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Paradise of Novelty—Or Loss of Human Capital? Exploring New Fields and Inventive Output

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Abstract. Does a person become more or less creative when exploring a new field? Exploring new fields exposes a person to new knowledge that might increase the novelty of inventive output; at the same time, exploration means a lack of prior expertise and a learning challenge that might harm the value of that output. Using new combinations as a measure of novelty and citations as a measure of value, we demonstrate correlations between exploring new fields and increased novelty—but decreased value—in an inventor–firm fixed effects panel. The negative effect of exploring new fields on value is muted when the novice collaborates with experts or uses the scientific literature in the new field. We find consistent results using an unintended change in noncompete labor law as an exogenous influence on exploring new fields. The research illustrates two opposite influences of exploration on creative output and suggests how inventors can reduce the downside of entering a new field.

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Keywords: creativity • novelty • inventor • search • exploration • field • novice • collaboration • science

Introduction

"Almost always the men who achieve these fundamental inventions of a new paradigm have been either very young or very new to the field whose paradigm they change."

—Thomas Kuhn, *The Structure of Scientific Revolutions*, p. 89–90.

"The man who employs either his labour or his stock in a grater variety of ways than his situation renders necessary... may hurt himself, and he generally does so. Jack of all trades will never be rich, says the proverb."

—Adam Smith, *An Inquiry into the Nature and Causes of the Wealth of Nations*, Book IV, Chapter V, p. 563.

Creative search is uncertain, and the optimal strategy rarely reveals itself beforehand (Radner and Rothschild 1975). March (1991) characterized the problem as a choice between exploiting known and proximal opportunities versus exploring new and distant possibilities. The analogy aptly describes the risky search process of invention (Audia and Goncalo 2007). On the one hand, people should exploit and build upon their prior knowledge and expertise (Smith 1776, Jovanovic 1979, Simon 1983). On the other hand, people should explore new fields and learn new knowledge (Campbell 1960; Kuhn 1970; Merton 1973). Exploration that proves successful provides the basis for future exploitation and the chance to mine a rich vein of value; however, with each creative search episode, the fundamental conundrum reappears.

We study the trade-off between these competing models of creative search, drawing theoretically from March (1991) and proceeding empirically with more nuanced metrics of inventive output that distinguish novelty from value (Amabile 2013, Kaplan and Vakili 2014). We argue that inventors who explore new fields are more likely to create novel inventions because of exposure to new knowledge and recombinant fertility (Frensch and Sternberg 1989) but less likely to create valuable inventions because they lack prior knowledge and expertise in the new field (Simon 1983). We also propose that collaboration with experts and reliance upon scientific literature in the new field can help novices to overcome the learning challenge of exploring new fields and the negative effect on value (Fleming and Sorenson 2004, Guimera et al. 2005).

To test our predictions, we use a variety of data and types of analysis. First, we select the full population of inventors with U.S. patents assigned to firms for 1975–2002 and estimate inventor–firm fixed effects panel models. Using repeated patents of the same inventor within the same firm, we illustrate how exploring new fields increases the novelty of the patent, measured by new combinations of subclasses (Fleming et al. 2007), but decreases the value of the patent, measured by forward citations (Harhoff et al. 1999, Hall et al. 2005). Second, we use an unintended change in noncompete labor law (the Michigan Anti-Trust Reform Act, hereafter MARA) that exogenously increased the cost to work in the same field of expertise at a different firm. Prior research has established that inventors who are subject to noncompetes and move between firms are more likely to leave their technical field of expertise and explore a new field, arguably to avoid a potential lawsuit (Marx 2011). We replicate these results by combining differences in the likelihood of exploring new fields across states (comparing inventors who move between firms within Michigan versus those who move between firms within states that continuously prohibit noncompetes) with differences across cohorts induced by the timing of the law change (pre- versus post-MARA). MARA had a strong and significant effect on exploring new fields, enabling an instrument in cross-sectional two-stage least squares models (Duflo 2001). These results hold for a variety of coarsened exact matching cuts and alternative measures (Iacus et al. 2009, Iacus et al. 2011).

The empirical models indicate that inventors who explore new fields create more novel patents. This result supports arguments that stress the importance of exposure to diversity and fresh perspectives. Yet the models also indicate that inventors who explore new fields create less valuable patents. This result supports arguments that stress the importance of experience and the accretion of specialized human capital. Speaking to the managerial challenge of how inventors and firms may reduce the risk of exploring a new field, our findings suggest that collaboration with experts and reliance on published science in the new field can reduce the decline in value. Extending the implications of the model to the U.S. state level, we illustrate how state-level enforceability of noncompete agreements increases the average novelty but reduces the average value of regional invention.

The work provides a better understanding of the conflicting theories and prior findings on the relationship between individual expertise and creative output (e.g., Weisberg 1999), suggests normative insights for technical professionals and their managers, and illustrates how noncompete labor law influences regional innovation.

Theory and Predictions

Economists have long argued for the benefits of specialization in labor (Smith 1776), and these paradigmatic assumptions strongly influence thinking about inventors and the process of invention. Because technological invention is a cumulative and recombinant search process, people typically rely upon prior knowledge and expertise (Rosenberg 1982, Weitzman 1998, Mokyr 2002). To first reach and then contribute to the state of the art in a field, a person needs to accumulate knowledge about the existing prior art in the field as well as field-specific learning and problem-solving skills (Cohen and Levinthal 1990). A person's field-specific knowledge and skills are the foundation on which the creative thinking process builds novelty (Simon 1983, Simon 1996). Case studies highlight the importance of deep immersion in a field of expertise prior to significant invention (Weisberg 1999). These assumptions suggest that scientists and engineers who explore a new field should create less valuable inventions. Novices lack deep knowledge and skills in the new field and need time to reach the frontier of knowledge (Chase and Simon 1973, Jones 2009).

Other scholars, mainly those who draw analogies to natural evolution (Darwin 1869), stress the importance of exploring new fields for inventive output. John Vaught, inventor of the HP inkjet printer, described it thus: "HP [Hewlett Packard] Labs was a wonderful place: I had to work in a single field for only two or three years and then like magic it was a whole new field: a paradise of creativity" (Fleming 2002, p. 1065). Exposure to social, cognitive, and physical diversity provides the raw material for recombinant novelty and helps to break a person's overly constrained and stale perspectives (Campbell 1960, Simonton 1999). From a purely combinatorial perspective, and completely ignoring any other influences on the first evolutionary stage of variation, a greater diversity in knowledge mechanically affords more possibilities. Beyond the increased but purely combinatorial possibilities, many have argued that exposure to new fields makes people more creative. Although prior learning and existing paradigms in a field help a person to interpret information and guide creative search, they may also cause myopia and constrain search (Allen and Marquis 1964, Ward 1995). Scholars have labeled this cognitive process that causes extant expertise to block novel insights as inflexibility of the information processing system, negative transfer, Einstellung, or mental block (e.g., Luchins and Luchins 1959, Frensch and Sternberg 1989). These perspectives imply that creative professionals should move between different fields of expertise and become generalists rather than specialists (e.g., Frensch and Sternberg 1989). By exploring new fields, they are freed from conventions and dogmas of a particular field, catalyzed to adopt fresh perspectives and heuristics, and prompted to approach problems with a helpful level of naïveté (Merton 1973). Inventors who explore new fields should create more novel inventions.

Extensions of both perspectives resonate throughout the literature on science and technology. Gilfillan (1935) and Kuhn (1970) argue that revolutionary discoveries are most likely made by people who are either very young or new to the field. Novices are unbound by conventions and dominant paradigms in the field and are, hence, more likely to adopt new and unconventional perspectives and heuristics to solve a particular problem (Ben-David 1960; Merton 1973; Gieryn and Hirsh 1983). Established cognitive maps, frames, and technological paradigms embody clear prescriptions of which search trajectory will be more productive (Dosi 1982, Kaplan and Tripsas 2008). They become institutionalized into a field so that specialists continue to work in the same direction. People with field-specific expertise are thought to be more reluctant to break with convention and depart from prior art even while novel or "revolutionary" ideas and inventions are thought to originate from breaking with the familiar trajectory and convention (Kuhn 1970, Arts and Veugelers 2015, Chai 2017). Audia and Goncalo (2007) illustrate that more experienced inventors favor the exploitation of familiar knowledge at the expense of the exploration of new knowledge. Conti et al. (2014) show that more experienced inventors—with a larger stock of prior patents—produce more patents but patents that are less likely to be breakthroughs. Jeppesen and Lakhani (2010) illustrate that winning solutions to problem-solving contests are more likely provided by individuals with technical expertise that is "distant" from the problem field. Azoulay et al. (2015) offer causal evidence that the death of a major scientist in a field occasions entry by novices and that this entry renews the field.

