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The Ties That No Longer Bind: Inventor Mobility and Patent Litigation*

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Abstract

The retention of inventor-employees represents a core strategic concern for firms in innovative industries. In this paper, we examine the impact of reduced patent enforceability on the mobility of inventor-employees and explore the related influence on firms' innovative activities. To analyze this potential relationship, we use the US Supreme Court ruling *eBay Inc. v. MercExchange, L.L.C.*, which decreased the use of injunctions in patent infringement cases and, consequently, the risk firms and individuals faced from being sued for patent infringement. Our analyses rely on difference-in-differences specifications that include state-year, firm, and technological fixed effects, and a host of other controls. Using patent application data to track the movements of 50,283 early career patent inventors before and after the ruling, we find that in the post period, inventor-employees at firms with a greater reliance on intellectual property are relatively more likely to leave their employer. Moreover, we find that employees most affected by the change are those involved in basic research and those with generalizable skills, suggesting that the change in patent enforceability may have improved the outside employment options for certain inventors. We further detect important implications for firm performance and the direction of firm innovation resulting from these patterns.

Keywords— mobility, inventors, patent enforceability, skills, strategic human capital

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1 Introduction

Human capital plays a fundamental role in the production of knowledge and subsequent value creation within a firm, especially in knowledge intensive industries (Coff 1997). As such, a long-standing stream of research suggests that the loss of skilled employees can be substantially harmful to the firm (Campbell et al. 2012b, Phillips 2002, Wezel et al. 2006), because when talent leaves, important knowledge, capabilities and expertise may also walk out the door. Prior literature has also shown how firms can use legal instruments, such as non-compete agreements (Marx et al. 2009, Starr et al. 2018) and patents (Ganco et al. 2015, Kim and Marschke 2005, Melero et al. 2020), to prevent valuable inventor-employees from leaving. Yet, we know far less about how changes to the legal infrastructure of intellectual property protection can affect employee mobility. In this paper, we address this gap by examining how the systematic enforceability of patents impacts the mobility of inventor-employees.

Although a vast literature has dedicated efforts towards examining the effect of changes in noncompete enforceability on the mobility of workers and the resulting effects on firms (Marx et al. 2009, Starr et al. 2018, 2019, Kang and Fleming 2020), to our knowledge, there has been no examination of how the enforceability of patent rights affects worker mobility. Unlike non-compete agreements, patents are not explicitly designed to prevent employee departure. Yet patents represent a key vehicle through which value is transferred from employees to the firm. They are important tools for codifying and assigning ownership of knowledge, and are oftentimes crucial resources for firms in obtaining and sustaining a competitive advantage. As such, by enabling the appropriation of value from investments into human capital and employees' R&D activities, the patent system as a whole can be an essential factor shaping the strategic human capital management of firms. However, the ability to appropriate value using a patent is not a permanent state, especially given that patents are probabilistic rights, can be disputed in court, and provided the mobile nature of those that create patents - employees (Lemley and Shapiro 2005, Palomeras and Melero 2010, Singh and Agrawal 2011). Moreover, in the most recent past, there have been substantial changes to the United States patent system, both through legislation and US Supreme Court rulings. Given the uncertainty engendered by these changes, it is important to understand the mechanisms through which the patent system can affect inventor-employee mobility.

Patents and patent litigation provide a method for firms to deter competitors from hiring away their inventor-employees. Because a patent prevents an inventor from practicing an invention at another firm, it renders a portion of their human capital as firm-specific (Melero et al. 2020). Thus this capital is lost when the employee leaves their job and makes hiring the employee less attractive to competitors, reducing the employee's outside employment options. However, a drop in the enforceability of patent rights could reduce this deterrence effect, since employees and other firms that hire them have less to fear from allowing the employee to practice technologies that are similar to their prior work.

In considering the potential effect of patent rights on employee mobility, it is important to clarify the factors that give these rights their potency. The strength of the patent system and resulting systemic effectiveness of patents can be split into three dimensions (Walsh et al. 2016). The first, patentability, is the range of inventions that patents can protect. The second dimension, the breadth of interpretation on the boundaries of claims, translates into how close a rival's invention can be without infringing on a patented invention. The third dimension, excludability, is determined by the penalty for those who are found guilty of infringing on a valid patent. Of all the dimensions, the latter may be the most critical for retaining inventor-employees (Ganco et al. 2015), because the threat of patent enforcement reduces employees' expected value from pursuing external commercialization options. But if excludability is weakened, because the penalties associated with patent infringement have fallen, then the ability of a firm to reduce their inventor-employees' outside options should also decrease.

In this paper, we ask: Does reducing the penalties associated with patent infringement increase inventor-employee mobility? Prior literature has shown that both developing a reputation for litigiousness (Ganco et al. 2015) and obtaining a patent (Melero et al. 2020) can deter inventor-employee exit. Yet it is unclear how patent enforceability affects these retention strategies. Firms may be able to deter mobility through their sheer volume of litigation and patents, rather than through the actual risks associated with losing a patent lawsuit. The vast majority of patent lawsuits settle before trial (Allison et al. 2014), and even a patent lawsuit where less than a million dollars is at risk is estimated to cost $700,000 in legal fees (American Intellectual Property Law Association 2019). Given that so few patent lawsuits ever make it to trial, it is possible that the financial costs and time loss associated with litigation deters mobility, rather than the penalties associated with losing in court.

To test the potential effect of reduced patent excludability on inventor-employee mobility, we use the US Supreme Court ruling *eBay Inc. v. MercExchange, L.L.C.*. This ruling reduced the penalties associated with patent litigation by decreasing the use of injunctions in patent infringement cases. By diminishing the likelihood that an injunction would be granted, the *eBay* ruling decreased the excludability of patents and the risk that firms and entrepreneurs faced from being sued for patent infringement. Prior literature has used this ruling to test the effect of a reduced litigation threat on the amount of innovation produced by firms (Mezzanotti 2021). In our case, the *eBay* ruling provides an excellent opportunity to test the effects of patent enforceability on the mobility of inventors.

Our analysis relies on a difference-in-differences specification, which uses patent application data to track the movements of 50,283 early career patent inventors before and after the *eBay* ruling. The level of treatment is defined based on the ratio of the number of granted patents the firm filed in the inventor-employee's field of work to the number of inventors the firm employs in the inventor-employee's field. Inventors at firms with a high patent-to-inventor ratio in their field should have been greatly affected by the ruling, while those at firms with a low ratio should not have been heavily affected. To rule out other possible confounding factors, we use state-year, firm, and technological fixed effects, along with a variety of other controls.

We find that inventor-employees at firms with a stronger reliance on patents increase their departure more after the *eBay* ruling. A ten percent increase in the ratio of related patents to inventors is associated with a 4% increase in probability of departure. Inventors with generalizable skills and inventors who engage in upstream research exit relatively more after the ruling, while inventors with more firm-specific skills are less affected by the ruling. Moreover, firms whose inventors increase their mobility after the ruling see their self-citations decrease and and experience a reduction in their exploratory research efforts.

Taken together, our findings provide novel insights that are relevant to at least three core streams of research. First, we contribute to the literature on the institutional factors that affect inventor mobility (Akcigit et al. 2016, Hombert and Matray 2017), by honing in on changes in the US patent system. Second, our results contribute new insights to the research on the use of intellectual property to restrict employee movement (Marx et al. 2009, Melero et al. 2020) by focusing on how changes to patent enforceability deter mobility. Finally, our findings also add to the research on micro-level dynamics in strategic factor markets (Barney 1991, Chatain 2014, Coff 1997, Ross 2012) by providing evidence on how changes to institutional settings can influence the retention of knowledge workers, and thereby affect the rate and direction of innovation (Chatterji and Fabrizio 2016, Pisano 2006, Teece 1996).

2 Conceptual Framework

Especially in knowledge intensive industries, inventor-employees play a fundamental role in the production of innovation and in value creation within a firm (Coff 1997). The retention of inventor-employees is a core strategic concern for firms in innovative industries, as the tacit knowledge skilled inventors embody is key for further development of the products they create (Zucker et al. 1998). Moreover, reducing employee turnover can be central to a firm's intellectual property strategy, given that employee mobility is a common channel through which trade secrets can leak to other firms (Friedman et al. 1991). Employee mobility puts firms in the precarious position of not only placing their competitive advantage at risk, but also benefiting their competitors through the transfer of ex-employees (Agarwal et al. 2009, Gambardella et al. 2015). In addition, the firm's disadvantage may be reinforced by the ability of departing employees to reestablish valuable complementary assets outside of the firm (Phillips 2002, Wezel et al. 2006). As such, threats to employee retention and methods of mitigating these challenges are an important topic of strategic management research.

A long standing stream of literature has built on the work of Arrow (1962) to establish the important role that the inter-firm mobility of skilled workers plays in the dissemination of knowledge, and the wide variety of individual, institutional, and organizational factors that affect mobility (Marx et al. 2009, Palomeras and Melero 2010, Paruchuri et al. 2006). Our analysis builds on this line of research and focuses on the role that patent excludability plays in the mobility of skilled employees. Specifically, we focus on the effect that a drop in the penalties associated with patent infringement has on the mobility of a firm's inventor-employees.

Although inventor-employees may generate the new inventions embodied in patents, they typically do not own the patents they produce. Instead, their contracts stipulate that the patents are held by their employers (Merges 1999). This is an important feature, since prior work suggests that firms can use the ownership of patents to discourage inventor-employee mobility (Melero et al. 2020). Moreover, additional literature shows that engaging in patent litigation can be an effective method for discouraging inventor-employees from leaving (Ganco et al. 2015).

Inventor-employees may have human capital that is specific to the inventions that their employer has patented (Melero et al. 2020). If inventors and/or their potential new employers believe that they cannot use this human capital after leaving without being sued, then inventors may not be able to use these skills after their departure. As prior literature suggests, the loss of this capital can deter inventor-employees from leaving (Ganco et al. 2015). Without this human capital, inventor-employees may be less valuable to competing employers, reducing the quality of their outside employment options and making them more likely to stay with their current employer. Inventors who engage in upstream research such as basic science may be especially vulnerable to this retention tactic, since any follow-on work is likely to infringe on their employers' patents.

As such, it seems possible that reducing patent excludability could encourage inventor mobility, since it may reduce firms' ability to use litigation to prevent employees from practicing their invention-specific skills elsewhere. If other firms are less concerned about the penalties associated with patent infringement, inventors may be able to use more of their human capital elsewhere, so employee departure may rise. Essentially, the decreasing threat of penalties may improve inventor-employees' outside employment options, thus increasing their rate of departure. As a further consequence, the increasing rate of employee departure may also decrease firms' ability to conduct follow-on innovation that is based on their prior work, and to conduct exploratory work in adjacent technological areas.

Contrarily, it is possible that the sheer volume of litigation and patents provides the primary barrier to inventor mobility, rather than the penalties associated with infringement. Prior literature indicates that even patent litigation that is considered "frivolous" can affect firms' innovation strategies (Appel et al. 2019, Cohen et al. 2019). It is thus possible that reducing the patent infringement penalties will not affect the loss of human capital associated with departure, since the cost of litigation, rather than the penalties associated with a successful lawsuit, could be enough to deter other firms from using the inventor's skills. Moreover, in this case, firms' ability to conduct follow-on innovation and enter adjacent technological areas should be unaffected.

Patents and patent litigation can be an effective method for reducing employee turnover (Ganco et al. 2015, Marx et al. 2009, Melero et al. 2020). Yet the role of patent enforceability in the mobility of skilled employees is unclear. In what follows, we set out to test whether a drop in the penalties associated with patent infringement increases inventor-employee exit. Understanding the mechanisms of patents' effect on inventor-employee mobility is crucial for employers seeking to optimize their use of intellectual property for employee retention.

