Patent Signaling

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Abstract

We propose and test a novel benefit to inventors of disclosing their intellectual property (IP): deterring competitors. We develop a model of strategic disclosure and derive conditions under which inventors disclose their IP early. We test the model's predictions by analyzing inventors' disclosure choices after the American Inventors' Protection Act of 1999, which allowed inventors to accelerate the disclosure of their inventions through patent applications. The empirical results are consistent with the model's predictions and show that (i) important inventions are disclosed sooner; and (ii) smaller firms, under-capitalized firms, and IP-rich firms disclose their inventions sooner; and (iii) inventors disclose sooner in fields where competitors learn from the disclosures more slowly. We use an event-study design to estimate the causal effects of invention disclosure, and show that at least 50 percent of the stock-market returns previously attributed to patent grants are due to the informational benefits of IP disclosures.

Keywords: Patent Publication, Invention Disclosure, Signaling, Innovation, Competition
JEL Codes: E02, D23, G24, L26, O34

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I Introduction

At least since Arrow (1962), disclosing intellectual property is considered costly for their owners as it can enable imitation by competitors, and expropriation by potential partners and buyers (*e.g.,* Horstmann, MacDonald and Slivinski, 1985; Modigliani et al., 1999; Anton and Yao, 2004). Yet, each year, a vast majority of inventors disclose their inventions sooner than they have to according to U.S. patent law. In particular, according to U.S.laws, after November 29, 2000, inventors can choose to publish their patent applications either at (A) 18 months from application date; or (B) at patent grant date, which occurs at about 37 months from application date for the average patent, by foregoing foreign patent protection for their invention. Data on patentees' disclosure choices shows that 91.3% of all U.S. patent applications filed after AIPA's enactment chose to early-disclose at 18 months. Figure 1 shows that even among applications that forego foreign patent protection (about 50 percent of all U.S. patent applications), 87.3% still chose to publish early.

Why do inventors disclose their IP, despite the imitation and expropriation risks of doing so? In this paper, we answer this question by developing a model of innovation under competition. In the model, inventors produce new ideas of varying quality. The ideas' quality (stemming from factors such as its technological superiority, lower cost, or the innovators' superior ability to commercialize the idea) is privately known by the inventor. Rivals attempt to infer the invention's quality before deciding whether to themselves imitate or improve upon the invention. IP disclosure (through patent publication in our context) reveals the invention's true quality to rivals. We derive that, in equilibrium, the best inventors signal their quality by disclosing their IP early as they can still profitably develop their ideas if rivals imitate, or attempt to improve upon, their ideas. By disclosing sooner, a low quality inventor stands to profit less in the event of entry because earlier disclosure allows the higher quality challengers to produce more.

We show that the probability of entry declines by the same amount as it does for a high quality inventor, but the resulting gain in revenues is smaller because the low qual-

ity inventors are able to produce less. Thus, the expected returns to low-quality inventors of mimicking the disclosure strategy of high type would be negative. Using the case of an isoelastic demand function, we then derive testable implications relating the inventors' disclosure strategy to industry-wide rate of learning and competitors' beliefs about the inventors' quality.

We empirically test the model's predictions by leveraging the choices provided by the American Inventors' Protection Act of 1999 (AIPA) which allowed inventors to choose the timing of their patent disclosures. As explained above, AIPA provided U.S. patent applicants the option of publishing their inventions at 18 months from patent application date, rather than at patent grant, which occurred roughly 37 months on average after application at the time of AIPA's enactment. Hence, for the average U.S. patent, AIPA cut down the period of secrecy by about half.

We examine both the choice of whether a patent is disclosed at 18 months or at grant (extensive margin), and the extent of delay if published upon grant, rather than at 18 months (intensive margin). This is because, even if a patentee forgoes publication at 18 months, she can affect disclosure timing by taking actions that affect the timing of patent grant. For example, the patentee can delay disclosure by delaying her responses to the patent office during the patent prosecution process, or can accelerate disclosure by accepting the patent examiners' recommendation to narrow the claims in the patent application. Thus, by publishing at 18-months, the inventor does not have to compromise on claims, and only experiences losses associated with disclosing her know-how early. On the other hand, publishing early after 18 months may require the inventor to sacrifice on claims as disclosure is tied to grant. Moreover, an additional signaling cost of delaying disclosure till grant date is that competitors learn the application date and infer how long the firm waited before disclosure.

