Paradise of Novelty – or Loss of Human Capital? A Natural Experiment in Switching Fields and Creative Output

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ABSTRACT

What happens to a person's creative output when they switch fields? Switching results in a loss of expertise that might harm subsequent productivity, yet exposure to new knowledge and approaches might also increase subsequent novelty. Using unintended labor law change as an exogenous source of variation in changing fields among inventors who change employers, we find that switching inventors create less useful yet more novel patents. Inventors that switch may also take longer to resume patenting after moving. Collaboration at the new firm and reliance on published science ameliorate the productivity loss while maintaining the increased novelty. The research introduces new metrics and the results resolve differing predictions of economic versus evolutionary theories of creativity and innovation.

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INTRODUCTION

"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, Book IV, Chapter V, p. 563.

"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, pp. 89-90.

Search is uncertain and the optimal strategy rarely reveals itself. 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 creativity and innovation. On the one hand – and more consistent with an economics perspective – people should exploit and build upon their prior success and expertise (Smith 1776, Jovanovic 1979). On the other hand – and more consistent with an evolutionary perspective – people should explore and learn new approaches in the hope of sparking creative insights and new combinations (Campbell 1960, Kuhn 1970, Merton 1973: 518).

We offer a resolution to these competing models of creative and innovative search, drawing theoretically from March (1991) and proceeding empirically with more nuanced metrics of creative output. While the random assignment of laboratory studies could establish causality, we instead exploit a natural experiment in non-compete labor law, the Michigan Antitrust Reform Act (Marx et al. 2009), and provide evidence from career moves of inventors. Prior econometric and field work has established that inventors subject to non-competes are more likely to take jobs in less familiar fields after they leave their ex-employer, arguably to avoid a potential lawsuit (Marx 2011). We first replicate these results by modeling a difference-in-differences specification to estimate the impact of the policy reform on inventors' switching fields. We also match on similar inventors in states that proscribed enforcement before and after the Michigan change (for a similar identification strategy across time and cohorts, see

Duflo 2001). In essence, this approach simulates a randomized match between a job-changer and the technical fit with his or her new firm.

Consistent with economic arguments that stress experience and the accretion of specialized human capital, we find that inventors who switch fields create less useful inventions, as measured by USPTO maintenance renewals and future citations (-35% and -37%, respectively). Consistent with evolutionary arguments that stress exposure to diversity and fresh perspectives, we find that inventors who switch fields create more novel inventions, as measured by new to the patent corpus words and fewer backwards citations (+54% and -34%, respectively). We also find that inventors who change fields take longer to start patenting again in the new field, though the effect is not quite significant. Split sample analyses indicate that collaboration and reference to published science can ameliorate the productivity loss while maintaining greater novelty.

The work highlights new and neglected measures for the creativity and innovation literature (maintenance renewal for usefulness or value, see Schankerman and Pakes 1986; Harhoff et al. 1999, and a completely novel measure, new to the patent corpus words for novelty, see Balsmeier et al. 2015a), a resolution to differing predictions from economic versus evolutionary theories of creative and innovative search, and normative insights for creative professionals and their managers. It provides some of the first well-identified evidence to 1) support the predictions of March (1991) and 2) observe how a job match influences an employee's subsequent output.

DEFINITIONS AND MODELS OF CREATIVTY

Economists have long argued for the benefits of specialization in labor and trade (Smith 1776, Ricardo 1817) and these paradigmatic fundamentals strongly influence economic thinking on innovation. Economic historians have argued that the origins of an innovation can almost always be traced to pre-existing knowledge and technology (Mokyr 1990). Because technological progress is a cumulative problem-solving process, people typically rely upon prior knowledge (Rosenberg 1982, Cohen and Levinthal 1990). In order to first reach and then contribute to the state of the art, people need to accumulate knowledge about the existing prior art in the field as well as field-specific learning and problem-solving skills (Jones 2009). Case studies point out that deep immersion in the field of expertise is crucial before any significant innovation can be produced by an individual; a person's field-specific knowledge and skills are the foundation on which the creative thinking process builds the new (Simon 1983, 1996). Assuming that people move to a better job match for their extant skill set, they should be more productive when they move voluntarily (Jovanovic 1979; for evidence, see Hoisl and Rassenfosse 2015).

Evolutionary scholars, however, stress the importance of diversity on creative output. Exposure to social, cognitive, and artifactual 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 raw material mechanically affords more possibilities. Beyond the increased but purely combinatorial possibilities, many have argued that exposure to diversity makes people more creative. While prior learning and existing paradigms help a person to interpret information and guide creative search, they may also cause learning myopia and constrain the direction of search (Allen and Marquis 1964, Ward 1995). Scholars have labeled this cognitive process that causes extant expertise to block creative insights as inflexibility of the information processing system, negative transfer, Einstellung, or mental block (e.g., Luchins and Luchins 1959, French and Sternberg 1989). Many have argued that creative professionals should move between fields and industries, and become generalists rather than specialists (e.g., French and Sternberg 1989: 183). By switching fields, they are freed from conventions and dogmas in any field, and triggered to adopt fresh perspectives and heuristics, and to approach problems with a certain level of naïveté (Merton 1973: 518). Psychologists have fallen into both the economic (which they label as "foundational") and evolutionary (labeled "tension", see Weisberg 1999) camps.

Extensions of the evolutionary argument resonate throughout the technology and science creativity literature. For instance, Gilfillan (1935) and Kuhn (1970) argue that revolutionary discoveries are most likely made by people working outside a field. Outsiders remain free and unbounded 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: 518, Gieryn and Hirsh 1983). Established cognitive maps and technological paradigms embody clear prescriptions on which search trajectory to follow (Dosi 1982). They become institutionalized into a field so that insiders 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 familiar trajectories, even while novel or "revolutionary" ideas and possibilities are thought to originate from breaking with the familiar trajectory (Kuhn 1970, Arts and Veugelers 2014). Supporting these prescriptions, Jeppesen and Lakhani (2010) find that the winning solutions to problem solving contests are more likely provided by inventors with technical expertise that is "distant" from the problem field.

We agree with many of these arguments and offer a simple model to resolve the controversy. We provide support for the model with more nuanced measures of creativity and innovation that explicitly distinguish novelty from usefulness. Following Henderson and Clark (1990), we define a new idea or invention as a combination of previously uncombined ideas or components or the re-arrangement of previously used ideas or components. This definition makes no comment on the creativity or success of that combination or re-arrangement (Kaplan and Vakili 2014). Amabile (1996) stipulates that creativity by definition requires novelty *and* usefulness; we agree these variables are crucial, however, we do not simultaneously require both and allow them to vary within a new idea or invention. By our definition, an invention can be useful but not very novel, novel but not very useful, or varying degrees of both. We will measure these characteristics continuously, assuming that the U.S. patent office saw a threshold of legal novelty that allowed the patent in the first place. This definition avoids the normative connotation that all innovation is intrinsically beneficial or successful, despite the empirical reality that most new ideas fail and/or have little impact. While our evidence comes from patent data and our prose often refers to inventors, these arguments should hold for other creative and mobile professionals such as scientists or designers.

Our simple model is thus: Inventors that change fields are exposed to new knowledge, perspectives, approaches, components and new ways to combine components. This exposure increases the likelihood that the inventor will create new components and combine them into more novel and original configurations, for a variety of reasons, including simple combinatorial opportunities, psychological refreshment, unblocking, and re-arrangement of extant knowledge structures. Working in a new field will encourage the inventor to question his or her assumptions, abstractions, creative goals, approaches, target customer or user, success metrics, and prior procedures and solutions. Field change and career exploration is difficult and requires time, however (Groysberg and Lee 2009); it causes mistakes, errors, and delay, while the inventor climbs the learning curve in the new field and connects their fresh ideas to their extant reservoir of experience (Rosenkopf and Almeida 2003). It demands flexibility and the re-arrangement and re-coding of prior knowledge (French and Sternberg 1989). As a result of unavoidable exploration, the inventor's productivity drops following a switch, however, the likelihood of novel output increases.

Hypothesis 1: Mobile inventors who do not switch fields create more useful inventions.

Hypothesis 2: Mobile inventors who switch fields create more novel inventions.

