Tolerance for Failure: Evidence from Patent Examination

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Abstract

We introduce a novel firm-level measure of failure tolerance based on firms' patenting histories. Specifically, we quantify failure tolerance as the largest scope loss during patent examination that does not terminate a firm's innovation sequence. Our results show that firms with greater failure tolerance tend to produce patents that are more valuable, more cited, more complex, yet also more likely to fail. At the same time, they file fewer patents and employ fewer inventors. The reduction in innovation quantity largely offsets the increase in quality, resulting in an ambiguous relationship between failure tolerance and total innovation output. Exploiting inventor job switches, we provide causal evidence that higher failure tolerance enhances inventor productivity. Taken together, our findings establish failure tolerance as a powerful incentive mechanism but also highlight its overlooked costs.

Keywords: failure tolerance, innovation, patent scope, patent examination, inventor productivity

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1 Introduction

Since innovation is inherently uncertain and often fails to deliver, a firm's attitude toward failure plays an essential role in its innovation efforts (Aghion & Tirole, 1994; Holmstrom, 1989). Scholars have theorized that tolerating short-term failure while rewarding long-term success can encourage innovation (Manso, 2011). Quantifying failure tolerance empirically, however, has proved challenging, particularly at the firm level.

We address this challenge by introducing a novel firm-level measure of failure tolerance based on firms' innovation histories. Innovation is typically cumulative: later advances build on earlier work, forming distinct innovation "sequences" (Dosi, 1982). The decision for firms to continue or terminate such sequences may reflect a firm's failure tolerance. For instance, in a different setting, Tian and Wang (2014) argue that failure-tolerant VC investors are less likely to terminate underperforming ventures, leading to longer funding sequences.

In this paper, we argue that when an innovation project underperforms, a failure-tolerant firm is more likely to persist in the same innovation sequence rather than abandon it and start anew. Accordingly, the presence of underperforming projects within a sequence indicates a high level of failure tolerance—the worse the performance, the greater the tolerance.

To operationalize this intuition, we map innovation projects to patents—one of the most commonly observable outputs of innovative effort, and proxy project performance with patent examination outcomes. We focus on examination outcomes because they carry important economic implications. A patent entitles its holder to legal protection against infringement, and the scope of that protection is central to its economic value. Because the examination process tests and often revises the scope initially claimed by the applicant, changes in scope during examination provide a revealing measure of changes in patent value.

Empirically, we measure failure tolerance as the largest scope loss that is still followed by continued patenting in the same sequence—i.e., a firm's upper bound of tolerable failure. Using detailed patent information from the US Patent and Trademark Office (USPTO), we first define innovation sequences based on continuity in both technology and inventors. We then leverage the rich textual content of patent documents to quantify the extent to which a patent's scope erodes over the course of examination. Lastly, for each firm, we compute our failure tolerance measure using 3-year rolling windows. Our final sample covers 1,110 COMPUSTAT firms, totaling 7,394 firm-year observations between 2002 and 2022. We also conduct extensive validation to ensure that our measure accurately captures the hypothesized economic mechanism.

With this measure in hand, we ask how failure tolerance shapes firms' innovation output. We start by examining patent quality. In the cross-section, more failure-tolerant firms tend to produce higher-quality patents, as reflected in both their dollar value and the citations they receive. Specifically, a one-standard-deviation increase in our failure tolerance measure is associated with a 17% increase in patent value (roughly $4.6 million in 2022 dollars based on the sample mean) and a 5% increase in citations per patent (roughly 0.3 citations). We find similar patterns on a per-inventor basis, suggesting that greater failure tolerance may enhance inventor productivity.

Next, we examine patent quantity. In contrast to the quality results, we find a negative association between failure tolerance and firms' patent counts: a one-standard-deviation increase in our failure tolerance measure is associated with a 10–11% decrease in the number of patents filed by a firm per year (roughly 12–13 fewer patents). However, this negative relationship does not hold on a per-inventor basis, suggesting that failure tolerance does not affect individual inventors' patenting volume. Moreover, we find no systematic relationship between failure tolerance and firms' aggregate patent value or total citations.

Taken together, these findings suggest that failure tolerance unambiguously increases inventors' productivity by incentivizing them to pursue higher-quality innovation. Yet this productivity gain does not translate into higher total innovation output at the firm level, because the associated reduction in patent quantity largely offsets it. Further analysis shows that failure-tolerant firms produce fewer patents primarily because they employ fewer inventors. Their patents also tend to be more complex (as measured by document length) and more likely to fail (as reflected in higher abandonment rates among patent applications). Such firms also have higher R&D expenses per inventor. Thus, our findings shed light on the possible costs associated with failure tolerance, which has been largely overlooked in the literature.

While our baseline analysis documents intriguing cross-sectional patterns, it does not support a causal interpretation. To establish causality, we exploit inventors who move between firms and thus experience an abrupt change in failure tolerance. We implement three progressively more stringent identification strategies to isolate the causal effect of failure tolerance on inventor productivity: difference-in-differences, matched triple differences, and the latter combined with an instrumental-variable approach. The results corroborate our cross-sectional findings: failure tolerance incentivizes the production of higher-value patents without reducing inventors' patenting volume.

Our research contributes to the growing literature in corporate finance and innovation. Several articles examine how more lenient laws impact individuals' or corporations' attitudes toward failure. This concept of legal forgiveness aligns closely with the idea of failure tolerance. One stream of the literature shows that more debtor-friendly or more forgiving personal bankruptcy laws are potential mechanisms through which failure tolerance and subsequent innovation output can be increased (Acharya & Subramanian, 2009; Armour & Cumming, 2008; Fan & White, 2003). In another vein, Acharya, Baghai, and Subramanian (2014) demonstrate that strict labor laws can boost innovation by ensuring that companies do not penalize employees for short-term failures. These studies collectively illustrate that legal leniency toward individual or organizational failures leads to increased entrepreneurial activities. A more direct effect of failure tolerance on corporate innovation has been documented by Chemmanur, Loutskina, and Tian (2014) and Tian and Wang (2014), who construct a measure for (corporate-) venture capital firms based on their average investment duration in eventually failed ventures, where longer investment duration would lead to higher failure tolerance of the respective venture capital firm. We contribute to this literature by introducing a novel empirical approach. To the best of our knowledge, we are the first to directly measure firms' attitudes toward failure.

We also speak to the literature analyzing the patent examination process. Most of the research has focused on the patent application behavior of firms and their consequences for the examination office (Comino & Graziano, 2015; Frakes & Wasserman, 2015; Schuett, 2013). Marco, Sarnoff, and deGrazia (2019) show how firms strategically apply for patents with a very wide scope, which subsequently gets reduced during the examination process. Marco, Sarnoff, and deGrazia (2019) are also the first to introduce a text-based measure for patent scope based on the independent claim length of each patent application. We contribute to this literature by extending the data set of Marco, Sarnoff, and deGrazia (2019) up until 2022. We also offer a fresh perspective on the patent examination process by looking at how firms react to patent examination outcomes.

The remainder of the paper is organized as follows. Section 2 introduces our measure of failure tolerance, details its construction, and provides validation for the underlying proxies and assumptions. Section 3 examines the relationship between failure tolerance and innovation outcomes at both the firm and inventor level, and explores the underlying mechanisms. Section 4 presents our identification strategy and causal evidence. Section 5 concludes the paper.

2 Methodology

In this section, we present our conceptual framework, provide the institutional background closely related to our empirical design, and detail the steps used to construct our failure-tolerance measure.

2.1 Conceptual framework

For illustrative purposes, consider a simple model where an innovation sequence produces multiple patents. The value of each patent V is a random draw from the same distribution $\mathcal{F}_V$ with a mean of μ. A firm would terminate the sequence if the nth patent's realized value V_n falls short of a fraction of its expected value μ:

$$V_n < (1-\alpha)\mu, \tag{1}$$

where α captures a firm's failure tolerance: a larger α makes it less likely for a sequence to terminate early, since the realized value V_n must fall below a lower threshold to trigger termination. Rearranging yields

$$\alpha < \frac{\mu - V_n}{\mu} = \theta_n, \tag{2}$$

where θ_n captures the *ex post* realized value loss of patent n relative to its expected value. Equivalently, for a sequence that survives up to the n-th patent, the following inequality must hold:

$$\alpha \geq \theta_i, \forall i < n. \tag{3}$$

Since α is an upper bound for θ_i for all $i < n$, we can estimate it as

$$\widehat{\alpha} = \max_{i<n} \theta_i, \tag{4}$$

which is the sample maximum of the value loss θ among all patents up to the last observed patent in a sequence.

We follow this simple framework to construct our failure tolerance measure. The rest of the section details how we define patent sequences and proxy their value loss θ.

2.2 Defining patent sequences

We define whether a patent terminates its current sequence by examining subsequent patenting activity. Specifically, we label a patent as "continued" if it is followed by another patent that (1) is assigned to the same firm, (2) is led by the same inventor, (3) is in the same technological field (CPC patent subclass), and (4) is filed within three years of the focal patent's grant date.

We impose Condition (1) because the firm is our unit of analysis for measuring failure tolerance.

Conditions (2) and (3) ensure continuity in expertise and the underlying knowledge base. Inventors typically operate within a relatively narrow research scope. Figure 1a shows that

71–84% of an average inventor's inventions in our sample fall within a single field, out of 9–667 patent categories. When we use the finest classification scheme (9,815 categories), almost half of an inventor's inventions still fall within a single field. For two consecutive inventions by the same inventor, the probability that they fall within the same field ranges from 66–84% (out of 9–667 categories). Even under the finest classification scheme, this probability remains 22%. Taken together, these patterns suggest that a change in the lead inventor or the technological field likely reflects a substantial shift in innovation trajectory and thus plausibly indicates the termination of an innovation sequence.

Condition (4) ensures that the focal patent's examination outcome is known by the time the next patent application in the same sequence is filed, and can therefore influence the decision to terminate the sequence. It also imposes a time cap to avoid attributing two temporally distant patents to the same sequence.

It is worth noting that these conditions are not intended to precisely establish the sequential order among patents, but rather to *exclude* patents that trigger termination. Our failure tolerance measure in Equation (4) can be estimated on subsets of continued patents, but it becomes biased if patents that trigger termination are mistakenly included. In other words, we impose strict conditions to include only patents that are unambiguously followed by continued effort, possibly at the cost of false negatives.

2.3 Quantifying patents' value loss

Patents grant their holders temporary, legally protected rights to exclusively commercialize the patented invention. The scope of this legal protection is a key determinant of a patent's economic value. An initial scope is claimed by the applicant based on her judgment. The examination process then scrutinizes and, if necessary, narrows that scope, thereby altering the patent's economic value. We base our measure of patent value loss, θ, on changes in scope during the examination process.

Measuring patent scope

Patent scope defines the boundaries of what is protected by a patent and, consequently, what activities would constitute infringement. Scope is determined by the *claims* in the patent document, which specify the aspects or features of the invention subject to legal protection.

Claims are classified as either independent or dependent. Independent claims are standalone statements that define the invention without reference to other claims. Dependent claims incorporate one or more earlier claims and add further limitations, thereby narrowing the scope of protection. For example:

- **Claim (1)**: *a bicycle comprising two triangular wheels.*
- **Claim (2)**: *the bicycle of Claim (1), further comprising a frame made of titanium alloy.*

Here, Claim (1) is independent, while Claim (2) depends on Claim (1). Naturally, independent claims better reflect a patent's effective scope than dependent claims, since the latter are necessarily more restrictive.

Independent claims affect a patent's scope along two dimensions. The first is their number: because independent claims do not overlap, more of them generally implies broader scope. The second is their length: Kuhn and Thompson (2019) and Marco, Sarnoff, and deGrazia (2019) show that shorter independent claims are associated with broader patent scope. To illustrate this relationship, consider the following two claims:

- **Claim (1)**: *a bicycle.*
- **Claim (2)**: *a bicycle comprising two triangular wheels.*

Claim (1) is much shorter but covers a far broader scope—i.e., any bicycle. By contrast, Claim (2) is longer, yet narrower in that it applies only to special bicycles with two triangular wheels.

Based on the intuition above, we implement two text-based measures of patent scope. First, we count words in a patent's shortest independent claim, following Kuhn and Thompson (2019) and Marco, Sarnoff, and deGrazia (2019):

$$S_p^{\mathrm{I}} = \min_{c \in \mathcal{I}_p} \{L_c\}, \tag{5}$$

where subscript p denotes a patent, L_c denotes the word count of claim c, and $\mathcal{I}_p$ denotes the set of independent claims of patent p. We expect S_p^{I} to decrease with patent scope. For validation, Figure 2a relates granted patents' S^I to their dollar value as estimated by Kogan et al. (2017) and shows a clear negative association, consistent with S^{I} decreasing in scope. Figure 2b relates S^{I} to the number of citations patents receive through 2022 and reveals a similar downward pattern.

Next, we propose an alternative measure that additionally captures the other dimension—the number of independent claims. Specifically, we sum the inverse of word count across independent claims:

$$S_p^{\mathrm{II}} = \sum_{c \in \mathcal{I}_p} {L_c}^{-1}. \tag{6}$$

We expect patent scope to increase in S_p^{II}. Figure 2c and Figure 2d repeat the same validation exercise for S^{II}. Both figures show that S^{II} is positively associated with patent value and citations, consistent with S^{II} increasing in scope.

Measuring scope loss during examination

The patent examination process begins when an inventor files a patent application with the USPTO. The application is then assigned to a patent examiner, whose responsibilities include comparing the application against publicly available patent and non-patent literature to determine whether the invention is novel and non-obvious.[1] This process is comparable to scholarly peer review, which serves as a form of quality control and evaluates a study's incremental contribution relative to existing work.

If the invention fails this test, the applicant can either abandon the application or amend the claims. Amendments typically reduce scope to eliminate overlap with prior literature and often involve adding limitations (i.e., more words) to existing claims or dropping claims altogether. Our two scope measures can closely track these changes. This gives us a unique opportunity to proxy for changes in patent value during examination—something no other existing proxies allow.