We agree with both perspectives and offer a simple model to clarify the trade-off. Support for the model comes from measures of invention that distinguish novelty from value. We conceptualize invention as a recombinant search process (Gilfillan 1935; Schumpeter 1939; Weitzman 1998), novelty as a new combination of ideas or components (Fleming et al. 2007, Uzzi et al. 2013), and value as the future use or success of the invention. Amabile (2013) stipulates that creativity and invention, by definition, require novelty *and* value. We agree these variables are crucial; however, we do not simultaneously require both and allow them to vary within an invention. By our definition, an invention can be novel but not very valuable, valuable but not very novel, or varying degrees of both (e.g., Kaplan and Vakili 2014, Conti et al. 2014). This definition avoids the normative and popular connotation that all inventions are intrinsically novel and valuable despite the empirical reality that most inventions are incremental improvements of formerly used combinations and/or have little value. Although our evidence comes from patent data and our prose usually refers to inventors, these arguments should hold for other creative professionals, such as scientists or designers.

Our simple model is that inventors who explore new fields are exposed to new knowledge, perspectives, and approaches (Merton 1973). They will see new components and new ways to arrange new and old components (Fleming 2001, Audia and Goncalo 2007). This exposure increases the likelihood that the inventor will create new combinations for a variety of reasons, including simple combinatorial opportunities, psychological refreshment, unblocking, and rearrangement of extant knowledge structures (Campbell 1960, Simonton 1999, Carnabuci and Bruggeman 2009). Working in a new field will encourage the inventor to question the inventor's assumptions, abstractions, creative goals, approaches, target customer or user, success metrics, and prior procedures and solutions. As a result, inventors who explore new fields should create more novel inventions.

Hypothesis 1. *Inventors who explore new fields create more novel inventions on average.*

Inventors who explore new fields lack prior field-specific knowledge and expertise and, thus, face a difficult and time-consuming learning challenge (Hayes 1989, Groysberg and Lee 2009, Jones 2009). Exploration causes mistakes, errors, and delay while the inventor climbs the learning curve in the new field and connects fresh ideas to the inventor's extant reservoir of experience (Weisberg 1999, Rosenkopf and Almeida 2003). It demands flexibility and the rearrangement and recoding of prior knowledge (Frensch and Sternberg 1989), and these efforts increase the rate and number of failed ideas. As a result, the likelihood of a successful—and valuable—invention decreases.

Hypothesis 2. *Inventors who explore new fields create less valuable inventions on average.*

March's (1991) original theory offered less insight to help the inventor avoid the downside of exploring new fields, the decline in the value of invention, while preserving the upside, the increase in novelty. Prior work suggests collaboration and published science might help scientists and engineers to deal with the learning challenge of exploring a new field (Sorenson and Fleming 2004, Wuchty et al. 2007).

Inventors who explore a new field but collaborate with experts in this new field could create more valuable inventions compared with novices who do not because collaboration can ease the "burden of knowledge" and make learning a new field less difficult and inefficient (Guimera et al. 2005, Jones 2009). Rather than methodically working through a great deal of new material from scratch to find what is useful and pertinent in a new field or stumbling on their own, a collaborating novice can simply ask the novice's knowledgeable colleague (Kehoe and Tzabbar 2015, Tzabbar et al. 2015). A collaborator with depth in the new field can guide the novice and winnow the novice's worst ideas while keeping the best (Singh and Fleming 2010). To draw an evolutionary analogy, expert collaborators can take advantage of their newcomer's creativity in the variation stage, but they can also filter the ideas that they recognize as previously tried and failed and unlikely to succeed in the selection stage (Gieryn and Hirsh 1983). This mechanism relies on more effective and efficient teaching, learning, and communication and does not rely on moving extant collaborative capital (commonly known as "lift-outs," see Wezel et al. 2006, Groysberg and Lee 2009). Collaboration with field experts should be particularly helpful for novices who lack prior knowledge and expertise in a field and, as such, face a tough learning challenge. Thus, the negative effect of exploring new fields on the value of invention should be less pronounced if the novice collaborates with experts in the new field.

Hypothesis 3. *The negative effect of exploring new fields on the value of invention is on average weaker for inventors who collaborate with experts in the new field.*

We expect similar benefits for inventors who explore new fields and draw upon published science because scientific theories reduce the degree of redundant effort and, thus, enable more efficient search (Nelson 1982). Scientific publication accelerates the diffusion of knowledge and lessens the need for learning from trial and error (Sorenson and Fleming 2004). Theory can suggest causality and help an inventor predict how a new combination might function. Awareness of published science facilitates prediction and decreases the need for empirical iteration, experimentation, and learning (Roach and Cohen 2013). Science can illuminate dead ends before they are explored empirically through models that can predict a lack of performance or publication of previous results that show an approach has already been tried unsuccessfully (Fleming and Sorenson 2004). Because scientific literature provides a map for inventive search, it could be particularly helpful for novices who lack prior knowledge and expertise in a field, reducing the negative effect of exploring new fields on the value of invention.

Hypothesis 4. *The negative effect of exploring new fields on the value of invention is on average weaker for inventors who rely on published science in the new field.*

Methods

Research Design and Data

To study how exploring new fields affects subsequent output of an inventor, we use the U.S. patent database for several reasons. First, patent data are publically available and provide a detailed insight into the output of a large sample of inventors across different fields. The database allows us to construct complete patenting careers (Li et al. 2014, Balsmeier et al. 2017). Second, given that the U.S. Patent and Trademark Office assigns patents into technology classes, the data allow us to identify whether an inventor explores new fields for each new patent the inventor invents (see Jones 2009; as we rely upon observing the same inventor across subsequent patents, our subjects need to patent at least twice).[1] Given a new field observed in a subsequent patent by the same inventor, we assess whether that subsequent patent is more or less novel and more or less valuable. Finally, a patent lists an assignee that is typically the employer of the inventor. To identify different corporate employers, we made use of the National Bureau of Economic Research assignee database containing harmonized names matched to firm identifiers for Compustat firms. This enables control for organizational characteristics that influence an inventor's output and identifying when an inventor moved between firms (Marx et al. 2009).

We use two different samples and research designs to test our predictions. First, we begin with the full population of inventors and collect all patents assigned to firms but, by design, must restrict the sample to inventors who have at least two patents assigned to the same firm. The advantage of this panel setup is that we can use inventor–firm fixed effect models to control for unobserved heterogeneity among inventors and firms, which arguably have a strong effect on the novelty and value of creative output. This approach basically uses repeated patents of the same inventor within the same firm to identify whether the inventor creates more or less novel—and more or less valuable—patents when any subsequent patent is categorized in a new field. The sample includes 2,705,431 patent–inventor observations assigned to 396,336 unique inventors and 46,880 unique firms, accounting for 473,419 unique inventor–firm pairs.

We complement the inventor–firm fixed effect models with a natural experiment, based on MARA, which exogenously increased the cost to work in the same field of expertise at a new employer, thereby nudging mobile inventors in Michigan after 1985 to explore new fields. The advantage of the natural experiment is in strengthening causal inference; the disadvantage is in failing to control for unobserved heterogeneity among inventors and firms. Moreover, the natural experiment only affected a subset of inventors, that is, inventors moving between firms in Michigan after 1985, which might be different from non-Michigan or nonmobile inventors and, therefore, not representative of the full population. The natural experiment might also affect the selection of treatment subjects in case different inventors and firms responded differently to the labor law reform. In robustness analyses, we find no significant differences between any of the subpopulations and carefully match inventors affected by the labor law change to those not affected. Consistent results across these complementary research designs strengthen our confidence in the underlying model of exploring new fields and creative output.

Measures

Outcome Variables. To assess patent value, we calculate *forward citations (ln)* as the logarithmic transformation of one plus the number of times a patent is referenced as prior art within 10 years. Forward citations are positively correlated with the private economic value of a patent, maintenance fee payments, and with the market value of the assigned company (Harhoff et al. 1999, Hall et al. 2005).

To assess patent novelty, we calculate *new combinations (ln)* as the logarithmic transformation of one plus the number of pairwise subclass combinations of a patent that appear for the first time in the U.S. patent database (Fleming et al. 2007, Jung and Jeongsik 2016). To do so, each pairwise combination of subclasses is compared with all pairwise combinations of all prior U.S. patents.

Independent Variables. All independent variables are calculated at the inventor–patent level (e.g., Marx et al. 2009). In case a patent lists multiple inventors, there will be multiple inventor–patent observations associated with the same patent.[2] For each inventor–patent observation, one inventor is treated as the focal inventor, and the other inventors listed on the patent are treated as coinventors.

For each inventor–patent observation, we retrieve the three-digit technology classes of all prior patents of the focal inventor and identify whether there is any overlap between the three-digit technology classes of the focal patent and the three-digit technology classes linked to all prior patents of the same inventor. We rely on all classes assigned to a patent rather than just the primary class. *Exploring new fields* is a binary indicator that equals one in the absence of any overlapping class between all prior patents and the focal patent.

For each inventor–patent observation, we identify whether there is any overlap between the three-digit technology classes of the focal patent and the three-digit technology classes linked to all prior patents of the coinventors on the patent (excluding the focal inventor). *Expert team* is a binary indicator that equals one if at least one of the coinventors has a prior patent in the same class(es) as the focal patent. The measure is used a moderator to test whether collaboration with experts reduces the negative effect of exploring new fields on value.