This informal model implies additional observable outcomes. After switching to a new field, a person will need time to bring him- or herself to the frontier of knowledge before he or she can contribute something (Jones 2009). For instance, Chase and Simon (1973) and Hayes (1989) found that creative individuals require an extensive amount of time between the initial exposure to the field and the creation of their first significant contribution. Empirically, we expect to observe that switching will lengthen the time an inventor needs in order to develop a subsequent patent, i.e. his or her first patent in the new field.

We also expect that the negative effect of switching fields on the usefulness of invention should be less pronounced if the inventor collaborates with others in their new firm. Likewise, the positive effect of switching fields on the novelty of invention should be larger for collaborative inventors compared to individual inventors. The first effect occurs because collaboration can ease the "burden of knowledge" (Jones 2009) and make learning a new field less difficult and inefficient. The second effect occurs because new collaborations can stimulate novel insights and creativity (Wuchty et al. 2007). Collaborators can take advantage of their newcomer's creativity but also filter the immature and naïve combinations. This mechanism relies on more effective and efficient teaching and learning and does not relay on moving extant collaborative capital (commonly known as "lift-outs" see Groysberg and Lee 2009). Thus collaboration improves both downsides.

We expect similar benefits from inventors who draw upon published science, because theories and prior empirical work enable more efficient search and suggest novel approaches. Awareness of published science facilitates prediction and decreases the need for empirical iteration, experimentation, and learning (Fleming and Sorenson 2004, Roach and Cohen 2013). Science can illuminate dead ends before they are explored, through models that can predict a lack of performance, or publication of previous results that show an approach has already been tried unsuccessfully. Exposure to the science literature should also increase an inventor's exposure to diversity and new ideas from other fields.

METHODS

Research Design and Identification Strategy

Any archival study that links a field switch to a change in creative output must confront a serious endogeneity challenge. As perhaps the most obvious problem, a person might choose to switch in order to become more creative – and had already identified a fruitful opportunity. Additional empirical challenges must also be considered. For example, more creative people might cross boundaries between fields more successfully due to their diverse knowledge base and cognitive flexibility. Alternatively, less creative or productive people might fail to find continuous employment in their area of expertise so that they are forced to switch fields. Finally, due to the increasing burden of knowledge on more recent generations, technical professionals have become increasingly specialized so that there is a decreasing tendency to switch fields over time (Jones 2009). To address these issues, the study design must provide an exogenous influence upon switching, consider similarly productive and creative subjects, and control for time, field, and other confounders. We address each of these in turn.

To overcome endogeneity, we exploit a natural experiment related to the inadvertent reversal of non-compete enforcement law in Michigan. In 1985, the Michigan Antitrust Reform Act (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 non-compete agreements in Michigan (Alterman 1985). After the passing of MARA in 1985, employers in Michigan obtained the legal means to prevent their ex-employees from working for competitors in the same field after they left the firm (Marx et al. 2009). As such, the Michigan experiment provides an exogenous pressure on inventors to switch fields after they left their former employer because of the threat of a potential lawsuit. Marx (2011) establishes this with interviews of 52 inventors, a survey of 1,029 inventors, and econometric models of inventor mobility. The policy reversal provides a natural experiment to the extent that it was an unintentional, unexpected and exogenous change (Alterman 1985, Bullard 1985) that had a significant impact on the endogenous explanatory variable, i.e. inventors changing technical fields after moving between employers within the state.

The time at which an inventor moves between firms (pre- or post-MARA) as well as his or her state of residence (Michigan versus other non-enforcing states) determine the likelihood that an inventor changes fields. Our identification strategy relies on the fact that only inventors residing in Michigan after the passing of MARA are affected by the exogenous change in non-compete enforcement; 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 switching technical fields within different states (Michigan versus other non-enforcing states) with differences across cohorts induced by the policy change (pre-MARA versus post-MARA). After controlling for Michigan residence and the policy-induced cohort effect (post-MARA), the interaction between Michigan residence and the policy-induced cohort can be interpreted as an exogenous variable capturing the causal effect of MARA, which can be used an instrument for switching fields. As such, we can estimate the relationship between an inventor switching fields and his or her creative output. For a similar identification strategy using the interaction between policy-induced cohort and region dummies as an instrument, see Duflo (2001).

If MARA exogenously increased the likelihood that mobile inventors in Michigan switched fields, the interaction between the Michigan residence dummy and the post-MARA dummy should have a positive and significant effect on the likelihood of switching fields while controlling for Michigan residence and cohort effects. This difference-in-differences (DD) specification controls for overall time trends in switching fields (across all states) and for time invariant unobserved differences between Michigan inventors and inventors from other non-enforcing states (Angrist and Pischke 2008). Furthermore, regression DD allows us to include additional inventor and field characteristics affecting the likelihood of switching as control variables. The DD can be interpreted as the causal effect of MARA, under the assumption that in the absence of MARA, the trend in switching fields would not have been systematically different between Michigan inventors and inventors from other non-enforcing states. To further strengthen the latter assumption, we use Coarsened Exact Matching (CEM) to match Michigan inventors to inventors from other non-enforcing states on pre-MARA characteristics such industry of employment, number of prior patents, number of received citations, and technical specialization, as explained below. An additional advantage of MARA is that it is expected to result in an exogenous increase in switching fields while there is an overall decreasing trend in switching.

Sample and Data Collection

We study the effect of switching fields on inventor output using the U.S. patent database for several reasons. First, patent data is publically available and provides a detailed insight into the output of a large sample of inventors. The US inventor disambiguated database allows us to construct the complete patenting history of an inventor (Li et al. 2014). Second, new metrics from patent data allow us to separately measure the novelty and usefulness of an inventor's inventions. Third, given that the USPTO assigned patents into technology classes, the data allows us to identify whether an inventor switched fields over time (Jones 2009). Fourth, a patent lists a filing date and the address of the inventor so that we can identify inventors residing in Michigan or other non-enforcing states both before and after the passing of MARA. As such, we can construct different treatments (before and after MARA, Michigan and non-Michigan inventors). Fifth, a patent lists an assignee that is typically the employer of the inventor. To identify different employers, we made use of the NBER harmonized assignee database containing harmonized names matched to firm identifiers for Compustat firms. The database helps us to correct for artificial moves for instance due to different name variant of the same firm and moves between different subsidiaries of the same firm.

In line with prior research, we select all U.S. inventors who patented in Michigan or in another non-enforcing 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). We retrieve all patents linked to this set of inventors from 1975-1995. Inventors who did not patent in a non-enforcing state or only did so after the passing of MARA are excluded. We only include inventors who were already active before the passing of MARA to ensure that MARA did not affect entry into our sample selection. In addition, only inventors who move between firms and who reside in a state where non-competes are enforceable are likely to switch fields to avoid a potential lawsuit (Marx 2011). Therefore, we further restrict the sample to intrastate mobile inventors who move between two firms as evidenced by having different corporate assignees on two successive patents. Only the *second* patent with the new employer as assignee is included in the statistical estimations. In case inventors move back and forth between firms, we only include the first patent with a new corporate assignee because the patent with a former employer might be filed after the inventor already left. Furthermore, we only include inventors who move between two firms but who do not change their state of residence because inventors can migrate to a state where non competes are non-enforceable to avoid a potential lawsuit without having to switch fields (Marx et al. 2015). Finally, we restrict the analysis to the 1975-1995 period, i.e. 10 years before and after the passing of MARA. The resulting dataset spans 21 years and consists of 13,723 patents linked to 9,269 unique mobile inventors.

To refine the comparability of treated and control subjects, we constructed a matched subsample of inventors using Coarsened Exact Matching (CEM). CEM is a nonparametric multivariate matching method that reduces the covariate imbalance between treated and control groups (Iacus et al. 2009, 2011). The objective of CEM is to improve the estimation of causal effects by reducing imbalance, model dependence and statistical bias. We first match mobile Michigan inventors to the control group of mobile inventors from other non-enforcing states on the following pre-MARA characteristics: (1) industry[1] (chemical, computer and communications, drugs and medical, electrical and electronic, mechanical, others), (2) technical specialization measured by the number of distinct NBER subcategories the inventor patented in (see appendix for an overview), (3) number of patents, (4) total number of received citations, (5) whether the inventor previously moved between employers, and (6) whether the inventor works alone or collaborates. We relied on CEM coarsening algorithm to develop coarsened strata. Jointly applying these 6 criteria, we obtain 3,610 strata. Only Michigan and non-Michigan inventors for which there is at least one control respectively treatment inventor in the same stratum are retained. The resulting sample consists of 6,246 patents (46% of the original sample) linked to 4,686 unique inventors (51% of the original sample). In the analysis, the matched patents of Michigan inventors get a weight of 1 and the matched control patents get a weight equal to (Iacus et al. 2011):

[1] To determine the industry of employment, we used the main technology class of the last patent of the inventor filed before 1985. See Appendix for an overview.

$$\left[\frac{\text{\# matched control patents in the stratum}}{\text{\# matched treated patents in the stratum}} \, x \, \frac{\text{\# treated patents in the stratum}}{\text{\# control patents in the stratum}}\right]$$

Measures

Outcome variables.