We observe each patent's scope at two points in time. The first comes from the pre-grant publication, which is typically released within 18 months of filing and, in most cases, precedes the first round of claim amendments in response to examiner feedback. The second comes from the granted patent.[2]

This allows us to measure patent p's relative scope loss as

$$\theta_p^{\mathrm{I}} = \frac{\max\left\{S_p^{\mathrm{I},post} - S_p^{\mathrm{I},pre}, 0\right\}}{0.5 \cdot (S_p^{\mathrm{I},post} + S_p^{\mathrm{I},pre})}, \tag{7}$$

$$\theta_p^{\mathrm{II}} = \frac{\max\left\{S_p^{\mathrm{II},pre} - S_p^{\mathrm{II},post}, 0\right\}}{0.5 \cdot (S_p^{\mathrm{II},post} + S_p^{\mathrm{II},pre})}, \tag{8}$$

where the superscript *pre* and *post* refer to the pre-grant publication and the granted patent, respectively. Both measures increase with scope loss and range between 0 and 2.[3] Appendix A.7 provides an illustrative example of our scope loss measures.

Figure 3 plots patents' dollar value and citation count against θ^{I} and θ^{II}, while controlling

[1] "Novel" means that the invention has not been invented by someone else or made available to the public (35 U.S. Code §102). "Non-obvious" means that the invention would not have been evident to a person having ordinary skill in the art (35 U.S. Code §103).

[2] Following the American Inventors Protection Act of 1999, most U.S. patent applications (with limited exceptions) must be published within 18 months of filing. As a result, for most granted patents filed after 1999, at least two texts are available: the pre-grant publication and the granted patent. Claim amendments in response to examiner office actions rarely occur within the first 18 months. In our sample, only 0.14% of applications were amended in response to an examiner action within 18 months of filing. We remove them from our sample.

[3] Most patents in our sample experience scope losses during examination, whereas scope expansion is less common (though possible). Such cases account for 7% and 18% of our sample patents based on S^{I} and S^{II} respectively.

for their pre-grant scope. Across all specifications, there is a clear downward trend, linking scope loss to a decline in economic value.

Combining our scope loss measures with a patent's status in the innovation sequence, Figure 4 shows a negative relationship between the likelihood that a patent is continued and its scope loss, for both θ^{I} and θ^{II}. Taken together, these results validate that our measures capture the hypothesized economic mechanisms and lend strong support to our empirical strategy thus far.

2.4 Measuring failure tolerance

Before we proceed to measuring failure tolerance, it is important to note that patents' scope loss during examination is far from random. For example, firms may strategically overstate the scope of their patent applications, leading to larger overall scope loss that is unrelated to failure tolerance . Moreover, because patent applications are drafted by attorneys, individual differences in their tendencies to over- or underclaim may also affect scope loss but need not reflect firms' failure tolerance.

To address this issue, we remove fixed effects attributable to attorneys, firms, inventors, examiners, application cohorts by technological field (CPC patent classes), and issue cohorts by technological field from θ^{I} and θ^{II}. This approach cleanses our scope loss measures of persistent influences from these agents, as well as common trends driven by macroeconomic conditions, technological breakthroughs, or shifts within the examination agency. Collectively, these fixed effects remove roughly 40% of the variation. We denote the cleansed variables as $\dot{\theta}^{\mathrm{I}}$ and $\dot{\theta}^{\mathrm{II}}$.

Following the conceptual framework in Section 2.1, we estimate a firm's failure tolerance as the maximum value loss—proxied by the (cleansed) scope loss—among continued patents. To allow failure tolerance to vary over time, we compute this measure using three-year rolling windows, $[t-3, t-1]$. For each continued patent p, let s denote the filing year of its subsequent patent in the same sequence. We focus on year s because it is the earliest point at which patent p can be classified as continued. We include patent p in the window $[t-3, t-1]$ if $s \in [t-3, t-1]$, which avoids look-ahead bias.

Formally, we compute firm i's failure tolerance in year t as

$$\alpha_{i,[t-3,t-1]} = \max_{p \in \mathcal{C}_{i,[t-3,t-1]}} \left\{ \dot{\theta}_p \right\}, \tag{9}$$

where $\mathcal{C}_{i,[t-3,t-1]} = \{p_{i,s} | s \in [t-3, t-1]\}$ denotes the set of continued patents that meet the conditions specified in Section 2.2, $\dot{\theta}_p$ denotes the cleansed scope loss, which can be either $\dot{\theta}^{\mathrm{I}}$ or $\dot{\theta}^{\mathrm{II}}$. However, as the maximum operator is not robust to measurement error and susceptible to right-tail outliers, we instead compute the sample 95th percentile:

$$\alpha_{i,[t-3,t-1]} = \underset{p \in \mathcal{C}_{i,[t-3,t-1]}}{P_{95}} \left\{ \dot{\theta}_p \right\}. \tag{10}$$

Notably, when the number of patents included in the calculation is small, the 95th percentile is obtained by linearly interpolating between the two adjacent order statistics. Accordingly, the minimum required sample size is two.

In addition, we record the number of observations used to estimate $\alpha_{i,[t-3,t-1]}$ and the average of the included $\dot{\theta}_p$. We denote these as $N_{i,[t-3,t-1]}$ and $\overline{\theta}_{i,[t-3,t-1]}$, respectively. We include them as control variables throughout our analysis to account for the mechanical effects of estimation based on different sample sizes, as well as any remaining non-random components of scope loss that could confound failure tolerance.

3 Analysis

With the failure tolerance measures in hand, we link them to firm-level innovation output. First, we describe our sample and the main variables used in our analysis. Next, we report cross-sectional regression results, focusing on innovation quality and quantity, and explore potential mechanisms underlying our findings.

3.1 Sample description

We source patent information from PatentsView, a publicly available USPTO database.[4] We then link patents to COMPUSTAT firms by firm name and aggregate patent output to the firm-year level. Appendix A.4 details our method.

We examine both the quality and quantity of the patents firms file. For the quality dimension, we use two measures already employed for validation in earlier sections: (1) the patent dollar value estimated by Kogan et al. (2017) and (2) citations received through 2022.[5] For each firm-year, we average these measures in two ways—across patents and across inventors. Following prior studies, we aggregate patents by filing year and focus only on patents that are ultimately granted .

For the quantity dimension, we count the number of patents filed by a firm each year (again, restricted to those that are ultimately granted), and compute the corresponding

[4]PatentsView can be accessed through the following link: https://patentsview.org/home.

[5]We do not explicitly adjust for the truncation problem for patent cohorts filed close to the end of the sample period, because we always compare patents within the same application cohort with year fixed effect throughout our analysis.

inventor-level average. To examine the joint effect of quality and quantity, we also compute total patent value and total citations by aggregating across patents within each firm-year.

Lerner and Seru (2022) caution about biases in patent and citation data that are correlated with firm characteristics. To address this issue, we draw financial information from COMPUSTAT. More specifically, we control for the following firm fundamentals: market capitalization (a proxy for size), Tobin's Q, return on asset (ROA), market leverage, R&D-to-sales ratio, and cash-to-asset ratio.

We end up with 7,394 firm-year observations involving 1,110 distinct firms from 2003 through 2022. Figure 5 depicts the distribution of sample firms across industries. The chemical and the electronic industries account for about a quarter of the sample each, ranking in the first and the second place. The following three places are instruments (16.1%), industrial machinery (12.3%), and business services (10.5%). Manufacturing firms dominate the sample, accounting for over 85% of firm-years.

Table 1 Panel A summarizes the characteristics of our sample firms. The distribution of size is highly skewed to the right. An average firm has a market capitalization of around \$14 billion (in 2022 dollars, same for all dollar values hereafter), while this number is merely \$1.7 billion for a medium firm. The average (median) Tobin's Q is 2.8 (2.1), indicating promising growth perspectives. However, an average (median) ROA of -3.5% (5.7%) positions the profitability of the sample firms at the lower end.

Regarding innovation, the sample demonstrates highly positively skewed distribution in terms of the number of patents filed per year (mean: 118; median: 13), the dollar value of an average patent (mean: \$27.0 million; median: \$8.9 million) and the citation received by an average patent (mean: 6.6; median: 2.1). An average firm files patents worth of \$2.5 billion each year, accounting for 18% of its market capitalization, which is very sizable.

In Panel B of Table 1, we also report statistics for a sample of inventors moving between linked COMPUSTAT firms ("movers"). We leverage this sample for our identification strategy in Section 4. The sample involves 20,627 job switches by 18,216 inventors. For each job switch, we include up to 5 inventor-years before and after the switch. The average (median) inventor produces 1.3 (1) patents per year. An average (median) patent is worth \$23 million (\$5 million) and receives 4.6 (1) citations.

3.2 Failure tolerance and innovation output

Patent dollar value

We first examine the association between failure tolerance and patent quality at the firm-year level. In Columns (1) and (2) of Table 2, we compute the average patent dollar value across patents. In Columns (3) and (4), we compute the average across inventors to capture per-inventor contribution.

The results show a clear positive relationship between patent dollar value and failure tolerance α, whether α is constructed using scope measure S^{I} or S^{II}, and whether patent value is averaged on a per-patent or per-inventor basis. The estimated effects are sizable and economically meaningful: a one-standard-deviation increase in α is associated with a 17% increase in dollar value per patent, or roughly $4.6 million. On a per-inventor basis, a one-standard-deviation increase in α is associated with an 12% increase in dollar value contributed by each inventor, corresponding to about $4 million.

Patent citation

Next, we use citations received as an alternative measure of patent quality. Table 3 reports regression results using the same right-hand-side specification as in Table 2.

Consistent with the results for patent dollar value, we find a positive relationship between citations and failure tolerance α across specifications. Specifically, a one-standard-deviation increase in α is associated with a 4.6%–4.9% increase in citations per patent, equivalent to about 0.3 additional citations (Columns (1) and (2)). On a per-inventor basis, a one-standard-deviation increase in α is associated with a 2.5%–3.6% increase in citations per inventor, corresponding to roughly 0.07–0.10 additional citations (Columns (3) and (4)).

Taken together, the results above indicate that more failure-tolerant firms tend to produce higher-quality patents, whether measured on a per-patent or per-inventor basis, consistent with prior studies. The estimated effects are sizable and economically meaningful. However, patent quality captures only one dimension of innovation. In the next section, we examine whether failure tolerance also affects patent quantity.

Patent and inventor count

We measure innovation quantity as the number of patents granted to each firm, aggregated by filing year. Likewise, we also compute volume contribution per inventor. Table 4 reports the results.

In contrast to prior studies, we document a strong and economically meaningful negative relationship between patent counts and failure tolerance. A one-standard-deviation increase in α is associated with a 10.0%–11.3% decline in the number of patents filed annually, corresponding to 11.8–13.3 fewer patents (Columns (1) and (2)). At the per-inventor level, however, we find no meaningful association (Columns (3) and (4)). This pattern suggests that the lower firm-level patent volume is primarily driven by a reduction in the number of inventors rather than a decline in individual productivity. Columns (5) and (6) support this interpretation: a one-standard-deviation increase in α is associated with an 8.4%–11.7% decrease in the number of inventors, comparable in magnitude to the effect on patent counts.

Total innovation output

Finally, we jointly examine innovation quality and quantity by aggregating patent dollar value and citations to the firm-year level. Table 5 presents the results. Columns (1) and (2) show that failure tolerance, α, is positively associated with total patent value; however, the coefficient is not statistically significant in either specification. Likewise, we find no statistically meaningful relationship between α and total citations. If anything, the estimates suggest a negative association.

Overall, these findings indicate that the higher quality but lower quantity of innovation associated with greater failure tolerance largely offset one another, resulting in an ambiguous net effect on total innovation output.

Taken together, these findings support the interpretation that firms choose their level of failure tolerance to balance a trade-off between innovation quality and quantity, with the objective of maximizing overall innovative output. Greater failure tolerance appears to enhance inventor productivity, manifested in higher patent quality without reducing quantity per inventor. However, this likely entails higher costs, which firms offset by employing fewer inventors.

3.3 Does greater failure tolerance entail higher costs?

Next, we examine whether greater failure tolerance is associated with higher costs. Specifically, we focus on three cost-related dimensions. The results are reported in Table 6.

Specification length. First, we analyze the nature of the research projects pursued by inventors. We argue that higher failure tolerance encourages inventors to undertake more complex research projects, which are inherently more likely to fail. Each patent application includes a section titled "Specification," which provides a detailed description of the invention sufficient to enable a person skilled in the relevant field to make and use it. We therefore posit that firms with greater failure tolerance produce patents with longer specifications, reflecting higher project complexity. We measure specification length by the number of pages and aggregate this measure to the firm-year level. Columns (1) and (2) report the results. In both specifications, greater failure tolerance is associated with longer specification sections, consistent with higher project complexity.

Abandonment rate. Second, we examine whether inventors operating under greater failure tolerance indeed experience higher failure rates. To this end, we collect data on abandoned patent applications from the USPTO for the period 2013 through 2022 and compute the abandonment rate as the ratio of abandoned applications to total applications at the firm-year level.[6] Columns (3) and (4) show that greater failure tolerance is associated with a higher abandonment rate, although the coefficient is statistically significant only in Column (4).

R&D expenses per inventor. Lastly, we examine whether more failure-tolerant firms spend more on R&D per inventor. Columns (5) and (6) show that failure tolerance is positively associated with R&D expenses per inventor, although the coefficient is statistically significant only in Column (5).

Taken together, these results provide consistent evidence that greater failure tolerance is associated with higher innovation-related costs. Firms with higher failure tolerance appear to commit more resources to each inventor and pursue more complex projects with a greater likelihood of failure, reflecting a shift toward riskier, yet potentially more impactful innovation strategies.

4 Identification

Our analysis so far sheds light on cross-sectional differences across firms: failure tolerance appears to balance innovation quality and quantity and, notably, enhances inventor productivity. However, these findings are correlational rather than causal.

To identify the causal effect of failure tolerance, we leverage a sample of inventors who move between firms ("movers"). When the new employer's failure tolerance differs from the old one, movers experience a sudden change in failure tolerance—effectively, a failure-tolerance "shock." We exploit these shocks as quasi-experiments to study the impact of failure tolerance on inventors' productivity.

To address the endogeneity associated with job switches, we devise three increasingly stringent empirical designs: difference-in-differences (DiD), matched-sample triple differences, and the former combined with an instrumental variable (IV).

[6] We cannot reliably assign abandoned patent applications to firms prior to 2013. Before the *Leahy-Smith America Invents Act* (AIA) took effect in 2012, patent applications had to be filed in the name of individual inventors. As a result, there is no direct way to determine the organization to which a patent would be assigned—if granted—until the patent is issued. Following the AIA, patent applications can be (and in most cases are) filed directly in the name of the inventors' organization, which allows us to link abandoned applications to firms.