Science is a binary indicator that equals one if the focal patent cites nonpatent prior art, which are typically scientific publications (Fleming and Sorenson 2004, Ahmadpoor and Jones 2017).[3] We rely on a supervised machine-learning approach to identify citations to scientific publications (Callaert et al. 2011). Such citations indicate an awareness of the inventor on the cited articles (Roach and Cohen 2013). Science is used a moderator to test whether reliance on scientific publications reduces the negative effect of exploring new fields on value.

Control Variables. For each inventor–patent observation, we calculate *prior patents (ln)*[4] as the number of prior patents of the focal inventor, *specialization* as a Herfindahl concentration index based on the three-digit technology classes of all prior patents of the focal inventor, *prior collaborations (ln)* as the number of unique coinventors linked to all prior patents of the focal inventor, a binary indicator *move* that is equal to one for the first patent of the focal inventor with a new firm as assignee, and a binary indicator for whether the focal inventor previously moved between employers (*prior move*). In line with prior research, an inventor is assumed to move in case different assignees appear on two successive patents of the same inventor. Inventors with a larger stock of prior patents, inventors who are generalists rather than specialists, and inventors who formerly collaborated with a larger number of coinventors or who moved between employers might create more or less novel and more or less valuable patents and might be more or less inclined to explore new fields. To control for the fact that inventors in the beginning or near the end of their career might be more or less likely to explore new fields, we include *days since first patent (ln)* as the number of days since the first patent of the inventor was filed. To control for the fact that an inventor who more recently patented in a field might be more or less likely to explore new fields, we include *days since last patent (ln)* as the number of days since the previous patent of the inventor was filed.

For each inventor–patent observation, we include additional controls for the characteristics of the coinventors on the team. *Team* is a binary indicator equal to one in case the patent lists more than one inventor, that is, there is at least one coinventor. *Team prior patents (ln)* is calculated as the average number of prior patents of the coinventors (excluding the focal inventor). *Team specialization* is the average specialization of the coinventors (excluding the focal inventor) using a Herfindahl concentration index based on the three-digit technology classes of all prior patents of the coinventors.

To control for firm size, we include *firm prior patents (ln)* as the number of patents assigned to the firm listed as assignee. Finally, we include *number of classes (ln)* as the patent's number of three-digit technology classes and *number of subclasses (ln)*. Three-digit *technology class* and *year* indicators control for secular trends in fields.[5] Because of the skew of count variables, we use their logarithmic transformation after adding one for variables with zero values (results are robust with nonlinear models). Table 1 presents a description and summary statistics for the full sample of inventors with at least one prior patent and at least two patents assigned to the same firm for observation period 1975–2002.

Results

Inventor–Firm Fixed Effects Model Results Table 2 illustrates the inventor–firm fixed effects models with and without interaction terms. We propose that inventors who explore a new field will gain exposure to new knowledge and perspectives and increase the combinatorial opportunities, such that the average novelty of their output will increase. Without interaction terms, Model 1 illustrates that exploring new fields significantly increases the number of new combinations by 6.7%.[6] We also proposed that inventors who explore a new field will lack field-specific knowledge and skills, such that the value of their output will decrease. Also, without interaction terms, Model 6 illustrates that exploring new fields significantly decreases the number of forward citations by 1.0%.

The preferred models include interaction terms. Considering the value models first, hypothesis 3 proposed that the learning challenge of exploring a new field can be eased by collaborating with people with expertise in the new field. As illustrated in Model 8, the predicted first-order effect of an expert team is positive, increasing forward citations by 4.3%. The predicted first-order effect of exploring new fields also strengthens, indicating a reduction in forward citations of 3.0%. The interaction between exploring new fields and expert team has the predicted positive effect and increases the number of forward citations by 8.3%. Thus, the decrease in value from exploring new fields can be more than fully recovered by collaborating with knowledgeable inventors in the new field. Collaborators with depth in the new field may be able to direct the novice and winnow the novice's worst ideas while keeping the best. Consistent with theoretical arguments, the interaction between exploring new fields and a nonexpert team is positive and significant although smaller compared with the interaction between exploring new fields and an expert team (result not shown). These findings illustrate that lone inventors who explore new fields on their own face a heavy burden of knowledge and suffer most from a decline in the value of their inventive output, relative to their collaborative peers.

Hypothesis 4 proposes that drawing upon published science should similarly reduce the decline in value associated with the exploration of new fields. The predicted first-order effect of science indicates an increase in citations of 7% (Model 9). The predicted first-order effect of exploring new fields strengthens, reducing forward citations by 2.5%. The interaction between exploring new fields and science has the predicted positive effect on value, however, increasing the number of forward citations by 6.0% and overcoming the negative first-order effect of exploring new fields. Hence, scientific literature appears to be helpful for novices who lack prior knowledge and expertise in a field. As illustrated in Model 10, expert team and science together help to fully overcome the challenge of exploring a new field. The total effect of exploring new fields on value, accounting for both first-order and interaction effects, is positive and significant, increasing forward citations by 9.3%.

We did not offer hypotheses on whether collaboration with experts and science moderate the effect of exploring new fields on the novelty of invention. Collaborating in a new field could make an inventor's output more novel if the inventor's collaborators embraced the inventor's new combinations, or it could make it less novel if they channeled the newcomer's ideas into their prior trajectories. Drawing upon science when exploring a new field could arguably increase novelty if it suggested new combinations (and the inventor was not already cognitively overloaded). It could also decrease novelty if it suggested a path to success that required less recombinant iteration (Fleming and Sorenson 2004).[7] We nonetheless estimate the interaction effects to better understand potential trade-offs related to relying on expert collaborators and scientific literature while exploring a new field.

The first-order effect of having collaborators with expertise in the field is negative and significant, decreasing new combinations by 3.9% (Model 3). This finding is consistent with Hypothesis 1. The interaction between exploring new fields and an expert team is positive and significant, however, increasing new combinations by 2.4%. Hence, the interaction partially ameliorates the negative first-order effect of expert team on the novelty of invention. Although collaborators with expertise in the new field appear to ease the burden of knowledge and overcome the negative effect of exploring new fields on value, they may also decrease the novelty of inventive output. By contrast, science has a small but positive and significant first-order effect on novelty, increasing new combinations by 0.5%. The interaction effect between exploring new fields and science is also positive and significant, increasing new combinations by 2.0%. Thus, science positively moderates the effect of exploring new fields on both novelty and value. Overall, the total effect of exploring new fields on novelty, accounting for both first-order and interaction effects, is positive and significant, increasing new combinations by 8.3%.

We test the robustness of these results in several ways. A first potential concern is that one patent is not sufficient to establish the field of expertise of an inventor. In Models 1–4 in Table 3, we reestimate the effect of exploring new fields for the subset of inventors

Table 1. Summary Statistics

Variable	Description	Mean	Standard deviation	Minimum	Maximum
New combinations (ln)	Number of pairwise subclass combinations of the focal patent that appear for the first time in the patent database. Measure for the novelty of the patent.	0.81	1.05	0.00	9.11
New citation combinations (ln)	Number of pairwise combinations of patents cited by the focal patent that appear for the first time in the patent database. Measure for the novelty of the patent.	2.27	1.64	0.00	12.33
Forward citations (ln)	Number of citations received by the focal patent within 10 years. Measure for the value of the patent.	1.79	1.06	0.00	6.82
Renewals (ln)	Number of times the focal patent is renewed by paying the renewal fees. A patent can be renewed after four, eight, and 12 years, resulting in the count of renewals being zero, one, two, or three. Available for patents since 1981. Measure for the value of the patent.	1.05	0.44	0.00	1.39
Exploring new fields	Binary: no overlap in the three-digit technology class(es) of the focal patent and the three-digit technology class(es) linked to all prior patents of the focal inventor.	0.28	0.45	0.00	1.00
Exploring new fields share	Share of the focal patent's three-digit technology class(es) new to the focal inventor.	0.44	0.42	0.00	1.00
Field distance	Weighted average distance between each of the three-digit technology classes of the focal patent and each of the three-digit technology classes linked to all prior patents of the same inventor. Class distance is calculated as one minus cosine similarity based on the joint occurrences of classes in patents. Class distances are weighted based on the focal inventor's number of prior patents in the particular class.	0.60	0.26	0.00	1.00
Expert team	Binary: coinventor(s) on the focal patent (excluding the focal inventor) have prior patent(s) in the same three-digit technology class(es) as the focal patent.	0.61	0.49	0.00	1.00
Science	Binary: focal patent cites scientific publication(s).	0.24	0.43	0.00	1.00
Prior patents (ln)	Number of prior patents of the focal inventor.	1.99	0.98	0.69	7.17
Specialization	Technical specialization of the focal inventor, calculated as a Herfindahl index based on the three-digit technology classes of all prior patents of the focal inventor.	0.62	0.31	0.02	1.00
Prior collaborations (ln)	Number of unique coinventors on all prior patents of the focal inventor.	1.97	0.97	0.00	6.37
Move	Binary: focal inventor moved between employers. Indicator is equal to one if the focal patent is assigned to a new assignee.	0.05	0.21	0.00	1.00
Prior move	Binary: focal inventor previously moved between employers.	0.20	0.40	0.00	1.00
Days since last patent (ln)	Number of days since the focal inventor's prior patent application.	4.51	2.18	0.00	10.41
Days since first patent (ln)	Number of days since the focal inventor's first patent application.	7.25	1.52	0.00	10.50
Team	Binary: focal patent lists multiple inventors, that is, the focal inventor has at least one coinventor.	0.83	0.38	0.00	1.00
Team prior patents (ln)	Average number of prior patents of the coinventors on the focal patent (excluding the focal inventor).	1.53	1.20	0.00	7.08
Team specialization	Average technical specialization of the coinventors on the focal patent (excluding the focal inventor).	0.75	0.26	0.02	1.00
Firm prior patents (ln)	Number of prior patents assigned to the firm listed as assignee.	6.13	2.57	0.00	10.69
Number of classes (ln)	Number of technology classes of the focal patent.	0.48	0.49	0.00	2.77
Number of subclasses (ln)	Number of technology subclasses of the focal patent.	1.30	0.68	0.00	5.15