Much of the contradiction between economic and evolutionary predictions can be resolved through more detailed measures of creativity and innovation. To paraphrase the current problems in thinking about and measuring innovation, just because something is an innovation does not guarantee it is useful or successful, and just because something is patented or cited does not mean that it is very novel. For example, firms can increase their patent and citation counts by exploiting prior expertise and shying away from new fields (Balsmeier, Fleming, and Manso 2015).

To assess usefulness, we calculate *renewals* as the number of times a patent is renewed by its owner. In order to remain valid, patent renewal fees must be paid to the US Patent and Trademark Office. This occurs after 3.5, 7.5, and 11.5 years. [4] Patents that are renewed are, on average, more useful and valuable to their owner (Schankerman and Pakes 1986). We also use the number of *forward citations* received within 10 years to measure the value or usefulness of a patent (Harhoff et al. 1999), though this measure is noisy (Bessen 2008; Kaplan and Vakili 2014) and correlates with examiner bias (Alcacer and Gittleman 2006), knowledge diffusion (Thompson and Fox-Kean 2005), and the size of the inventive team (Wuchty et al. 2007). While we find consistent results with renewals and forward citations, we believe renewals provide a cleaner measure of our theoretical construct.

We use two metrics to assess novelty. First, we count the number of *new words* appearing in a patent for the first time in the US patent corpus. To calculate the measure, we tokenized all words in the title, abstract, and claims, for all patents back to 1975. No stop words were removed nor were spelling errors identified, though numbers and hyphens were removed. In order to provide a baseline in the years

[4] For more information, see http://www.uspto.gov/learning-and-resources/fees-and-payment/uspto-fee-schedule. 28% of the patents in our sample are not renewed 4 years after grant while 42% are renewed three times (the maximum).

of 1975-1979, the measure only begins in 1980. Second, we count for each patent the number of *backward citations*. Patents with fewer backward citations rely less on technical prior art and might be considered more novel (Ahuja and Lampert 2001). All measures illustrate consistent though not always significant results. Alternate measures of new subclass combinations or new combinations of citations also showed consistent results.

Independent variables.

Switching fields. We retrieve the patent classes of an inventor's prior patents and identify whether there is any overlap between the class(es) of the focal patent assigned to the new employer and the class(es) of the previous patents. Switching fields is a binary variable that is coded one in case there is no overlap.

Control variables.

The control variables include binary variables for inventor residence in *Michigan,* a *postmara* patent application date of 1986 or later, and inventor residence in a *non-enforcing state.* The latter control is included because the inventors in our sample might have moved to an enforcing state. Michigan and postmara are interacted to create a binary variable for inventors affected by the exogenous change in non-compete enforcement. The interaction will be used as the instrumental variable for switching. The turbulence in the auto industry in Michigan during the observed period (both pre and post-MARA) might affect the likelihood of changing fields compared to inventors in other states. To control for a potential bias, we include *auto industry* as a binary variable coded one for auto patents. The appendix provides an overview of the different patent classes associated with the auto industry (Marx et al. 2009).

Additional controls are included for an inventor's *number of prior patents, technical specialization* (measured as a Herfindahl concentration index of an inventor's prior patents across three-digit USPTO classes), *number of prior collaborations*, and whether the inventor previously switched employers (*prior move*). More productive inventors, inventors who are technology generalists rather than specialists, and inventors who formerly collaborated with a larger number of co-inventors, or who switched between employers, might be more or less inclined to switch 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 switch fields, we include the number of days since the first patent of the inventor was filed (*time since first patent).* To control for the fact an inventor who more recently moved between firms might be more or less likely to switch fields, we include the number of days since the previous patent of the inventor was filed (*time since last patent*). To control for respectively team and firm size, we include the *number of inventors* on the patent and the total *number of prior patents of the recruiting firm*. Finally, we include *number of classes* as the patent's number of three-digit patent classes and *number of subclasses*. *Year dummies* control for period differences and the decreasing tendency to switch fields over time. Three-digit *technology class dummies* control for the fact that specialization and switching fields differ across technology fields. Table 1 presents a description and descriptive statistics for all variables used in our study and Table 2 presents correlations among the different variables.

Insert Tables 1 and 2 here

Models

To estimate the effect of switching fields on the novelty and usefulness 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: 143). For a recent application of the approach, see Galasso and Schankerman (2015). First, we estimate the likelihood of switching fields with a logit model in a difference-in-differences configuration. We include the interaction between Michigan residence and the policy-induced cohort effect (post-MARA) as an exogenous variable capturing the causal effect of the inadvertent policy reversal, Michigan residence, post-MARA, and all other control variables. Using logit instead of OLS in the first stage results in a better fit. Second, we calculate the fitted probabilities of switching and use these nonlinear fitted values bound between 0 and 1 as an instrument for switching in the 2SLS models. Using fitted values as instrument is the same as plugging in fitted values when the first stage is estimated by OLS, but the advantage is that we get a better predictor of switching in the first stage compared to OLS (Angrist and Pischke 2008). Our 2SLS model uses a single instrument resulting in just-identified estimates. Standard errors are clustered at the inventor level across all models to control for repeated observations of the same inventor.

RESULTS

Descriptive Statistics

We first compare the observed annual rate of switching fields of Michigan inventors who left their former employer and joined another firm to mobile inventors from other non-enforcing states. Figure 1 displays the average annual rate of switching measured by the share of patents in the respective states that indicate that the inventor switched fields. Figure 2 is constructed in an analogous way but shows the two-year moving average in order to smooth out annual fluctuations and highlight the long-term trends.

Insert Figures 1 and 2 here

In line with prior research, we find an overall decreasing trend in switching fields over time. This decrease in switching has been attributed to the increasing burden of knowledge that has shifted inventors to become more specialized over time (Jones 2009). Because we only include inventors with at least one patent filed before MARA was passed in 1985, the decrease is possibly also driven by the declining tendency of an inventor to switch fields at a later stage in their career (for which we find support in the regressions). Figure 2 illustrates that while the rate of switching fields is somewhat lower for Michigan inventors in the years preceding MARA, it follows a similar decreasing trend. As expected, the passing of MARA in 1985 causes an increase in the rate at which mobile inventors in Michigan switched fields. Ten years after MARA, mobile inventors in Michigan are still more likely to switch fields compared to the control group of inventors from non-enforcing states while they were less likely to switch pre-MARA.

Table 3 compares the rate of switching fields for mobile inventors in Michigan versus the control group of mobile inventors from other non-enforcing states, both pre- and post-MARA, for both the full sample and the CEM subsample.

Insert Table 3 here

The rate of switching fields decreased slightly in Michigan post-MARA, from 0.49 to 0.48 for the full sample and from 0.53 to 0.52 for the CEM subsample. Yet, the rate of switching decreased sharply in the other non-enforcing states, from 0.53 to 0.43 for the full sample and from 0.60 to 0.48 for the CEM subsample. 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 switching. The treatment effect of MARA is 0.09 in the full sample and 0.10 in the CEM subsample. This change represents a relative increase of 18% respectively 19% compared to the average pre-MARA rate of switching fields in Michigan.

Multivariate Analysis

We first estimate the first stage of the 2SLS models, predicting the likelihood of switching fields as a function of the policy reversal in Michigan and control variables. We use linear probability and logit models for the CEM subsample of inventors, as displayed in Table 4. The interaction between Michigan and postmara, capturing the causal effect of MARA, has a significant positive effect on the likelihood of switching fields across all models. Marginal effects indicate that MARA increased the likelihood of switching fields with 0.10 in absolute terms, which represent a relative increase compared to the average pre-MARA likelihood of switching fields in Michigan of 19%. Overall, the results from the first stage indicate that the natural experiment had a strong positive effect on switching fields. Given that MARA exogenously triggered mobile inventors to explore formerly unfamiliar territory, the natural experiment provides a good instrument (Duflo 2001, Angrist and Pischke 2008).