4.1 Difference-in-differences

Job switches are endogenous decisions: the formation and dissolution of employment ties between firms and inventors is a two-sided matching process. A typical job switch is likely preceded by a mismatch between an inventor and their former employer (e.g., due to technological changes or skill development) and followed by an improved match with their new employer. As a result, job switches may increase an inventor's productivity regardless of any failure-tolerance shock.

To address this first concern, we compare movers who experience failure-tolerance shocks of varying magnitudes and in different directions—toward higher or lower tolerance—against each other. This approach allows us to net out the common effect of job switching per se, while isolating relative productivity differences across movers along a fine gradient of shocks.

Empirically, this maps into a DiD design with a continuous shock. For a mover switching from origin firm o to destination firm d in year τ, we define the continuous treatment as

$$\Delta\alpha = \alpha_{d,[\tau-3,\tau-1]} - \alpha_{o,[\tau-4,\tau-2]}, \tag{11}$$

which captures the change in failure tolerance the mover experiences upon switching employers. We estimate the following regression:

$$Y_{ift} = \rho \cdot \Delta\alpha_i \times Post_{it} + \mathbf{X}_{f,t-1}\mathbf{\Gamma} + \alpha_i + \alpha_{kt} + \alpha_{ct} + \alpha_s + \varepsilon_{ift}, \tag{12}$$

where i denotes an inventor, f denotes the inventor's employer, and t denotes calendar year. We use k to denotes 2-digit SIC industry of the employer, c the country in which the inventor works, and s the event year. The dependent variable Y_{ift} reflects inventor productivity. $Post_{it}$ is an indicator that equals one when the mover is employed by the destination firm, and zero otherwise. $\mathbf{X}_{f,t-1}$ contains employer control variables measured in year $t-1$. The coefficient ρ captures the impact of the failure-tolerance shock $\Delta\alpha$ on inventors' productivity.

However, this setting still relies on the strong assumption that movers do not select into the change in failure tolerance, $\Delta\alpha_i$. We argue that this concern is likely less serious than it may appear. Specifically, we examine correlations between $\Delta\alpha$ (based on S^{I} or S^{II}) and movers' pre-switch characteristics, including gender, career span, and patenting outcomes over the past five years (counts, average dollar value, and citations). Across all specifications, the correlation coefficients are consistently below 0.05. We further address this concern with an IV in Section 4.3.

Results. Table 7 reports the coefficient estimates. Columns (1) and (2) show that, after switching, movers exposed to a more positive failure-tolerance shock $\Delta\alpha$ produce patents with higher dollar value. Specifically, a one-standard-deviation increase in $\Delta\alpha$ is associated with a 20–27% increase in the dollar value of the average patent, corresponding to $200,000–300,000 per patent. This finding strongly corroborates our cross-sectional evidence that higher failure tolerance is linked to higher patent quality. The results for citations point in the same direction but are statistically weaker, as shown in columns (3) and (4).

On the quantity side, columns (5) and (6) show that changes in failure tolerance do not significantly affect the number of patents an inventor produces, consistent with the cross-sectional findings.

4.2 Matched triple differences

Job switches might not be randomly distributed over time and might coincide with macroeconomic shocks that subsequently affect inventor productivity. If such shocks systematically push inventors toward more or less failure-tolerant employers, our DiD design could inadvertently capture differential exposure to macroeconomic conditions rather than the causal effect of failure tolerance.

To address this concern, we add a third layer of differencing by comparing each mover to a matched non-mover with similar pre-switch characteristics. Specifically, we require the non-mover to be observed in the same calendar year, to work in the same country and 2-digit SIC industry, and to have the same gender. Among all eligible candidates, we compute Euclidean distance based on career span, patenting outcomes over the past five years (counts, dollar value, and citations), and employer fundamentals (α, market capitalization, Tobin's Q, ROA, market leverage, cash-to-assets, and R&D-to-sales).[7] Table 8 reports the matching diagnostics.

Specifically, we estimate the following regression:

$$
\begin{aligned}
Y_{ift} = \phi \cdot \Delta\alpha_i \times Post_{it} \times Mover_i + \psi \cdot \Delta\alpha_i \times Post_{it} + \chi \cdot Mover_i \times Post_{it} \\
+ \mathbf{X}_{f,t-1}\mathbf{\Gamma} + \alpha_i + \alpha_{kt} + \alpha_{ct} + \alpha_s + \varepsilon_{ift}, \qquad (13)
\end{aligned}
$$

where $Mover_i$ is an indicator that equals one for movers, and zero for matched non-movers. The subscripts and other variables are the same as in Equation (12). The coefficient ϕ captures the impact of the failure-tolerance shock $\Delta\alpha$ on inventors' productivity, relative to comparable non-movers. In addition, we also specify a dynamic version of Equation (13) to examine pre-trends:

[7] We normalize each matching variable by dividing it by the standard deviation of that variable across movers.

$$
\begin{aligned}
Y_{ift} = &\sum_{s=-5}^{5} \phi_s \cdot \Delta\alpha_i \times \mathbb{1}(t-\tau=s) \times Mover_i + \sum_{s=-5}^{5} \psi_s \cdot \Delta\alpha_i \times \mathbb{1}(t-\tau=s) \\
&+ \sum_{s=-5}^{5} \chi_s \cdot Mover_i \times \mathbb{1}(t-\tau=s) + \mathbf{X}_{f,t-1}\mathbf{\Gamma} + \alpha_i + \alpha_{kt} + \alpha_{ct} + \alpha_s + \varepsilon_{ift}, \qquad (14)
\end{aligned}
$$

where $\mathbb{1}(t-\tau=s)$ is an indicator that equals 1 if an observation is $s \in [-5,5]$ years away relative to the job switch in year τ.

Results. The results are reported in Table 8. The coefficients on the triple-interaction term are qualitatively similar to those in Table 7: after controlling for confounding trends using matched non-movers, more positive failure-tolerance shocks improve inventors' patent quality without compromising quantity. These results further corroborate our earlier findings. Figure 6 plots the estimates of Equation (14). The results corroborate the findings in Table 8 and largely rule out the presence of pre-trends.

Positive and negative failure-tolerance shocks may affect inventors asymmetrically. Table 9 splits $\Delta\alpha$ into a positive component, $\Delta\alpha^+$, and a negative component, $\Delta\alpha^-$. The results show that the effect is driven primarily by movers who join less tolerant employers: they substitute patent quantity for quality. However, the increase in quantity does not offset the substantial drop in quality, leading to a net loss in innovation output. On the contrary, movers joining more tolerant employers manage to increase patent quantity without compromising quality.

4.3 Instrumental variable

To further strengthen causal identification, we exploit exogenous variation in failure-tolerance differences between employers. Specifically, we leverage the fact that movers predominantly join employers located near their previous employer. In our sample, 92% of job switches land in the same country, 76% of new employers are within 200 kilometers of the old one, 54% of movers stay in the same city. Hence, the average failure-tolerance level in the area surrounding a mover's previous employer should predict that of the new employer, independent of the inventor's choice.

Based on this intuition, for each job switch in year τ, we calculate the average failure tolerance among other employers within a 200-kilometer radius of mover i's origin employer o:

$$
\overline{\alpha}_{o,[\tau-3,\tau-1]} = \frac{\sum_{g\in\Omega_o} E_g \cdot \alpha_{g,[\tau-3,\tau-1]}}{\sum_{g\in\Omega_o} E_g}, \qquad (15)
$$

where Ω_o denotes the set of employers within a 200-kilometer radius of firm o, and E_g denotes the number of inventors employed by firm g within that radius.

Next, we compute the average failure-tolerance shock an inventor would experience if she were to join an employer within that radius:

$$\overline{\Delta\alpha}_i = \overline{\alpha}_{o,[\tau-3,\tau-1]} - \alpha_{o,[\tau-4,\tau-2]}. \tag{16}$$

This ex ante measure is strongly correlated with the realized change in failure tolerance, $\Delta\alpha_i$, with a correlation coefficient of 0.62 when computed using either S^{I} or S^{II}.

Results. Using this IV, we re-estimate equation (13). Table 10 reports the coefficient estimates. Across all specifications, both the Kleibergen–Paap rk Wald F statistics and the Kleibergen–Paap rk LM statistics exceed conventional thresholds, indicating a strong relationship between the IV and the endogenous variables. In columns (1) and (2), a more positive failure-tolerance shock increases patent value, consistent with our earlier findings. Columns (3) through (6) yield insignificant coefficients on the triple-interaction term, indicating no detectable effect of failure tolerance on citations or patent quantity.

Overall, these results provide strong support for a causal interpretation of the relationship between failure tolerance and inventor productivity: on average, greater failure tolerance leads to higher patent quality.

5 Conclusion

In this paper, we create a novel firm-level measure of failure tolerance based on firms' patent histories. Specifically, we measure it as the worst patent examination outcome before a firm terminates an innovation sequence.

We show that failure tolerance reflects how firms balance the trade-off between innovation quality and quantity under resource constraints. Rather than simply increasing total innovation output, greater failure tolerance shifts innovative effort toward more ambitious, complex, and uncertain projects.

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A Appendix

A.1 Variable definitions

Table A1: Description of variables. This table defines the main numerical variables used in the paper. All other variables are defined in the respective captions of the tables using them.

Variable	Definition	Source
Panel A: Firm sample		
Dollar value per patent	Average patent value (million 2022 USD) across patents filed by a firm in a given year. The log specification is $log(Dollar\ value\ per\ patent)$.	Kogan et al. (2017)
Dollar value per inventor	$Totaldollarvalue$ divided by $Inventorcount$. The log specification is $log(Dollar\ value\ per\ inventor)$.	Kogan et al. (2017), PatentsView
Total dollar value	Total patent value (million 2022 USD) across patents filed by a firm in a given year. The log specification is $log(Total\ dollar\ value)$.	Kogan et al. (2017)
Citation per patent	Average number of citations received (through 2022) per patent, computed across patents filed by a firm in a given year. The log specification is $log(1 + Citation\ per\ patent)$.	PatentsView
Citation per inventor	Total citation divided by $Inventorcount$. The log specification is $log(1 + citation\ per\ inventor)$.	PatentsView
Total citation	Total number of citations received (through 2022) per patent, computed across patents filed by a firm in a given year. The log specification is $log(1 + Total\ citation)$.	PatentsView
Patent count	Number of patents filed by a firm in a given year. The log specification is $log(1 + Patent\ count)$.	PatentsView
Patent count per inventor	$Patentcount$ divided by $Inventorcount$. The log specification is $log(1 + Patent\ count\ per\ inventor)$.	PatentsView
Inventor count	Number of inventors associated with a firm in a given year. The log specification is $log(Inventor\ count)$.	PatentsView
Specification length	Average page number of the specification section per patent, computed across patents filed by a firm in a given year. The log specification is $log(Specification\ length)$.	PatentsView
Abandonment rate	Abandoned patent applications as a percentage of all applications files by a firm in a given year.	PatEx
S^{I}	Independent claim length, calculated as the word count of the shortest independent claim of a patent. See Section 2.3.	PatentsView
S^{II}	Weighted independent claim count, calculated by summing one over word count across a patent's independent claims. See Section 2.3.	PatentsView
θ	Relative patent scope loss, defined as the scope difference between a patent's pre-grant publication and its granted document, normalized by their average. Patent scope is proxied by S^{I} or S^{II}. See Section 2.3.	PatentsView
$\alpha_{[t-3,t-1]}$	Failure tolerance, defined as the 95th percentile of θ across patents whose sequel patent was filed between year $t-3$ and year $t-1$. See Section 2.4.	PatentsView
$\overline{\theta}_{[t-3,t-1]}$	Average θ across patents whose sequel patent was filed between year $t-3$ and year $t-1$. See Section 2.4.	PatentsView

Table A1: Description of variables. (*continued*)

Variable	Definition	Source
$N_{[t-3,t-1]}$	Number of patents whose sequel patent was filed between year $t-3$ and year $t-1$. The log specification is $log(N_{[t-3,t-1]})$. See Section 2.4.	PatentsView
Market cap	The product of the year-end stock closing price and the number of shares outstanding (2022 USD). The log specification is $log(Market\ cap)$.	Compustat
Tobin's Q	(Total assets - book equity + market capitalization) / total assets	Compustat
ROA	EBITDA divided by total assets.	Compustat
Leverage	Book debt divided by enterprise value.	Compustat
Cash/asset	Cash divided by total asset.	Compustat
R&D/sales	R&D expenditure divided by sales.	Compustat
Panel B: Mover sample		
Dollar value per patent	Average patent value (million 2022 USD) across patents filed by an inventor under a firm in a given year. The log specification is $log(Dollar\ value\ per\ patent)$.	PatentsView
Citation per patent	Average number of citations received (through 2022) per patent, computed across patents filed by an inventor under a firm in a given year. The log specification is $log(1 + Citation\ per\ patent)$.	PatentsView
Patent count	Number of patents filed by an inventor under a firm in a given year. The log specification is $log(1 + Patent\ count)$.	PatentsView
$\Delta\alpha$	The destination firm's $\alpha_{[t-3,t-1]}$ minus that of the origin firm. The failure tolerance of both firms is measured in the year of the job switch.	PatentsView
$\Delta\alpha^+$	Equals $\Delta\alpha$ if $\Delta\alpha > 0$, and zero otherwise.	PatentsView
$\Delta\alpha^-$	Equals $\Delta\alpha$ if $\Delta\alpha \leq 0$, and zero otherwise.	PatentsView
Post	Equals one from the year a mover is associated with the destination firms onward, and zero otherwise.	
Mover	Equals one for movers, and zero for matched non-movers.	

A.2 Technical notation

Table A2: Description of technical terms. This table defines patent-related technical terms used throughout the paper.