Notes. This sample includes all patents of inventors that are assigned to a firm, filed, and granted between 1975 and 2002. This sample is restricted to inventors with at least one prior patent (and, hence, are at the risk of exploring new fields) and who have at least two patents assigned to the same firm. The sample includes 2,705,431 inventor–patent observations, 473,419 inventor–firm pairs, 396,336 inventors, and 46,880 firms. "(ln)" indicates logarithmic transformation after adding one for measures with zero values.

Table 2. Inventor–Firm Fixed Effects Models Exploring New Fields

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	New comb. (ln)	New comb. (ln)	New comb. (ln)	New comb. (ln)	New comb. (ln)	Forward cit. (ln)	Forward cit. (ln)	Forward cit. (ln)	Forward cit. (ln)	Forward cit. (ln)
Exploring new fields	0.0646***	0.0636***	0.0444***	0.0589***	0.0407***	−0.0104***	−0.0118***	−0.0306***	−0.0250***	−0.0407***
	(0.0012)	(0.0014)	(0.0017)	(0.0014)	(0.0018)	(0.0016)	(0.0018)	(0.0023)	(0.0019)	(0.0024)
Exploring new fields × expert team			0.0233***		0.0219***			0.0793***		0.0757***
			(0.0023)		(0.0024)			(0.0030)		(0.0030)
Exploring new fields × science				0.0212***	0.0194***				0.0586***	0.0525***
				(0.0027)	(0.0027)				(0.0033)	(0.0033)
Expert team			−0.0399***		−0.0394***			0.0423***		0.0435***
			(0.0018)		(0.0018)			(0.0023)		(0.0023)
Science				0.0048***	0.0053***				0.0673***	0.0687***
				(0.0018)	(0.0018)				(0.0022)	(0.0022)
Prior patents (ln)		−0.0239***	−0.0262***	−0.0237***	−0.0260***		−0.1590***	−0.1560***	−0.1579***	−0.1548***
		(0.0022)	(0.0022)	(0.0022)	(0.0022)		(0.0030)	(0.0030)	(0.0030)	(0.0030)
Specialization		−0.0075**	−0.0061*	−0.0073**	−0.0060*		−0.1030***	−0.1005***	−0.1025***	−0.1002***
		(0.0036)	(0.0036)	(0.0036)	(0.0036)		(0.0053)	(0.0053)	(0.0053)	(0.0053)
Prior collaborations (ln)		0.0021	0.0047***	0.0023	0.0048***		−0.0183***	−0.0114***	−0.0176***	−0.0111***
		(0.0017)	(0.0017)	(0.0017)	(0.0017)		(0.0024)	(0.0024)	(0.0024)	(0.0024)
Move		−0.0097***	−0.0105***	−0.0099***	−0.0106***		0.0093**	0.0088**	0.0082**	0.0077**
		(0.0026)	(0.0026)	(0.0026)	(0.0026)		(0.0038)	(0.0038)	(0.0038)	(0.0038)
Prior move		−0.0008	−0.0008	−0.0006	−0.0006		0.0124**	0.0119**	0.0129***	0.0123**
		(0.0031)	(0.0031)	(0.0031)	(0.0031)		(0.0049)	(0.0049)	(0.0049)	(0.0049)
Days since last patent (ln)		0.0090***	0.0090***	0.0090***	0.0091***		0.0027***	0.0025***	0.0028***	0.0027***
		(0.0003)	(0.0003)	(0.0003)	(0.0003)		(0.0003)	(0.0003)	(0.0003)	(0.0003)
Days since first patent (ln)		0.0053***	0.0048***	0.0053***	0.0048***		0.0032***	0.0032***	0.0032***	0.0033***
		(0.0008)	(0.0008)	(0.0008)	(0.0008)		(0.0012)	(0.0012)	(0.0012)	(0.0012)
Team		0.0332***	0.0439***	0.0331***	0.0436***		0.1170***	0.1039***	0.1164***	0.1030***
		(0.0019)	(0.0019)	(0.0019)	(0.0019)		(0.0025)	(0.0026)	(0.0025)	(0.0026)
Team prior patents (ln)		−0.0200***	−0.0132***	−0.0200***	−0.0133***		0.0003	−0.0102***	0.0002	−0.0104***
		(0.0010)	(0.0011)	(0.0010)	(0.0011)		(0.0015)	(0.0016)	(0.0015)	(0.0016)
Team specialization		0.0002	−0.0052	0.0001	−0.0053		0.0616***	0.0786***	0.0617***	0.0785***
		(0.0037)	(0.0037)	(0.0037)	(0.0037)		(0.0049)	(0.0050)	(0.0049)	(0.0050)
Firm prior patents (ln)		−0.0237***	−0.0238***	−0.0237***	−0.0238***		−0.1003***	−0.1026***	−0.1005***	−0.1027***
		(0.0019)	(0.0019)	(0.0019)	(0.0019)		(0.0035)	(0.0035)	(0.0035)	(0.0035)
Constant	0.1031	0.1597*	0.1688*	0.1635*	0.1718**	1.6068**	1.8427**	1.8701**	1.8513**	1.8761**
	(0.0778)	(0.0868)	(0.0870)	(0.0871)	(0.0873)	(0.7120)	(0.7244)	(0.7349)	(0.7255)	(0.7358)
R-squared	0.538	0.539	0.539	0.539	0.539	0.036	0.066	0.067	0.067	0.068

Notes. The sample includes all patents of inventors that are assigned to a firm, filed, and granted between 1975 and 2002. The sample is restricted to inventors with at least one prior patent (and, hence, are at the risk of exploring new fields) and who have at least two patents assigned to the same firm. The sample includes 2,705,431 inventor–patent observations. All models include controls for number of classes (ln), number of subclasses (ln), year and technology class indicators, and inventor–firm level fixed effects. Robust standard errors in parentheses.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

with at least 13 prior patents, that is, the 75th percentile in the distribution of prior patents, and for inventors with less than 13 patents, respectively. We find consistent support for all four hypotheses across all models. As expected, the effect of exploring new fields is stronger for inventors with more prior patents, who arguably accumulated more knowledge and expertise. In addition, the effect of exploring new fields might differ for more specialized inventors with a narrow field of expertise compared with inventors with broader expertise. Furthermore, although we include for each focal inventor a control for the number of unique prior coinventors, a potential concern is that the classes of prior patents capture the expertise of the coinventors on the patents rather than the expertise of the focal inventor (Jones 2009). In Models 5 to 8 in Table 3, we find consistent support for all hypotheses for the subset of inventors with specialization equal to the maximum of one (all prior patents classified in the same class, i.e., the 75th percentile in the distribution of specialization) and for the subset of less specialized inventors. In Models 9–12, we find consistent support for all hypotheses for the subset of inventors with a maximum of two prior coinventors, that is, the 25th percentile in the distribution of prior collaborations, and for the subset of inventors with more than two prior coinventors.

Another potential concern is that we used a conservative and discrete measure for exploring new fields, that is, a binary measure indicating there is no overlap between the classes of the focal patent and any of the classes of all prior patents of the focal inventor. As illustrated in Table A.1 in the online appendix, we find consistent support for all hypotheses using a less conservative and continuous measure, *exploring new fields share*, measuring the share of the focal patent's three-digit technology class(es) new to the focal inventor. Furthermore, the distance between the old and the new field has important implications for the learning process (Schilling et al. 2003). Because of the large heterogeneity in distance between patent classes, we also calculate *field distance* as the weighted average distance between each of the three-digit technology classes of the focal patent and each of the three-digit technology classes linked to all prior patents of the same inventor, weighted by the inventor's number of prior patents in the particular class. The distance between two patent classes is calculated as one minus the cosine similarity between two class vectors each capturing the joint occurrence of the focal class with all other classes in the population of U.S. patents (e.g., Breschi et al. 2003). Each class i is represented as a vector (P_{i1}, P_{i2}, ... P_{in}) with P_{ij} equal to the number of patents jointly assigned to class i and class j and n the number of distinct patent classes in the U.S. Patent Classification System. As illustrated in Table A.2 in the online appendix, we find consistent results for all four hypotheses. In line with theory predictions, accounting for distance between fields strengthens the first-order and interaction effects.