Insert Table 4 here

Table 5 reports the results of the second stage of the 2SLS models for the CEM sample, estimating the usefulness of invention measured by renewals and future citations, the novelty of invention measured by new words and backward citations, and the time since last patent. Inventors who switch fields create less useful inventions; their first post switch patent is renewed 35% less frequently and future citations decrease by 37%. In contrast to the decrease in usefulness, switching fields has a significant and positive effect on the novelty of invention. The first patent after the switch has 54% more new words on average and its number of backward citations drops by 34%. The effects are consistent across the redundant and diverse measures, which include a financial payment by the patent owner and the citations by future inventors and patent examiners, and new to the patent corpus words and the number of backward citations listed by the inventor and patent examiners. These results are similar and close in magnitude to those reported by Hoisl and Rassenfosse (2015), who measured movement with a survey and productivity with patent citations. Model 5 indicates that switching fields increases the time to first patent, though the effect is not significant (P>|z|=0.18).

Insert Table 5 here

How can inventors and their managers cope with this tradeoff between novelty and usefulness? In particular, how can they minimize the penalty to the person switching fields? Table 6 reports the effect of switching fields on the two measures of the usefulness of invention with split samples, by whether the inventor collaborates in their new position and whether they reference non-patent prior art (mainly peer reviewed science publications, see Fleming and Sorenson 2004). Switching fields has a particularly strong negative effect on renewals and forward citations for individual inventors compared to collaborative inventors (the effect is robust to excluding former collaborators, who account for approximately 10% of the sample). While the effect of switching is also negative for collaborative inventors, it is less precisely estimated and significantly less negative compared to individual inventors. Likewise, inventors who switch fields and do not rely on the non-patent literature are less likely to have their patents renewed, though the effect is not quite significantly different from inventors that do use the literature.

Insert Table 6 here

Table 7 illustrates how switching fields affects the novelty of invention for individual versus collaborative inventors, and for inventors who rely on the non-patent literature versus inventors who do not. With regards to the number of new words, the point estimate of switching for the non-collaborative inventor is slightly higher than for his or her collaborative colleague, however, only the collaborative result is significant at $p < 0.10$ and the results are not significantly different from one another. The standard errors indicate that collaboration also reduces the variability of the novelty of output for inventors who switch. The results for the number of backwards citations measure are insignificant.

Insert Table 7 here

ROBUSTNESS CHECKS

To study how switching fields affect creative output, we used a sample of mobile inventors and exploited a natural experiment. Nonetheless, inventors might also switch fields while staying with their current employer, as John Vaught, the inventor of the HP inkjet printer, describes, “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). The question remains to what extent our findings are generalizable to all inventors who switch fields or whether they only hold for mobile inventors who switch fields. Furthermore, given the cross-sectional nature of our data, we are unable to control for the unobserved heterogeneity among inventors and firms; both could arguably affect the creativity of inventors.

To test whether switching fields has a significant effect for all inventors, including those who do not change employers, and to control for unobserved heterogeneity among inventors and firms, we replicate the analyses using inventor-firm fixed effects models. We select for the same observation period 1975-1995, the full population of US inventors with at least one prior patent, and hence are at the risk of switching fields, and who work for a firm. The sample is necessarily restricted to inventors who have at least two patents assigned to the same firm. Table 8 provides an overview of summary statistics for the sample of 1,706,832 patents assigned to 270,851 unique inventors and 33,195 unique firms, accounting for 310,389 unique inventor-firm pairs. We calculate the same measures as before and also include a binary indicator *move* being one for inventors who switched employers, i.e. for the first patent of an inventor with the recruiting firm as assignee. Table 9 provides an overview of the fixed effects models and illustrates a smaller but similar and highly significant set of effects. The size of the coefficient of switching fields becomes smaller compared to the cross-sectional findings, yet remains highly significant. This finding helps to generalize the result and provide a robustness check for the use of the Michigan law change.

Insert Tables 8 and 9 here

Another concern related to restricting the analysis to mobile inventors is that MARA affected the type of inventor who moves between firms in Michigan (our treatment group), arguably because they know that they have to switch fields. In other words, the natural experiment influenced selection of the treatment subjects. This could introduce a bias in our sample selection because these inventors might be different from non-moving inventors, non-Michigan inventors, and/or inventors active before MARA. For instance, a more prolific inventor in Michigan might decide to stay with their current firm and field rather than moving to a new firm and having to switch fields. Such an inventor probably has greater bargaining power, to stay or go, and this could influence their decision to move and subsequently be observed in our dataset.

To investigate this source of potential bias, we first identify all U.S. inventors with at least one patent in Michigan or in another non-enforcing state between 1975 and the passing of MARA in 1985. We restrict this inventor sample to patents that have been assigned to firms. We then collect all these inventors' subsequent patents, both before and after MARA and in and out of Michigan (that is, in Michigan and all control states). This results in the full sample of output by inventors at risk of moving between firms both in Michigan and in other non-enforcing states, before and after MARA. Table 10 provides an overview of summary statistics.

Insert Table 10 here

To assess whether these populations are different, we calculate binary indicators for *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* and the likelihood of being observed in our sample). For dependent variables, we calculate for each patent the inventor's number of prior patents, the average number of citations the inventor's prior patents had received within ten years, technical specialization (number of NBER subcategories linked to prior patents, see Appendix for an overview), number of prior co-inventors, and number of prior moves between firms. Characterizing each inventor based on prior patents provides insight into the profile of inventor at risk of moving to a new firm. The triple interaction term in Table 11 indicates no significant differences in the population of inventors that moved in Michigan after MARA, relative to inventors that moved before MARA, or moved anytime outside the state. This decreases the likelihood that the main results are driven by differences in the populations.

Insert Table 11 here

DISCUSSION

This work makes three main contributions. First, it applies a natural experiment in labor law that provides identification for the impact of switching fields upon subsequent creative and innovative output. Second, it offers more nuanced measures of creativity and innovation that enable the integration of predictions from economics and the evolutionary innovation literatures. The experiment and new measures together illustrate how switching both decreases useful output and increases the novelty of that output. Third, split sample analyses illustrate potential ways that inventors and firms might decrease the negative impact of switching. Stepping back from the immediate contributions, the work also provides 1) some of the first well-identified evidence for the value of March's 1991 theory, and 2) an exogenous and arguably random match of people's skillsets to new jobs.

Our findings have implications for inventors, their firms, and policymakers. First, and in contrast to prior research that stresses the lack of exploitation upside, these results illustrate the pitfalls of exploration for individuals and in turn, for the firms that hire those individuals (Audia and Goncalo 2007, Groysberg and Lee 2009, Hoisl and Rassenfosse 2015). Though exploration connotes bravery, discovery, and success, it more often results in 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, Fleming, and Manso 2015). While the evidence is well identified, this is not a new idea and indeed, is a central tenet of March's 1991 arguments.

Second, we illustrate a practical and legal challenge for creative 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. If the firm operates in a region that enforces non-competes, they will more often be forced to hire someone with less pertinent skills and retrain them. The explorative inventor and his or her firm will suffer decreased productivity (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 then create greater novelty; furthermore, embedding that candidate within networks of collaborators or hiring someone with facility in using the published scientific literature can mitigate switching problems. One implication of the current work is that scientists who can access the literature may suffer fewer mobility losses than more empirical and assumedly more insular inventors.

Third, and in nuanced contradiction to Silicon Valley's reputation as a hotbed of innovation, this work implies that regions that enforce non-competes invent more novel patents. Conti (2014) makes a similar argument, though with different mechanisms, namely, firms undertake riskier research and development because of decreased outbound mobility and subsequent knowledge leakage. Using changes in Texas and Florida non-compete law, he shows a flattening of the patent citation distribution (corresponding to riskier and hence more breakthrough and failed patents) and increased entry into new classes. Independent of such resource allocation decisions, two mobility mechanisms could also cause regions that enforce non-competes to invent more creative 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 change technical fields within their current employer as well. Indeed, in unreported regressions, we found a positive though not always significant impact of MARA upon the distance of intra-firms moves as well. The downside of the greater distance moves is lack of productivity, 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. For examples of potential questions, are regions that enforce non-competes 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 non-enforcing regions? Marx et al. (2015) demonstrate that better inventors (as measured by citations to their patents) are more likely to emigrate to non-enforcing states, following MARA; are these inventors carrying more novel and original knowledge as well? These questions strike us as a fruitful area for future research.