Term	Definition
Patent Scope	The extent of legal protection a patent provides, determined by the patent's claims. Scope is used to assess infringement: broader claims generally mean broader protection.
Patent Claims	Numbered statements in a patent that define the invention's protected features and jointly determine the patent's scope. Claims are typically independent or dependent.
Independent Patent Claims	Claims that stand on their own and define the invention's core protection in the broadest terms, without referencing other claims.
Dependent Patent Claims	Claims that refer to earlier claims and add specific limitations or features, thereby narrowing and refining the scope of protection.
Pre-Grant Publication	The public release of a patent application before grant, making the application's contents accessible through patent office publications or databases.
Patent Examination Process	The patent office's review of an application to determine whether it satisfies patentability requirements and should be granted.
CPC-Patent Class	A hierarchical classification code from the USPTO and EPO's Cooperative Patent Classification system that categorizes patents by technical subject matter at increasing levels of specificity.

A.3 Correlation tables

Table A3: Firm level correlation table. This table reports the coefficients of correlation between firm-level numerical variables that are employed for analysis in this paper. *, **, *** indicate significance level of 10%, 5% and 1% respectively.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	Log dollar value per patent	1.00										
(2)	Log dollar value per inventor	0.78***	1.00									
(3)	Log total dollar value	0.69***	0.75***	1.00								
(4)	Log citation per patent	-0.03**	-0.07***	0.12***	1.00							
(5)	Log citation per inventor	-0.10***	-0.03**	0.10***	0.92***	1.00						
(6)	Log total citation	0.02	0.06***	0.54***	0.75***	0.71***	1.00					
(7)	Log patent count	0.07***	0.15***	0.70***	0.22***	0.25***	0.78***	1.00				
(8)	Log patent count per inventor	-0.17***	0.12***	0.01	-0.10***	0.20***	0.03***	0.26***	1.00			
(9)	Log inventor count	0.14***	0.12***	0.70***	0.27***	0.19***	0.78***	0.95***	-0.05***	1.00		
(10)	Log specification length	0.15***	0.11***	0.10***	-0.07***	-0.08***	-0.02	0.06***	0.00	0.07***	1.00	
(11)	Abandonment rate	0.02	-0.04**	-0.11***	0.05***	-0.01	-0.06***	-0.23***	-0.25***	-0.15***	0.08***	1.00
(12)	$\alpha_{[t-3,t-1]}$ (S^{I})	0.08***	0.09***	0.19***	0.03**	0.01	0.17***	0.25***	0.03***	0.25***	0.14***	0.05***
(13)	$\underline{\alpha}_{[t-3,t-1]}$ (S^{II})	0.08***	0.07***	0.18***	0.01	0.00	0.14***	0.23***	0.05***	0.22***	0.14***	0.03*
(14)	$\overline{\theta}_{[t-3,t-1]}$ (S^{I})	-0.01	-0.01	-0.03**	0.01	-0.01	-0.02	-0.03***	-0.02	-0.03**	0.04***	0.00
(15)	$\overline{\theta}_{[t-3,t-1]}$ (S^{II})	-0.02	-0.03**	-0.03*	0.02*	0.01	0.00	-0.02*	-0.02	-0.02	0.02	-0.01
(16)	Log $N_{[t-3,t-1]}$	0.07***	0.14***	0.51***	-0.09***	-0.06***	0.39***	0.72***	0.16***	0.68***	0.14***	-0.15***
(17)	Log market cap.	0.55***	0.57***	0.79***	-0.02*	-0.05***	0.36***	0.61***	0.02	0.62***	0.09***	-0.10***
(18)	Tobin's Q	0.26***	0.20***	0.09***	-0.04***	-0.01	-0.13***	-0.13***	0.04***	-0.14***	0.16***	0.00
(19)	ROA	0.26***	0.25***	0.38***	0.07***	0.04***	0.24***	0.32***	-0.02	0.34***	-0.11***	-0.15***
(20)	Leverage	0.07***	0.10***	0.11***	-0.11***	-0.14***	-0.02	0.08***	-0.04***	0.10***	-0.04***	0.02
(21)	Cash/asset	-0.16***	-0.16***	-0.25***	0.00	0.04***	-0.15***	-0.24***	0.05***	-0.26***	0.09***	0.10***
(22)	R&D/sales	-0.06***	-0.10***	-0.19***	-0.04***	-0.04***	-0.15***	-0.21***	-0.03***	-0.20***	0.17***	0.18***

		(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(12)	$\alpha_{[t-3,t-1]}$ (S^{I})	1.00										
(13)	$\underline{\alpha}_{[t-3,t-1]}$ (S^{II})	0.78***	1.00									
(14)	$\overline{\theta}_{[t-3,t-1]}$ (S^{I})	0.58***	0.43***	1.00								
(15)	$\overline{\theta}_{[t-3,t-1]}$ (S^{II})	0.45***	0.58***	0.77***	1.00							
(16)	Log $N_{[t-3,t-1]}$	0.42***	0.40***	-0.03**	-0.03**	1.00						
(17)	Log market cap.	0.17***	0.18***	-0.05***	-0.03***	0.52***	1.00					
(18)	Tobin's Q	0.02	0.02*	0.01	0.00	-0.04***	0.07***	1.00				
(19)	ROA	0.04***	0.04***	-0.05***	-0.04***	0.22***	0.50***	-0.24***	1.00			
(20)	Leverage	-0.03***	-0.03**	-0.02	-0.01	0.07***	0.09***	-0.31***	0.05***	1.00		
(21)	Cash/asset	-0.01	0.00	0.02*	0.03**	-0.15***	-0.37***	0.28***	-0.44***	-0.29***	1.00	
(22)	R&D/sales	-0.01	0.00	0.02*	0.02*	-0.14***	-0.26***	0.14***	-0.54***	-0.11***	0.32***	1.00

Table A4: Mover level correlation table. This table reports the coefficients of correlation between mover-level numerical variables that are employed for analysis in this paper. *, **, *** indicate significance level of 10%, 5% and 1% respectively.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	$\Delta\alpha$ (S^{I})	1.000									
(2)	$\Delta\alpha$ (S^{II})	0.807***	1.000								
(3)	Patent count	0.011***	0.001	1.000							
(4)	Dollar value per patent	0.013***	0.020***	-0.019***	1.000						
(5)	Citation per patent	-0.002	0.000	-0.000	-0.014***	1.000					
(6)	Log patent count	0.010***	0.002	0.796***	-0.021***	0.006	1.000				
(7)	Log dollar value	0.004	-0.007	0.025***	0.489***	0.036***	0.024***	1.000			
(8)	Log citation	0.005	0.002	0.060***	-0.052***	0.575***	0.099***	0.034***	1.000		
(9)	Market cap. (bn)	0.021***	0.014***	0.049***	0.327***	-0.037***	0.065***	0.410***	-0.091***	1.000	
(10)	ROA	0.044***	0.030***	0.031***	0.150***	0.010***	0.030***	0.317***	0.023***	0.340***	1.000
(11)	Leverage	-0.023***	-0.007**	-0.031***	-0.049***	-0.041***	-0.041***	-0.095***	-0.051***	-0.129***	-0.280***
		(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	
(12)	Tobin's Q	-0.442***	1.000								
(13)	Cash/asset	-0.313***	0.322***	1.000							
(14)	R&D/sales	-0.080***	0.152***	0.191***	1.000						
(15)	Log market cap.	-0.126***	0.182***	-0.338***	-0.223***	1.000					
(16)	$\overline{\theta}_{[t-3,t-1]}$ (S^{II})	0.005*	-0.015***	-0.008***	0.024***	-0.015***	1.000				
(17)	$\overline{\theta}_{[t-3,t-1]}$ (S^{I})	-0.051***	-0.013***	0.016***	0.047***	-0.007**	0.738***	1.000			
(18)	$N_{[t-3,t-1]}$	-0.018***	-0.033***	-0.157***	-0.074***	0.385***	0.003	-0.004	1.000		
(19)	Log $N_{[t-3,t-1]}$	0.047***	-0.147***	-0.284***	-0.173***	0.577***	0.018***	-0.018***	0.685***	1.000	

A.4 Name matching

We start from the universe of USPTO patent assignees and the universe of CapitalIQ companies. We standardize all assignee and firm names and apply a frequency-based name matching algorithm to link the two data sets following Hall, Jaffe, and Trajtenberg (2001).

The name standardization routine and the name matching algorithm can be downloaded from the following link: https://sites.google.com/site/patentdataproject/Home. We adapt the codes to our sample. To maximize precision while minimizing data losses, we require assignee-company pairs matched by the algorithm with non-identical standardized names to have a normalized Levenshtein distance of at least 0.5. All pairs below the threshold are dropped. The normalized Levenshtein distance is defined as the Levenshtein distance between two strings divided by the string length of the longer component. We further require each matched CapitalIQ firm to be assigned at least one patent within its sample period.

A.5 Linking patent scope to variables of interest

This appendix describes the methodology underlying Figure 2-4. The sample includes 1,604,815 domestic utility patents which are filed between 2000 and 2022, linked to a CapitalIQ firm, published before the applicant responds to the first rejection with the text of the pre-grant publication and the patent grant available, and is supplemented with forward citation up to 2022. The sample for Figure 2a, 2c, 3a and 3c is further combined with patent dollar value estimated by Kogan et al. (2017). For each patent, we measure its pre-examination patent scope, post-examination patent scope and scope reduction as defined in Section 2.3. We classify a patent as terminating a sequence according to our definition in Section 2.2. To investigate the relationship between variables of interest and our scope measures, we estimate the following regression model:

$$y_{pkf} = \alpha_{kf} + \beta \cdot x_{pkf} + \mathbf{Z}_{pkf} \cdot \boldsymbol{\gamma} + \varepsilon_{pkf}, \tag{17}$$

where y_{pkf} can be log dollar value, log citation or a successor dummy. The follow-on dummy equals one if a patent has a successor, and zero otherwise. p denotes a patent, f denotes its filing year and k denotes its three-digit CPC patent class. α_{kf} denotes time-varying factors within patent classes. x_p is the variable of interest. $\mathbf{Z}_p$ is a vector of controls. ε_{pkf} is the error term. To single out the partial relationship between y_{pkf} and x_p, we estimate two partitioned regressions:

$$y_{pkf} = \delta_{kf} + \mathbf{Z}_{pkf} \cdot \boldsymbol{\eta} + \zeta_{pkf} \tag{18}$$

$$x_{pkf} = \phi_{kf} + \mathbf{Z}_{pkf} \cdot \boldsymbol{\psi} + \xi_{pkf}, \tag{19}$$

and define the partialled-out versions of y_{pkf} and x_p as the respective estimated residual plus their unconditional mean:

$$y^{\partial}_{pkf} = \hat{\zeta}_{pkf} + \bar{y}_{pkf} \tag{20}$$

$$x^{\partial}_{pkf} = \hat{\xi}_{pkf} + \bar{x}_{pkf}. \tag{21}$$

Lastly, to visualize the relationship between y^{∂}_{pkf} and x^{∂}_{pkf}, we sort the sample by x^{∂}_{pkf} into 20 quantiles and plot the average y^{∂}_{pkf} against the average x^{∂}_{pkf} for each quantile.

Table A5 reports the OLS estimates of Eq. 17. Figure 2a, 2c, 2b, 2d, 3a, 3c, 3b, 3d, 4a and 4b correspond to Column 1-10 respectively. The slope of the fitted line in each figure equals the respective coefficient on the x-axis variable.

Table A5: Linking patent scope to variables of interest. This table reports regression results of Eq. 17. The sample includes 1,604,815 domestic utility patents filed between 2000 and 2022. *Log dollar value* is the patent dollar value as estimated in Kogan et al. (2017) in logarithm. *Log adj. citation* is the citation received by a patent plus one in logarithms. *Terminate* equals one if a patent terminates a sequence as defined in Section 2.2, and zero otherwise. S^{I} and S^{II} are patent scope measures. S^{pre} is measured before patent examination. S^{post} is measured after patent examination. θ is the relative scope reduction. *Class* stands for three-digit CPC patent classes and *cohort* for the filing year. Scope measures are defined in Table A1. All standard errors are clustered at the class $\times$ cohort level and t-statistics are reported in parentheses. *, **, *** indicate significance level of 10%, 5% and 1% respectively.

Dep. var.:	Log patent value		Log citation		Log patent value		Log citation		Terminate dummy	
Scope measure:	S^{I}	S^{II}	S^{I}	S^{II}	S^{I}	S^{II}	S^{I}	S^{II}	S^{I}	S^{II}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
log S^{post}	-0.421***	0.394***	-0.022***	0.030***						
	(-22.62)	(25.42)	(-8.62)	(15.91)						
θ					-0.312***	-0.317***	-0.024***	-0.029***	0.067***	0.047***
					(-14.33)	(-15.41)	(-5.37)	(-9.44)	(17.73)	(14.82)
log S^{pre}					-0.496***	0.537***	-0.020***	0.047***	0.010***	-0.018***
					(-20.12)	(28.35)	(-6.50)	(14.52)	(5.94)	(-9.46)
Class $\times$ cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.140	0.148	0.033	0.034	0.142	0.158	0.033	0.036	0.062	0.061
N	789,637	789,637	1,604,815	1,604,815	789,637	789,637	1,604,815	1,604,815	1,604,815	1,604,815
Figure	2a	2c	2b	2d	3a	3c	3b	3d	4a	4b

A.6 Matching Diagnostics

Table A6: Matching diagnostics. This table reports summary statistics for all variables used in the matching procedure, separately for movers and their matched non-movers. All variables are measured in year $t-1$, relative to the move. Matching is based on the Euclidean distance computed over career characteristics and recent patenting activity, including career length and patent outcomes over the past five years (counts, citation-weighted counts, and dollar value), as well as employer characteristics (α, market capitalization, Tobin's Q, ROA, leverage, cash-to-assets, and R&D-to-sales). Career length is the number of years since an inventor's first patent application with an assigned employer. The final column reports the Imbens-Wooldridge statistics between movers and matched non-movers. All other variables are defined in Table A1.