3 Estimation Strategy

3.1 The Ideal Experiment

In considering our estimation strategy, it may be useful to conduct a thought experiment first. Intuitively, we would like to run an experiment that would randomly assign inventor-employees to a treatment group or a control group. The penalties associated with litigation for subjects in the treatment group would all be reduced by the same amount, while the penalties for those in the control group would remain unaffected. We would have the full record of all patent inventors' employment history, and we could simply compare the average mobility of inventor-employees in the treatment group to the average mobility of the control group. The difference in the averages would equal the effect of reduced patent excludability on inventor mobility.

While we cannot implement the experiment described above, it provides a useful guideline for designing an empirical test and addressing possible threats to identification. For instance, it illustrates the need for a shock or event that affects certain inventors, and leaves others relatively unaffected, providing us with treatment and control groups. Otherwise, we may run into the risk of omitted variable bias, where a variable that is correlated with reduced infringement penalties also affects mobility. Additionally, the ideal experiment highlights the potential danger of selection bias, specifically through attrition. If half the inventors in the treatment group disappear midway through the ideal experiment, while the inventors in the control group remain the same, comparing the average mobility rates for the full period will not capture the true effect of reduced infringement penalties.

While the ideal experiment described above is not feasible, we have identified a shock that had a similar effect: the US Supreme Court ruling *eBay Inc. v. MercExchange, L.L.C.* This event supplies a useful opportunity to test the effect of reduced patent excludability on inventor-employee mobility. As we will explain further in the next section, the heterogeneous effects of this ruling make it an advantageous setting for exploring this relationship.

3.2 eBay Inc. v. MercExchange, L.L.C.

The US Supreme Court ruling *eBay Inc. v. MercExchange, L.L.C.* substantially weakened the excludability of patents, and thus provides a mechanism for testing the effect of reduced infringment penalties on inventor-employee mobility. The ruling's key effect was reducing the use of permanent injunctions in patent infringement cases. A permanent injunction is a court order that forbids an entity from engaging in certain activities. In cases of patent infringement, if a defendant is found to be infringing on the plaintiff's intellectual property, a court may issue a permanent injunction forbidding the defendant from continuing to infringe, in addition to awarding damages related to past infringement. If the defendant wishes to continue using the infringing technology, they must negotiate an agreement with the plaintiff.

The risk of a permanent injunction provides plaintiffs with a powerful bargaining position. Even if the infringed patent covers only a small portion of a product, an injunction gives the plaintiff the ability to prevent the defendant from selling the product if they cannot work around the infringement. This potentially allows the plaintiff to extract more value than the technological innovation embodied by the patent generates (Shapiro 2016). In particular, *eBay* reduced the use of permanent injunctions in patent litigation cases, thus improving the bargaining positions of defendants in negotiations related to alleged infringement. This shift in bargaining power decreased the potential penalties faced by infringing parties.

In what follows, we will provide a brief summary of the case. In 2001, MercExchange sued eBay in the US District Court for the Eastern District, alleging that eBay willfully infringed patents assigned to MercExchange. A jury found that eBay had infringed MercExchange's patents and held eBay liable for $35 million in damages. However, the district court did not grant MercExchange a permanent injunction, which would have prevented eBay from practicing the technology used in the patents until they had reached a deal with MercExchange. In response, MercExchange appealed to the US Court of Appeals for the Federal Circuit in order to seek a permanent injunction. The Federal Circuit unanimously reversed the district court's denial and granted the permanent injunction, noting that there was a "general rule" that permanent injunctions should be granted after findings of infringement. At this point, eBay appealed to the Supreme Court to vacate the injunction. The court heard oral arguments on March 29, 2006, and issued its opinion on May 15, 2006, vacating the injunction, while rejecting the notion of a "general rule" that automatically granted injunctions in cases of infringement.

According to the Supreme Court ruling, in order for a permanent injunction to be issued after a finding of infringement, the plaintiff must demonstrate that it meets the terms of a four factor test: (1) that it has suffered an irreparable injury; (2) that remedies available at law are inadequate to compensate for that injury; (3) that considering the balance of hardships between the plaintiff and defendant, a remedy in equity is warranted; and (4) that the public interest would not be disserved by a permanent injunction. Prior to the ruling, courts had almost always issued permanent injunctions against future infringement after a finding that a defendant had infringed a patent.

Following the ruling, receiving a permanent injunction after a finding of infringement was no longer nearly automatic. Chien and Lemley (2012) find that the likelihood of obtaining an injunction fell from 95 percent to 75 percent after the ruling. Moreover, the share of cases where plaintiffs filed for a permanent injunction fell from 1.9% to 1.1% after the ruling (Gupta and Kesan 2017), since many plaintiffs believed their injunction motions would fail. This reduced threat of injunction strengthened the bargaining position of defendants in their negotiations with plaintiffs (Shapiro 2016). By lowering the risk of injunction, the *eBay* ruling decreased the penalties associated with infringement. Yet as Figure 1 and Figure 2 demonstrate, the ruling did not lower the volume of patent litigation or patent applications. By reducing the penalties associated with patent infringement without decreasing the probability of being sued, the *eBay* ruling enables us to specifically test how the enforceability of patents affects the mobility of inventors.

3.3 Data

Our analysis relies on data from several different sources. We start with the USPTO Patent Examination Research Dataset ("Patex"), which sources its data from the public Patent Application Information Retrieval database ("PAIR"). PAIR contains information on published patent applications filed with the USPTO. This includes data about the applications, such as the classifications, application types, and filing dates, as well as information about the examination process, including the names of the examiners (Graham et al. 2015). Within this dataset, we identify every original utility application filed from 2002 to 2010.

To track inventors across applications, we rely on data from the USPTO's PatentsView program. This dataset contains the results of the disambiguation algorithm specific to the inventor data provided in Li et al. (2014), which allows for the robust identification of individual inventors across applications and granted patents. To identify the firm that owns the application, we use data from the USPTO Patent Assignment Dataset (Marco et al. 2015), which provides information on reassignments of applications from inventors to their employers. The employer reassignment data runs until September 2012, when it became possible for firms to apply for patents themselves. Prior to September 2012, only inventors could apply for patents, and inventors had to reassign patent rights to their employer after applying.

We map application owners to firms that are included in the Standard and Poor's (S&P) Capital IQ database, which provides names and merger information for a large set of private and public firms. To match Capital IQ firm names with assignee names, we first apply the name standardization procedure used in the National Bureau of Economic Research (NBER) patent data project. We then run the Jaro–Winkler algorithm to correct for typos and misspellings, grouping together the best matches with an overlap of 90 percent or higher. Finally, we apply exact string matching to select the final list of standardized assignee names that coincide exactly with standardized firm names in Capital IQ. Note that this means we are limiting our sample to firms in the Capital IQ database. Although Capital IQ covers over 100,000 public firms and millions of private firms, this still means our analysis will not include inventors outside this data, such as the self-employed and those who only patent outside the US. Since our analysis is focused on the efforts of employers to retain their employees, and the *eBay* ruling only affected US patents, we believe these exclusions are reasonable.

We define inventor mobility based on changes in assignee(s) between two consecutive applications. A similar method has been used previously in the literature for both patents (Marx et al. 2009, Palomeras and Melero 2010, Singh and Agrawal 2011, Ganco et al. 2015) and patent applications (Melero et al. 2020). Relying on this method comes with a number of limitations. An inventor's career can only be tracked if they have multiple applications. Moreover, we can only track moves to employers where the applicant filed patent applications; employers with no applications will be missing from the data. To address concerns about sample attrition, we run several robustness tests, and find that our results remain consistent.

One potential issue that may arise with this method is that it may misclassify applicants as movers in case of an acquisition or if the inventor is performing contract R&D. To address this last problem, we do not consider as actual moves the following changes in assignee(s): (i) those that are followed by a return to the initial employer within less than one year, as these cases most likely reflect contract research or collaborations, and (ii) those as a result of mergers and acquisitions, which are detected through information provided by Capital IQ. Despite following these careful steps, some misclassification error possibly remains given the nature of the large-scale representative sample used in our study. However, to our understanding, it is not clear that misclassification is correlated with being more or less affected by the *eBay* ruling. To the extent that misclassification produces noise, it should bias our estimates towards zero. To further alleviate any misidentification concerns and provide the most stringent approach, we impose two key restrictions on the dataset. First, we only include inventors who filed their first patent application between 2001 and the *eBay* ruling, and who had a patent granted based on a patent filed prior to the ruling. This sample represents a subset of inventors who are relatively early in their careers. We believe the careers of these inventors are likely to be more sensitive to changes in the threat of patent infringement penalties. Moreover, early career inventors are more likely to have their value defined by their inventions and patents, rather than managerial abilities that may become more relevant later in their career. Second, we restrict our pool of inventors to those whose first application was assigned to a Capital IQ firm. This allows us to use firm fixed effects in our regressions, and to consistently measure employer changes.

Our final dataset starts in 2002 and ends in 2009. We track inventors throughout this period. The unit of observation is an inventor-year. Inventors enter the dataset when they file their first original patent application and exit the dataset when they leave their first employer or when they file their last original application. Inventor moves are dated based on the midpoint between two consecutive application dates, and inventors with a gap of more than four years between original applications are dropped (Singh and Agrawal 2011). In order to address attrition concerns, we drop any inventors who stop filing original applications before the *eBay* ruling. The dataset used in our analysis consists of 227,335 observations of 50,283 unique inventors and 3,682 unique firms[1]. We track 12,462 employment changes, and find that the average probability of a move is .055. In the next section, we will explain how we use this data to explore the relationship between reduced patent excludability and employee departure.

4 Patent Excludability and Inventor Mobility

4.1 Empirical Design

In order to test the effect of the *eBay* ruling on inventor-employee mobility, we need to establish certain firms and inventors as differentially affected in comparison to others. Since the ruling applied to all patents, there is no obvious control group. However, the shock from this ruling did not affect every firm-inventor pairing in the same way, since pairings will vary in the ratio of patents the firm owns in the inventor's field to the number of inventors the firm employees in that field. This patent-to-inventor ratio should indicate the firm's ability to retain inventors in a given field through the threat of patent infringement penalties, since each additional patent in a field should reduce an inventor-employees' ability to use their skills outside the firm without infringing. Inventor-employees at firms with a low patent-to-inventor ratio in the employee's field should be relatively unaffected by the decision. Contrarily, the ruling was very salient for inventor-employees at firms with a high patent-to-inventor ratio in their technological area.

Following this logic, we exploit variation in the intensity of the treatment—measured by the firm's patent-to-inventor ratio in the inventor employee's technological field—to identify the impact of the decision on inventor-employee mobility. Specifically, we calculate the number of eventually granted original patent applications the firm filed from 2001 until the the *eBay* ruling within the USPC classes in which the inventor-employee filed successful patent applications during this period. We then divide this by the number of inventors the firm employed in these classes during this period who filed successful original patent

[1] Unique firms are counted based on the parent company of the inventor's initial original application. Each unique company is a Capital IQ Company ID.

applications. The resulting figure is the *Related Patent-Inventor Ratio* for the given firm-employee pairing. Because this measure skews rightward, we take the natural log to get *Log Related Patent-Inventor Ratio.* In our framework, inventor-employees with a low *Log Related Patent-Inventor Ratio*, who theoretically were less affected by the shock, provide a counterfactual for inventor-employees at firms with a high patent-to-inventor ratio in the inventors' classes.