The metrics developed here also warrant further application and refinement. The use of renewals as measure of value or usefulness has strong face validity; firms should be less likely to pay maintenance fees on patents that have no value. Yet, very few papers use renewals as an outcome measure (and typically rely upon the easily and widely available measure of citations). The new word measure and other less conflated measures of creativity also offer the opportunity to separate novelty from success. These are new and less characterized measures, for example, the new word measure is fundamentally challenged in differentiating typos from technical novelty (dictionaries for typos are not technical enough to identify errors). Once individual words can be accurately tokenized (that is, used to represent a particular document), then bigram and trigrams can be developed. Such multi-word tokens would offer a method to cleanly operationalize architectural innovation (Henderson and Clark, 1990).

CONCLUSION

Creative and innovative search is risky and the optimal strategy uncertain; inventors face a fundamental tradeoff between local search and exploitation versus distant search and exploration (March 1991). Inventors fundamentally cannot avoid this question; every time they create they choose implicitly or explicitly to work within more familiar areas or learn new approaches to some degree. This choice is typically endogenous and thus causes first order methodological problems in studying the impact of search strategy on creative output. This study approached these problems by relying on an unforeseen labor law reform that forced inventors to change their fields when changing jobs. We further exploited differences in differences and matching approaches that enabled close comparison of mobile inventors that were and were not exogenously forced to change fields.

Armed with these methodological tools, we fashioned an informal model from two seemingly conflicting perspectives. Economic perspectives begin with the value of specialization and accumulated expertise upon productivity; these perspectives imply greater innovation from not switching fields. Evolutionary perspectives begin with the value of diversity and recombinant fecundity; these perspectives imply the opposite prediction; greater innovation comes from switching and learning new fields. We believe both of these arguments have merit and offered an empirical resolution through more nuanced measures of innovation. Inventors that move but do not switch fields remain more productive and invent patents that are renewed and cited more often; inventors that move and switch invent patents with more novel words and fewer backward citations. Furthermore, we provided split sample analyses that illustrated how the productive and creative handicaps caused by switching fields can be minimized through collaboration in the new field and the application of scientific knowledge to the technical challenge.

The influence of March's seminal paper can be observed by over 15,000 Google Scholar citations, mainly in the organizations literature but increasingly in economics, finance, and operations. Surprisingly, however, this follow on work provides little causal evidence. Though one might characterize our contribution as an empirical exploitation of a popular idea, we hope that it opens up explorative opportunity for future work.

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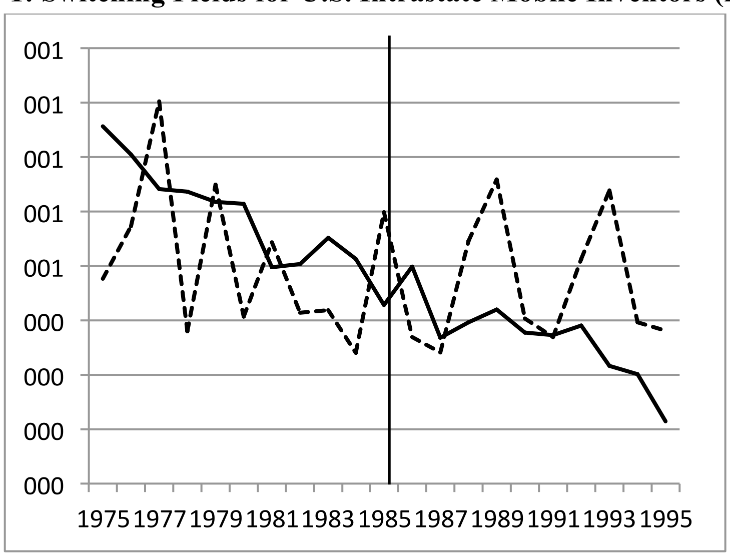
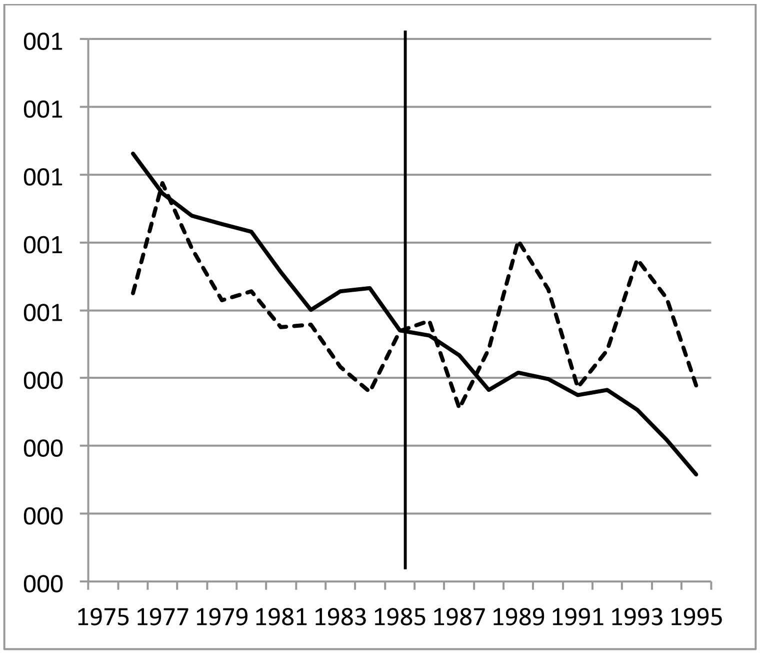
FIGURE 1: Switching Fields for U.S. Intrastate Mobile Inventors (n=13,720)



Michigan inventors are represented by the dashed line. Inventors from other non-enforcing states are represented by the solid line. The vertical line represents the year of the Michigan Antitrust Reform Act.

FIGURE 2: Switching Fields for U.S. Intrastate Mobile Inventors: Two Year Moving Average (n=13,720)



Michigan inventors are represented by the dashed line. Inventors from other non-enforcing states are represented by the solid line. The vertical line represents the year of the Michigan Antitrust Reform Act.

TABLE 1: Summary Statistics for U.S. Intrastate Mobile Inventors (1975-1995; n=13,720)

Variable	Description	Mean	Stdev.	Min.	Max.
Renewals	Number of times a granted patent is renewed by paying the renewal fees. A patent can be renewed after 4, 8 and 12 years resulting in the count of renewals being 0, 1, 2, or 3. Measure for the usefulness of the patent. Available for patents filed since 1981.	1.01	0.48	0.00	1.39
Forward citations	Number of citations received by the patent within 10 years. Measure for the usefulness of the patent.	1.91	1.06	0.00	6.00
New words	Number of words in the patent appearing for the first time in the US patent database. Available for patents filed since 1980. Measure for the novelty of the patent.	0.34	0.57	0.00	4.51
Backward citations	Number of backward prior art citations. Measure for the novelty of the patent.	2.11	0.76	0.00	5.61
Switching fields	Binary: inventor has no prior patent in three-digit US patent class(es)	0.47		0.00	1.00
Michigan	Binary: inventor resides in Michigan	0.13		0.00	1.00
Postmara	Binary: patent is filed after 1985	0.58		0.00	1.00
Michigan* Postmara	Binary: inventor resides in Michigan and patent is filed after 1985	0.07		0.00	1.00
Non-enforcing state	Binary: inventor resides in a non-enforcing state	0.93		0.00	1.00
Auto industry	Binary: auto industry patent (see appendix B)	0.04		0.00	1.00
Number of prior patents	Number of prior patents developed by the inventor	1.54	0.75	0.69	5.00
Technical specialization	Technical specialization of the inventor. Herfindahl index based on three-digit US classes of prior patents.	0.62	0.31	0.05	1.00
Number of prior collaborations	Number of unique prior co-authors(s) of the focal inventor	1.49	0.64	0.00	4.42
Prior move	Binary: inventor previously switched employers	0.30	0.46	0.00	1.00
Time since last patent	Number of days since the inventor's prior patent application	6.43	1.67	0.00	10.30
Time since first patent	Number of days since the inventor's first patent application	7.84	1.01	0.00	10.37
Number of inventors	Number of inventors on the patent	0.72	0.58	0.00	3.53
Number of prior patents recruiting firm	Number of prior patents assigned to the firm listed as assignee	2.58	2.59	0.00	9.77
Number of classes	Number of patent classes	0.53	0.50	0.00	2.48
Number of subclasses	Number of patent subclasses	1.29	0.64	0.00	4.19

All count variables are logged before adding one for variables with zero values.