Besides testing the robustness of our results using alternative measures for exploring new fields, we test the robustness of our results using alternative outcome measures for novelty and value. We calculate an alternative to novelty as *new citation combinations*, the focal patent's number of pairwise combinations of cited patents that appear for the first time in the patent database (Uzzi et al. 2013), and include the overall number of cited patents as a control variable. To do so, each pairwise combination of cited patents is compared with all pairwise combinations of all prior U.S. patents. Thus, the measure is calculated in the same way as *new combinations* except for using cited patents instead of subclasses assigned to a patent. We also calculate an alternative to value as *renewals*, the number of times a patent is renewed by paying the maintenance fees (e.g., Harhoff et al. 1999). A patent can be renewed after four, eight, and 12 years, resulting in the count of renewals being zero, one, two, or three. As illustrated in Table A.3 in the online appendix, we find consistent support for all hypotheses using these alternative outcome measures.

A Natural Experiment to Strengthen Causal Inference

The Michigan Antitrust Reform Act. Any archival study that purports to link the exploration of new fields with creative output must confront endogeneity issues. As perhaps the most obvious problem, a person might choose to explore new fields to become more creative and had already identified a fruitful opportunity. As a further example, more creative people might cross boundaries between fields more successfully because of their diverse knowledge base and cognitive flexibility. Alternatively, less productive people might fail to find continuous employment in their field of expertise so that they are forced to explore new fields. Finally, because of the increasing burden of knowledge on more recent generations, technical professionals have become increasingly specialized so that there is a decreasing tendency to explore new fields over time (Jones 2009). To address these issues, the study design must provide an exogenous influence upon exploring new fields; consider similarly productive and creative subjects; and control for time, field, and other confounders. We address each of these in turn.

We exploit a natural experiment related to the inadvertent reversal of noncompete enforcement law in Michigan as an exogenous increase in the cost to work in the same field of expertise at a new employer. Using interviews of 52 inventors and a survey of 1,029 engineers, Marx (2011) established that ex-employees subject to noncompetes are more likely to explore

Table 3. Subsamples of Inventors Split by Prior Patents, Specialization, and Prior Collaborations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	New comb. (ln)	New comb. (ln)	Forward cit. (ln)	Forward cit. (ln)	New comb. (ln)	New comb. (ln)	Forward cit. (ln)	Forward cit. (ln)	New comb. (ln)	New comb. (ln)	Forward cit. (ln)	Forward cit. (ln
Sample	Prior patents≥13	Prior patents<13	Prior patents≥13	Prior patents<13	Special.=1	Special.<1	Special.=1	Special.<1	Prior collab.<=2	Prior collab.>2	Prior collab. <=2	Prior collab.>2
Exploring new fields	0.0510***	0.0393***	−0.0480***	−0.0415***	0.0620***	0.0426***	−0.0465***	−0.0489***	0.0459***	0.0448***	−0.0292***	−0.0487***
	(0.0047)	(0.0020)	(0.0066)	(0.0025)	(0.0039)	(0.0023)	(0.0049)	(0.0031)	(0.0038)	(0.0023)	(0.0047)	(0.0030)
Exploring new fields × expert team	0.0154**	0.0201***	0.0829***	0.0756***	0.0094**	0.0219***	0.0500***	0.0867***	0.0023	0.0224***	0.0883***	0.0785***
	(0.0068)	(0.0026)	(0.0089)	(0.0032)	(0.0046)	(0.0033)	(0.0057)	(0.0043)	(0.0061)	(0.0029)	(0.0074)	(0.0038)
Exploring new fields × science	0.0039	0.0219***	0.0607***	0.0515***	0.0092*	0.0148***	0.0409***	0.0582***	0.0106	0.0176***	0.0184**	0.0626***
	(0.0075)	(0.0030)	(0.0096)	(0.0035)	(0.0055)	(0.0038)	(0.0063)	(0.0048)	(0.0073)	(0.0033)	(0.0085)	(0.0041)
Expert team	−0.0466***	−0.0378***	0.0641***	0.0322***	−0.0224***	−0.0423***	0.0371***	0.0519***	−0.0257***	−0.0404***	0.0255***	0.0492***
	(0.0038)	(0.0020)	(0.0050)	(0.0025)	(0.0037)	(0.0022)	(0.0047)	(0.0028)	(0.0051)	(0.0021)	(0.0061)	(0.0026)
Science	0.0144***	−0.0005	0.0789***	0.0635***	0.0035	0.0085***	0.0578***	0.0710***	−0.0054	0.0078***	0.0678***	0.0687***
	(0.0032)	(0.0021)	(0.0042)	(0.0025)	(0.0040)	(0.0021)	(0.0046)	(0.0027)	(0.0058)	(0.0019)	(0.0068)	(0.0024)
R-squared	0.524	0.544	0.065	0.062	0.510	0.541	0.051	0.068	0.547	0.536	0.054	0.068
N	683,874	2,021,557	683,874	2,021,557	903,952	1,801,479	903,952	1,801,479	578,536	2,126,895	578,536	2,126,895

Notes. The sample includes all patents of inventors that are assigned to a firm, filed, and granted between 1975 and 2002. The sample is restricted to inventors with at least one prior patent (and, hence, are at the risk of exploring new fields) and who have at least two patents assigned to the same firm (n = 2,705,431 inventor–patent combinations). All models include controls for prior patents (ln), specialization, prior collaborations (ln), move, prior move, days since last patent (ln), days since first patent (ln), team, team prior patents (ln), team specialization, firm prior patents (ln), number of classes (ln), number of subclasses (ln), year and technology class indicators, and inventor–firm level fixed effects. Robust standard errors in parentheses.

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

new fields to avoid a potential lawsuit. A noncompete agreement prevents an ex-employee from working for competitors in the same field and, hence, exploiting their field-specific knowledge and expertise. As such, the change in noncompete labor law exogenously increased the cost to continue working in the same field at a new employer, triggering technical professionals to explore new fields. In 1985, MARA was passed with the intention of harmonizing state law with the uniform state antitrust act (Bullard 1985). However, while passing MARA, legislators unintentionally revoked statute 445.761, which prohibited the enforcement of noncompete agreements in Michigan (Alterman 1985). After the passing of MARA, employers in Michigan suddenly obtained the legal means to prevent their ex-employees from working in the same field at a different firm (Marx et al. 2009). As such, the Michigan experiment provided an exogenous pressure on inventors to explore new fields after they left their former employer.

The time at which an inventor moves between firms (pre- or post-MARA) as well as the inventor's state of residence (Michigan versus non-Michigan) determine the likelihood that an inventor explored new fields. Our identification relies on the fact that only mobile inventors residing in Michigan after the passing of MARA are affected; Michigan inventors before MARA and inventors from other states before and after MARA are not affected by the policy change. Therefore, we can combine differences in exploring new fields between inventors from different states (Michigan versus non-Michigan) with differences between cohorts induced by the timing of MARA (pre- versus post-MARA). The interaction between binary indicators for Michigan residence and post-MARA is expected to have a positive significant effect on the likelihood of exploring new fields. Thus, this difference-in-differences (DD) can be used as an instrument for exploring new fields (Duflo 2001). The DD specification controls for overall time trends in exploring new fields (across all states) and for time-invariant unobserved differences between Michigan and non-Michigan inventors (Angrist and Pischke 2008). Furthermore, regression DD allows us to include additional inventor and field characteristics affecting the likelihood of exploring new fields as controls. The main assumption is that, in the absence of MARA, the trend in exploring new fields would not have been systematically different between Michigan and non-Michigan mobile inventors.

Sample Selection. In line with prior research, we select all U.S. inventors who patented in Michigan or in another nonenforcing state before the passing of MARA in 1985, including Alaska, California, Connecticut, Minnesota, Montana, Nevada, North Dakota, Oklahoma, Washington, and West Virginia (Malsberger 1996; Marx et al. 2009, Marx et al. 2015). Inventors who did not patent in a nonenforcing state or only did so after the passing of MARA are excluded to ensure that MARA did not affect sample selection. We track all subsequent patents linked to this set of inventors and assigned to a firm and identify each move between firms (again, the design relies upon inventors patenting at least twice). Only intrastate moves are taken into account because inventors can emigrate from Michigan to a nonenforcing state to avoid a lawsuit (Marx et al. 2015). Finally, we restrict the analysis to the 1975–1995 period, that is, 10 years before and after the passing of MARA. Notice that we collect all patents, both before and after MARA and in and out of Michigan. This results in the full sample of patents by inventors at risk for moving between firms both in Michigan and elsewhere before and after MARA. The resulting data set spans 21 years and consists of 29,956 inventors and 162,586 patents of which 13,723 patents represent a *move*, that is, the first subsequent patent of an inventor after moving to a new firm. The final analysis is restricted to these mobile inventors because the pressure to explore new fields because of MARA only affects inventors who move between firms.