This design functionally resembles a difference-in-differences model, where we examine how mobility changed as a function of the patent-to-inventor ratio. In our baseline specification, each observation is an inventor-year. We use a linear probability model to estimate the likelihood that an inventor moves between one year and the next as follows:

$$\begin{aligned} Prob(Move)_{ijt} = \alpha + \beta Post_t \times LogRelatedPatent - InventorRatio_{ij} \\ + \gamma LogRelatedPatent - InventorRatio_{ij} + \delta D_i + \zeta_j + \eta_t + \theta_{it} + \epsilon_{ijt} \end{aligned} \tag{1}$$

where i indexes inventors, j indexes firms, and t indexes year. *Move* is a binary variable that indicates whether the inventor changed employers. *Post* is a binary variable that indicates whether the year is 2007 or later. The coefficient β is our estimate of the differential effect of the *eBay* ruling on the mobility of subjects with a higher *Log Related Patent-Inventor Ratio* indicating that an inventor is more affected by patent enforcement. The vector δD_i contains a set of inventor characteristics, while ζ_j and η_t represent firm and state-year fixed effects, respectively. The vector θ_{it} contains a set of technological category fixed effects based on the six nonexclusive NBER categories, which are equal to one if the inventor has filed an application in the respective category. By default, we exclude data from the year 2006, because it does not fall entirely inside or outside the treatment period. We cluster the standard errors at the firm level.

Although our approach cannot perfectly mimic the ideal experiment, it has several key strengths. Because the ruling affected a wide array of industries, we are able to use a broad cross-section of inventors rather than focus on a small set that operate within a particular type of technology. Moreover, having a spectrum of treatment rather than a binary treatment effect allows us to capture the effects of a continuum of changes to the level of excludability, which is more realistic for managers and policymakers. Finally, the *eBay* ruling provides a suitable exogenous shock, with little threat of anticipation or selection into treatment (Mezzanotti 2021).

While our approach has many strengths, we must also acknowledge several potential weaknesses. First, the patent application data is an incomplete record of inventors' employment history. If an inventor was employed by a firm where they did not have a patent application, that firm will not show up in their employment history, so moves may be missed. Second, as mentioned previously, our analysis contains only observations where the inventors' prior applications belonged to firms in the Capital IQ database. Capital IQ covers over 100,000 public firms and millions of private firms, allowing us to provide accurate estimates of the effects of excludability on inventor-employees. However, our analysis does not allow us to capture how this ruling affected the careers of inventors that may fall outside of this data, such as the self-employed, and those who only filed patents outside the US. Although these features may be viewed as limitations, we believe that we are nonetheless likely capturing a highly relevant population.

4.1.1 Summary Statistics.

Table 1 provides a set of summary statistics for the variables used in this paper. The unit of observation in our analysis is the inventor-year. The figures indicate that the average inventor in the dataset has filed 7.1 patent applications and has been granted 1.8 patents. The average probability that an inventor will move is .059. The average *Related Patent-Inventor Ratio* is .491 and the average *Log Related Patent-Inventor Ratio* is -.814. Please refer to the Appendix Table A1, for further summary statistics.

Insert Table 1 and Figure 1 about here.

4.1.2 Patent Litigation Risk and Inventor Mobility.

Panel (a) in Figure 1 compares the average mobility between inventor-firm pairings in the top 25 percent of *Log Related Patent-Inventor Ratio* and those in the bottom 25 percent of *Log Related Patent-Inventor Ratio*. It provides a first visual depiction of our main result: prior to the *eBay* ruling, inventors with higher *Log Related Patent-Inventor Ratio* were substantially less mobile than those with a low *Log Related Patent-Inventor Ratio*. After the ruling, the groups converged, and the inventors with a higher patent-to-inventor ratio eventually became more mobile than the inventors with a lower patent-to-inventor ratio.

Table 3 provides the main results of our analysis. Each specification includes firm, state-year, and technological category fixed effects, along with additional controls for inventor characteristics. Inventor characteristics include *Patents Granted*, *Inventor Years*, *Applications Filed*, *Inventor Patent Quality* and *Inventor Exposure*. *Patents Granted* is the number of patents that the inventor has been granted as of the year in question. *Inventor Years* indicates the number of years since the inventor's first filed application. *Applications Filed* is the number of utility patent applications that the inventor has filed as of the year in question. *Inventor Patent Quality* is the average quality of the patents the inventor has filed as of the year in question, as measured by citations.

Inventor Exposure is a measure of the general prevalence of patent litigation in the technological areas in which the inventor operates. Following the methodology of Mezzanotti (2021), we calculate the propensity of patent litigation in each of the USPTO's USPC patent classes from 2000 until the *eBay* ruling. We then calculate the share of each inventor's granted patents that were filed from 2000 until the *eBay* ruling that were in each USPC class. Finally, we generate *Inventor Exposure* as the weighted average of litigation propensity, with the inventor patent shares as the weights. See Appendix Table A2 for the equation for this calculation.

In Table 2, column (1) we present the baseline estimate relating mobility to reduced patent litigation threat without inventor controls. We find that inventors with a high *Log Related Patent-Inventor Ratio* increase their mobility relative to other investors following the ruling. A ten percent increase in *Log Related Patent-Inventor Ratio* is associated with a .2 percentage point increase in mobility after the ruling. Comparing this estimate to the average mobility in the post-ruling period, this implies an increase in mobility of about 4.4 percent.

In column (2) we present the baseline estimate relating mobility to reduced patent litigation threat with inventor controls included. We find that inventors whose employers have high *Log Related Patent-Inventor Ratio* increase their mobility relative to other investors following the ruling. A ten percent increase in *Log Related Patent-Inventor Ratio* is associated with a .2 percentage point increase in mobility after the ruling. Comparing this estimate to the average mobility in the post-ruling period, this implies an increase in mobility of about 4.2 percent.

Insert Table 2 about here.

Panel (b) of Figure 1 plots the year-specific differences in mobility associated with inventors with higher *Log Related Patent-Inventor Ratio*, β_{jt}, and their 95-percent confidence intervals based on the following specification (2005 is the baseline year):

$$\begin{aligned} Prob(Move)_{ijt} = \alpha &+ \beta Post_t \times LogRelatedPatent - InventorRatio_{ij} \\ &+ \sum_{i=1}^{7} \gamma LogRelatedPatent - InventorRatio_{ij} \times Year_t \\ &+ \delta LogRelatedPatent - InventorRatio_{ij} + \zeta D_i + \eta_j + \theta_t + \iota_{it} + \epsilon_{ijt} \end{aligned} \tag{2}$$

where i indexes inventors, j indexes firms, and t indexes year. *Move* is a binary variable that indicates whether the inventor changed employers. The β coefficients are our yearly estimate of the differential mobility of subjects with higher *Log Related Patent-Inventor Ratio* relative to the baseline year. The vector γD_i contains a set of inventor characteristics, while δ_j and ζ_t represent firm and state-year fixed effects, respectively. The vector η_{it} contains a set of technological category fixed effects based on the six nonexclusive NBER categories, which are equal to one if the inventor has filed an application in the respective category. We cluster the standard errors at the firm level.

The estimated coefficients prior to 2005 are not significantly different from 2005. The year-specific coefficient in 2006 is substantially larger than 2005, but not at statistically significant level, as the year was only partly affected by the ruling. The year-specific coefficients in 2007 and after are consistently statistically significant and positive. The estimates have an increasing trend, which may be explained by firms and employees learning to adjust to the change in intellectual property regime over time.

Overall, these results provide evidence suggesting that, on average, reduced patent excludability encourages employee mobility. In the Online Appendix, Tables A3 and A4, we present the results from performing a number of heterogeneity analyses by inventor attributes, and do not find results that are statistically significant on conventional levels. We test potential concerns about the robustness of our estimates in the next section.

In the Online Appendix, Table A5, we test whether results differ by the number of inventors employed by the firm, and find that firms that employ more inventors are less affected by the ruling.

4.1.3 Robustness Checks.

In this section, we conduct a variety of tests to confirm the robustness of our baseline findings. We explore concerns related to data structure, the measurement of litigation exposure, and the effects of sample attrition. Results from all tests can be found in Table 3.

As we noted earlier, we structure our data as an inventor-year panel, where observations for each inventor begin with their first original application year or in 2002, depending on which is later. Each inventor is then tracked in the data until they leave their original employer, file their last original application, or reach the year 2009, depending on which is earlier. Between these first and last years, we include years where the inventor has not filed any original applications, which may downwardly bias our estimates of inventor mobility. In column 1 we exclude years with no original applications and rerun our baseline regression. We find that the coefficient on $Post \times LogRelatedPatent - InventorRatio$ remains positive and statistically significant.

Next, we test whether our results are sensitive to the use of a panel structure. We restructure our data so that each observation is a unique inventor-filing date, thus estimating the probability that an inventor leaves their employer between original applications filings rather than on a yearly basis. In column 2 we run our baseline regression with this data structure and find that the coefficient on $Post \times LogRelatedPatent - InventorRatio$ remains positive and statistically significant.

Finally, we perform several tests to address concerns related to sample attrition. Because we track inventors using patent applications, we only observe inventors if they continue to file applications. This would be a problem for our study if moving inventors had different probabilities of filing new applications and those differences were affected by the *eBay* ruling. We test the possible effects of a drop in continued applications on our results using several approaches.

First, we restrict the sample to inventors who filed their first original application before 2003. By restricting to inventors who started filing before 2003, we are able to test our results for inventors who have the largest window to file applications in the 2002 to 2009 time period. We rerun our baseline regression with these data in column 6, and we find that the coefficient on $Post \times LogRelatedPatent - InventorRatio$ remains positive and statistically significant.

Second, we explore how results vary based on changes in application patterns across USPC classes in the pre and post-eBay periods. For each USPC class, we calculate the average annual original applications in the five years prior to the ruling and in the three years after the ruling. We then calculate *USPC Growth*, which measures how the annual original application counts changed between these two periods. Next, we calculate *Inventor USPC Growth* as the weighted average of *USPC Growth*, with the number of original applications that the inventor filed in each USPC class in the five years before the ruling serving as the weights. Having calculated these measures, we split the inventors into high and low-growth samples, with inventors in the top 50 percent of *Inventor USPC Growth* in the high-growth sample and all other inventors in the low-growth sample. We then run the baseline regressions for each sample in columns 7 and 8, respectively. In both samples, we find that the coefficient on $Post \times LogRelatedPatent - InventorRatio$ remains positive and statistically significant.

Third, we explore how our results vary based on overall application propensities for different technologies. For each USPC class, we calculate *USPC Intensity*, which measures the number of original applications per inventor in the class for the five year prior to and three years following the *eBay* ruling. Next, we calculate the measure *Inventor USPC Intensity* as the weighted average of *USPC Intensity*, with the number of original applications that the inventor filed in each USPC class in the five years before the ruling and three years after the ruling serving as the weights. Having calculated these measures, we split the inventors into high and low-intensity samples, with inventors in the top 50 percent of *Inventor USPC Intensity* in the high-intensity sample and all other inventors in the low-intensity sample. We then run the baseline regressions for each sample in columns 9 and 10, respectively. In both samples, we find that the coefficient on $Post \times LogRelatedPatent - InventorRatio$ remains positive and statistically significant.

Overall, we find that our results for $Post \times LogRelatedPatent - InventorRatio$ are highly robust. This is consistent with the view that a drop in the threat of patent litigation increases the rate of exit by inventor-employees. Next, we will investigate potential heterogeneous effects that the ruling may have had on inventor-employees.

Insert Table 3 about here.

5 Patent Excludability, Inventor Mobility, and Heterogeneous Effects

So far, our evidence indicates that decreasing the threat of patent enforcement increases the mobility of inventor-employees. This suggests that patent excludability plays a key role in rendering inventor's human capital as firm-specific (Melero et al. 2020), preventing them from leaving for other employers. When the enforceability of patents drops, inventor-employees exit at an increasing rate. In what follows, we examine potential characteristics that may affect inventors' reaction to the ruling.

5.1 Inventor Firm-Specificity

5.1.1 Empirical Design.

Firm-specific human capital plays a significant role in preventing employees from leaving their firms (Topel 1991, Lazear 2009). Patents can increase the firm-specificity of inventors' skills, but they are far from the only factor that renders human capital firm-specific. Human capital will be more specific when employees work on projects that are highly unique to the firm, and which require skill combinations that are unique to the firm (Mayer et al. 2012, Lazear 2009). Non-patent factors that make inventor-employees human capital more firm specific may reduce the effect of a drop in excludability on inventor mobility. In this section, we test how the firm-specificity of the inventor-employee's projects impacts their response to the *eBay* ruling.