TABLE 2: Correlations for U.S. Intrastate Mobile Inventors (1975-1995; n=13,720)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1) Forward citations	1.00																			
(2) Renewals	0.19	1.00																		
(3) New words	0.03	0.01	1.00																	
(4) Backward citations	0.18	0.04	-0.08	1.00																
(5) Switching fields	-0.01	-0.05	-0.04	0.00	1.00															
(6) Michigan	-0.07	-0.04	-0.03	0.01	0.02	1.00														
(7) Postmara	0.21	0.05	-0.02	0.15	-0.05	-0.05	1.00													
(8) Michigan* Postmara	-0.02	-0.03	-0.03	0.03	0.01	0.78	0.20	1.00												
(9) Non-enforcing state	0.01	0.00	-0.02	-0.02	0.08	0.10	-0.06	0.08	1.00											
(10) Auto industry	-0.01	-0.03	-0.04	0.02	0.00	0.17	-0.02	0.14	0.02	1.00										
(11) Number of prior patents	0.01	-0.01	0.05	0.05	-0.28	-0.03	0.21	0.02	-0.20	-0.03	1.00									
(12) Technical specialization	-0.03	0.01	-0.01	-0.07	0.16	0.04	-0.18	-0.02	0.13	0.02	-0.61	1.00								
(13) Number of prior collaborations	0.08	0.05	0.07	0.07	-0.22	-0.07	0.26	0.00	-0.15	-0.04	0.67	-0.49	1.00							
(14) Prior move	0.09	0.01	0.01	0.07	-0.13	-0.05	0.18	-0.01	-0.15	-0.02	0.45	-0.39	0.38	1.00						
(15) Time since last patent	0.03	0.01	-0.06	-0.01	0.15	0.02	0.10	0.06	0.11	0.01	-0.40	0.23	-0.25	-0.28	1.00					
(16) Time since first patent	0.10	0.00	-0.04	0.12	-0.12	-0.04	0.49	0.09	-0.10	0.00	0.39	-0.39	0.39	0.26	0.24	1.00				
(17) Number of inventors	0.16	0.11	0.11	0.11	0.02	-0.04	0.15	0.00	-0.02	-0.04	0.07	-0.04	0.26	0.05	-0.04	0.05	1.00			
(18) Number of prior patents recruiting firm	-0.05	0.11	0.05	-0.06	0.01	0.00	0.01	0.00	-0.04	0.00	0.01	0.03	0.05	-0.04	0.05	0.00	0.11	1.00		
(19) Number of classes	0.10	-0.01	0.07	0.04	-0.08	0.00	-0.04	-0.02	0.01	0.02	0.00	-0.04	0.02	0.01	-0.03	-0.04	0.04	-0.01	1.00	
(20) Number of subclasses	0.11	0.00	0.10	0.09	-0.11	-0.02	0.00	-0.03	-0.02	-0.03	0.05	-0.05	0.06	0.02	-0.04	-0.01	0.06	0.01	0.60	1.00

TABLE 3: Comparison of Switching Fields of U.S. Intrastate Mobile Inventors

Full sample (n=13,720)	Premara	Postmara	difference
Michigan	0.49	0.48	-0.01
Other non-enforcing states	0.53	0.43	-0.10
Difference	-0.04	0.05	0.09
CEM sample (n=6,246)	Premara	Postmara	difference
Michigan	0.53	0.52	-0.01
Other non-enforcing states	0.60	0.49	-0.11
Difference	-0.07	0.03	0.10

TABLE 4: Switching Fields of U.S. Intrastate Mobile Inventors

	(1)	(2)
Model	OLS	Logit
Sample	CEM	CEM
Michigan	-0.06**	-0.30**
	(0.03)	(0.14)
Postmara	0.03	0.09
	(0.07)	(0.48)
Michigan*Postmara	0.10***	0.48***
	(0.03)	(0.18)
Non-enforcing state	-0.01	-0.05
	(0.03)	(0.22)
Auto industry	-0.04	-0.04
	(0.26)	(1.28)
Number of prior patents	-0.18***	-0.92***
	(0.02)	(0.13)
Technical specialization	0.03	0.04
	(0.03)	(0.18)
Number of prior collaborations	-0.06***	-0.31***
	(0.02)	(0.10)
Prior move	0.04*	0.19
	(0.02)	(0.12)
Time since last patent	0.02***	0.12***
	(0.01)	(0.04)
Time since first patent	-0.02**	-0.11*
	(0.01)	(0.06)
Number of inventors	0.03**	0.15**
	(0.01)	(0.08)
Number of prior patents recruiting firm	0.01***	0.04**
	(0.00)	(0.02)
Number of classes	-0.05***	-0.26**
	(0.02)	(0.11)
Number of subclasses	-0.04***	-0.20**
	(0.01)	(0.09)
Constant	1.00***	2.44**
	(0.24)	(1.18)
Technology class dummies	Yes	Yes
Year dummies	Yes	Yes
Log-likelihood		-3563.67
N	6,246	6,246

Robust standard errors in parentheses, clustered by inventor *** p<0.01, ** p<0.05, * p<0.10

TABLE 5: Impact of Switching Fields of U.S. Intrastate Mobile Inventors on Usefulness, Novelty, and Time Since Last Patent (1975-1995; CEM sample, n=6,246)

	(1)	(2)	(3)	(4)	(5)
Outcome	Renewals	Forward citations	New words	Backward citations	Time since last patent
Model	2SLS	2SLS	2SLS	2SLS	2SLS
Switching fields	-0.43**	-0.47*	0.43**	-0.41*	1.01
	(0.19)	(0.27)	(0.20)	(0.22)	(0.76)
Michigan	-0.02	0.03	0.02	0.02	0.00
	(0.02)	(0.03)	(0.02)	(0.02)	(0.04)
Postmara	0.08**	0.96***	-0.00	0.52***	-0.06
	(0.04)	(0.13)	(0.04)	(0.11)	(0.18)
Non-enforcing state	0.04	-0.00	0.04	-0.04	0.25***
	(0.03)	(0.05)	(0.03)	(0.04)	(0.07)
Auto industry	0.42	0.25	0.18	-0.11	-1.56**
	(0.27)	(0.49)	(0.30)	(0.39)	(0.64)
Number of prior patents	-0.10**	-0.07	0.07*	-0.09*	-1.04***
	(0.04)	(0.06)	(0.04)	(0.05)	(0.16)
Technical specialization	-0.09***	0.03	-0.03	-0.01	0.10
	(0.03)	(0.05)	(0.03)	(0.04)	(0.07)
Number of prior collaborations	-0.05**	-0.06*	0.00	-0.03	-0.02
	(0.02)	(0.03)	(0.02)	(0.03)	(0.06)
Prior move	0.05**	0.09***	0.00	0.10***	-0.58***
	(0.02)	(0.04)	(0.02)	(0.03)	(0.05)
Time since last patent	0.02***	0.02**	-0.01	-0.01	
	(0.01)	(0.01)	(0.01)	(0.01)	
Time since first patent	-0.03**	-0.02	0.01	0.01	0.99***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
Number of inventors	0.08***	0.19***	0.05***	0.08***	-0.09**
	(0.01)	(0.02)	(0.02)	(0.02)	(0.04)
Number of prior patents recruiting firm	0.02***	-0.01	0.00	-0.00	0.02**
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
Number of classes	-0.04*	0.11***	-0.00	-0.09***	0.09
	(0.02)	(0.03)	(0.02)	(0.03)	(0.05)
Number of subclasses	-0.03*	0.18***	0.08***	0.16***	0.03
	(0.02)	(0.03)	(0.02)	(0.02)	(0.05)
Constant	1.20***	1.04**	-0.44	2.22***	-1.14
	(0.31)	(0.52)	(0.33)	(0.41)	(0.94)
Technology class dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
F stat	28.51	46.06	31.26	46.06	46.06
N	5,676	6,246	5,817	6,246	6,246

CEM sample, robust standard errors in parentheses, clustered by inventor *** p<0.01, ** p<0.05, * p<0.10