	Movers (N = 11,186)			Matched non-movers (N = 11,186)			
	Mean	Median	SD	Mean	Median	SD	IW-stat
ROA	0.084	0.082	0.131	0.086	0.083	0.123	-0.006
Leverage	0.131	0.102	0.116	0.129	0.102	0.113	0.008
Tobin's Q	1.994	1.700	1.185	1.990	1.703	1.164	0.001
Cash/asset	0.133	0.097	0.106	0.133	0.097	0.102	0.002
R&D/sales	0.180	0.079	0.728	0.170	0.078	0.664	0.005
Log market cap.	9.914	10.129	1.830	9.952	10.129	1.790	-0.007
$\alpha_{t-3\rightarrow\text{t-1}}$ (S^{I})	0.717	0.740	0.263	0.718	0.740	0.261	-0.002
$\alpha_{t-3\rightarrow\text{t-1}}$ (S^{II})	0.569	0.599	0.212	0.571	0.599	0.209	-0.003
Log career length	2.263	2.303	0.747	2.244	2.303	0.732	0.009
Log patent count past 5 years	1.631	1.609	0.708	1.628	1.609	0.704	0.001
Log avg. citation past 5 years	1.602	1.504	1.056	1.598	1.496	1.020	0.002
Log avg. dollar value past 5 years	1.668	1.583	1.355	1.667	1.605	1.345	0.000

A.7 Example of Patent Scope Reduction

We provide an example of independent claims of a patent application and their altered versions at grant. We omit all dependent claims. The example comprises a patent for a three rack dishwasher. The shortest independent claim length at application was *Claim 29* with 12 words. After the examination process, the final patent grant document shows that the shortest independent claim is *Claim 24* with 41 words, i.e., 29 words have been added after the patent examination. Please note that the order of claims has shifted, which affected the claim enumeration but does not impact our patent scope measure. For the patent at hand we would calculate the following estimates for patent scope (S^{I} and S^{II}) and patent scope reduction:

- $S^{\mathrm{I},pre} = 12$, $S^{\mathrm{II},post} = 41$
- $S^{\mathrm{II,pre}} = 0.2401$, $S^{\mathrm{II,post}} = 0.0748$
- $\theta^{\mathrm{I}} = 1.0943$, $\theta^{\mathrm{II}} = 1.0498$

U.S. Patent Application (US 2003/0226580 A1, filed: Dec. 11, 2003)

Claim 1. A dishwasher comprising: a lower rack; a middle rack; an upper rack; a rotable lower spray arm associated with the lower rack; a rotatable middle spray arm associated with the middle rack; and a rotatable upper spray arm associated with the upper rack.

Claim 10. A dishwasher comprising: a lower rack; a middle rack; an upper rack; the middle and upper racks each having a sloped bottom portion, with the slope of each bottom portion in opposite directions.

Claim 17. A dishwasher comprising: a flat lower rack without tines; a sloped middle rack; and a sloped upper rack.

Claim 25. A dishwasher comprising: a pair of racks each having a sloped bottom portion; the bottom portions being sloped in opposite directions.

Claim 29. A dishwasher comprising: a pair of racks; each rack being vertically adjustable.

U.S. Patent (US 7032604 B2, granted: Apr. 25, 2006)

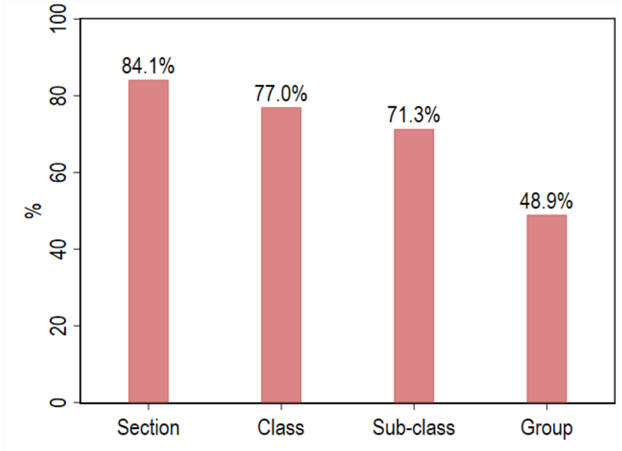
Claim 1. A dishwasher comprising: a lower rack; a middle rack; an upper rack; wherein the middle and upper racks each being rectangular and each having opposite sides with lower edges located at different elevations so as to define sloped bottoms; a rotatable lower spray arm associated with the lower rack; a rotatable middle spray arm associated with the middle rack; a rotatable upper arm associated with the upper rack.

Claim 9. A dishwasher comprising: a washing chamber; a lower rackl a middle rack; an upper rack, the racks each extending substantially across the washing chamber; the middle and upper racks, each being rectangular and each having opposite sides with lower edges located at different elevations so as to define bottoms sloped in opposite directions from one another.

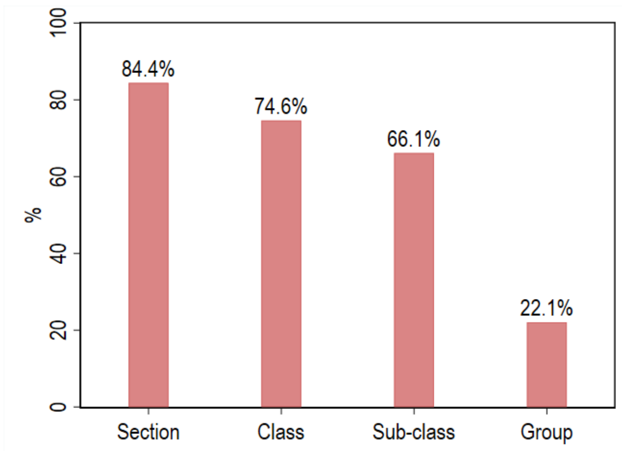
Claim 16. A dishwasher comprising: a flat lower rack without tines; a middle rack; an upper rack, the middle and upper racks being rectangular and each having opposite sides with lower edges located at different elevations so that the racks are inclined with respect to a horizontal plane; and the upper rack being positioned over the middle rack.

Claim 24. A dishwasher comprising: a wash chamber; a pair of rectangular racks positioned above the other, and each having opposite sides with lower edges located at different elevations so as to define sloped bottoms; and the bottoms being sloped in opposite direcetions.

B Figures

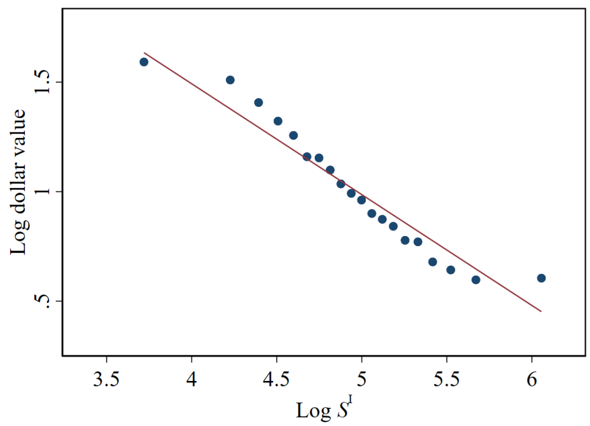


(a) Concentration

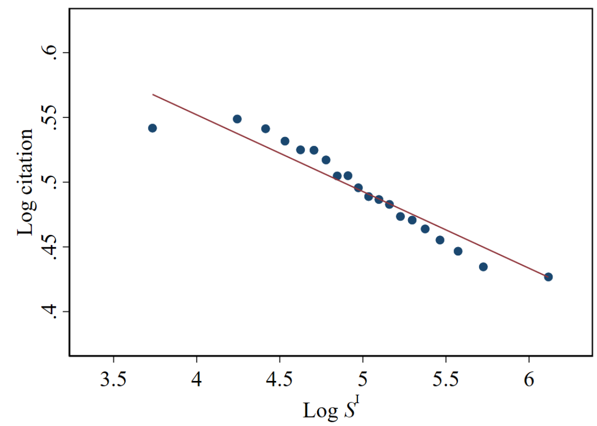


(b) Continuity

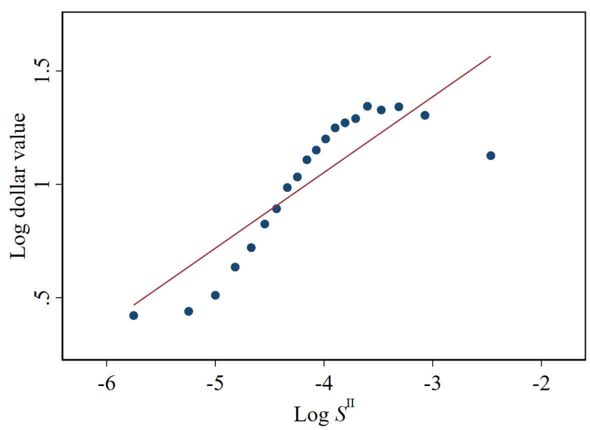
Figure 1: Investors' research scope This figure characterises the research fields of a representative inventor in this paper. Figure 1a plots the maximum percentage of a representative inventor' inventions that can be attributed to a single technological field. The sample includes 344,852 distinct inventors with at least two inventions. Figure 1b plots the percentage of inventions that are followed by another invention invented by the same inventor within three years that is classified in the same technological field. The sample includes 896,107 inventions that are followed by at least on invention by the same inventor within three years. On the x-axis are technological fields defined on different granularity, corresponding to the first four levels in the Cooperative Patent Classification system. The number of categories within each level is (as of Jan 2024): 9 (Section), 137 (Class), 677 (Sub-class) and 9815 (Group).



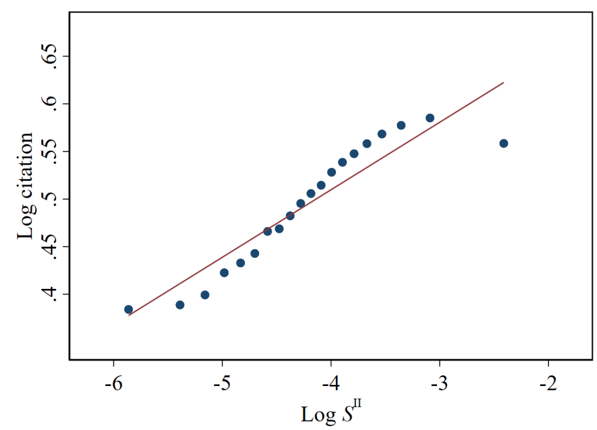
(a) Log patent value - log $S^{\mathrm{I,post}}$



(b) Log citation - log $S^{\mathrm{I,post}}$

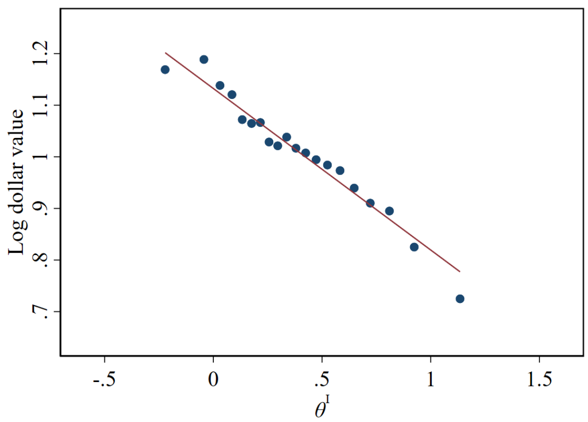


(c) Log patent value - log $S^{\mathrm{II,post}}$

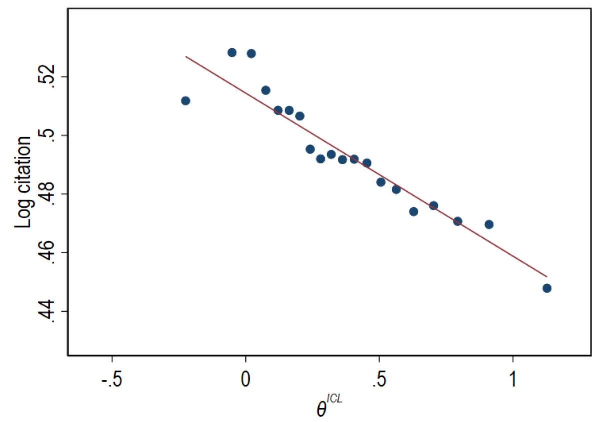


(d) Log citation - log $S^{\mathrm{II,post}}$

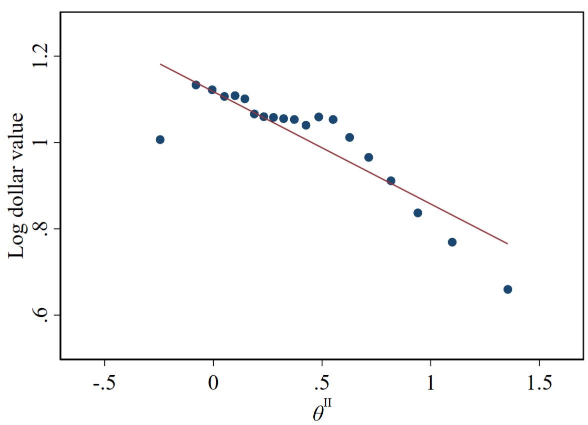
Figure 2: Patent value, citation and scope. This figure depicts the relationship between patent dollar value or citation and our patent scope measures. The sample includes 1,604,815 domestic utility patents filed between 2000 and 2022. The x-axis variable is post-examination patent scope $S^{\mathrm{I,post}}$ or $S^{\mathrm{II,post}}$ in logarithm. The y-axis variable is either patent value or citation in logarithm. *Patent value* is the patent dollar value estimated by Kogan et al. (2017). *Citation* is calculates as the number of cites received until 2022. All figures control for factors specific to each cohort within each class. The sample is sorted into 20 bins sorted by the x-axis variable. Each dot represents the sample average of a bin. A detailed description of the methodology is provided in Appendix A.5. Scope measures are defined in Table A1.