To proxy for firm specificity, we use the proximity of the inventor's work to other innovation happening within the firm, as an indicator of how tightly the inventor-employee's projects match with other projects at the firm. To calculate this, we measure the similarity of the inventor's patents to other patents filed by their employer. Using data from the Patent Similarity Dataset (Whalen et al. 2020), we measure the vector space model-based similarity of each of the granted patents that each inventor filed to all the other granted patents filed by their employer from 2000 until the *eBay* ruling. We then take the average of the three highest similarity scores for each patent, and finally take the average of these scores across the inventors' patents to generate the measure *Inventor Firm-Specificity*. Next, we normalize this measure across inventors by subtracting the mean and dividing by the standard deviation. The formula for this measure can be found in the Appendix, Table A2.

To determine whether the effects of *eBay* differ based on firm-specificity, we run a triple difference-in-differences estimation using the following specification:

$$\begin{aligned} Prob(Move)_{ijt} = {} & \alpha + \beta Post_t \times LogRelatedPatent - InventorRatio_{ij} \\ & + \theta InventorFirm - Specificity_{ij} + \iota Post_t \times InventorFirm - Specificity_{ij} \\ & + \mu LogRelatedPatent - InventorRatio_{ij} \times InventorFirm - Specificity_{ij} \\ & + \kappa Post_t \times LogRelatedPatent - InventorRatio_{ij} \times InventorFirm - Specificity_{ij} \\ & + \gamma D_i + \delta_j + \zeta_t + \eta_{it} + \epsilon_{ijt} \end{aligned} \tag{3}$$

where i indexes inventors, j indexes firms, and t indexes year. The coefficient κ is the difference in differences in differences estimator. This provides the estimate of how having a higher firm-specificity influences the impact of the reduction of patent excludability on inventor-employee mobility. As in our prior specifications, the vector γD_i contains a set of inventor characteristics, while δ_j and ζ_t represent firm and state-year fixed effects, respectively. The vector η_{it} contains a set of technological category fixed effects based on the six nonexclusive NBER categories, which are equal to one if the inventor has filed an application in the respective category. We cluster the standard errors at the firm level.

5.1.2 Results.

Table 4 below provides the results from examining the differential impact of *eBay* on inventors with higher *Inventor Firm-Specificity*. In accordance with the firm-specific capital literature, we expect to find that having greater firm-specificity should mitigate the impacts of a decrease in excludability. Across specifications, we find that inventors with greater firm-specificity are less heavily affected by the ruling than inventors with lower firm-specificity.

In columns (1) and (2) we present the results of running the regressions without and with controls for inventor characteristics, respectively. We find that, after the ruling, having a firm-specificity that is one standard deviation higher decreases the mobility associated with *Log Related Patent-Inventor Ratio* by .5 and .5 percentage points, respectively. In other words, every additional standard deviation above average in firm-specificity mitigates the post-ruling increase in mobility associated with higher *Log Related Patent-Inventor Ratio* by 46% (.00522/.0114) and 51% (.00541/.0106), respectively. These results are both statistically significant at the five percent level. The mobility of inventor-employees with a stronger firm-specificity appears less affected by the drop in infringement penalties, indicating that their firm-specificity mitigated the impact of the drop in excludability.[2] This finding is consistent with the notion that having inventors with more firm-specific skills can help firms withstand unexpected legal shocks and retain their employees.

[2]This finding remains consistent when the sample is split based on firm-specificity.

Insert Table 4 about here.

5.2 Basic Research

5.2.1 Empirical Design.

A key factor in the effect of patent excludability on mobility is the extent to which the firm's patents are "upstream" of other innovations. If the inventor's work is further upstream, then their most valuable projects are likely to rely on their prior innovations, and they will not be able to pursue these projects outside the firm without infringing (Galasso and Schankerman 2015). Whereas if the inventor-employee projects at the firm are downstream, the inventor's most critical innovations are less likely to rely on their prior work at the firm. If upstream inventors are more affected by the threat of infringement penalties, they may increase their exit rate more than other inventors when this threat drops.

To measure the extent to which an inventor-employees' innovations are upstream, we examine how much they rely on basic scientific research. Basic research tends to rely on more tacit, and less codified knowledge (Cassiman et al. 2018). This makes the presence of individuals with experience working with basic research highly beneficial in producing a related commercial product (Zucker et al. 2002). Basic research has a high potential to produce follow-on innovations (Akcigit et al. 2021), and firms that engage in more exploratory research are more likely to allocate resources towards basic research (Bercovitz and Feldman 2007). To measure the extent to which an inventor's work relies on basic research, we rely on the nonpatent literature (NPL) cited in the patents the inventor filed before the *eBay* ruling (Arora et al. 2018, Fleming and Sorenson 2004). Using data from the Reliance on Science project, we measure the share of NPL cites that are to scientific journals that are in the top 10% for impact in their field (Marx and Fuegi 2020, 2022). We take the average of this share across the inventor's patents to generate the measure *Basic Research Share*.

To determine whether the effects of *eBay* differ based on inventor-employee's proximity to basic research, we run a triple difference-in-differences estimation using the same specification as in Equation 3, but replacing *Inventor Firm-Specificity* with *Basic Research Share*.

5.2.2 Results.

Table 5 below provides the results from examining the differential impact of *eBay* on inventors with higher *Basic Research Share*. Inventor-employees that are more proximate to basic research likely work on projects that are more upstream. Across specifications, we find that inventors with greater *Basic Research Share* are more heavily affected by the ruling than inventors with lower *Basic Research Share*.

In columns (1) and (2) we present the results of running the regressions without and with controls for inventor characteristics, respectively. We find that, after the ruling, having *Basic Research Share* that is ten percentage points higher increases the mobility associated with *Log Related Patent-Inventor Ratio* by .26 and .25 percentage points, respectively. In other words, every additional ten percentage points in *Basic Research Share* raises the post-ruling increase in mobility associated with *Log Related Patent-Inventor Ratio* by 11.5% (.00257/.0224) and 11.4% (.00248/.0218), respectively. These results are both statistically significant at the five percent level, and suggest that inventor-employees whose work is farther upstream are more impacted by the reduction in infringement penalties, as patents play a larger role in restricting their mobility.[3] This indicates that firms facing a drop in excludability may risk losing some of their most valuable inventor-employees: those who conduct upstream innovation. These inventors' play a critical role in firm's exploration of new areas of technology (Bercovitz and Feldman 2007), and their presence is highly important to the success of the projects they conduct for the firm (Cassiman et al. 2018, Zucker et al. 1998).

Insert Table 5 about here.

5.3 Inventor Generalizability

5.3.1 Empirical Design.

A key factor in a inventor-employee's decision to leave their firm will be the quality of their outside employment options (Campbell et al. 2012a). Patent infringement penalties allow employers to reduce the quality of their inventors' employment options. If an inventor cannot use a portion of their skills outside the firm without infringing on their employers patents, this will make them less attractive to other employers. Yet patent enforcement is far from the only determinant of an inventors' outside employment options (Campbell et al. 2012a, Lazear 2009). Prior work indicates that the generalizability of an employee's skillset plays a key role in facilitating their intrafirm mobility (Miric and Ozalp 2020). A worker with skills that can be used in a broader set of contexts should have a wider array of outside employment options. Thus, when the threat of infringement penalties, generalist inventors may increase their mobility more than other inventors.

To measure the generalizability of an inventor-employee's skills, we examine the extent to which their skills transfer across patent classes. Inventors with greater potential to enter new fields likely possess competencies that are more generalizable. To measure this potential, we look at the USPC classes in which the inventor filed successful original patent application prior to the ruling. For each 3 digit class in which the inventor filed, we measure the likelihood that any inventor would who filed in that class would also have

[3] This finding remains consistent when the sample is split based on *Basic Research Share*.

filed in another given USPC class. We count the number of classes where the likelihood is 5% or greater, and where the inventor has never filed in that class, and we call that count *Inventor Generalizability.* Because this metric skews right and includes zeroes, we take the IVS transformation[4] to get the variable *Log Inventor Generalizability*, which we use as our measure of the generalizability of the inventor-employees' skillset.

To determine whether the effects of *eBay* differ based on inventor-employee's generalizability, we run a triple difference-in-differences estimation using the same specification as Equation 3, but replacing *Inventor Firm-Specificity* with *Log Inventor Generalizability.*

5.3.2 Results.

Table 6 below provides the results from examining the differential impact of *eBay* on inventors with higher *Log Inventor Generalizability.* Inventor-employees that are more proximate to basic research likely work on projects that are more upstream. Across specifications, we find that inventors with greater *Log Inventor Generalizability* are more heavily affected by the ruling than inventors with lower *Log Inventor Generalizability.*

In columns (1) and (2) we present the results of running the regressions without and with controls for inventor characteristics, respectively. We find that, after the ruling, having *Inventor Generalizability* that is ten percent higher increases the mobility associated with *Log Related Patent-Inventor Ratio* by .9 and .8 percent, respectively. These results are both statistically significant at the five percent level, and suggest that inventor-employees with more generalizable skills are more impacted by the reduction in infringement penalties, as they have a superior set of outside options.[5] Losing generalist inventors poses a significant problem for firms. Prior research indicates that inventors with diversified skillsets are more likely to integrate knowledge from beyond their field to produce high-impact innovations (Nagle and Teodoridis 2020). As firms lose their innovators who conduct upstream researchers and possess generalist skillsets, the drop in patent excludability may affect firms' abilities to explore new technological areas. In our next section, we test the impact of a drop in excludability on firms' investigation of new fields.

Insert Table 6 about here.

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[4]The IVS transformation formula is ln(x + ((x^2 +1)^0.5))

[5]This finding remains consistent when the sample is split based on generalizability.

6 Patent Excludability, Inventor Mobility, and Firm-Level Effects

The evidence we have provided thus far, indicates that a drop in excludability increases the rate of exit for inventor-employees. This increase is especially high for generalists and inventors engaged in upstream research. Because these types of workers play a key role in firms' exploration of new technological fields, it is possible that losing them reduces the extent of firms' exploratory work. In what follows, we examine firm exploration following the *eBay* ruling.

6.1 New Class Entry

6.1.1 Empirical Design.

One way to examine the extent to which firms are conducting exploratory work is to consider whether they are entering new technological fields. The ability to incorporate information from distant fields of knowledge is often key to producing breakthrough innovations (Boudreau et al. 2016, Chatterji and Fabrizio 2014, Nagle and Teodoridis 2020) and to continuously be able to adapt to a changing environment. To measure the extent to which firms are entering new technological fields, we examine the rate at which they are patenting in new USPC classes (Ganco et al. 2020). USPC classes represent a set of patent applications that are in the same technical field (Hall et al. 2001). Thus, when a firm successfully files a patent in a new USPC class, this is a reasonable indicator that they are entering a new technological field.

As a dependent variable, we construct a measure, *New Classes*, which is equal to the number of new classes in which the firm filed a successful patent application in a given year. A class is considered new if the firm has not filed a successful patent application in that class within the past five years. Because the patent applications data is not complete before 2001, we can only use granted patents for this part of the analysis, and this portion of the analysis relies on the the UVA Global Corporate Patent Dataset (Bena et al. 2017) for the firm-patent mapping. In order to include firm financial metrics in our data, we limit our analysis to firms that appear in the Compustat data. Since our data relies on US patents, we only include firms headquartered in the United States, in order to properly capture their entry into new fields. Finally, we only include firms with more than twenty inventors that had filed original patent applications between 2001 and the *eBay* ruling, so that the firm-level effects cannot be heavily affected by a single inventor. We generate a panel dataset with 308 firms observed on a yearly basis from 2002 to 2009, with 2006 excluded. The firms included in this panel represent 56% of the observations in our main dataset.

