-0.001
	(0.005)	(0.005)
Inventor Experience X Breadth		-6.15e-05*
		(2.99e-05)
Constant	-1.286***	-1.309***
	(0.078)	(0.079)
Observations	7,623	7,623

Standard errors in parentheses
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

3.7 Discussion

The purpose of this paper is to gain an understanding of the origins of creative inventions by individual inventors. The results from this paper suggest that experience enables inventors to create breakthrough patents, which start new technological trajectories using fresh vocabularies. Experienced inventors are better able to harness their experience to be creative, resulting in inventions that shift existing cognitive frames and disrupt prevailing paradigms. However, the nature of the inventor's experience makes a difference as well; those who specialize deeply within a narrow range of knowledge domains are more likely to create breakthroughs than those who spread themselves too thin across knowledge domains.

3.7.1 Contributions

From a theoretical perspective, who creates novel inventions and how they do so are of keen interest (Hargadon & Sutton, 1997; Shah & Tripsas, 2007). More recently, the focus has shifted to understand the origin of breakthroughs through the lens of their inventors, as breakthroughs are particularly valuable and disruptive. Moreover, the inventors of such breakthroughs surpass ordinary knowledge recombination, instead bringing new perspectives to a technology in an inherently creative manner. As a result, the mechanisms underlying an inventor's successful breakthrough creation are important and yet understudied (Teodoris, Bikard, & Vakili, 2019; Nagle & Teodoris, 2020).

While prior work has highlighted the advantages of broad expertise (Hargadon & Sutton, 1997; Audia & Goncalo, 2007; Jeppesen & Lakhani, 2010), a similarly-sized body of work has highlighted the benefits to narrow specialization (Leahey, 2007; Jones, 2009; Conti, Gambardella, & Mariani, 2013). Moreover, much of the theory on creativity recognizes the nature of individual-level creativity, but in team or organizational contexts. In this paper, the setting of the entire domain of patented inventions allows for a much broader context to study the impact of specialization of single individuals in individual contexts.

From an empirical perspective, prior research on knowledge creation has focused on value creation through patents by measuring forward citations (Fleming, 2001; Sorenson, Rivkin, & Fleming, 2006). Patents with more forward citations are more useful and commercializable (Maggitti, Smith, & Katila, 2013). However, these citations capture tend to capture visibility, rather than novelty or creativity. While important, visibility can occur for other reasons that are theoretically distinct from creativity, such as the inventor knowing about a patent through previous random experience, or the lawyer trying to hide knowledge that the inventor might know about in order to have a greater claim, or exclusive right, granted to the patent applicant. Unfortunately, these issues obfuscate the process of knowledge search and creativity in new patents. While new patents are presumed to be valuable because they protect breakthrough knowledge, citation counts cannot confirm that empirically. In contrast, this paper uses machine learning to isolate creativity by capturing true cognitive breakthroughs, which inject fresh vocabularies and perspectives into established technological paradigms. As a result, these newly-created empirical measures can more accurately reflect the pre-existing theory on creativity and search.

3.7.2 Limitations and future research

This paper sought to understand how individual inventor experience and focus affect the creation of breakthrough inventions. While these aspects are indisputably critical to the process of invention and creativity, future research on individual level characteristics such as education, personality traits, and personal values, can add nuance to this discussion.

Moreover, given the richness of this data, more work can be done to understand the strategic nature of an individual inventor's choice to focus on a narrow domain or to broaden their horizons. Over time, inventors may change their areas of interest, crossing from specialization to generalization or vice versa. These choices may be driven by individual level differences, as well as broader contextual cues that are shaped by the knowledge domain of interest or by larger environmental trends.

Finally, this paper focused solely on individual level processes. Future research should more deeply examine creativity and search processes within teams and firms, observing the genesis and evolution of knowledge through changing language in patents. Indeed, with this new measurement of cognitive breakthroughs, there is a new potential to answer questions about knowledge flows, the creation of disruptive versus reinforcing breakthroughs, and even how breakthroughs and non-market strategies can align (Abernathy & Clark, 1985; Henderson & Clark, 1990; Tushman & Anderson, 1986).

4 Conclusion

In this dissertation, I explored the antecedents to inventions in terms of the environment in which they were created, as well as the inventors who created them. I examine how the environment of a firm shapes its inventive search process. I also study how an inventor's experience affects their likelihood of creating a breakthrough invention.

In my first essay, I explore how the norms of the societies in which firms are embedded influence the direction by which they deviate from routine to problemistic search. I find that, when Japanese and South Korean automotive firms experience involuntary product recalls, they tend to become increasingly conservative: solutions created in an affected technical space relied less on external technologies than did those derived prior to the recall. On the other hand, U.S. automotive firms clung more closely to their routine search patterns in response to product recalls in terms of their reliance on external technologies. These results are in line with the general propensity to take risk within their societies. I also find that the firms that pursued riskier problemistic search in response to their involuntary recalls by relying on external technologies were more likely to experience subsequent recalls than did firms that took a more conservative stance. Overall, my results suggest that injecting risk into the recovery process for product recalls may ultimately be counterproductive.

In my second paper, I use machine learning algorithms to study breakthrough inventions from derivative inventions. Breakthrough inventions are particularly creative inventions, which start new technological trajectories by using fresh vocabularies in their language. I find that experienced inventors are better able to harness their experience to be creative, resulting in inventions that shift existing cognitive frames and disrupt prevailing paradigms. However, the nature of the inventor's experience makes a difference; those who specialize deeply within a narrow range of knowledge domains are more likely to create breakthroughs than those who spread themselves too thinly across domains. Consequently, I find that an inventor who strives to create a breakthrough invention is better positioned to do so if they are a “master of one” than a “jack of all trades.”

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