We find, consistent with our model's predictions, that high-quality inventions are disclosed sooner. Our measures of invention quality are the forward citations accrued by the underlying patent 5-years and 10-years after patent publication, and the number of claims

published in the patent. These measures have been extensively used in the literature as measures of quality (*e.g.,* Jaffe, Trajtenberg and Henderson, 1993). Important to our context, forward citations and claims are visible to the public only after the inventors' decision to publish their patent application. Hence, to the backward looking econometrician, the measures reveal the idea's quality – something that was likely private information at the time of the patent's publication.

Next, we estimate the relationship between invention disclosure delays and learning by rivals on the one hand and invention quality on the other, using a Nonlinear Least Squares model to fit the theoretically derived relationship. Model estimates suggest the following: (i) patent disclosures in fields like drugs and medicine facilitate gradual learning over time while, disclosures in fields like computers and communication facilitate instantaneous learning upon disclosure (what we call the 'Eureka moment'); (ii) process innovation disclosures facilitate learning over time, while product innovation disclosures are associated with 'Eureka' moments. We also find that observable characteristics of inventors that can be used by competitors to guess the quality of their inventions, including firm size, R&D intensity, capital intensity and technology fields affect disclosure timing. In particular, for a given quality, inventors are more likely to delay patent disclosure for above-median levels of capital intensity and firm size as they have a greater capacity, publicly known, to capture value with superior resources and down-stream assets.

Hidden inventor type is hard to empirically verify, since, by definition, it is privately known by the inventor alone. We deploy an event-study design which estimates the causal effects of patent disclosure on the inventing firm's stock market valuation. Under the assumption that the stock market responds to new, economically significant, information, we show that stock markets respond to patent disclosures. In particular, we find that patent applications that are disclosed late after AIPA (that is, at patent grant date, rather than 18-months after application) are associated with lower stock market returns, while firms that disclose their patents sooner – at 18-months from application date – experience a larger jump

in stock market returns. Stock market response at patent disclosure provides evidence that information about the underlying information was private. The larger positive response for earlier disclosures is consistent with higher quality inventions being disclosed sooner.

Existing research treats invention disclosure as costly to inventors (e.g., Arrow, 1972; Horstmann, MacDonald and Slivinski, 1985; Bhattacharya, Glazer and Sappington, 1992; Anton and Yao, 1994, 2004; Bhattacharya and Guriev, 2006). This is in contrast to the insight of canonical signaling models that high-quality agents can be better off by revealing information that credibly signals their quality (a la Spence, 1973). We advance theory on innovation disclosures by modeling inventors' strategy in a competitive environment where challengers learn from, and invent around, the originator's ideas. In doing so, we address the puzzle as to why so many inventors, and particularly those with high-quality inventions, choose to reveal their ideas sooner, despite the risk of imitation. The insights provided by our analyses are general enough that they can be applied to other settings that involve the production of new ideas, including, for example, the scientific publication process. Our paper also complements recent empirical efforts that document industry-wide benefits of invention disclosure (e.g., Johnson and Popp, 2003; Furman, Nagler and Watzinger, 2021; Lück et al., 2020; Gross et al., 2019; Ganglmair and Reimers, 2019; Hegde, Herkenhoff and Zhu, 2023) by providing evidence for the private benefits of disclosure to inventors.

Of course, signaling to competitors, as we have proposed here, is just one reason to disclose inventions early. Another reason may be to attract resources needed to develop the idea, for example, from potential development partners or venture capitalists. However, this alternative does not necessarily suggest that those in need of external resources preferentially disclose only their most valuable ideas (as our signaling explanation does) and our regression analysis controls for proxies of external resource dependence through variables like firms' capital intensity and size.