To measure the extent to which the *eBay* ruling may have influenced the firm, we calculate the *Related Patent Inventor Ratio* for every inventor that filed a successful original patent application for the firm between 2001 and the *eBay* ruling. We then calculate the weighted average of this measure, with each inventor being weighted by the number of successful patent applications they filed before the ruling. Finally, we take the natural log of this weighted average to produce *Log Weighted Average Patent Inventor Ratio*, our measure of the firm-level mobility shock produced by the ruling.

To determine how *eBay* may have influenced the rate at which firms entered new fields, we run an estimation using the following specification:

$$\begin{aligned} NewClasses_{jt} = \alpha &+ \beta Post_t + \gamma Post_t \times LogWeightedAveragePatentInventorRatio_j \\ &+ \delta LogPreviousClassCount_{jt} + \zeta LogPreviousInventorsCount_{jt} \\ &+ \kappa PreviousPatents_{jt} + \tau NewPatents_{jt} + \theta LogRevenue_{jt} \\ &+ \iota ResearchandDevelopment_{jt} + \lambda OperatingMargin_{jt} + \mu T_j + \nu I_j + \xi_i + \eta_j + \epsilon_{jt} \end{aligned} \tag{4}$$

where j indexes firms and t indexes year. The coefficient γ is the coefficient of interest. This provides the estimate of how having a higher exposure to the effect of *eBay* on mobility influences the firm's entrance into new classes. *Post* is a binary variable that is equal to 1 in any year 2007 or later. The variable *Log Previous Class Count* indicates the natural log of the number of USPC classes where the firm filed successful utility patent applications in the previous five years, while *Log Previous Inventors Count* is the natural log of the number of inventors who filed successful utility patent applications in the previous five years, *Previous Patents* represents the number of successful patent applications the firm filed in the previous five years, and *New Patents* represents the number of successful patent applications the firm filed in the focal year. We also include financial metrics for the focal year. These include *Log Revenue*, the natural log of the firm's annual revenue, *Research and Development*, the total the firm spent on research and development, and *Operating Margin*, which is equal to the firm's earnings before income and taxes divided by its total revenue. We also include a series of fixed effects and dummy variables: the vector μT_j contains a set of dummy variables for the NBER sub-categories in which the firm has patented over the previous five years, while νI_j, ξi and η_j represent industry, year, and firm fixed effects, respectively. We cluster the standard errors at the firm level.

6.1.2 Results.

Table 7 below provides the results from examining the differential impact of *eBay* on firms with higher *Log Weighted Average Patent Inventor Ratio*. Because these firms lost generalist inventors and inventors that engaged in basic research, these firms may have slowed the rate at which they entered new classes. Across specifications, we find that firms with greater *Log Weighted Average Patent Inventor Ratio* relatively decreased their entry into new classes after the ruling.

In columns (1) and (2) we present the results of running the Poisson fixed effect regressions without and with controls for firm financials, respectively. We find that, after the ruling, having a *Weighted Average Patent Inventor Ratio* that is 10% higher is associated with a decrease in the *New Classes* rate of 2% ($e^{ln(1.1)\times .203}-1$)

and 1.9% ($e^{ln(1.1)\times.200} - 1$), respectively. These results are both statistically significant at the ten percent level. Taken together, our findings suggest that the loss of generalist inventors and basic research inventors associated with the drop in excludability may inhibit firms' ability to enter new technological fields. In the next of part of our analysis, we test how the loss of these employees may have influenced firms' reliance on technology outside the boundaries of the firm.

Insert Table 7 about here.

6.2 Firm Citations

6.2.1 Empirical Design.

Another way to examine the extent to which a firm's innovative direction changes after the eBay ruling is to consider the sources from which each firm draws knowledge. If the firm relies less on internal knowledge after the ruling, while external knowledge flows remain constant, this may indicate that the ability of the firm to carry out its own exploratory innovation has declined. Firms often seek out external knowledge in order to carry out more exploratory work (Foss et al. 2013, Laursen and Salter 2006). Moreover, exploratory innovation is more impactful on technological evolution than other innovation, and therefore produces greater knowledge flows (Rosenkopf and Nerkar 2001). Thus if external knowledge flows stay constant while internal knowledge flows drop, this may indicate that the firm can no longer rely on its own inventors to explore new technological areas.

Patent citations are a common method for tracking knowledge flows (Jaffe et al. 1993, Almeida and Kogut 1999). Yet there are limitations to the use of patent citations as a measure of knowledge flows: citations can be added by examiners (Alcácer and Gittelman 2006), and they vary in their flow measurement accuracy based on the applicants' patent strategies, the type of knowledge sources used, the filing jurisdiction, and the technology of the underlying invention (Corsino et al. 2019). However, knowledge flows from competitors are relatively likely to be tracked by patent citations, which is especially important for this context (Corsino et al. 2019). To compare internal and external knowledge flows, we measure the number of citations each firm makes to its own patents and the number of citations it makes to patents it does not own, excluding citations added by examiners. To the extent that measurement error is not correlated with the exogenous shock of the *eBay* ruling, we believe these are appropriate measures of internal and external knowledge flows for our analysis, especially external knowledge flows from competitors.

As dependent variables, we construct two measures, *Firm Self-Citations* and *Firm Outside Citations*, which are equal to the number of citations the firms' successful utility patent applications made in a given year to the firm's own patents and to patents the firm does not own, respectively. Because we need patents from before the patent application dataset begins, this portion of the analysis relies on the the Global Corporate Patent Dataset (Bena et al. 2017) for the firm-patent and citation data. We use the same sample of 308 US Compustat firms with more than 20 inventors that was used in the class entry analysis.

To measure the extent to which the *eBay* ruling may have influenced the firm, we calculate the *Related Patent Inventor Ratio* for every inventor that filed a successful original patent application for the firm between 2001 and the *eBay* ruling. We then calculate the weighted average of this measure, with each inventor being weighted by the number of successful patent applications they filed before the ruling. Finally, we take the natural log of this weighted average to produce *Log Weighted Average Patent Inventor Ratio*, our measure of the firm-level mobility shock produced by the ruling.

To determine how *eBay* may have influenced the rate at which firms relied on internal and external knowledge flows, we run an estimation using the following specification:

$$\begin{aligned} &FirmSelf-Citations_{jt}/FirmOutsideCitations_{jt} = \alpha + \beta Post_t \\ &\quad + \gamma Post_t \times LogWeightedAveragePatentInventorRatio_j + \delta LogPreviousInventorsCount_{jt} \\ &\quad + \zeta TotalFirmCitations_{jt} + \theta PreviousPatents_{jt} + \kappa NewPatents_{jt} + \iota LogRevenue_{jt} \\ &\quad + \lambda ResearchandDevelopment_{jt} + \mu OperatingMargin_{jt} + \nu T_j + \xi I_j + \eta_i + \tau_j + \epsilon_{jt} \end{aligned} \tag{5}$$

where j indexes firms and t indexes year. The coefficient γ is the coefficient of interest. This provides the estimate of how having a higher exposure to the effect of *eBay* on mobility influences the the number of times the firm cited its own patents or outside patents. *Post* is a binary variable that is equal to 1 in any year 2007 or later. The variable *Log Previous Inventors Count* is the natural log of the number of inventors who filed successful utility patent applications in the previous five years, while *Total Firm Citations* indicates the number of citations the firm made to prior utility patents in the given year, *New Patents* is the number of successful patent applications the firm filed, *Previous Patents* represents the natural log of the number of successful patent applications the firm filed in the previous five years, and *New Patents* represents the number of successful patent applications the firm filed in the focal year. We also include financial metrics for the focal year. These include *Log Revenue*, the natural log of the firm's annual revenue, *Research and Development*, the total the firm spent on research and development, and *Operating Margin*, which is equal to the firm's earnings before income and taxes divided by its total revenue. We also include a series of fixed effects and dummy variables: the vector νT_j contains a set of dummy variables for the NBER sub-categories in which the firm has patented over the previous five years, while ξI_j, ηi and τ_j represent industry, year, and firm fixed effects, respectively. We cluster the standard errors at the firm level.

6.2.2 Results.

Table 8 below provides the results from examining the differential impact of *eBay* on firms with higher *Log Weighted Average Patent Inventor Ratio.* Because these firms lost generalist inventors and inventors that engaged in basic research, these firms may have needed to rely more on external knowledge flows in order to innovate. Across specifications, we find that firms with greater *Log Weighted Average Patent Inventor Ratio* relatively decreased the number of citations they made to their own patents, while the number of citations they made to outside patents was unaffected.

In columns (1) and (2) we present the results of running Poisson fixed effect regressions with *Firm Self-Citations Firm Outside Citations*, respectively. We find that, after the ruling, having a *Weighted Average Patent Inventor Ratio* that is 10% higher is associated with a decrease in the *Firm Self-Citation* rate of 3% ($e^{ln(1.1)\times.615} - 1$), which is statistically significant at the five percent level. Meanwhile, we find no statistically significant effect on *Firm Outside Citations.* This indicates that firms more affected by the *eBay* ruling decrease the share of their citations that went to their own patents after the ruling. These patterns may suggest that these firms become relatively more dependent on external knowledge flows to fuel their own innovations given they experience a drop in reference to their own, but not to outside patents. The drop in self-citations may indicate that losing their inventor-employees renders firms less able to produce follow-on innovations to the previous work of their inventors (Moser et al. 2018).

Insert Table 8 about here.

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7 Discussion and Conclusion

In this paper, we examine the impact of reduced patent enforceability on the mobility of individual knowledge workers between companies. We do so by exploiting a regulatory shock that only reduced patent enforceability for a subset of inventors: the US Supreme Court ruling *eBay Inc. v. MercExchange, L.L.C.* Our analysis relies on data from several different sources, including the USPTO Patent Examination Research Dataset, S&P Capital IQ, the Patent Similarity Dataset, and Compustat. We use this data to track 50,283 inventors from 2002 to 2009 and apply a difference-in-differences type model to estimate the likelihood of an inventor move.

Following this approach, we find that inventor-employees at firms with a stronger reliance on patents increase their departure more after the *eBay* ruling. A ten percent increase in *Log Related Patent-Inventor Ratio* is associated with a 4.2 percent increase in the probability of departure. Inventors with more broadly applicable skills and inventors who engage in upstream research are relatively more likely to leave a focal firm after the ruling, while inventors with more firm-specific skills are less affected by the ruling. This suggests that the weakening of patent enforceability may have increased the outside options of certain inventors. For firms aiming to create competitive advantage by pushing the boundaries of knowledge these may be considered the most valuable inventors (Nagle and Teodoridis 2020). In line with this argument, we further detect that firms that, on average, experience an increase in inventor mobility after the ruling observe a reduction in the extent to which follow-on invention builds on their existing stock of knowledge and a stark reduction in exploratory research. As such, though suggestive, these patterns indicate a possible shift in the direction of a firm's inventive activity and potentially critical changes in the capabilities of a firm.

Overall, our results are robust to controlling for a wide array of relevant fixed effects and rely on exploiting a regulatory shock that reduced the threat of patent enforceability more for certain inventors than for others. Although this provides a suitable setting and the necessary properties for a "quasi-experimental" empirical design, in absence of a true "natural experiment", we cannot completely rule out the possibility of other confounds, such as selection effects and attrition bias. However, we address these concerns as far as possible by running a variety of robustness tests, and our main results remain consistent.