Sample Selection Bias. Our sample selection strategy could result in bias because treatment and control subjects were already different before the natural experiment, potentially confounding the results. Moreover, the natural experiment might affect the selection of treatment subjects, that is, inventors who move between firms in Michigan post-MARA. Although MARA provides an exogenous change in the cost to work in the same field of expertise at a different employer, more or less creative inventors might respond differently by (1) staying with their current employer rather than moving to a new firm and having to explore new fields, (2) moving to a different firm in the same state and presumably exploring new fields, (3) moving to another state and avoiding a lawsuit, or (4) stopping work for the time of the agreement. As one example of potential bias, more creative inventors probably have greater bargaining power to stay or go and have greater job opportunities inside or outside the same firm and state. This could influence their decision to move, the decision of the recruiting firm to hire them, and the decision to be included or excluded from the sample (Starr et al. 2018). To analyze whether sample selection is likely to affect our results, we compare a battery of inventor characteristics of the full population of both mobile and nonmobile inventors, both pre- and post-MARA, both in Michigan and other states.

To assess whether our treatment group is different, we calculate binary indicators of *Michigan* residence, a *postmara* application date of 1986 or later, and whether a subsequent patent is assigned to a new firm (and, thus, indicates a *move*). For inventor characteristics, we calculate all the study dependent variables: *sum new combinations (ln)* (total number of new pairwise subclass combinations for all prior patents of the focal inventor); *sum forward citations (ln)* (total number of forward citations received within 10 years for all prior patents of the focal inventor); and additional inventor characteristics *prior patents (ln)*, *specialization*, *prior collaborations (ln)*, *prior move*, and *days since first patent (ln)*. Table A.4 in the online appendix provides a description and summary statistics for the full population of inventors at risk for moving, both before and after MARA and in and out of Michigan.

The full interaction between the three indicators—*Michigan*, *postmara*, and *move*—identifies any dissimilarity of the treated inventors. Table A.5 in the online appendix illustrates that the treatment subjects are not significantly different in any of the characteristics. This reduces the likelihood that MARA influenced selection of the treatment subjects and that our results suffer from sample selection bias. Still, there might be other unobserved inventor characteristics affecting sample selection, and hence, caution remains warranted in the causal interpretation of results.

Coarsened Exact Matching. In an experiment, one ideally observes two identical groups of subjects over time, whereby one group is affected by an exogenous treatment at a particular point in time. To decrease the chance that pretreatment differences between the treated and control inventors confound the results, we construct a matched subsample of inventors using coarsened exact matching (CEM). This nonparametrical matching method segments the joint distribution of inventor characteristics into a finite number of strata using cut points for each characteristic, resulting in a subsample of similar treatment and control inventors belonging to the same strata while discarding others (Iacus et al. 2009, Iacus et al. 2011). We match mobile Michigan inventors to mobile inventors from other states on the following pre-MARA characteristics (cut points in parentheses): (1) number of prior patents (1, 2, 3, 4, 5, 6–10, 11–25, 26–50, >50), (2) total number of forward citations received by all prior patents within 10 years (0, 1, 2, 3, 4, 5, 6–10, 11–25, 26–50, 51–100, >100), (3) total number of new subclass combinations on all prior patents (0, 1, 2, 3, 4, 5, 6–10, 11–25, 26–50, 51–100, >100), (4) specialization (0, 0–0.25, 0.25–0.50, 0.50–0.75, >0.75), (5) whether the inventor previously moved between employers, and (6) whether the inventor works alone or collaborates (indicator that is one in case there are no coinventers on prior patents of the inventor). Jointly applying these six criteria, we obtain 1,969 strata. Only Michigan and non-Michigan mobile inventors for which there is at least one control, respectively, treatment inventor in the same stratum are retained. The resulting CEM sample consists of 9,270 observations (68% of the original sample), which is used as a robustness check for the full sample results. We obtain consistent results using the full and CEM samples and other samples as well.

Results. Table 4 provides summary statistics for the full sample of mobile inventors that is used in the analysis. We include two additional control variables that were not used in the inventor–firm fixed effects analysis. First, we include a binary indicator for inventor residence in a *nonenforcing state*. Although all subjects had at least one prior patent before MARA in a nonenforcing state, they might have moved to an enforcing state afterward. The likelihood of moving between firms and exploring new fields will be different for enforcing versus nonenforcing states (Marx et al. 2009). Second, because the turbulence in the auto industry in Michigan during the observed period (both pre- and post-MARA) might affect our results, we include *auto industry* as a binary indicator for auto patents (as identified by Marx et al. 2009).

Table 5 illustrates the differential trends that enable using MARA as a natural experiment, comparing the average rate of exploring new fields—calculated by dividing the number of patents indicating the exploration of new fields by the total number of patents—for mobile inventors in Michigan versus mobile inventors from other states, both pre- and post-MARA. The average rate of exploring new fields decreased slightly in Michigan post-MARA from 0.49 to 0.48. Yet the average rate of exploring new fields decreased sharply in the other states from 0.53 to 0.43. This decrease is often attributed to the increasing burden of knowledge that has shifted inventors to become more specialized over time (Jones 2009). Given that our sample only includes inventors with pre-MARA patents, the decrease is presumably also driven by the declining tendency of inventors to explore new fields later in their career. The difference-in-differences subtracts the difference in the comparison states from the difference in Michigan to determine the net effect of MARA. By doing so, DD controls for the overall declining trend in exploring new fields. The treatment effect of MARA is 0.09, representing a relative increase of 18% compared with the average pre-MARA rate of exploring new fields in Michigan.

To estimate the effect of exploring new fields on the novelty and value of invention, we use a two-stage least square model (2SLS). Because the endogenous variable is binary, we use the approach suggested by Angrist (2001) and Angrist and Pischke (2008). For a recent application of the approach, see Galasso and Schankerman (2015). First, we estimate the likelihood of exploring new fields with a logit model in a difference-in-differences configuration. We include the interaction between *Michigan* and *postmara* as an

Table 4. Summary Statistics MARA Sample

Variable	Mean	Standard deviation	Minimum	Maximum
New combinations (ln)	0.99	1.07	0.00	6.14
Forward citations (ln)	1.91	1.06	0.00	6.00
Exploring new fields	0.47	0.50	0.00	1.00
Expert team	0.33	0.47	0.00	1.00
Science	0.19	0.39	0.00	1.00
Michigan	0.13	0.34	0.00	1.00
Postmara	0.58	0.49	0.00	1.00
*Michigan*Postmara*	0.07	0.25	0.00	1.00
Nonenforcing state	0.93	0.25	0.00	1.00
Auto industry	0.04	0.18	0.00	1.00
Prior patents (ln)	1.54	0.75	0.69	5.00
Specialization	0.62	0.31	0.05	1.00
Prior collaborations (ln)	1.49	0.64	0.00	4.42
Prior move	0.30	0.46	0.00	1.00
Days since last patent (ln)	6.43	1.67	0.00	10.30
Days since first patent (ln)	7.84	1.01	0.00	10.37
Team	0.69	0.46	0.00	1.00
Team prior patents (ln)	0.70	0.90	0.00	4.58
Team specialization	0.86	0.23	0.07	1.00
Firm prior patents (ln)	2.58	2.59	0.00	9.77
Number of classes (ln)	0.53	0.50	0.00	2.48
Number of subclasses (ln)	1.29	0.64	0.00	4.19

Notes. The sample includes the first patent of an inventor after the inventor moved between two firms within the same state as evidenced by a different corporate assignee compared with the previous patent of the inventor. The sample is restricted to inventors with at least one prior patent before MARA (1985) in a nonenforcing state and to patents filed between 1975 and 1995 (10 years before and after MARA). The sample includes 13,723 inventor–patent observations. Nonenforcing state is a binary measure equal to one in case the inventor resides in a nonenforcing state. Auto industry is a binary measure equal to one for auto patents (see Marx et al. 2009). "(ln)" indicates logarithmic transformation after adding one for measures with zero values.

exogenous variable capturing the effect of the policy reversal. Using logit instead of OLS in the first stage results in a better fit. Second, we calculate the fitted probabilities of exploring new fields and use these nonlinear fitted values bound between zero and one as an instrument for exploring new fields in the 2SLS models. Using nonlinear fitted values as an instrument is the same as plugging in fitted values when the first stage is estimated by OLS, but the advantage is a better predictor of exploring new fields in the first stage (Angrist and Pischke 2008). The 2SLS model uses a single instrument, resulting in just-identified estimates. Standard errors are clustered at the inventor level to control for repeated observations. Table 6 shows the first stage predicting the likelihood to explore new fields for both the full and CEM samples. The coefficient of *Michigan* × *postmara* across the different models implies that MARA increased the likelihood of exploring new fields by 6%–7% in absolute terms in addition to the pre-MARA baseline of exploring new fields in Michigan of 49%. The *F* statistic for the first stage regression is consistently above 10, thus passing conventional tests of instrument strength (Stock and Yogo 2005).