Our model does not include a preemption motive for patenting – this force is modeled by Hopenhayn and Squintani (2016) show that competing firms may patent their innovations

too early for fear of being preempted in a patent race and they cite supporting evidence. And Hopenhayn and Squintani (2011) find that when R&D output is secret, firms take longer to patent inventions so that secrecy slows disclosure down. In our model it is the secrecy – the privacy of information about the patent – that validates early disclosure as a signal of quality.

The rest of the paper is organized as follows. Section II develops a theoretical model of invention disclosure under competition. Section III describes the sample and descriptives. Section IV empirically tests our main theoretical proposition and estimates model parameters. Finally, section V offers concluding thoughts.

II Model

Consider a two-stage game between an inventor and a potential imitator, both competing for the same market. The inventor, referred to as the "incumbent," has a type α, representing the output generated by his idea, which we refer to as the idea's "quality." The incumbent's only decision is how early to disclose the idea as described in the patent application.

The imitator is a potential entrant, or "challenger," who has a type c, representing his cost of entering the market should he decide to do so. The parameter c is privately known by the challenger, while the incumbent only knows that it is drawn from the cumulative distribution function $F(c)$. This is similar to Milgrom and Roberts (1982). Likewise, the parameter α is privately known by the incumbent. The challenger only knows that it is drawn from the cumulative distribution function $G(\alpha)$.

We denote by δ the measure of how well the challenger can copy, develop, and possibly extend the incumbent's idea if given x periods to do so. It is measured in units of output that the challenger can produce, and δ is increasing in x, which is the amount of time that the challenger has to work on the idea. It is the waiting time between patent publication and the start of production.

The patent application is filed at date 0, and $t \geq 0$ is the disclosure, or "publication date," measured as the time elapsed since the application. Production starts at date T, at which point the challenger decides whether or not to enter. If he does enter, his output will be $\delta(x)$, where

$$x = T - t. \tag{1}$$

The incumbent discloses at date t. However, it is more convenient to use $x = T - t$ as the decision variable. Let $\tau : A \to [0, T]$ be the policy function, i.e., $x = \tau(\alpha)$ is optimal for an incumbent of type α. If a higher α means that disclosure happens earlier, then $\tau(\alpha)$ is an increasing function.

The copying function δ is increasing in x. Therefore, if α were common knowledge, it would be optimal to set $t = T$, making $x = 0$ and δ as small as possible. Since δ does not depend on α, all patents are equally helpful to the challenger. This is a simplifying assumption that helps us solve the model by hand.

Demand and Production. Industry output, Q, is homogeneous and given by

$$Q = \begin{cases} \alpha & \text{if the challenger stays out,} \\ \alpha + \delta(x) & \text{if he comes in.} \end{cases}$$

The demand curve is specified as,

$$p = \begin{cases} D(\alpha) & \text{if the challenger stays out,} \\ D(\alpha + \delta(x)) & \text{if he comes in.} \end{cases}$$

Production costs are zero and the incumbent's payoff consists of sales revenues alone:

$$\text{Incumbent's payoff} = \begin{cases} \alpha D(\alpha) & \text{if the challenger does not come in,} \\ \alpha D(\alpha + \delta(x)) & \text{if he does.} \end{cases}$$

Challenger's Entry Decision. We denote by $\hat{\alpha}$ the challenger's belief about α, which is a real number in the separating equilibrium. The challenger's payoff is given by:

$$\text{Challenger's payoff} = \begin{cases} \delta(x) D[\hat{\alpha} + \delta(x)] - c & \text{if he enters,} \\ 0 & \text{if he stays out.} \end{cases} . \tag{2}$$

The challenger enters if the first line of (2) is positive. The probability of entry, ω, then is given by:

$$\omega(x, \hat{\alpha}) = F(\delta(x) D[\hat{\alpha} + \delta(x)]) . \tag{3}$$

Incumbent's policy. Given $(\alpha, \hat{\alpha}, x)$, the incumbent's payoff is

$$U(\alpha, \hat{\alpha}, x) = \omega(x, \hat{\alpha}) \alpha D(\alpha + \delta(x)) + (1 - \omega(x, \hat{\alpha})) \alpha D(\alpha) . \tag{4}$$