TABLE 6: Switching Fields and Usefulness of Invention: Split Samples by Lone Inventor and Science (1975-1995; CEM sample, n=6,246)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome	Renewals	Renewals	Forward citations	Forward citations	Renewals	Renewals	Forward citations	Forward citations
Sample	Lone inventor	Team	Lone inventor	Team	Science	No Science	Science	No Science
Switching fields	-0.84***	-0.20	-0.81**	-0.24	0.02	-0.29*	-0.05	-0.25
	(0.25)	(0.13)	(0.33)	(0.22)	(0.16)	(0.16)	(0.32)	(0.26)
Michigan	-0.11**	0.02	-0.00	0.03	-0.03	-0.01	-0.02	0.04
	(0.04)	(0.02)	(0.05)	(0.04)	(0.04)	(0.02)	(0.08)	(0.03)
Postmara	0.05	0.11**	1.20***	0.90***	0.09	0.12***	0.74*	0.98***
	(0.09)	(0.04)	(0.24)	(0.17)	(0.07)	(0.05)	(0.43)	(0.15)
Non-enforcing state	0.00	0.03	-0.19*	0.05	0.06	0.02	0.06	-0.03
	(0.08)	(0.03)	(0.11)	(0.06)	(0.06)	(0.04)	(0.11)	(0.06)
Auto industry	0.90**	0.00	0.29	0.36	-0.22	0.57**	1.05**	0.36
	(0.44)	(0.36)	(0.64)	(0.68)	(0.23)	(0.26)	(0.47)	(0.46)
Number of prior patents	-0.15**	-0.07**	-0.22***	0.01	0.03	-0.08**	-0.09	0.01
	(0.06)	(0.03)	(0.08)	(0.06)	(0.04)	(0.04)	(0.08)	(0.06)
Technical specialization	-0.08	-0.12***	-0.00	0.00	-0.04	-0.11***	0.13	0.00
	(0.07)	(0.04)	(0.09)	(0.07)	(0.06)	(0.04)	(0.11)	(0.06)
Number of prior collaborations	-0.01	-0.03	0.13**	-0.10**	-0.04	-0.05**	0.06	-0.06
	(0.05)	(0.02)	(0.06)	(0.04)	(0.03)	(0.02)	(0.06)	(0.04)
Prior move	0.09*	0.04*	0.10	0.11***	0.01	0.04*	-0.03	0.09**
	(0.05)	(0.02)	(0.07)	(0.04)	(0.03)	(0.02)	(0.07)	(0.04)
Time since last patent	0.06***	0.02**	0.08***	0.02	0.01	0.02**	-0.01	0.03**
	(0.02)	(0.01)	(0.03)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Time since first patent	-0.07*	-0.03**	-0.12**	-0.02	-0.04**	-0.01	0.03	-0.02
	(0.04)	(0.01)	(0.05)	(0.02)	(0.02)	(0.01)	(0.04)	(0.02)
Number of inventors		0.12***		0.35***	0.06**	0.10***	0.11**	0.20***
		(0.02)		(0.04)	(0.02)	(0.02)	(0.05)	(0.03)
Number of prior patents recruiting firm	0.02***	0.01***	-0.00	-0.01*	0.00	0.03***	-0.00	-0.01
	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
Number of classes	-0.02	-0.01	-0.04	0.18***	0.01	-0.02	0.21***	0.07**
	(0.04)	(0.02)	(0.06)	(0.04)	(0.03)	(0.02)	(0.07)	(0.04)
Number of subclasses	-0.00	-0.04*	0.40***	0.10***	-0.04	-0.01	0.06	0.26***
	(0.04)	(0.02)	(0.05)	(0.03)	(0.03)	(0.02)	(0.06)	(0.03)
Constant	1.35**	1.29***	2.04***	0.19	1.64***	0.95***	-0.54	0.69
	(0.56)	(0.33)	(0.78)	(0.62)	(0.28)	(0.29)	(0.70)	(0.50)
Technology class dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F stat	21.80	58.04	26.99	74.57	30.09	35.22	32.17	42.27
N	1,567	4,109	1,793	4,453	1,941	3,735	2,014	4,232

CEM sample, 2SLS models, robust standard error, clustered by inventor *** p<0.01, ** p<0.05, * p<0.10

TABLE 7: Switching Fields and Novelty of Invention: Split Samples by Lone Inventor and Science (1975-1995; CEM sample, n=6,246)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome	New words	New words	Backward citations	Backward citations	New words	New words	Backward citations	Backward citations
Sample	Lone inventor	Team	Lone inventor	Team	Science	No Science	Science	No Science
Switching fields	0.32	0.24*	-0.17	-0.24	0.38*	0.14	0.17	-0.24
	(0.23)	(0.14)	(0.25)	(0.17)	(0.22)	(0.16)	(0.27)	(0.20)
Michigan	-0.01	0.03	0.08*	0.01	0.13**	0.00	0.10	0.05**
	(0.03)	(0.02)	(0.04)	(0.03)	(0.06)	(0.02)	(0.07)	(0.03)
Postmara	-0.09	-0.02	0.41**	0.66***	0.10	-0.07	1.20***	0.40***
	(0.07)	(0.05)	(0.18)	(0.13)	(0.09)	(0.04)	(0.36)	(0.11)
Non-enforcing state	0.14**	-0.02	-0.14*	-0.01	-0.13*	0.10***	0.11	-0.11**
	(0.06)	(0.04)	(0.08)	(0.05)	(0.08)	(0.03)	(0.10)	(0.04)
Auto industry	-0.04	0.29	-0.32	-0.05	0.61**	0.17	0.18	-0.16
	(0.35)	(0.41)	(0.48)	(0.54)	(0.31)	(0.26)	(0.40)	(0.35)
Number of prior patents	0.00	0.06	-0.02	-0.05	0.04	0.01	0.03	-0.06
	(0.05)	(0.04)	(0.06)	(0.04)	(0.05)	(0.04)	(0.07)	(0.05)
Technical specialization	-0.04	-0.00	0.12*	-0.01	0.11	-0.08**	-0.12	0.03
	(0.06)	(0.04)	(0.07)	(0.05)	(0.07)	(0.04)	(0.09)	(0.05)
Number of prior collaborations	-0.08**	0.01	0.06	-0.05	0.04	-0.02	0.03	-0.05*
	(0.04)	(0.02)	(0.05)	(0.03)	(0.04)	(0.02)	(0.05)	(0.03)
Prior move	0.11***	-0.04	0.12**	0.10***	-0.04	0.03	0.03	0.12***
	(0.04)	(0.03)	(0.05)	(0.03)	(0.04)	(0.02)	(0.06)	(0.03)
Time since last patent	-0.02	0.00	-0.02	-0.01	-0.00	-0.01	-0.04**	-0.01
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Time since first patent	0.07**	-0.01	0.02	-0.01	-0.00	0.01	0.03	0.02
	(0.03)	(0.01)	(0.04)	(0.02)	(0.03)	(0.01)	(0.03)	(0.02)
Number of inventors		0.08***		0.20***	-0.04	0.09***	0.13***	0.02
		(0.03)		(0.03)	(0.03)	(0.02)	(0.04)	(0.02)
Number of prior patents recruiting firm	0.01*	-0.00	-0.01*	-0.00	0.01	0.00	-0.00	-0.00
	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Number of classes	-0.01	-0.02	-0.09**	-0.07**	0.04	-0.03	-0.04	-0.08***
	(0.03)	(0.02)	(0.04)	(0.03)	(0.05)	(0.02)	(0.06)	(0.03)
Number of subclasses	0.09***	0.07***	0.25***	0.14***	0.13***	0.05***	0.16***	0.16***
	(0.03)	(0.02)	(0.04)	(0.03)	(0.04)	(0.02)	(0.05)	(0.02)
Constant	-0.82*	0.06	1.71***	1.94***	-0.32	-0.12	0.98	2.05***
	(0.48)	(0.37)	(0.59)	(0.49)	(0.37)	(0.28)	(0.60)	(0.38)
Technology class dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F stat	16.15	59.12	26.99	74.57	29.65	38.61	32.17	42.27
N	1,616	4,201	1,793	4,453	1,963	3,854	2,014	4,232

CEM sample, 2SLS models, robust standard errors in parentheses, clustered by inventor *** p<0.01, ** p<0.05, * p<0.10

TABLE 8: Summary Statistics Full Sample U.S. Inventors with at Least One Prior Patent (1975-1995; n=1,706,832; 310,389 unique inventor-firm pairs)

Variable	Mean	Stdev.	Min.	Max.
Renewals	1.04	0.46	0.00	1.39
Forward citations	1.69	1.02	0.00	6.63
New words	0.38	0.64	0.00	7.16
Backward citations	1.86	0.77	0.00	7.11
Switching fields	0.30	0.46	0.00	1.00
Number of prior patents	1.91	0.93	0.69	6.25
Technical specialization	0.63	0.31	0.02	1.00
Number of prior collaborations	1.85	0.93	0.00	6.13
Move	0.04	0.20	0.00	1.00
Prior move	0.16	0.36	0.00	1.00
Time since last patent	4.60	2.16	0.00	10.41
Time since first patent	7.19	1.51	0.00	10.44
Number of inventors	0.98	0.63	0.00	3.53
Number of prior patents firm	5.96	2.46	0.00	10.10
Number of classes	0.50	0.50	0.00	2.77
Number of subclasses	1.30	0.68	0.00	5.15

All count variables are logged before adding one for variables with zero values.