Table 5. Difference-in-Differences Average Rate of Exploring New Fields

	Premara	Postmara	Difference
Michigan	0.49	0.48	−0.01
Non-Michigan	0.53	0.43	−0.10
Difference	−0.04	0.05	0.09

Notes. The average rates of exploring new fields are calculated by dividing the number of patents indicating the exploration of new fields by the total number of patents. The sample includes the first patent of an inventor after the inventor moved between two firms within the same state as evidenced by a different corporate assignee compared with the previous patent of the inventor. The sample is restricted to inventors with at least one prior patent before MARA (1985) in a nonenforcing state. The sample includes 13,723 inventor–patent observations. Rates are shown for Michigan inventors versus non-Michigan inventors, pre- and post-MARA. Although the rate of exploring new fields decreases strongly for non-Michigan inventors post-MARA, it remains more or less stable for Michigan inventors. The *difference-in-differences* indicates that MARA triggered mobile inventors in Michigan to explore new fields.

Table 7 displays OLS models and the second stage of the 2SLS models for both the full and CEM samples. It illustrates consistent and predicted results for all hypotheses. In line with hypothesis 1, mobile inventors who explore new fields create more novel inventions, increasing new combinations by 6%–7% in the OLS models (Models 1–3) and by 48%–65% in the 2SLS models (Models 4–6). Consistent with hypothesis 2, exploring new fields significantly and negatively affects the value of inventive output, decreasing forward citations by 1%–7% in the OLS models (Models 7–9) and by 41%–59% in the 2SLS models (Models 10–12). The only exception is the nonsignificance of exploring new fields in Model 7.[8] Collaboration with experts in the new field helps an inventor to overcome the learning challenge in the OLS models—the interaction effect increases citations by 14%–16% (Models 8 and 9)—but only partially ameliorates the negative first-order effect of exploring new fields in the 2SLS models; the interaction effect increases citations by 34%–36% (Models 11 and 12). Similarly, the interaction between exploring new fields and science is positive and significant and compensates the negative first-order effect of exploring new fields in the OLS models, increasing forward citations by 8%–11% (Models 8 and 9). In the 2SLS models, the interaction between exploring new fields and science only partially reduces the negative first-order effect of exploring new fields, increasing forward citations by 26%–35% (Models 11–12). Nonetheless, interaction effects with expert team and science together also outweigh the negative first-order effect of exploring new fields in the 2SLS models, resulting in a positive total effect on forward citations of 14%–18% (Models 11 and 12) compared with a total effect of exploring new fields of 15%–22% in the OLS models (Models 8 and 9).

Table 6. Regression Difference-in-Differences of the Likelihood to Explore New Fields

	(1)	(2)	(3)	(4)	(5)	(6)
Model	OLS	OLS	OLS	Logit	Logit	Logit
Sample	Full	Full	CEM	Full	Full	CEM
Michigan	−0.04**	−0.04**	−0.05**	−0.20**	−0.20**	−0.25**
	(0.02)	(0.02)	(0.02)	(0.09)	(0.09)	(0.10)
Postmara	−0.23***	0.04	0.05	−1.04***	0.20	0.26
	(0.03)	(0.03)	(0.05)	(0.16)	(0.18)	(0.23)
Michigan × postmara	0.07***	0.06**	0.06**	0.30***	0.28**	0.31**
	(0.03)	(0.02)	(0.03)	(0.11)	(0.12)	(0.13)
Expert team		−0.30***	−0.30***		−1.48***	−1.50***
		(0.01)	(0.01)		(0.06)	(0.08)
Science		−0.02	−0.03**		−0.09	−0.17**
		(0.01)	(0.01)		(0.06)	(0.07)
Log likelihood				−8,728.87	−7,865.13	−5,262.15
R-squared	0.103	0.209	0.220			
N	13,723	13,723	9,270	13,723	13,723	9,270

Notes. The dependent variable is exploring new fields. The sample includes the first patent of an inventor after the inventor moved between two firms within the same state as evidenced by a different corporate assignee compared with the previous patent of the inventor. The sample is restricted to inventors with at least one prior patent before MARA (1985) in a nonenforcing state and to patents filed between 1975 and 1995 (n = 13,723 inventor–patent observations). CEM indicates subsample of matched inventors using coarsened exact matching (n = 9,270 inventor–patent observations). All models include controls for number of classes (ln), number of subclasses (ln), year and technology class indicators. Models 2, 3, 5, and 6 include additional controls for nonenforcing state, auto industry, prior patents (ln), specialization, prior collaborations (ln), prior move, days since last patent (ln), days since first patent (ln), team, team prior patents (ln), team specialization, firm prior patents (ln). Robust standard errors in parentheses, clustered by inventor. The interaction *Michigan* × *postmara* captures the effect of MARA and illustrates how MARA triggered mobile inventors in Michigan to explore new fields.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Overall, the results from the 2SLS models are stronger compared with the results of the OLS models and the inventor–firm fixed effects models, which did not correct for the potential endogeneity of exploring new fields. They are close in magnitude to those reported by Hoisl and Rassenfosse (2014), who measured inventor mobility with a survey and patent value using forward citations. We offer one potential explanation that MARA provides an exogenous change in the cost to work in the same field of expertise at a different employer, thereby nudging mobile inventors to explore new fields, compared with a situation in which inventors voluntarily explore new fields.

Discussion

This work makes four main contributions. First, it integrates opposite theories and predictions of the relationship between individual field-specific expertise and creative output by offering a simple model of search that distinguishes between novelty and value. Second, it provides evidence for the impact of exploring new fields on inventive output, combining inventor–firm fixed effects models on a large population of inventors with difference-in-differences models that exploit a change in labor law as a natural experiment. The models and measures together illustrate how exploring new fields both increases the novelty of inventive output—arguably because of knowledge diversity and combinatorial opportunities—but decreases the value of that output, presumably because of the learning challenge in the new field. Third, the work suggests potential ways that inventors and firms might overcome the negative impact of exploring new fields through collaboration with experts and reliance on published science in the new field. Finally, as explored as follows, it extends the implications of a social–psychological and economic model of invention at the individual level to a regional level.

The study has several limitations. First, the typical reservations concerning the use of patent data apply. Not all inventive output is patented and subsequently granted, particularly failed or less successful inventive attempts. Second, the results also rely upon inventor disambiguation and inventors with at least two patents. Third, although an analysis of a larger population of inventors demonstrates that the treatment group affected by the natural experiment is not significantly different in any of the observable characteristics, it remains possible that other unobserved characteristics caused inventors and firms to respond differently to the labor law change and thereby resulted in bias. In particular, the unobservable nature of inventors' stock of ideas might drive selection into moving to a different firm and exploring new fields. Fourth, although we

Table 7. OLS and 2SLS Models Exploring New Fields MARA Sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	New comb. (ln)	New comb. (ln)	New comb. (ln)	New comb. (ln)	New comb. (ln)	New comb. (ln)	Forward cit. (ln)	Forward cit. (ln)	Forward cit. (ln)	Forward cit. (ln)	Forward cit. (ln)	Forward cit. (ln)
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS	OLS	OLS	OLS	2SLS	2SLS	2SLS
Sample	Full	Full	CEM	Full	Full	CEM	Full	Full	CEM	Full	Full	CEM
Exploring new fields	0.07***	0.06***	0.06***	0.49*	0.50*	0.39*	−0.01	−0.07***	−0.05**	−0.88**	−0.84**	−0.53*
	(0.01)	(0.02)	(0.02)	(0.27)	(0.27)	(0.22)	(0.02)	(0.02)	(0.03)	(0.38)	(0.37)	(0.31)
Exploring new fields × expert team		0.05*	0.04		0.26***	0.15*		0.13***	0.15***		0.31***	0.29**
		(0.03)	(0.03)		(0.08)	(0.08)		(0.04)	(0.05)		(0.11)	(0.11)
Exploring new fields × science		−0.03	−0.03		−0.01	0.04		0.08*	0.10*		0.30***	0.23*
		(0.03)	(0.04)		(0.09)	(0.09)		(0.04)	(0.05)		(0.12)	(0.13)
Expert team	−0.05***	−0.07***	−0.05*	0.08	−0.01	0.01	0.05**	−0.00	−0.03	−0.21*	−0.29**	−0.22*
	(0.02)	(0.02)	(0.03)	(0.08)	(0.09)	(0.08)	(0.03)	(0.03)	(0.04)	(0.12)	(0.12)	(0.11)
Science	0.01	0.02	0.04	0.02	0.02	0.03	0.15***	0.11***	0.12***	0.13***	0.01	0.05
	(0.02)	(0.02)	(0.03)	(0.02)	(0.04)	(0.05)	(0.02)	(0.03)	(0.04)	(0.03)	(0.06)	(0.07)
IV test. F statistic first stage.				61.88		82.54				61.88		82.54
R-squared	0.645	0.645	0.643	0.613	0.598	0.616	0.297	0.298	0.306	0.160	0.210	0.270
N	13,723	13,723	9,270	13,723	13,723	9,270	13,723	13,723	9,270	13,723	13,723	9,270

Notes. The sample includes the first patent of an inventor after the inventor moved between two firms within the same state as evidenced by a different corporate assignee compared with the previous patent of the inventor. The sample is restricted to inventors with at least one prior patent before MARA (1985) in a nonenforcing state and to patents filed between 1975 and 1995 (n = 13,723 inventor–patent observations). CEM indicates subsample of matched inventors using coarsened exact matching (n = 9,270 inventor–patent observations). All models include controls for Michigan, postmara, nonenforcing state, auto industry, prior patents (ln), specialization, prior collaborations (ln), prior move, days since last patent (ln), days since first patent (ln), team, team prior patents (ln), team specialization, firm prior patents (ln), number of classes (ln), number of subclasses (ln), year and technology class indicators. The interaction *Michigan* × *postmara* is used as an instrument for exploring new fields in the 2SLS models. Robust standard errors in parentheses, clustered by inventor.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

provide an instrument for exploring new fields, we unfortunately have no instruments for collaboration with experts and reliance on published science. The positive interaction between exploring new fields and expert team might, for example, be driven by the fact that experts help ex post with a better diffusion of the invention rather than by ex ante helping and directing the novice during the invention process itself. The novice might lack legitimacy in the new field (Cattani et al. 2017). Or novices with unobserved higher quality ideas might convince experts in the field to collaborate with them. Similarly, citing scientific publications might be a proxy for better and more fundamental inventions. Finally, future work might use text to measure patent novelty and similarity (Arts et al. 2018, Balsmeier et al. 2018).