However, in a separating equilibrium, beliefs $\hat{\alpha}$ depend on the observed decision x. Thus, if the optimal decision $\tau(\alpha)$ is unique, strictly monotone, and hence invertible, then $\hat{\alpha} = \tau^{-1}(x)$. Equilibrium then requires that

$$\tau(\alpha) = \arg\max_x U\left(\alpha, \tau^{-1}(x), x\right) \quad \forall \alpha, \tag{5}$$

and the associated first-order condition is

$$U_2(\alpha, \hat{\alpha}, x) \frac{d\hat{\alpha}}{dx} + U_3(\alpha, \hat{\alpha}, x) = 0 \tag{6}$$

II.A Isoelastic demand example

We now describe the example that we shall solve and estimate. Suppose that (1) incumbent types fall within the interval $\alpha \in [\alpha_{\min}, \alpha_{\max}]$; (2) the product demand is isoelastic, i.e. $D(Q) = Q^{-\beta}$; (3) the entry cost is uniformly distributed, such that $F(c) = c$ for $c \in [0, 1]$; and (4) the challenger learns linearly as a function of time x before production starts, expressed

as $\delta(x) = a + bx$, where $a \geq 0$ measures instant learning or "Eureka" learning, and $b \geq 0$ measures incremental learning.

The Appendix proves the following result:

Proposition 1. *If $\beta = 1$ and*

$$\frac{\alpha_{\max}}{\alpha_{\min}} < \left(1 + \frac{b}{a}T\right)^2, \tag{7}$$

then the incumbent's posting decision has the solution

$$\alpha(x) = \alpha_{\min}\left(1 + \frac{b}{a}x\right)^2 \tag{8}$$

for $x \in \left[0, \frac{a}{b}\left(\sqrt{\frac{\alpha_{\max}}{\alpha_{\min}}} - 1\right)\right]$. *Inverting (8) yields*

$$x = \frac{a}{b}\sqrt{\frac{\alpha}{\alpha_{\min}} - 1} \tag{9}$$

If all we have data on are measures of patent quality, α, and information about the disclosure lead time x, then we cannot separately identify (a, b) but only the ratio

$$\frac{b}{a} = \frac{\text{Incremental learning}}{\text{Eureka learning}}.$$

Remark. Consider a case where $\beta = 1$. The entrant's revenue upon entry is given by

$$R_E = (a + bx) \cdot \frac{1}{\alpha + a + bx}$$

for a given quality of patent, α. Plugging in the solution from equation (8), we can show that

$$R_E = \frac{1}{1 + \frac{\alpha_{\min}}{a^2}(a + bx)}. \tag{10}$$

Therefore, since a higher-quality patent also implies a larger x, equation (10) indicates lower profit for the entrant and thus stronger deterrence.

II.B Public information and the challenger's beliefs

The challenger's prior beliefs before observing x are described by the single parameter $\alpha_{\min}$, which represents the smallest possible incumbent output. A large firm would be expected to produce more with any fixed quality of patent, and that would be reflected in a larger $\alpha_{\min}$. But that does not necessarily mean that the parameters a and b are larger—as Arora et al. (2023) argue, "average invention value increases with firm size even though average invention quality declines because larger firms have a greater capacity to capture value from their inventions." If true, this statement suggests that when comparing large and small firms' inventions, α relates negatively or not at all to the parameters a and b.

We find in Table 3 that publicly owned firms tend to have a significantly larger $\alpha_{\min}$ with not much difference among firms in the other classes, and in Table 4 we find that patents of new products have a higher $\alpha_{\min}$ than those for new processes.

II.C Stock-price response to the publication gap t

The publication gap is the waiting time, t, between application date and publication. Publishing at t gives the challenger a lead time of $x = T - t$.