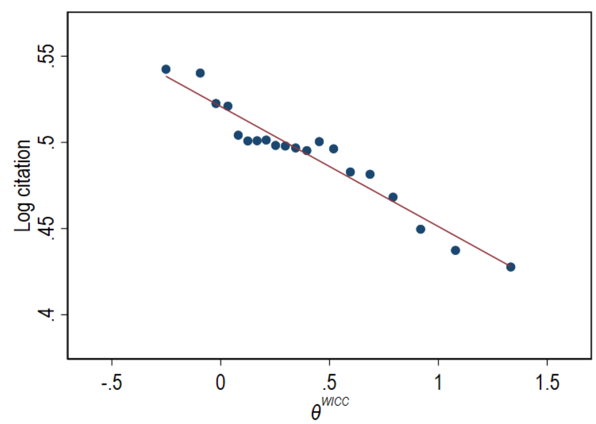
(a) Log patent value - θ^{I}



(b) Log citation - θ^{I}

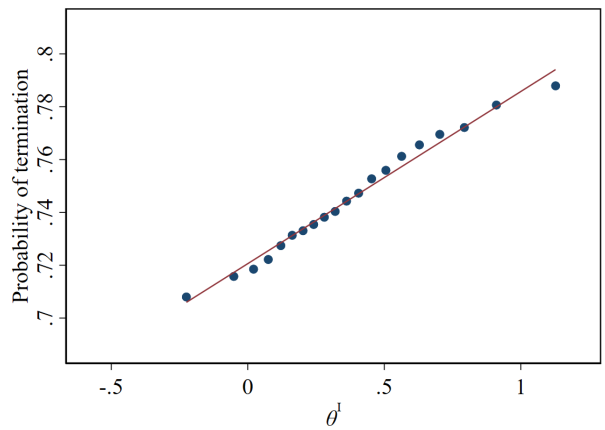


(c) Log patent value - θ^{II}

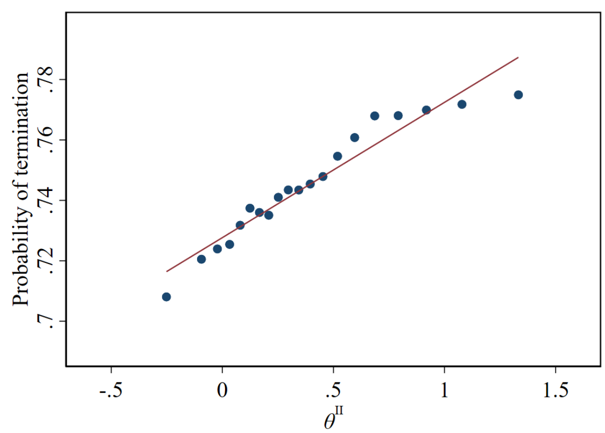


(d) Log citation - θ^{II}

Figure 3: Patent value, citation and scope reduction. This figure depicts the relationship between patent dollar value or citation and patent scope reduction. The sample includes 1,604,815 domestic utility patents filed between 2000 and 2022. The x-axis variable is reduction of patent scope during patent examination θ^{I} or θ^{II}. The y-axis variable is either patent dollar value or citation in logarithm. *Patent value* is the patent dollar value estimated by Kogan et al. (2017). *Citation* is calculates as the number of cites received until 2022. All figures control for factors specific to each cohort within each class and the log of respective pre-examination patent scope $S^{\mathrm{I,pre}}$ or $S^{\mathrm{II,pre}}$. The sample is sorted into 20 quantiles according to the x-axis variable. Each dot represents the sample average of a quantile. A detailed description of the methodology is provided in Appendix A.5. Scope measures are defined in Table A1.



(a) Probability of terminating a sequence - θ^{I}



(b) Probability of terminating a sequence - θ^{II}

Figure 4: Sequence termination and scope loss. This figure depicts the relationship between the probability of a patent terminating an innovation sequence and its scope reduction in patent examination. The sample includes 1,604,815 domestic utility patents filed between 2000 and 2022. The x-axis variable is reduction of patent scope during patent examination θ^{I} or θ^{II}. The y-axis variable is a dummy that equals one if a patent terminates a patent sequence as defined in Section 2.2, and zero otherwise. All figures control for factors specific to each cohort (filling year) within each three-digit CPC patent class and the log of respective pre-examination patent scope $S^{\mathrm{I,pre}}$ or $S^{\mathrm{II,pre}}$. The sample is sorted into 20 bins sorted by the x-axis variable. Each dot represents the sample average of a bin. A detailed description of the methodology is provided in Appendix A.5. Scope measures are defined in Table A1.

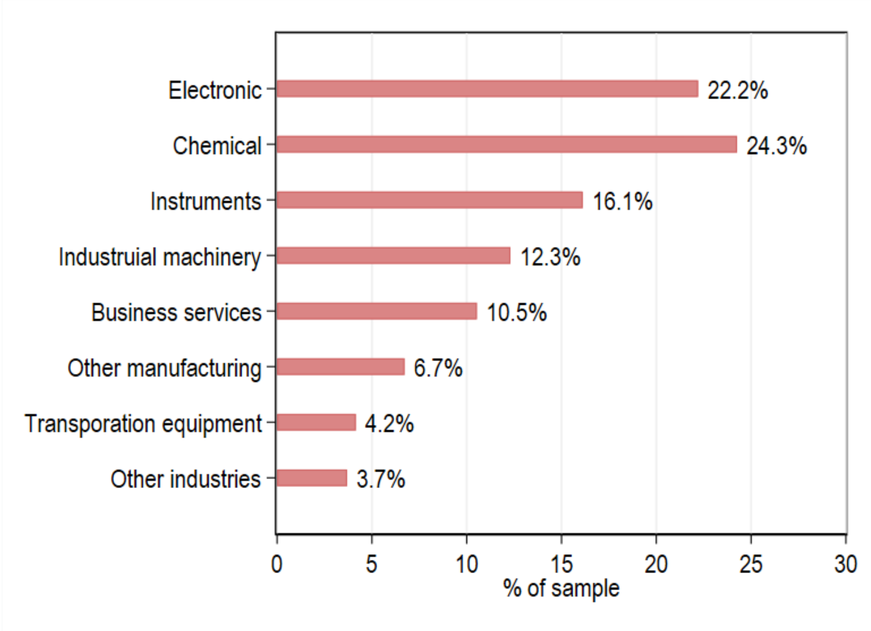
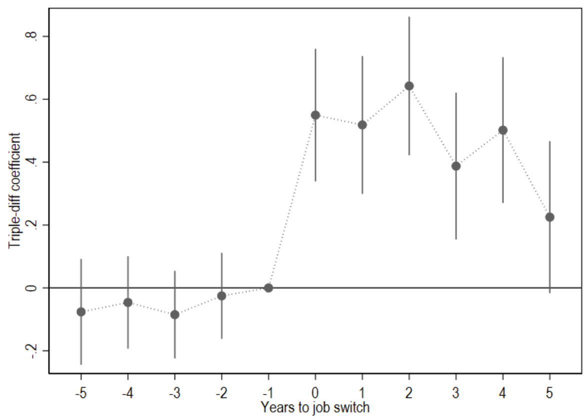
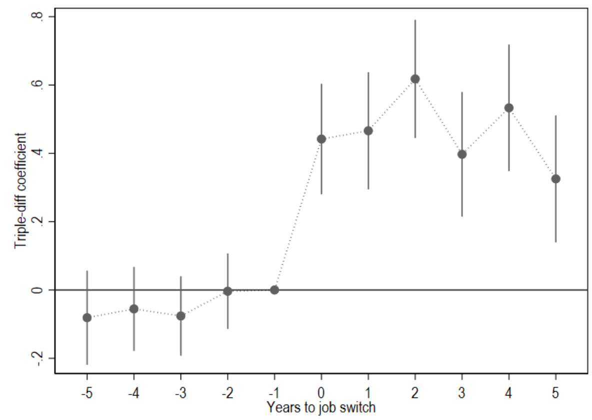


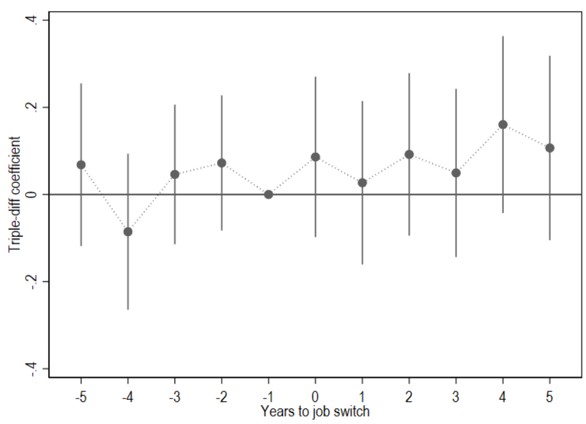
Figure 5: Sample breakdown by industry. This chart demonstrates the sample composition across industries. The sample includes 7,394 firm-year observations involving 1,110 distinct firms from 2003 to 2022. The SIC codes for the industries on the vertical axis are 28 (chemical), 36 (electronic), 38 (instruments), 35 (industrial machinery), 73 (business services), 37 (transportation equipment), D excluding the two-digit codes mentioned before (other manufacturing), and all others (other industries).



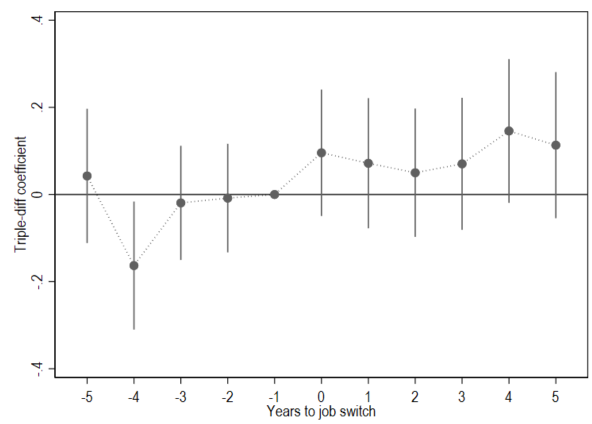
(a) Patent value around job switches - $\Delta\alpha$ (S^{I})



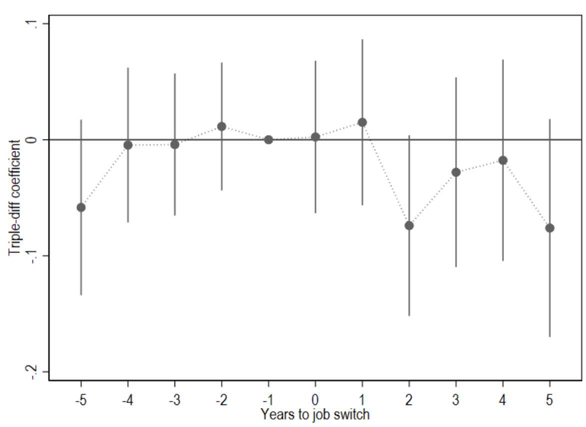
(b) Patent value around job switches - $\Delta\alpha$ (S^{II})



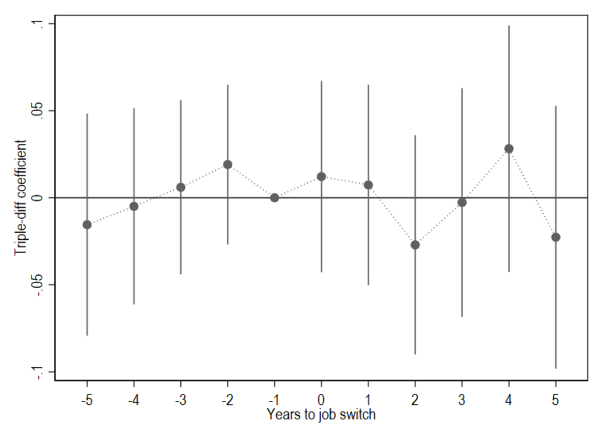
(c) Citations around job switches - $\Delta\alpha$ (S^{I})



(d) Citations around job switches - $\Delta\alpha$ (S^{II})



(e) Patent count around job switches - $\Delta\alpha$ (S^{I})



(f) Patent count around job switches - $\Delta\alpha$ (S^{II})

Figure 6: Inventor productivity around job switches. This figure depicts the coefficients on the triple interaction terms in Equation (14). The dependent variables include average patent dollar value, average citations received, and patent count.

C Tables

Table 1: Summary statistics. This table provides summary statistics of all firm-level and inventor-level numeric variables used for analysis in this paper. All variables are defined in Table A1.

	N	Mean	SD	P1	P25	Median	P75	P99
Panel A: Firm sample								
Dollar value per patent (mn)	5,504	27.031	63.631	0.058	3.010	8.931	23.736	283.907
Log dollar value per patent	5,504	2.081	1.683	-2.853	1.102	2.190	3.167	5.649
Dollar value per inventor (mn)	5,492	34.470	862.580	0.019	0.937	3.103	8.710	201.484
Log dollar value per inventor	5,492	1.613	1.233	0.018	0.661	1.412	2.273	5.311
Total dollar value (bn)	5,504	2.540	11.705	0.000	0.024	0.153	1.014	38.195
Log total dollar value	5,504	5.107	2.494	0.345	3.218	5.039	6.923	10.551
Citation per patent	7,132	6.603	22.742	0.000	0.333	2.125	6.413	64.750
Log citation per patent	7,132	1.270	1.076	0.000	0.288	1.139	2.003	4.186
Citation per inventor	7,101	2.829	10.414	0	0	1	3	31
Log citation per inventor	7,101	0.805	0.826	0.000	0.125	0.574	1.253	3.466
Total citation	7,132	628.770	2,866.348	0	3	35	250	11,706
Log total citation	7,132	3.579	2.555	0.000	1.386	3.584	5.526	9.368
Patent count	7,394	118.247	458.133	0	4	13	50	2,167
Log patent count	7,394	2.901	1.726	0.000	1.609	2.639	3.932	7.682
Patent count per inventor	7,332	0.456	0.350	0.000	0.250	0.385	0.565	1.750
Log patent count per inventor	7,332	0.354	0.197	0.000	0.223	0.325	0.448	1.012
Inventor count	7,394	254.771	909.005	1	12	35	122	4,248
Log inventor count	7,394	3.774	1.728	0.693	2.565	3.584	4.812	8.354
Specification length	7,093	27.391	32.862	1.000	12.500	18.550	29.132	164.862
Log specification length	7,093	2.930	0.891	0.000	2.526	2.921	3.372	5.105
Abandonment rate	4,568	0.164	0.215	0.000	0.000	0.079	0.250	1.000
$\alpha_{[t-3,t-1]}$ (S^{I})	7,394	0.459	0.332	-0.256	0.231	0.476	0.658	1.319
$\alpha_{[t-3,t-1]}$ (S^{II})	7,394	0.561	0.382	-0.343	0.294	0.602	0.833	1.395
$\overline{\theta}_{[t-3,t-1]}$ (S^{I})	7,394	0.008	0.148	-0.373	-0.065	0.000	0.068	0.491
$\overline{\theta}_{[t-3,t-1]}$ (S^{II})	7,394	0.010	0.183	-0.456	-0.079	0.001	0.084	0.587
$N_{[t-3,t-1]}$	7,394	76.181	382.548	2	3	8	25	1,595
Log $N_{[t-3,t-1]}$	7,394	2.412	1.533	0.693	1.099	2.079	3.219	7.375
Market cap. (bn)	7,394	14.029	49.434	0.010	0.352	1.673	8.934	168.285
Log market cap.	7,394	7.447	2.243	2.291	5.864	7.422	9.098	12.033
Tobin's Q	7,394	2.845	2.284	0.746	1.426	2.100	3.309	13.798
ROA	7,394	-0.035	0.298	-1.287	-0.080	0.057	0.122	0.401
Leverage	7,394	0.100	0.115	0.000	0.002	0.068	0.152	0.482
Cash/asset	7,394	0.213	0.189	0.010	0.081	0.156	0.279	0.878
R&D/sales	7,394	0.761	2.264	0.002	0.045	0.132	0.263	13.119