Our findings have implications for inventors, their firms, and policymakers. First, and in contrast to prior research that ignores the upside of exploitation, these results illustrate the pitfalls of exploration for individuals and, in turn, for the firms that employ those individuals (Audia and Goncalo 2007, Groysberg and Lee 2009, Hoisl and Rassenfosse 2014). Although exploration connotes bravery, discovery, and success, reality often means failure, especially in the short term. The current results are consistent with other quasi-experimental work that illustrates performance benefits to exploitation at the firm level (Balsmeier et al. 2017). This is not a new idea and, indeed, constitutes a central tenet of March's (1991) arguments.

Second, we illustrate a practical and legal challenge for technical professionals and the firms that employ them. Firms want to find professionals with a particular set of skills and expertise, and that expertise has typically been gained at a prior employer (Tzabbar 2009, Tzabbar et al. 2015). If the firm operates in a region that enforces noncompetes, it will more often be forced to hire someone with less pertinent skills and retrain that person. The explorative inventor and the inventor's firm will suffer decreased value of output (Groysberg and Lee (2009) make similar arguments for securities analysts and investment banks). This may not be entirely bad as the more technically distant candidate should also create greater novelty. Furthermore, embedding the exploration candidate within networks of experts or hiring someone with facility in using the published scientific literature can greatly mitigate the risks of exploration. One implication of the current work is that individuals who collaborate with experts in the new field or who can access the literature may overcome the downside of exploration more quickly, and more empirical and insular inventors may take longer.

Third, and in nuanced contradiction to Silicon Valley's reputation as a hotbed of invention, this work implies that regions that enforce noncompetes invent more novel patents on average. As shown in Table A.6 in the online appendix, we find evidence that enforcing states invent patents with more new combinations, on average, but fewer forward citations, and that higher enforceability—measured by the state-level time-varying enforceability index of Garmaise (2009)—relates positively to new combinations and negatively to forward citations. We confirm these predictions using the Michigan experiment as an exogenous change in enforceability (Table A.7 in the online appendix).

Conti (2014) makes a different argument with similar outcomes; namely, firms consciously undertake riskier research and development because of decreased outbound mobility of their engineers and assumedly less knowledge leakage. Using changes in Texas and Florida noncompete laws, he illustrated increased entry of firms into new technology classes. Whether this results from strategic action or unrealized differences in labor mobility remains unclear (and a good topic for future investigation). Independent of resource allocation decisions, our results illustrate how two mobility mechanisms could cause regions that enforce noncompetes to invent more novel patents. First, as illustrated here, inventors move further in technical distance from their old expertise when changing jobs; this greater movement results in more novel patents. Second, if inventors' outside options become more limited, they might be more likely to explore new fields within their current employer as well. Indeed, in unreported regressions, we found a positive though not always significant impact of MARA on intrafirm field exploration as well. The downside is less valuable output as illustrated here.

If these mechanisms aggregate to the regional level, then Silicon Valley's advantage may derive not from its ability to invent new technologies as much as to exploit and refine already identified and productive trajectories or promising breakthroughs. This line of reasoning implies multiple questions; for example, are regions that enforce noncompetes doing greater exploration and, in effect, subsidizing search for regions that proscribe their enforcement? If so, do we see a flow of promising exploration breakthroughs in ideas and/or people from enforcing to nonenforcing regions? Marx and Fleming (2012) demonstrate that better inventors (as measured by citations to their patents or propensity to collaborate) are more likely to emigrate from enforcing to nonenforcing states. Are these inventors carrying more novel and original knowledge as well? Is novelty planted in regions that enforce but harvested in regions that do not?

Finally, exploring new fields may or may not increase the chance of a breakthrough; both predictions can be motivated. On the one hand, when a field-experienced inventor creates novelty, one might expect that novelty to have greater future use, on average, because a field-experienced inventor can probably winnow failures more effectively. On the other hand, when a field-exploring inventor creates novelty, one might expect greater upside and fertility and less chance of incremental improvement. In line with the predictions of Gilfillan (1935) and Kuhn (1970) that breakthroughs are often made by novices who are new to the field, the fixed effects models illustrate a positive first-order effect of exploring new fields on the likelihood to invent a breakthrough measured as a binary indicator equal to one for patents in the top 5% in terms of forward citations among patents from the same class and year (e.g., Singh and Fleming 2010, Ahmadpoor and Jones 2017). Results are displayed in Table A.8 in the online appendix. As such, exploring new fields increases the novelty of inventive output and the chance of a breakthrough but simultaneously reduces the average value of that output (March 1991, Fleming 2001). The inclusion of interactions with expert team and science renders the first-order effect of exploring new fields on the likelihood of breakthrough insignificant, illustrating that successful exploration benefits from reliance on scientific prior art in the new field or—to a smaller extent in this context—collaboration with experts. Unfortunately, the MARA data are too thin to test these predictions, and we lack instruments for expert collaboration and science. Future work should develop and test these ideas in a new context with stronger identification.

Conclusion

Creative search is risky, and the optimal strategy uncertain. Inventors face a fundamental trade-off between local search and exploitation versus distant search and exploration (March 1991, Audia and Goncalo 2007). Inventors cannot avoid this fundamental conundrum; every time they create, they choose—implicitly or explicitly—to work within more or less familiar approaches. This endogenous choice, thus, causes first-order methodological problems in studying the impact of search strategy on inventive output. We approached this problem by considering within firm and inventor fixed effects models and an unforeseen labor law reform that nudged inventors to explore new fields when moving to a new firm. We further exploited difference-in-differences and matching approaches that enabled close comparison of inventors that were and were not affected by the change in labor law.

Armed with these methodological tools, we fashioned an informal model from two conflicting perspectives. One perspective begins with the returns of specialization and accumulated expertise upon the value of inventive output and implies greater creativity from remaining within the existing fields of expertise. Another perspective begins with the value of knowledge diversity and recombinant fecundity and implies the opposite prediction: greater creativity from exploring new fields. We believe both of these arguments have merit and contribute to the debate by separately estimating the impact of exploration on two different characteristics of creative output, novelty, and value. Consistent with our informal model, inventors who explore new fields invent more novel patents; inventors who do not explore new fields invent more valuable patents. Inventors can overcome the difficulties of exploration and the associated decline in value through collaboration and application of scientific knowledge.

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Endnotes

[1] As illustrated later, we find consistent support for all hypotheses using a subsample of inventors with at least 13 prior patents, that is, the 75th percentile in the distribution of prior patents.

[2] Our main findings are robust for the subset of single-authored patents (e.g., Jones 2009). Results not shown.

[3] We find consistent results using the number of citations to scientific literature rather than a binary measure (results not shown).

[4] (ln) indicates the logarithmic transformation of a measure after adding one for measures with zero values.

[5] New combinations and forward citations vary over fields and time. Including additional control variables for the average number of new combinations and for the average number of forward citations received by patents from the same class and year does not change any of our findings (results not shown).

[6] $e^{(0.0646)} - 1 = 6.7\%$. Because all outcome variables capturing novelty and value are calculated as the logarithmic transformation of count measures after adding one and because exploring new fields—and its interaction with expert team and science—are binary measures, the marginal effects are calculated as $[e^{(\textit{estimated coefficient})} - 1]$. The average number of new combinations is 2.7, so a 1% increase corresponds with an absolute increase of 0.03 new combinations per patent, and a 6.7% increase corresponds with an absolute increase of 0.18 new combinations per patent (Table 2, Model 1). The average number of forward citations is 5.99, so a 1% decrease corresponds to an absolute decrease of 0.06 citations per patent, and a 4% decrease corresponds to an absolute decrease of 0.24 citations per patent (Table 2, Model 10).

[7] We would like to thank a reviewer who pointed out these competing possibilities.

[8] For the MARA sample, the average number of new combinations is 4.65, so a 1% increase corresponds with an absolute increase of 0.05 new combinations per patent, and a 65% increase corresponds with

an absolute increase of three new combinations per patent. The average number of forward citations is 11.22, so a 1% decrease corresponds with an absolute decrease of 0.11 citations per patent, and a 59% decrease corresponds with an absolute decrease of 6.62 citations per patent.

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