A type-α incumbent has an equilibrium expected utility $U(\alpha, \alpha, \tau(\alpha))$. We assume that the shareholders of a publicly traded firm do not know α any better than the challenger does. Therefore if the market knows only that the firm has applied for a patent, the value of the firm should be its expected value

$$V = \frac{1}{\alpha_{\max} - \alpha_{\min}} \int_{\alpha_{\min}}^{\alpha_{\max}} U(\alpha, \alpha, \tau(\alpha))\, d\alpha. \tag{11}$$

Then after the firm has chosen its publication gap t, i.e., its lead-time $x = T - t$, and its choice becomes public knowledge, the stock price should change by the amount

$$\Delta(x) = U\left(\tau^{-1}(x), \tau^{-1}(x), x\right) - V, \tag{12}$$

where $\tau^{-1}(x) = \alpha(x)$ in Eq. (8) so that $\alpha'(x) = \frac{2b\alpha_{\min}}{a}\left(1 + \frac{b}{a}x\right) > 0$

Because x solves the first-order condition (6), the term U_2 and U_3 drop out and the stock-price response to a unit rise in t (i.e., its response to a unit fall in x) should be

$$-\Delta'(x) = -U_1(\alpha(x), \alpha(x), x)\,\alpha'(x) < 0. \tag{13}$$

Therefore the stock prices also will identify only the ratio b/a.

Thus, three points are relevant for what the data will show. Firstly, disclosing later leads to a smaller change in V, possibly a decline. Or if we plot x on the horizontal axis, the gain should be larger.

Secondly, the jump of size Δ should occur at t if the market learns about the patent *and its application date* at the time the disclosure occurs.

Thirdly, if instead the market learns about the patent application when it occurs, then the value of the firm should immediately jump up by the amount V. I.e., the upward jump should occur at the application date. After that, value should fall continuously until the disclosure date and it then should jump up and stabilize. To explain better: suppose that a is uniformly distributed on $[\alpha_{\min}, \alpha_{\max}]$. Upon application (if that's publicly known), the price jumps up to V as given in equation (11), which we can write as

$$V = E(U \mid \alpha \in [\alpha_{\min}, \alpha_{\max}])$$

Then as time passes and there is no disclosure yet, and x shrinks, the price shrinks to

$$V_x = E\left(U \mid \alpha \in \left[\alpha_{\min}, \tau^{-1}(x)\right]\right) \tag{14}$$

and as x shrinks, $\tau^{-1}(x)$ shrinks and V falls. And then at the actual disclosure date, there

is an upward jump of size

$$\Delta_x = U_1\left(\tau^{-1}(x), \tau^{-1}(x), x\right) - V_x$$

where V_x is the prior belief after t periods of nondisclosure. I.e., disclosure tells the market that α is at the upper bound of the posterior range that the market had an instant before the disclosure. But the later the disclosure (i.e., the smaller is x), the smaller the upward jump is and when x reaches $x_{\max}$,disclosure has no effect.

In words, at application (if the market sees there was an application) V jumps by the amount equal to the value of an **average** additional patent. Then if disclosure is early, the market infers the patent was above average and the price jumps up further at disclosure. If the disclosure is later, the market keeps revising downward its belief over the patent's quality, and V gradually declines, equal to the conditional expectation of the patent's value at each date. And finally at disclosure there is an upward jump because the market then infers that the quality is at the upper bound of its posterior.

II.D Policy issues

External effect. The incumbent bestows a positive external effect: Industry output is $\alpha + \delta(x)$ in the event that the challenger enters, and this is the likeliest to happen if $x = T$. So, since δ is increasing in x, if the quality of the idea α was generated exogenously (as our paper has assumed), it would be socially optimal to require *immediate* publication so that x (and hence $\delta(x)$) would be maximized at $\delta(T)$.