Table 1: Summary statistics. (*continued*)

	N	Mean	SD	P1	P25	Median	P75	P99
Panel B: Mover sample								
Dollar value per patent	51,022	22.984	63.581	0.015	0.538	5.221	16.936	273.290
Log dollar value	51,022	1.152	2.460	-4.198	-0.621	1.653	2.829	5.611
Citation per patent	68,488	4.604	17.452	0	0	1	4	57
Log citation	68,488	0.961	1.012	0.000	0.000	0.693	1.609	4.052
Patent count	118,675	1.259	2.406	0	0	1	2	10
Log patent count	118,675	0.584	0.610	0.000	0.000	0.693	1.099	2.398
$\Delta\alpha$ (S^{I})	118,675	-0.014	0.321	-0.916	-0.137	-0.012	0.114	0.881
$\Delta\alpha$ (S^{II})	118,675	-0.019	0.396	-1.194	-0.180	-0.011	0.145	1.073
$\overline{\theta}$ (S^{I})	118,675	0.004	0.072	-0.204	-0.017	0.002	0.021	0.249
$\overline{\theta}$ (S^{II})	118,675	0.005	0.091	-0.278	-0.019	0.004	0.028	0.307
Log $N(\theta)$	118,675	5.385	2.148	0.000	3.784	5.849	7.095	8.903
Log market cap.	118,675	9.955	1.712	5.000	8.918	10.044	11.156	13.270
Tobin's Q	118,675	2.010	1.328	0.820	1.122	1.629	2.478	7.085
ROA	118,675	0.087	0.126	-0.364	0.032	0.078	0.154	0.380
Leverage	118,675	0.131	0.117	0.000	0.039	0.102	0.193	0.490
Cash/asset	118,675	0.135	0.107	0.018	0.066	0.101	0.171	0.536
R&D/sales	118,675	0.160	0.664	0.011	0.053	0.073	0.151	1.248

Table 2: Failure tolerance and patent dollar value. This table reports OLS estimates of regression coefficients. The dependent variable is the log of average patent dollar value per patent or per inventor in a year. Patent dollar value is estimated by Kogan et al. (2017). $\alpha_{[t-3,t-1]}$ is the tolerance threshold, defined as the 95th percentile of the relative patent scope loss across patents whose sequel patent was filed between year $t-3$ and year $t-1$. Patent scope is proxied by S^{I} or S^{II}. All variables are defined in Table A1. *Year* is defined on calendar years. *Industry* is defined on two-digit SIC codes. Standard errors are clustered on the firm level. T-statistics are enclosed in parentheses. *, **, *** indicate significance level of 10%, 5% and 1% respectively.

Dep. var.:	Log dollar value per patent		Log dollar value per inventor	
Scope measure:	S^{I}	S^{II}	S^{I}	S^{II}
	(1)	(2)	(3)	(4)
$\alpha_{[t-3,t-1]}$	0.448***	0.519***	0.304***	0.346***
	(2.59)	(3.39)	(3.16)	(4.10)
$\overline{\theta}_{[t-3,t-1]}$	-0.584**	-0.616***	-0.534***	-0.371***
	(-2.11)	(-2.76)	(-3.16)	(-2.66)
Log $N_{[t-3,t-1]}$	-0.371***	-0.393***	-0.241***	-0.254***
	(-5.10)	(-5.35)	(-6.69)	(-6.98)
Log market cap$_{t-1}$	0.530***	0.533***	0.418***	0.420***
	(16.73)	(16.85)	(14.72)	(14.83)
Tobin's Q$_{t-1}$	0.152***	0.149***	0.075***	0.074***
	(6.61)	(6.53)	(4.46)	(4.38)
ROA$_{t-1}$	0.560***	0.558***	0.062	0.061
	(3.30)	(3.31)	(0.52)	(0.52)
Leverage$_{t-1}$	1.228***	1.237***	1.099***	1.103***
	(2.66)	(2.71)	(4.11)	(4.15)
Cash/asset$_{t-1}$	-0.043	-0.046	0.193	0.186
	(-0.21)	(-0.23)	(1.45)	(1.41)
R&D/sales$_{t-1}$	0.028**	0.031**	0.012	0.013
	(1.98)	(2.14)	(1.07)	(1.19)
Year × industry FE	Yes	Yes	Yes	Yes
Adj. R^2	0.502	0.505	0.472	0.474
N	5,476	5,476	5,463	5,463

Table 3: Failure tolerance and patent citation. This table reports OLS estimates of regression coefficients. The dependent variable is the log of one plus the average citation received by patents filed by a firm or inventor in a year. $\alpha_{[t-3,t-1]}$ is the measure of failure tolerance. See Section 2.4. Patent scope is proxied by S^{I} or S^{II}. All variables are defined in Table A1. $Year$ is defined on calendar years. $Industry$ is defined on two-digit SIC codes. Standard errors are clustered on the firm level. T-statistics are enclosed in parentheses. *, **, *** indicate significance level of 10%, 5% and 1% respectively.

Dep. var.:	Log citation per patent		Log citation per inventor	
Scope measure:	S^{I}	S^{II}	S^{I}	S^{II}
	(1)	(2)	(3)	(4)
$\alpha_{[t-3,t-1]}$	0.128**	0.140***	0.093*	0.075*
	(2.19)	(2.78)	(1.88)	(1.78)
$\overline{\theta}_{[t-3,t-1]}$	-0.068	-0.198**	-0.135	-0.178**
	(-0.59)	(-2.18)	(-1.39)	(-2.33)
Log $N_{[t-3,t-1]}$	0.008	0.003	0.030**	0.030**
	(0.53)	(0.19)	(2.14)	(2.08)
Log market cap$_{t-1}$	0.008	0.009	-0.015	-0.015
	(0.71)	(0.75)	(-1.33)	(-1.33)
Tobin's Q$_{t-1}$	0.053***	0.052***	0.047***	0.047***
	(6.38)	(6.33)	(6.01)	(6.01)
ROA$_{t-1}$	0.005	0.003	0.000	0.000
	(0.05)	(0.04)	(0.00)	(-0.00)
Leverage$_{t-1}$	-0.195	-0.190	-0.314***	-0.314***
	(-1.30)	(-1.27)	(-2.74)	(-2.76)
Cash/asset$_{t-1}$	0.229**	0.232**	0.275***	0.277***
	(2.21)	(2.25)	(2.96)	(2.99)
R&D/sales$_{t-1}$	0.012	0.012	0.006	0.006
	(1.61)	(1.64)	(0.82)	(0.83)
Year $\times$ industry FE	Yes	Yes	Yes	Yes
Adj. R^2	0.584	0.585	0.451	0.451
N	7,128	7,128	7,095	7,095

Table 4: Failure tolerance and patent count. This table reports OLS estimates of regression coefficients. The dependent variable is the log of one plus the number of certified patents filed by a firm or inventor in a year. $\alpha_{[t-3,t-1]}$ is the measure of failure tolerance. See Section 2.4. Patent scope is proxied by S^{I} or S^{II}.. All variables are defined in Table A1. $Year$ is defined on calendar years. $Industry$ is defined on two-digit SIC codes. Standard errors are clustered on the firm level. T-statistics are enclosed in parentheses. *, **, *** indicate significance level of 10%, 5% and 1% respectively.

Dep. var.:	Log patent count		Log patent count per inventor		Log inventor count	
Scope measure:	S^{I}	S^{II}	S^{I}	S^{II}	S^{I}	S^{II}
	(1)	(2)	(3)	(4)	(5)	(6)
$\alpha_{[t-3,t-1]}$	-0.295***	-0.300***	0.022	0.003	-0.305***	-0.253***
	(-4.20)	(-4.97)	(1.51)	(0.20)	(-3.74)	(-3.79)
$\overline{\theta}_{[t-3,t-1]}$	0.389***	0.336***	-0.052*	-0.022	0.464***	0.328**
	(2.69)	(3.02)	(-1.87)	(-0.96)	(2.63)	(2.52)
Log $N_{[t-3,t-1]}$	0.654***	0.662***	0.017***	0.018***	0.614***	0.615***
	(35.16)	(36.31)	(4.39)	(4.91)	(29.25)	(29.93)
Log market cap$_{t-1}$	0.283***	0.282***	-0.004	-0.004	0.307***	0.307***
	(17.59)	(17.65)	(-1.41)	(-1.47)	(16.36)	(16.40)
Tobin's Q$_{t-1}$	-0.024***	-0.024***	0.002	0.002	-0.029***	-0.028***
	(-2.76)	(-2.72)	(0.85)	(0.89)	(-2.91)	(-2.89)
ROA$_{t-1}$	-0.238***	-0.243***	-0.020	-0.020	-0.186**	-0.192**
	(-3.11)	(-3.18)	(-1.06)	(-1.02)	(-2.29)	(-2.36)
Leverage$_{t-1}$	0.290	0.276	-0.058	-0.060	0.479**	0.474**
	(1.48)	(1.41)	(-1.58)	(-1.63)	(2.14)	(2.11)
Cash/asset$_{t-1}$	0.253***	0.249**	0.054**	0.055**	0.102	0.098
	(2.60)	(2.56)	(2.28)	(2.30)	(0.91)	(0.87)
R&D/sales$_{t-1}$	0.009	0.008	0.000	0.000	0.013	0.012
	(1.17)	(1.07)	(0.12)	(0.10)	(1.43)	(1.38)
Year × industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.770	0.771	0.137	0.136	0.765	0.764
N	7,394	7,394	7,330	7,330	7,394	7,394

Table 5: Failure tolerance and total innovation output. This table reports OLS estimates of regression coefficients. The dependent variable is the log of one plus the product of the number of certified patents filed by a firm in a year and the corresponding average patent dollar value or the corresponding citation. $\alpha_{[t-3,t-1]}$ is the measure of failure tolerance. See Section 2.4. Patent scope is proxied by S^{I} or S^{II}. All variables are defined in Table A1. *Year* is defined on calendar years. *Industry* is defined on two-digit SIC codes. Standard errors are clustered on the firm level. T-statistics are enclosed in parentheses. *, **, *** indicate significance level of 10%, 5% and 1% respectively.

Dep. var.:	Log total dollar value		Log total citation	
Scope measure:	S^{I}	S^{II}	S^{I}	S^{II}
	(1)	(2)	(3)	(4)
$\alpha_{[t-3,t-1]}$	0.151	0.173	-0.131	-0.100
	(0.93)	(1.19)	(-1.27)	(-1.09)
$\overline{\theta}_{[t-3,t-1]}$	-0.288	-0.191	0.253	0.028
	(-1.04)	(-0.84)	(1.20)	(0.17)
Log $N_{[t-3,t-1]}$	0.209***	0.202***	0.608***	0.608***
	(3.40)	(3.24)	(23.43)	(23.31)
Log market cap$_{t-1}$	0.881***	0.882***	0.292***	0.292***
	(30.25)	(30.24)	(12.78)	(12.77)
Tobin's Q$_{t-1}$	0.081***	0.080***	0.037**	0.037**
	(3.37)	(3.34)	(2.55)	(2.55)
ROA$_{t-1}$	0.058	0.058	-0.259*	-0.264*
	(0.33)	(0.33)	(-1.71)	(-1.75)
Leverage$_{t-1}$	1.634***	1.637***	-0.078	-0.081
	(3.56)	(3.57)	(-0.25)	(-0.26)
Cash/asset$_{t-1}$	0.332	0.327	0.671***	0.670***
	(1.53)	(1.52)	(3.77)	(3.76)
R&D/sales$_{t-1}$	0.026*	0.027*	0.027*	0.027*
	(1.69)	(1.72)	(1.94)	(1.93)
Year × industry FE	Yes	Yes	Yes	Yes
Adj. R^2	0.705	0.705	0.737	0.737
N	5,476	5,476	7,128	7,128

Table 6: Quality-quantity trade-off: Mechanism. This table reports OLS estimates of regression coefficients. Specification length is the page count of a patent's specification text, averaged across all patents filed by a firm in a year. *Log specificaiton length* is the log of specification length. Abandonment rate is computed as the number of applications abandoned over the number of all applications filed by a firm in a year. $\alpha_{[t-3,t-1]}$ is the measure of failure tolerance. See Section 2.4. All variables are defined in Table A1. *Year* is defined on calendar years. *Industry* is defined on two-digit SIC codes. Standard errors are clustered on the firm level. T-statistics are enclosed in parentheses. *, **, *** indicate significance level of 10%, 5% and 1% respectively.