Taken together, our findings provide novel insights that are relevant to at least three core streams of strategy research. First, we contribute to the literature on the institutional factors that affect inventor mobility (Akcigit et al. 2016, Hombert and Matray 2017), by honing in on changes in the US patent system. Second, our results contribute new insights to the research on the use of intellectual property to restrict employee movement (Marx et al. 2009, Melero et al. 2020) by focusing on how changes to patent enforceability deter mobility. Finally, our findings also add to the research on micro-level dynamics in strategic factor markets (Barney 1991, Chatain 2014, Coff 1997, Ross 2012) by unveiling critical heterogeneity with regards to how changes to institutional settings can influence the retention of knowledge workers, and thereby affect the rate and direction of innovation (Chatterji and Fabrizio 2016, Pisano 2006, Teece 1996). In particular, we find that although patents per se may be useful tools to "lock in" knowledge workers, the type of inventors most sensitive to changes in enforceability appear to be those especially crucial for the upstream and more exploratory inventive capacity of a firm. In the long-run this may severely impede a firm's ability to continuously innovate and absorb more basic research (Chatterji and Fabrizio 2014, Fleming 2001, Cohen and Levinthal 1989).

References

Agarwal R, Ganco M, Ziedonis RH (2009) Reputations for toughness in patent enforcement: Implications for knowledge spillovers via inventor mobility. *Strategic Management Journal* 30(13):1349–1374.

Akcigit U, Baslandze S, Stantcheva S (2016) Taxation and the international mobility of inventors. *American Economic Review* 106(10):2930–2981.

Akcigit U, Hanley D, Serrano-Velarde N (2021) Back to basics: Basic research spillovers, innovation policy, and growth. *The Review of Economic Studies* 88(1):1–43.

Alcácer J, Gittelman M (2006) Patent citations as a measure of knowledge flows: The influence of examiner citations. *The Review of Economics and Statistics* 88(4):774–779.

Allison JR, Lemley MA, Schwartz DL (2014) Understanding the realities of modern patent litigation. *Texas Law Review* 92(7):1769–1801.

Almeida P, Kogut B (1999) Localization of knowledge and the mobility of engineers in regional networks. *Management Science* 45(7):905–917.

American Intellectual Property Law Association (2019) Aipla: 2019 report of the economic survey. Technical report.

Appel I, Farre-Mensa J, Simintzi E (2019) Patent trolls and startup employment. *Journal of Financial Economics* 133(3):708–725.

Arora A, Belenzon S, Patacconi A (2018) The decline of science in corporate rd. *Strategic Management Journal* 39(1):3–32.

Arrow KJ (1962) The economic implications of learning by doing. *The Review of Economic Studies* 29(3):155–173.

Barney J (1991) Firm resources and sustained competitive advantage. *Journal of Management* 17(1):99–120.

Bena J, Ferreira MA, Matos P, Pires P (2017) Are foreign investors locusts? the long-term effects of foreign institutional ownership. *Journal of Financial Economics* 126(1):122–146.

Bercovitz JE, Feldman MP (2007) Fishing upstream: Firm innovation strategy and university research alliances. *Research Policy* 36(7):930–948.

Boudreau KJ, Guinan EC, Lakhani KR, Riedl C (2016) Looking across and looking beyond the knowledge frontier: Intellectual distance, novelty, and resource allocation in science. *Management Science* 62(10):2765–2783.

Campbell BA, Coff R, Kryscynski D (2012a) Rethinking sustained competitive advantage from human capital. *Academy of Management Review* 37(3):376–395.

Campbell BA, Ganco M, Franco AM, Agarwal R (2012b) Who leaves, where to, and why worry? Employee mobility, entrepreneurship and effects on source firm performance. *Strategic Management Journal* 33(1):65–87.

Cassiman B, Veugelers R, Arts S (2018) Mind the gap: Capturing value from basic research through combining mobile inventors and partnerships. *Research Policy* 47(9):1811–1824.

Chatain O (2014) How do strategic factor markets respond to rivalry in the product market? *Strategic Management Journal* 35(13):1952–1971.

Chatterji AK, Fabrizio KR (2014) Using users: When does external knowledge enhance corporate product innovation? *Strategic Management Journal* 35(10):1427–1445.

Chatterji AK, Fabrizio KR (2016) Does the market for ideas influence the rate and direction of innovative activity? evidence from the medical device industry. *Strategic Management Journal* 37(3):447–465.

Chien CV, Lemley MA (2012) Patent holdup, the ITC, and the public interest. *Cornell Law Review* 98(1):1–46.

Coff RW (1997) Human assets and management dilemmas: Coping with hazards on the road to resource-based theory. *The Academy of Management Review* 22(2):374–402.

Cohen L, Gurun UG, Kominers SD (2019) Patent trolls: Evidence from targeted firms. *Management Science* 65(12):5461–5486.

Cohen WM, Levinthal DA (1989) Innovation and learning: The two faces of R&D. *The Economic Journal* 99(397):569–596.

Corsino M, Mariani M, Torrisi S (2019) Firm strategic behavior and the measurement of knowledge flows with patent citations. *Strategic Management Journal* 40(7):1040–1069.

Fleming L (2001) Recombinant uncertainty in technological search. *Management Science* 47(1):117–132.

Fleming L, Sorenson O (2004) Science as a map in technological search. *Strategic Management Journal* 25(8-9):909–928.

Foss NJ, Lyngsie J, Zahra SA (2013) The role of external knowledge sources and organizational design in the process of opportunity exploitation. *Strategic Management Journal* 34(12):1453–1471.

Friedman DD, Landes WM, Posner RA (1991) Some economics of trade secret law. *Journal of Economic Perspectives* 5(1):61–72.

Galasso A, Schankerman M (2015) Patents and cumulative innovation: Causal evidence from the courts. *The Quarterly Journal of Economics* 130(1):317–369.

Gambardella A, Ganco M, Honoré F (2015) Using what you know: Patented knowledge in incumbent firms and employee entrepreneurship. *Organization Science* 26(2):456–474.

Ganco M, Miller CD, Toh PK (2020) From litigation to innovation: Firms' ability to litigate and technological diversification through human capital. *Strategic Management Journal* 41(13):2436–2473.

Ganco M, Ziedonis RH, Agarwal R (2015) More stars stay, but the brightest ones still leave: Job hopping in the shadow of patent enforcement. *Strategic Management Journal* 36(5):659–685.

Graham SJ, Marco AC, Miller R (2015) The USPTO patent examination research dataset: A window on the process of patent examination. Working Paper 2015-4, USPTO.

Gupta K, Kesan JP (2017) Studying the impact of eBay on injunctive relief in patent cases. Working Paper 17004, Hoover Institution Working Group on Intellectual Property, Innovation, and Prosperity.

Hall BH, Jaffe AB, Trajtenberg M (2001) The NBER patent citation data file: Lessons, insights and methodological tools. Working Paper 8498, National Bureau of Economic Research.

Hombert J, Matray A (2017) The real effects of lending relationships on innovative firms and inventor mobility. *The Review of Financial Studies* 30(7):2413–2445.

Jaffe AB, Trajtenberg M, Henderson R (1993) Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics* 108(3):577–598.

Kang H, Fleming L (2020) Non-competes, business dynamism, and concentration: Evidence from a florida case study. *Journal of Economics and Management Strategy* 29(3):663–685.

Kim J, Marschke G (2005) Labor mobility of scientists, technological diffusion, and the firm's patenting decision. *The RAND Journal of Economics* 36(2):298–317.

Laursen K, Salter A (2006) Open for innovation: the role of openness in explaining innovation performance among u.k. manufacturing firms. *Strategic Management Journal* 27(2):131–150.

Lazear EP (2009) Firm-specific human capital: A skill-weights approach. *Journal of Political Economy* 117(5):914–940.

Lemley MA, Shapiro C (2005) Probabilistic patents. *Journal of Economic Perspectives* 19(2):75–98.

Li GC, Lai R, D'Amour A, Doolin DM, Sun Y, Torvik VI, Yu AZ, Fleming L (2014) Disambiguation and co-authorship networks of the U.S. patent inventor database (1975–2010). *Research Policy* 43(6):941–955.

Marco AC, Graham SJ, Myers AF, D'Agostino PA, Apple K (2015) The USPTO patent assignment dataset: Descriptions and analysis. Working Paper 2015-2, USPTO.

Marx M, Fuegi A (2020) Reliance on science: Worldwide front-page patent citations to scientific articles. *Strategic Management Journal* 41(9):1572–1594.

Marx M, Fuegi A (2022) Reliance on science by inventors: Hybrid extraction of in-text patent-to-article citations. *Journal of economics and management strategy* 31(2):369–392.

Marx M, Strumsky D, Fleming L (2009) Mobility, skills, and the Michigan non-compete experiment. *Management Science* 55(6):875–889.

Mayer KJ, Somaya D, Williamson IO (2012) Firm-specific, industry-specific, and occupational human capital and the sourcing of knowledge work. *Organization Science* 23(5):1311–1329.

Melero E, Palomeras N, Wehrheim D (2020) The effect of patent protection on inventor mobility. *Management Science* 66(12):5485–6064.

Merges RP (1999) The law and economics of employee inventions. *Harvard Journal of Law & Technology* 13(1):1–54.

Mezzanotti F (2021) Roadblock to innovation: The role of patent litigation in corporate R&D. *Management Science* 67(12):7362–7390.

Miric M, Ozalp H (2020) Standardized tools and the generalizability of human capital: The impact of standardized technologies on employee mobility. Working paper, USC.

Moser P, Ohmstedt J, Rhode PW (2018) Patent citations—an analysis of quality differences and citing practices in hybrid corn. *Management Science* 64(4):1926–1940.

Nagle F, Teodoridis F (2020) Jack of all trades and master of knowledge: The role of diversification in new distant knowledge integration. *Strategic Management Journal* 41(1):55–85.

Palomeras N, Melero E (2010) Markets for inventors: Learning-by-hiring as a driver of mobility. *Management Science* 56(5):881–895.

Paruchuri S, Nerkar A, Hambrick DC (2006) Acquisition integration and productivity losses in the technical core: Disruption of inventors in acquired companies. *Organization Science* 17(5):545–562.

Phillips DJ (2002) A genealogical approach to organizational life chances: The parent-progeny transfer among Silicon Valley law firms, 1946–1996. *Administrative Science Quarterly* 47(3):474–506.

Pisano G (2006) Profiting from innovation and the intellectual property revolution. *Research Policy* 35(8):1122–1130.

Rosenkopf L, Nerkar A (2001) Beyond local search: boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal* 22(4):287–306.

Ross DG (2012) On evaluation costs in strategic factor markets: The implications for competition and organizational design. *Management Science* 58(4):791–804.

Seaman CB (2016) Permanent injunctions in patent litigation after ebay: An empirical study. *Iowa Law Review* 101(5):1949–2020.

Shapiro C (2016) Patent remedies. *American Economic Review: Papers & Proceedings* 106(5):198–202.

Singh J, Agrawal A (2011) Recruiting for ideas: How firms exploit the prior inventions of new hires. *Management Science* 57(1):129–150.

Starr E, Balasubramanian N, Sakakibara M (2018) Screening spinouts? How noncompete enforceability affects the creation, growth, and survival of new firms. *Management Science* 64(2):552–572.

Starr E, Frake J, Agarwal R (2019) Mobility constraint externalities. *Organization Science* 30(5):961–980.

Teece DJ (1996) Firm organization, industrial structure, and technological innovation. *Journal of Economic Behavior and Organization* 31(2):193–224.

Topel R (1991) Specific capital, mobility, and wages: Wages rise with job seniority. *Journal of Political Economy* 99(1):145–176.

Walsh JP, Lee YN, Jung T (2016) Win, lose or draw? The fate of patented inventions. *Research Policy* 45(7):1362–1373.