TABLE 9: Inventor-Firm Fixed Effects Full Sample U.S. Inventors with at Least One Prior Patent (1975-1995; n=1,706,832; 310,389 unique inventor-firm pairs)

	(1)	(2)	(3)	(4)
Outcome	Renewals	Forward citations	New words	Backward citations
Model	xtreg fe	xtreg fe	xtreg fe	xtreg fe
Sample	1981-1995	1975-1995	1980-1995	1975-1995
Switching fields	-0.0117***	-0.0109***	0.0078***	-0.0177***
	(0.0011)	(0.0021)	(0.0016)	(0.0016)
Number of prior patents	-0.0279***	-0.1565***	-0.0509***	0.0196***
	(0.0020)	(0.0037)	(0.0027)	(0.0027)
Technical specialization	-0.0003	-0.0978***	-0.0212***	0.0075*
	(0.0031)	(0.0059)	(0.0043)	(0.0044)
Number of prior collaborations	0.0053***	-0.0227***	-0.0191***	-0.0137***
	(0.0014)	(0.0028)	(0.0020)	(0.0020)
Move	0.0040*	0.0139***	0.0431***	0.0410***
	(0.0021)	(0.0045)	(0.0031)	(0.0033)
Prior move	0.0084***	0.0263***	-0.0004	-0.0059
	(0.0028)	(0.0062)	(0.0039)	(0.0044)
Time since last patent	0.0007***	0.0034***	-0.0012***	-0.0037***
	(0.0002)	(0.0004)	(0.0003)	(0.0003)
Time since first patent	-0.0010	0.0064***	0.0011	-0.0006
	(0.0007)	(0.0013)	(0.0010)	(0.0009)
Number of inventors	0.0375***	0.1288***	0.0399***	0.0659***
	(0.0010)	(0.0020)	(0.0014)	(0.0015)
Number of prior patents firm	-0.0319***	-0.0922***	0.0081***	0.0593***
	(0.0019)	(0.0041)	(0.0026)	(0.0030)
Number of classes	-0.0030***	0.0511***	-0.0107***	0.0151***
	(0.0011)	(0.0021)	(0.0016)	(0.0016)
Number of subclasses	0.0019**	0.2113***	0.0653***	0.0977***
	(0.0008)	(0.0017)	(0.0014)	(0.0013)
Constant	0.8373***	0.2380	1.0442***	1.7232***
	(0.0264)	(0.2024)	(0.0602)	(0.1513)
Technology class dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Inventor-firm fixed effects	Yes	Yes	Yes	Yes

***** p<0.01, ** p<0.05, * p<0.1**

TABLE 10: Summary Statistics for U.S. Inventors at Risk of Moving in Michigan and Other Non-enforcing States (1975-1995; n= 162,586 patents; 29,956 inventors)

Variables	Mean	Stdev.	Min.	Max.
Number of prior patents	10.59	18.62	1.00	338.00
Average number of citations within 10 years for prior patents	6.75	9.06	0.00	232.50
Technical specialization (number of prior NBER subcategories)	3.83	2.76	1.00	32.00
Number of prior collaborations	6.00	7.36	0.00	444.00
Number of prior moves	0.35	0.85	0.00	16.00
Michigan	0.18	0.39	0.00	1.00
Postmara	0.46	0.50	0.00	1.00
Move	0.08	0.28	0.00	1.00
Michigan*Postmara	0.07	0.26	0.00	1.00
Michigan*Move	0.01	0.10	0.00	1.00
Postmara*Move	0.05	0.22	0.00	1.00
Michigan*Postmara*Move	0.01	0.08	0.00	1.00

TABLE 11: Characteristics of U.S. Inventors at Risk of Moving in Michigan and Other Non-enforcing States (1975-1995; n= 162,586 patents; 29,956 inventors)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Number of prior patents	Average number of citations within 10 years for prior patents	Technical specialization (number of prior NBER subcategories)	Number of prior collaborations	Number of prior moves
MODEL	PQML	OLS	PQML	PQML	PQML
Michigan	0.32	-1.01***	-0.03	-0.07*	-0.43***
	(0.21)	(0.11)	(0.03)	(0.04)	(0.12)
Postmara	0.87***	5.29***	0.53***	0.95***	1.56***
	(0.07)	(0.27)	(0.02)	(0.02)	(0.05)
Move	-0.62***	0.12	0.02	-0.17***	0.55***
	(0.04)	(0.09)	(0.01)	(0.02)	(0.05)
Michigan*Postmara	-0.37*	-2.16***	0.03	0.01	-0.13
	(0.22)	(0.34)	(0.03)	(0.06)	(0.14)
Michigan*Move	-0.30	-0.14	0.02	0.05	0.17
	(0.22)	(0.17)	(0.04)	(0.05)	(0.21)
Postmara*Move	-0.20***	-1.97***	-0.20***	-0.32***	-0.47***
	(0.07)	(0.28)	(0.02)	(0.03)	(0.06)
Michigan*Postmara*Move	0.27	0.28	-0.07	-0.11	0.18
	(0.23)	(0.39)	(0.05)	(0.09)	(0.17)
Constant	1.90***	4.74***	1.06***	1.29***	-2.01***
	(0.04)	(0.05)	(0.01)	(0.02)	(0.04)
Log-likelihood	-1396770.9		-367527.23	-614526.91	-122693.12
Observations	162,586	162,586	162,586	162,586	162,586

Robust standard errors in parentheses, clustered by inventor, *** p<0.01, ** p<0.05, * p<0.10

APPENDIX

Table A: Overview of Different Fields (Hall, Jaffe, and Trajtenberg, 2001)

Fields	Code
Chemical	
Agriculture, food, and textiles	11
Coating	12
Gas	13
Organic compounds	14
Resins	15
Miscellaneous-chemical	19
Computer and communications	
Communications	21
Computer hardware and software	22
Computer peripherals	23
Information storage	24
Electronic business methods and software	25
Drugs and medical	
Drugs	31
Surgery and medical instruments	32
Genetics	33
Miscellaneous-drugs and medical	39
Electrical and electronic	
Electrical devices	41
Electrical lighting	42
Measuring and testing	43
Nuclear and x-rays	44
Power systems	45
Semiconductor devices	46
Miscellaneous-electrical and electronic	49
Mechanical	
Materials processing and handling	51
Metal working	52
Motors, engines, and parts	53
Optics	54
Transportation	55
Miscellaneous-mechanical	59
Others	
.Agriculture, husbandry, and food	61
Amusement devices	62
Apparel and textile	63
Earth working and wells	64
Furniture, house fixtures	65
Heating	66
Pipes and joints	67
Receptacles	68
Miscellaneous-others	69

Table B: Patent Classes Auto Industry (Marx, Strumsky, and Fleming, 2009)

Class 180	Motor vehicles
Class 188	Brakes
Class 152	Resilient tires and wheels
Class 191	Electricity: transmission to vehicles
Class 296	Land vehicles: bodies and tops
Class 298	Land vehicles: dumping
Class 301	Land vehicles: wheels and axles
Class 303	Fluid-pressure and analogous brake systems
Class 305	Wheel substitutes for land vehicles
Class 903	Hybrid electric vehicles
Class 307	Electrical transmission or interconnection systems
Class 310	Electrical generator or motor structure
Class 91	Motors: expansible chamber type
Class 92	Expansible chamber devices
Class 192	Clutches and power-stop control
Class 280	Land vehicles
Class 123	Internal-combustion engines
Class D12	Transportation