Dep. var.:	Log specification length		Abandonment rate		Log R&D expenses per inventor	
Scope measure:	S^{I}	S^{II}	S^{I}	S^{II}	S^{I}	S^{II}
	(1)	(2)	(3)	(4)	(5)	(6)
$\alpha_{[t-3,t-1]}$	0.144**	0.129**	0.029	0.041**	0.211**	0.131
	(2.00)	(2.14)	(1.51)	(2.50)	(1.99)	(1.40)
$\overline{\theta}_{[t-3,t-1]}$	-0.134	-0.038	-0.086**	-0.090***	-0.159	-0.097
	(-1.01)	(-0.35)	(-2.47)	(-2.86)	(-0.81)	(-0.59)
Log $N_{[t-3,t-1]}$	0.083***	0.081***	-0.009**	-0.011***	-0.437***	-0.433***
	(5.15)	(4.90)	(-2.44)	(-2.85)	(-16.83)	(-16.17)
Log market cap$_{t-1}$	0.028**	0.028**	0.001	0.001	0.424***	0.424***
	(2.32)	(2.36)	(0.19)	(0.24)	(17.36)	(17.31)
Tobin's Q$_{t-1}$	0.017*	0.017*	-0.004*	-0.004*	-0.124***	-0.124***
	(1.74)	(1.71)	(-1.76)	(-1.77)	(-9.24)	(-9.24)
ROA$_{t-1}$	-0.129	-0.127	-0.024	-0.024	-0.477***	-0.474***
	(-1.49)	(-1.47)	(-1.16)	(-1.16)	(-4.20)	(-4.18)
Leverage$_{t-1}$	-0.104	-0.100	0.044	0.046	0.949***	0.944***
	(-0.69)	(-0.67)	(0.99)	(1.05)	(3.21)	(3.19)
Cash/asset$_{t-1}$	0.007	0.009	0.022	0.022	0.137	0.143
	(0.05)	(0.07)	(0.80)	(0.79)	(0.94)	(0.98)
R&D/sales$_{t-1}$	0.018	0.018	-0.001	-0.001	0.043***	0.044***
	(1.50)	(1.53)	(-0.31)	(-0.28)	(3.62)	(3.67)
Year × industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.166	0.166	0.210	0.211	0.486	0.485
N	7,098	7,098	4,578	4,578	6,447	6,447

Table 7: Mover difference-in-difference. This table reports the estimates of Equation (12). $\Delta\alpha$ is the difference in failure tolerance a mover is exposed to. *Post* is an indicator equal to one from the year a mover is associated with the destination firms onward. All other variables are defined in Table A1. *Year* is defined on calendar years. *Industry* is defined on two-digit SIC codes. Standard errors are clustered on the firm level. T-statistics are enclosed in parentheses. *, **, *** indicate significance level of 10%, 5% and 1% respectively.

Dep. var.:	Log dollar value		Log citation		Log patent count	
Scope measure:	S^{I}	S^{II}	S^{I}	S^{II}	S^{I}	S^{II}
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\alpha \times$ Post	0.672***	0.621***	0.041	0.073*	-0.022	-0.020
	(8.75)	(10.33)	(0.90)	(1.94)	(-1.21)	(-1.26)
$\overline{\theta}_{[t-3,t-1]}$	-0.303***	-0.107	-0.201**	-0.161**	-0.048	-0.013
	(-3.08)	(-1.34)	(-2.51)	(-2.50)	(-1.57)	(-0.55)
Log $N_{[t-3,t-1]}$	-0.331***	-0.342***	-0.041***	-0.043***	0.001	0.001
	(-28.30)	(-29.07)	(-7.11)	(-7.27)	(0.19)	(0.36)
Log market cap_{t-1}	0.441***	0.444***	0.018***	0.018**	0.005	0.005
	(34.91)	(35.21)	(2.59)	(2.49)	(1.53)	(1.42)
Tobin's Q_{t-1}	0.140***	0.135***	0.024***	0.025***	-0.003	-0.003
	(14.46)	(14.12)	(4.91)	(5.03)	(-1.15)	(-1.02)
ROA_{t-1}	1.074***	1.092***	-0.161***	-0.161***	-0.005	-0.004
	(10.85)	(11.08)	(-2.63)	(-2.63)	(-0.18)	(-0.15)
Leverage_{t-1}	1.233***	1.234***	-0.057	-0.044	-0.005	-0.003
	(8.28)	(8.29)	(-0.77)	(-0.60)	(-0.14)	(-0.08)
Cash/asset_{t-1}	-0.010	-0.003	0.005	0.005	0.122***	0.121***
	(-0.12)	(-0.04)	(0.08)	(0.08)	(4.09)	(4.06)
$\text{R\&D/sales}_{t-1}$	0.041***	0.043***	-0.003	-0.003	0.001	0.001
	(2.65)	(2.73)	(-0.31)	(-0.32)	(0.27)	(0.22)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Event Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.908	0.909	0.428	0.428	0.267	0.267
N	47,490	47,490	65,350	65,350	118,675	118,675

Table 8: Mover triple difference-in-difference. This table reports the estimates of Equation (13). $\Delta\alpha$ is the difference in failure tolerance a mover is exposed to. *Post* is an indicator equal to one from the year a mover is associated with the destination firms onward. *Mover* is an indicator equal to one for movers. All other variables are defined in Table A1. *Year* is defined on calendar years. *Industry* is defined on two-digit SIC codes. Standard errors are clustered on the firm level. T-statistics are enclosed in parentheses. *, **, *** indicate significance level of 10%, 5% and 1% respectively.

Dep. var.:	Log dollar value		Log citation		Log patent count	
Scope measure:	S^{I}	S^{II}	S^{I}	S^{II}	S^{I}	S^{II}
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\alpha$ × Mover × Post	0.538***	0.504***	0.056	0.109**	-0.023	-0.007
	(6.49)	(7.80)	(1.02)	(2.42)	(-0.98)	(-0.38)
$\Delta\alpha$ × Post	0.120***	0.055**	-0.009	-0.023	-0.009	-0.013
	(4.25)	(2.39)	(-0.29)	(-0.91)	(-0.63)	(-1.14)
Post×Mover	0.281***	0.287***	0.175***	0.177***	0.050***	0.051***
	(10.80)	(11.07)	(11.92)	(11.76)	(6.56)	(6.63)
$\overline{\theta}_{[t-3,t-1]}$	-0.238***	-0.022	-0.077	-0.063	-0.021	-0.012
	(-3.34)	(-0.37)	(-1.12)	(-1.13)	(-0.76)	(-0.54)
Log $N_{[t-3,t-1]}$	-0.277***	-0.283***	-0.035***	-0.037***	0.001	0.001
	(-25.95)	(-26.41)	(-6.05)	(-6.11)	(0.31)	(0.34)
Log market cap$_{t-1}$	0.394***	0.394***	0.011	0.010	0.006*	0.006*
	(34.27)	(34.29)	(1.58)	(1.44)	(1.91)	(1.83)
Tobin's Q$_{t-1}$	0.103***	0.101***	0.022***	0.022***	0.000	0.000
	(13.08)	(12.88)	(4.85)	(4.74)	(-0.11)	(-0.03)
ROA$_{t-1}$	0.811***	0.823***	-0.074	-0.073	-0.006	-0.006
	(10.28)	(10.43)	(-1.29)	(-1.24)	(-0.23)	(-0.23)
Leverage$_{t-1}$	1.182***	1.173***	0.052	0.057	-0.063*	-0.061*
	(9.28)	(9.17)	(0.73)	(0.77)	(-1.73)	(-1.68)
Cash/asset$_{t-1}$	0.063	0.062	-0.051	-0.050	0.065**	0.065**
	(0.93)	(0.92)	(-0.96)	(-0.92)	(2.32)	(2.31)
R&D/sales$_{t-1}$	0.023**	0.024**	0.000	0.000	0.003	0.003
	(1.96)	(1.99)	(-0.00)	(-0.02)	(0.87)	(0.85)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Event Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.919	0.919	0.442	0.392	0.288	0.288
N	74,174	74,174	86,701	86,701	152,578	152,578

Table 9: Heterogeneous Effect. This table reports heterogeneous effects across movers. $\Delta\alpha^+$ equals $\Delta\alpha$ if the latter is positive, and zero otherwise. $\Delta\alpha^-$ equals $\Delta\alpha$ if the latter is negative, and zero otherwise. $\Delta\alpha$ is the difference in failure tolerance a mover is exposed to. *Post* is an indicator equal to one from the year a mover is associated with the destination firms onward. *Mover* is an indicator equal to one for movers. All other variables are defined in Table A1. *Year* is defined on calendar years. *Industry* is defined on two-digit SIC codes. Standard errors are clustered on the firm level. T-statistics are enclosed in parentheses. *, **, *** indicate significance level of 10%, 5% and 1% respectively.

Dep. var.:	Log dollar value		Log citation		Log patent count	
Scope measure:	S^{I}	S^{II}	S^{I}	S^{II}	S^{I}	S^{II}
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\alpha^+$ × Mover × Post	0.166	0.091	-0.059	0.053	0.022	0.082**
	(1.13)	(0.72)	(-0.56)	(0.60)	(0.53)	(2.34)
$\Delta\alpha^-$ × Mover × Post	0.800***	0.774***	0.144*	0.154**	-0.058*	-0.062**
	(6.52)	(8.31)	(1.89)	(2.50)	(-1.69)	(-2.28)
$\Delta\alpha^+$ × Post	0.298***	0.165***	-0.037	-0.088	-0.012	-0.071***
	(4.80)	(3.03)	(-0.58)	(-1.59)	(-0.40)	(-2.89)
$\Delta\alpha^-$ × Post	0.019	0.000	0.008	0.010	-0.007	0.019
	(0.48)	(-0.01)	(0.18)	(0.29)	(-0.34)	(1.23)
Post×Mover	0.343***	0.370***	0.194***	0.190***	0.042***	0.033***
	(9.92)	(10.34)	(10.44)	(9.59)	(4.15)	(3.17)
$\overline{\theta}_{[t-3,t-1]}$	-0.241***	-0.030	-0.077	-0.064	-0.021	-0.010
	(-3.39)	(-0.50)	(-1.12)	(-1.14)	(-0.76)	(-0.46)
Log $N_{[t-3,t-1]}$	-0.276***	-0.283***	-0.034***	-0.037***	0.001	0.001
	(-25.93)	(-26.34)	(-6.02)	(-6.04)	(0.30)	(0.32)
Log market cap$_{t-1}$	0.393***	0.393***	0.010	0.010	0.007*	0.006*
	(34.10)	(34.14)	(1.52)	(1.41)	(1.93)	(1.85)
Tobin's Q$_{t-1}$	0.103***	0.102***	0.022***	0.023***	0.000	0.000
	(13.07)	(12.96)	(4.89)	(4.82)	(-0.14)	(-0.03)
ROA$_{t-1}$	0.814***	0.826***	-0.073	-0.074	-0.006	-0.006
	(10.32)	(10.49)	(-1.28)	(-1.25)	(-0.22)	(-0.23)
Leverage$_{t-1}$	1.173***	1.163***	0.044	0.051	-0.060*	-0.059
	(9.21)	(9.10)	(0.61)	(0.69)	(-1.67)	(-1.63)
Cash/asset$_{t-1}$	0.065	0.063	-0.049	-0.050	0.064**	0.065**
	(0.95)	(0.93)	(-0.92)	(-0.92)	(2.29)	(2.32)
R&D/sales$_{t-1}$	0.024**	0.024**	0.000	0.000	0.003	0.003
	(2.04)	(2.02)	(-0.00)	(-0.02)	(0.87)	(0.84)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Event Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.919	0.919	0.442	0.392	0.288	0.288
N	74,174	74,174	86,701	86,701	152,578	152,578

Table 10: IV Approach. This table reports the IV estimates of Equation (13). $\Delta\alpha^{+}$ equals $\Delta\alpha$ if the latter is positive, and zero otherwise. $\Delta\alpha^{-}$ equals $\Delta\alpha$ if the latter is negative, and zero otherwise. $\Delta\alpha$ is the difference in failure tolerance a mover is exposed to. *Post* is an indicator equal to one from the year a mover is associated with the destination firms onward. *Mover* is an indicator equal to one for movers. All other variables are defined in Table A1. *Year* is defined on calendar years. *Industry* is defined on two-digit SIC codes. Standard errors are clustered on the firm level. T-statistics are enclosed in parentheses. *, **, *** indicate significance level of 10%, 5% and 1% respectively.

Dep. var.:	Log dollar value		Log citation		Log patent count	
Scope measure:	S^{I}	S^{II}	S^{I}	S^{II}	S^{I}	S^{II}
	(1)	(2)	(3)	(4)	(5)	(6)
$(\Delta\alpha \times \widehat{\text{Mover}} \times \text{Post})$	0.329**	0.283**	-0.107	-0.036	0.014	0.026
	(2.37)	(2.40)	(-1.17)	(-0.48)	(0.38)	(0.78)
$(\Delta\alpha \widehat{\times \text{Post}})$	0.176***	0.092**	-0.075	-0.111**	-0.030	-0.052***
	(3.37)	(2.04)	(-1.31)	(-2.49)	(-1.25)	(-2.63)
Post × Mover	0.273***	0.277***	0.173***	0.177***	0.052***	0.054***
	(10.40)	(10.19)	(11.56)	(11.91)	(6.75)	(6.88)
$\overline{\theta}_{[t-3,t-1]}$	-0.205***	0.014	-0.017	-0.008	-0.024	-0.008
	(-2.72)	(0.21)	(-0.24)	(-0.13)	(-0.84)	(-0.34)
Log $N_{[t-3,t-1]}$	-0.271***	-0.274***	-0.027***	-0.025***	0.000	0.001
	(-24.10)	(-22.48)	(-4.45)	(-3.90)	(0.10)	(0.43)
Log market cap$_{t-1}$	0.394***	0.395***	0.012*	0.012*	0.006*	0.006*
	(34.38)	(33.11)	(1.80)	(1.68)	(1.87)	(1.81)
Tobin's Q$_{t-1}$	0.102***	0.101***	0.021***	0.022***	0.000	0.000
	(13.03)	(12.42)	(4.67)	(4.85)	(-0.09)	(-0.01)
ROA$_{t-1}$	0.813***	0.823***	-0.068	-0.066	-0.007	-0.006
	(10.27)	(10.02)	(-1.18)	(-1.16)	(-0.26)	(-0.22)
Leverage$_{t-1}$	1.167***	1.157***	0.038	0.043	-0.061*	-0.060
	(9.07)	(8.64)	(0.52)	(0.61)	(-1.68)	(-1.63)
Cash/asset$_{t-1}$	0.058	0.056	-0.059	-0.059	0.066**	0.065**
	(0.85)	(0.80)	(-1.11)	(-1.10)	(2.34)	(2.29)
R&D/sales$_{t-1}$	0.023**	0.024*	0.000	0.000	0.003	0.003
	(1.97)	(1.93)	(0.02)	(-0.00)	(0.88)	(0.84)
Inventor FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Event Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F-stat	1003.179	1056.948	1211.703	1534.500	1779.586	2003.077
Kleibergen-Paap rk LM stat	613.280	605.767	736.636	763.610	966.583	1025.880
Kleibergen-Paap rk LM p-value	0.000	0.000	0.000	0.000	0.000	0.000
Adj. R^2	0.172	0.108	-0.005	-0.005	-0.006	-0.044
N	74,165	74,165	86,691	86,691	152,564	152,564