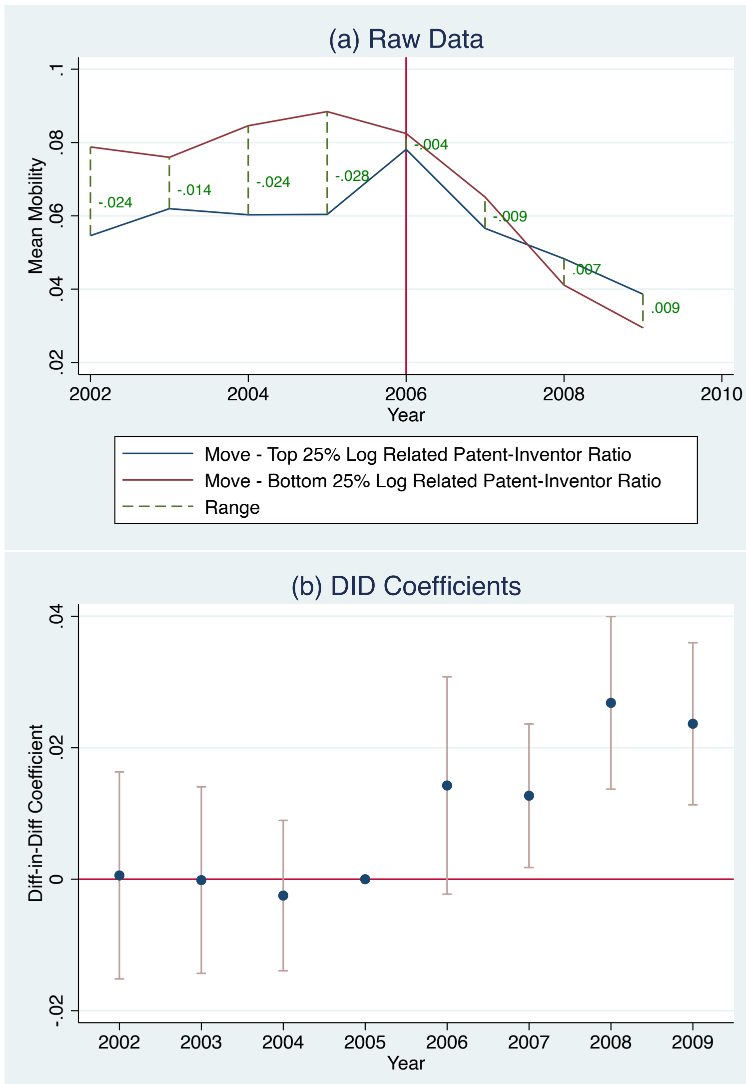
Wezel FC, Cattani G, Pennings JM (2006) Competitive implications of interfirm mobility. *Organization Science* 17(6):691–709.

Whalen R, Lungeanu A, DeChurch L, Contractor N (2020) Patent similarity data and innovation metrics. *Journal of Empirical Legal Studies* 17(3):615–639.

Zucker LG, Darby MR, Brewer MB (1998) Intellectual human capital and the birth of U.S. biotechnology enterprises. *American Economic Review* 88(1):290–306.

Zucker LG, Darby MR, Torero M (2002) Labor mobility from academe to commerce. *Journal of Labor Economics* 20(3):629–660.

Figure 1: Mobility by Year



Notes: Panel (a) is based on raw data and plots the average mobility for inventors with top 25% Log Related Patent-Inventor Ratio versus other inventors with bottom 25% Log Related Patent-Inventor Ratio. Panel (b) plots year-specific DID coefficients estimated from Equation 1, along with 95% confidence intervals. The estimated coefficients before 2005 are not significantly different from 2005.

Table 1: Summary Statistics

	Mean	SD	p10	p50	p90	Obs.
Move	0.055	0.228	0.000	0.000	0.000	227,335
Related Patent-Inventor Ratio	0.491	0.437	0.261	0.451	0.700	227,335
Log Related Patent-Inventor Ratio	-0.814	0.443	-1.345	-0.797	-0.357	227,335
Year	2005.441	2.215	2003.000	2005.000	2009.000	227,335
Applications Filed	7.148	10.537	1.000	4.000	16.000	227,335
Inventor Years	2.790	2.180	0.000	2.000	6.000	227,335
Inventor Exposure	0.594	0.530	0.108	0.469	1.195	227,335
Patents Granted	1.778	3.929	0.000	1.000	5.000	227,335
Applications Filed	7.148	10.537	1.000	4.000	16.000	227,335
Inventor Patent Quality	0.520	0.176	0.311	0.507	0.738	227,335
Inventor Firm Specificity	0.006	0.992	-1.128	-0.028	1.179	158,888
Basic Research Share	0.110	0.204	0.000	0.000	0.389	159,656
Inventor Generalizability	7.436	5.305	1.000	7.000	14.000	227,335
Log Inventor Generalizability	2.372	0.951	0.881	2.644	3.333	227,335

Notes: This table reports summary statistics on an inventor-year basis for the sample used in the regressions.

Table 2: Mobility Results

DV: Move	(1)	(2)
Log Related Patent-Inventor Ratio	-0.0205***	-0.0208***
	(0.00582)	(0.00598)
Post=1 × Log Related Patent-Inventor Ratio	0.0205***	0.0198***
	(0.00583)	(0.00587)
Inventor Exposure		-0.00110
		(0.00181)
Inventor Years		-0.00251***
		(0.000598)
Applications Filed		-0.000420***
		(0.000125)
Patents Granted		0.00111***
		(0.000224)
Inventor Patent Quality		-0.00631*
		(0.00348)
State-Year FE	Yes	Yes
Firm FE	Yes	Yes
Tech-Year FE	Yes	Yes
Adjusted R-Squared	0.06271	0.06301
Observations	227,335	227,335

Notes: The unit of analysis is the inventor-year. Column (1) displays results without controls for inventor characteristics, while column (2) displays results with these controls included. The number of inventors is 50,283 and the number of firms is 3,682. The estimation period is from 2002 to 2009. Robust standard errors are clustered by firm.

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

Table 3: Mobility Robustness

DV: Move	(1) Only App. Years	(2) By Filing Date	(3) 2003-2008 Data	(4) 2002 Inventors	(5) High USPC Growth	(6) Low USPC Growth	(7) High USPC Intensity	(8) Low USPC Intensity
Post=1 × Log Related Patent-Inventor Ratio	0.0191***	0.0157*	0.0187***	0.0217***	0.0285***	0.0127**	0.0292***	0.0103***
	(0.00564)	(0.00903)	(0.00613)	(0.00725)	(0.00676)	(0.00599)	(0.0104)	(0.00368)
State-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tech-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.05413	0.1793	0.06500	0.07238	0.06823	0.06718	0.06346	0.07474
Observations	128,373	147,236	203,693	56,060	113,539	112,329	114,303	112,970

Notes: The unit of analysis is the inventor-year. This table presents the results of a series of robustness checks, which are as follows:
1: All years where the inventor filed no original applications are dropped. 2: The unit of observation if inventor-filing date rather than inventor-year.
3: 2003-2008 replaces 2002-2009 as the analysis period. 4: Only inventors who filed their first original application in 2002 are included.
5: Only inventors with high USPC Growth are included. 6: Only inventors with low USPC Growth are included.
7: Only inventors with high USPC Intensity are included. 8: Only inventors with low USPC Intensity are included.
Robust standard errors are clustered by firm.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Results by Inventor Firm-Specificity

DV: Move	(1)	(2)
Log Related Patent-Inventor Ratio	-0.00999**	-0.0104**
	(0.00454)	(0.00464)
Post=1 × Log Related Patent-Inventor Ratio	0.0114**	0.0106*
	(0.00557)	(0.00557)
Inventor Firm Specificity	-0.0155***	-0.0154***
	(0.00212)	(0.00211)
Post=1 × Inventor Firm Specificity	0.0114***	0.0112***
	(0.00267)	(0.00268)
Log Related Patent-Inventor Ratio × Inventor Firm Specificity	0.00458**	0.00459**
	(0.00188)	(0.00187)
Post=1 × Log Related Patent-Inventor Ratio × Inventor Firm Specificity	-0.00522**	-0.00541**
	(0.00264)	(0.00265)
State-Year FE	Yes	Yes
Firm FE	Yes	Yes
Tech-Year FE	Yes	Yes
Inventor Controls	No	Yes
Adjusted R-Squared	0.05903	0.05918
Observations	158,868	158,868

Notes: The unit of analysis is the inventor-year. *Inventor Firm-Specificity* is calculated based on patent similarity. Column (1) displays results without controls for inventor characteristics, while column (2) displays results with these controls included. The number of inventors is 50,283 and the number of firms is 3,682. The estimation period is from 2002 to 2009. Robust standard errors are clustered by firm.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Results by Basic Research Share

DV: Move	(1)	(2)
Log Related Patent-Inventor Ratio	-0.0234***	-0.0233***
	(0.00851)	(0.00868)
Post=1 × Log Related Patent-Inventor Ratio	0.0224***	0.0218***
	(0.00772)	(0.00777)
Basic Research Share	0.00421	0.00428
	(0.00906)	(0.00913)
Post=1 × Basic Research Share	0.0150	0.0138
	(0.0121)	(0.0124)
Log Related Patent-Inventor Ratio × Basic Research Share	-0.00352	-0.00357
	(0.0105)	(0.0105)
Post=1 × Log Related Patent-Inventor Ratio × Basic Research Share	0.0257**	0.0248**
	(0.0121)	(0.0124)
State-Year FE	Yes	Yes
Firm FE	Yes	Yes
Tech-Year FE	Yes	Yes
Inventor Controls	No	Yes
Adjusted R-Squared	0.06342	0.06359
Observations	159,627	159,627

Notes: The unit of analysis is the inventor-year. The number of inventors is 50,283 and the number of firms is 3,682. Column (1) displays results without controls for inventor characteristics, while column (2) displays results with these controls included. The estimation period is from 2002 to 2009. Robust standard errors are clustered by firm.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Results by Inventor Generalizability

DV: Move	(1)	(2)
Log Related Patent-Inventor Ratio	-0.00882*	-0.00897*
	(0.00526)	(0.00539)
Post=1 × Log Related Patent-Inventor Ratio	0.00327	0.00351
	(0.00636)	(0.00638)
Log Inventor Generalizability	-0.0132***	-0.0132***
	(0.00304)	(0.00304)
Post=1 × Log Inventor Generalizability	0.0153***	0.0156***
	(0.00412)	(0.00411)
Log Related Patent-Inventor Ratio × Log Inventor Generalizability	-0.00618**	-0.00622**
	(0.00307)	(0.00301)
Post=1 × Log Related Patent-Inventor Ratio × Log Inventor Generalizability	0.00909**	0.00866**
	(0.00420)	(0.00423)
State-Year FE	Yes	Yes
Firm FE	Yes	Yes
Tech-Year FE	Yes	Yes
Inventor Controls	No	Yes
Adjusted R-Squared	0.06311	0.06341
Observations	227,335	227,335

Notes: The unit of analysis is the inventor-year. The number of inventors is 50,283 and the number of firms is 3,682. Column (1) displays results without controls for inventor characteristics, while column (2) displays results with these controls included. The estimation period is from 2002 to 2009. Robust standard errors are clustered by firm.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: New Class Entry Results

DV: New Classes	(1)	(2)
Post=1	-0.298***	-0.334***
	(0.0872)	(0.0896)
Post=1 × Log Weighted Average Related Patent-Inventor Ratio	-0.203*	-0.200*
	(0.118)	(0.119)
Log Previous Class Count	-0.816***	-0.805***
	(0.171)	(0.172)
Log Previous Inventors Count	0.527***	0.476***
	(0.116)	(0.127)
Previous Patents	-0.000132*	-0.000128*
	(0.0000680)	(0.0000716)
New Patents	0.000361***	0.000362***
	(0.000126)	(0.000121)
Log Revenue		0.130**
		(0.0648)
Research and Development		-0.0000217
		(0.0000599)
Operating Margin		-0.0000944
		(0.000397)
Technology Subcategory Dummies	Yes	Yes
Industry FE	Yes	Yes
Year & Firm FE	Yes	Yes
Observations	2,142	2,142
Log Pseudolikelihood	-3698.2	-3693.3

Notes: The unit of analysis is the firm-year. The number of firms is 308. Only firms that are in the Compustat database, headquartered in the United States, and have more than twenty inventors are included. Column (1) displays results using a Poisson fixed effects model, and column (2) adds controls for firm financials. The estimation period is from 2002 to 2009. Robust standard errors are clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Firm Self-Citation and Outside Citation Results

	(1) Firm Self-Citations	(2) Firm Outside Citations
Post=1	-0.183**	-0.0610
	(0.0836)	(0.0744)
Post=1 × Log Weighted Average Related Patent-Inventor Ratio	-0.309**	-0.0700
	(0.130)	(0.101)
Log Previous Inventors Count	0.641***	0.299***
	(0.149)	(0.0886)
Total Firm Citations	0.0000243***	0.0000353***
	(0.00000510)	(0.00000374)
Previous Patents	-0.0000129	0.00000769
	(0.0000197)	(0.0000126)
New Patents	0.0000248	-0.0000621
	(0.0000568)	(0.0000586)
Technology Subcategory Dummies	Yes	Yes
Year & Firm FE	Yes	Yes
Firm Financials	Yes	Yes
Observations	2,037	2,149
Log Pseudolikelihood	-36783.5	-209348.4

Notes: The unit of analysis is the firm-year. The number of firms is 308. Only firms that are in the Compustat database, headquartered in the United States, and have more than twenty inventors are included. Column (1) displays results from a Poisson fixed effect model with *Firm Self-Citations* as the dependent variable. Column (2) displays results from a Poisson fixed effect model with *Firm Outside Citations* as the dependent variable. The estimation period is from 2002 to 2009. Robust standard errors are clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Supplementary Appendix

for

The Ties That No Longer Bind: Inventor Mobility and Patent Litigation

Table A1: Full Sample Summary Statistics

	Mean	SD	p10	p50	p90	Obs.
Move	0.059	0.235	0.000	0.000	0.000	276,104
Related Patent-Inventor Ratio	0.485	0.430	0.250	0.448	0.699	276,070
Log Related Patent-Inventor Ratio	-0.815	0.444	-1.351	-0.798	-0.355	273,379
Year	2005.529	2.032	2003.000	2006.000	2008.000	276,104
Applications Filed	7.147	10.372	1.000	4.000	16.000	276,104
Inventor Years	2.797	2.087	0.000	3.000	6.000	276,104
Inventor Exposure	0.597	0.539	0.106	0.469	1.206	276,104
Patents Granted	1.761	3.810	0.000	1.000	5.000	276,104
Applications Filed	7.147	10.372	1.000	4.000	16.000	276,104
Inventor Patent Quality	0.521	0.174	0.315	0.507	0.737	276,104
Inventor Firm Specificity	-0.000	1.000	-1.141	-0.034	1.180	194,226
Basic Research Share	0.110	0.204	0.000	0.000	0.389	191,214
Inventor Generalizability	7.346	5.278	1.000	7.000	14.000	276,104
Log Inventor Generalizability	2.356	0.956	0.881	2.644	3.333	276,104

Notes: This table reports summary statistics on an inventor-year basis for the full sample.

Table A2: Calculated Variable Definitions

Variable Name	Description	Definition
Inventor Exposure	Measures the exposure of the inventor to patent litigation.	$InventorExposure_i = \sum_{k=1}^{T} \sigma_{ik} p_k$ $p_k = \frac{100 \sum_{c \in cases} \#Patents_c^k}{\sum_{i \in Tech.Classes} 100 \sum_{c \in cases} \#Patents_c^k}$
Inventor Firm Specificity	Measures the similarity of the inventor's patents to other patents filed by their employer.	$InventorFirmSpecificity_{ij} = 1/(3A) \sum_{a \in inventorpatents}^{A} V_\alpha + V_\beta + V_\gamma$ $V_\alpha = V(a) V_\beta = V(a, b_0) V_\gamma = V(a, [b_0, b_1])$ $V(a,c)_1 =_{b \neq c \in firmpatents} simscore(a,b)$

Notes: This table provides descriptions and definitions for several variables we calculate for inventors.

Table A3: Top Patent Results

DV: Move	(1)	(2)
Log Related Patent-Inventor Ratio	-0.0208***	-0.0206***
	(0.00605)	(0.00602)
Post=1 × Log Related Patent-Inventor Ratio	0.0189***	0.0191***
	(0.00607)	(0.00603)
Top Patent Filed=1	-0.00299	
	(0.00470)	
Post=1 × Top Patent Filed=1	0.0128**	
	(0.00612)	
Top Patent Filed=1 × Log Related Patent-Inventor Ratio	0.00131	
	(0.00531)	
Post=1 × Top Patent Filed=1 × Log Related Patent-Inventor Ratio	0.00404	
	(0.00644)	
Inventor Exposure	-0.00112	-0.00112
	(0.00181)	(0.00181)
Inventor Years	-0.00248***	-0.00254***
	(0.000598)	(0.000596)
Applications Filed	-0.000437***	-0.000425***
	(0.000126)	(0.000126)
Patents Granted	0.00105***	0.00104***
	(0.000222)	(0.000223)
Inventor Patent Quality	-0.00601*	-0.00692**
	(0.00357)	(0.00348)
Top Patent Granted=1		0.00249
		(0.00881)
Post=1 × Top Patent Granted=1		0.00511
		(0.00997)
Top Patent Granted=1 × Log Related Patent-Inventor Ratio		-0.00354
		(0.0108)
Post=1 × Top Patent Granted=1 × Log Related Patent-Inventor Ratio		0.00956
		(0.0121)
State-Year FE	Yes	Yes
Firm FE	Yes	Yes
Tech-Year FE	Yes	Yes
Adjusted R-Squared	0.06306	0.06301
Observations	227,335	227,335

Notes: The unit of analysis is the inventor-year. This table displays the results from regressions with *Top Patent Filed* and *Top Patent Granted* as the key differentiating variables. *Top Patents* are those that are in the top 5% most cited compared to other patents granted in the same quarter and NBER category. *Top Patent Filed* is equal to one if the inventor filed a *Top Patent* before the *eBay* ruling, while *Top Patent Granted* is equal to one if the inventor was granted a *Top Patent* before the *eBay* ruling. Column (1) displays results for *Top Patent Filed* and column (2) displays results for *Top Patent Filed*. Standard errors are clustered by firm.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Top Scope Patent Results

DV: Move	(1)	(2)
Log Related Patent-Inventor Ratio	-0.0198***	-0.0207***
	(0.00573)	(0.00602)
Post=1 × Log Related Patent-Inventor Ratio	0.0179***	0.0193***
	(0.00571)	(0.00600)
Top Scope Patent Filed=1	-0.00989	
	(0.00633)	
Post=1 × Top Scope Patent Filed=1	0.0135*	
	(0.00775)	
Top Scope Patent Filed=1 × Log Related Patent-Inventor Ratio	-0.00353	
	(0.00482)	
Post=1 × Top Scope Patent Filed=1 × Log Related Patent-Inventor Ratio	0.00744	
	(0.00618)	
Inventor Exposure	-0.00107	-0.00112
	(0.00180)	(0.00181)
Inventor Years	-0.00246***	-0.00249***
	(0.000588)	(0.000585)
Applications Filed	-0.000387***	-0.000416***
	(0.000113)	(0.000123)
Patents Granted	0.00104***	0.00109***
	(0.000219)	(0.000234)
Inventor Patent Quality	-0.00615*	-0.00629*
	(0.00342)	(0.00347)
Top Scope Patent Granted=1		-0.00435
		(0.00631)
Post=1 × Top Scope Patent Granted=1		0.00790
		(0.00709)
Top Scope Patent Granted=1 × Log Related Patent-Inventor Ratio		0.00171
		(0.00766)
Post=1 × Top Scope Patent Granted=1 × Log Related Patent-Inventor Ratio		0.00123
		(0.00832)
State-Year FE	Yes	Yes
Firm FE	Yes	Yes
Tech-Year FE	Yes	Yes
Adjusted R-Squared	0.06307	0.06301
Observations	227,335	227,335

Notes: The unit of analysis is the inventor-year. This table displays the results from regressions with *Top Scope Patent Filed* and *Top Scope Patent Granted* as the key differentiating variables. *Top Patents* are those that are in the top 5% for scope compared to other patents granted in the same quarter and NBER category. We proxy for scope using the number of words in the first independent claim of the patent, with fewer words indicating a greater scope. *Top Scope Patent Filed* is equal to one if the inventor filed a *Top Scope Patent* before the *eBay* ruling, while *Top Scope Patent Granted* is equal to one if the inventor was granted a *Top Scope Patent* before the *eBay* ruling. Column (1) displays results for *Top Scope Patent Filed* and column (2) displays results for *Top Scope Patent Filed*. Standard errors are clustered by firm. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Firm Inventor Count Results

DV: Move	(1)	(2)
Log Related Patent-Inventor Ratio	-0.0299***	-0.0300***
	(0.00377)	(0.00381)
Post=1 × Log Related Patent-Inventor Ratio	0.0270***	0.0265***
	(0.00473)	(0.00474)
Post=1 × Firm Inventor Count	-0.00000194	-0.00000190
	(0.00000157)	(0.00000159)
Log Related Patent-Inventor Ratio × Firm Inventor Count	0.00000330**	0.00000327**
	(0.00000129)	(0.00000131)
Post=1 × Log Related Patent-Inventor Ratio × Firm Inventor Count	-0.00000299**	-0.00000300**
	(0.00000146)	(0.00000147)
Inventor Exposure		-0.000927
		(0.00187)
Inventor Years		-0.00249***
		(0.000604)
Applications Filed		-0.000422***
		(0.000130)
Patents Granted		0.00109***
		(0.000234)
Inventor Patent Quality		-0.00669**
		(0.00330)
State-Year FE	Yes	Yes
Firm FE	Yes	Yes
Tech-Year FE	Yes	Yes
Adjusted R-Squared	0.06306	0.06336
Observations	227,335	227,335

Notes: The unit of analysis is inventor-year. This table displays the results from regressions with *Firm Inventor Count* as the key differentiating variable. Column (1) displays results without controls for inventor characteristics, while column (2) displays results with these controls included. *Firm Inventor Count* measures the number of unique patent inventors associated with the inventor-employee's firm. Standard errors are clustered by firm.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Results by Technological Field

DV: Move	(1) Biotech	(2) Pharma	(3) Mechanical	(4) Medical Devices	(5) Software
Post=1 × Log Related Patent-Inventor Ratio	0.0181	0.0188	0.0104	0.0561***	0.0497*
	(0.0177)	(0.0231)	(0.00928)	(0.0175)	(0.0254)
State-Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Tech-Year FE	Yes	Yes	Yes	Yes	Yes
Inventor Controls	Yes	Yes	Yes	Yes	Yes
Adjusted R-Squared	-0.03904	0.1159	0.08693	0.1191	0.09073
Observations	240	4,070	34,546	11,366	24,218
Injunct. Grant Rate	100%	92%	75%	65%	53%

Notes: The unit of analysis is inventor-year. This table displays the results from regressions with inventors that have filed in different technological fields. Column (1) displays results for inventors who have filed patents in NBER sub-category 33, column (2) displays results for inventors who have filed patents in NBER sub-category 31, column (3) displays results for inventors who have filed patents in NBER category 5, column (4) displays results for inventors who have filed patents in NBER sub-category 32, and column (5) displays results for inventors who have filed in USPC classes 715, 716, 717, 718, 719, 725, 726, 901, or 902. *Injunct. Grant Rate* is the share of permanent injunction filings in the technological field that were granted in the 7.5 years after the *eBay* ruling, based on data from (Seaman 2016).Note that (Seaman 2016) assigns patents to technological field manually rather than by class. Standard errors are clustered by firm.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.