Disclosure should be immediate and as detailed as possible. But the incumbents payoff conditional on α would be smaller than its equilibrium payoff, i.e.,

$$\begin{aligned} U(\alpha, \alpha, T) &= \omega(T, \alpha)\,\alpha D(\alpha + \delta(T)) + (1 - \omega(T, \alpha))\,\alpha D(\alpha) && (15) \\ &\leq U(\alpha, \alpha, \tau(\alpha)). && (16) \end{aligned}$$

The positive external effect means that if the generation of α does require costly research, then that research should be subsidized, and the subsidy would need to be even larger if the innovator is forced to disclose his idea immediately. I.e., if the results of research are automatically publicized and perhaps imitated, the innovator would then need to be compensated more for the costs of invention.

Delaying publication amounts to a lengthening of the period in which the idea is kept secret; Levin et al. (1987) discuss some of the issues surrounding secrecy of ideas. And Klette, Møen and Griliches (2000) survey the evidence on the effectiveness of research subsidies.

II.E Heterogeneous Capital

Let k be the firm's capital stock, and assume

$$\text{incumbent's output} = q(\alpha, k)$$

with q an increasing function, with

$$q_{\min} \equiv \min_{(\alpha,k)} q(\alpha, k).$$

Let

$$x = \tau^*(\alpha) = \frac{a}{b}\left(\sqrt{\frac{\alpha}{\alpha_{\min}}} - 1\right)$$

be the equilibrium signal we derived for the case $\beta = 1$. Then we can show that one can simply replace α by $q(\alpha, k)$ and that the same equilibrium then holds with the incumbent signaling q instead of α. And then we shall find in condition (18) below that if α and k are substitutes in production, that is sufficient but not necessary for larger firms to have smaller sloped relations between α and x.

Formally, we have the following result, the proof of which is deferred to Appendix B.

Proposition 2. *If* $\beta = 1$,

$$\tau(\alpha, k) = \tau^*(q(\alpha, k)) = \frac{a}{b}\left(\sqrt{\frac{q(\alpha, k)}{\alpha_{\min}}} - 1\right) \tag{17}$$

with

$$\min_{(\alpha,k)} \tau(\alpha, k) = \tau^*(q_{min}).$$

And since τ^* *is concave in* α,

$$\frac{\partial^2 q}{\partial \alpha \partial k} < 0 \Rightarrow \frac{\partial}{\partial k}\left(\frac{\partial x}{\partial \alpha}\right) < 0, \tag{18}$$

i.e., the slope $\partial x/\partial \alpha$ *is smaller for firms with larger* k.

Substitutes case—Exponential Form. Consider

$$q = D - \exp(-\gamma\alpha - \delta k)$$

The marginal product of α and of k are both positive

$$\frac{\partial q}{\partial \alpha} = \gamma \exp(-\gamma\alpha - \delta k) \quad \text{and} \quad \frac{\partial q}{\partial k} = \delta \exp(-\gamma\alpha - \delta k)$$

and

$$\frac{\partial^2 q}{\partial \alpha \partial k} = -\gamma\delta \exp(-\gamma\alpha - \delta k) < 0. \tag{19}$$

And when we substitute from (19) into (17), we have a negative effect of k on the slope of x with respect to α.

II.F Other Possible Extensions

Size of sector. If we add a multiplicative parameter to the demand curve so that

$$p = AD(q),$$

then it is easy to see that this raises the probability of entry as follows: The entrant's revenue rises by the factor A, so that equation (3) reads

$$\omega(x, \hat{\alpha}) = F(\delta(x) AD[\hat{\alpha} + \delta(x)]). \tag{20}$$

With c distributed uniformly on $[0, c_{\max}]$, such that $F(c) = c/c_{\max}$, the probability of entry would rise by the factor A. To preserve the solution, $A/c_{\max}$ cannot be too large, otherwise ω would exceed the upper bound of unity, rendering the solution invalid.

Superstar inventions. They have a large α, which would require a large $\alpha_{\max}$. This could lead to a failure of condition (7) and, with the finiteness of T, would result in partial pooling—the weakest types would pool at $x = 0$, i.e., at $t = T$, and enough of them would need to do so to leave sufficient time for the other types to separate on the interval $[0, t)$.

III Data and Descriptive Results

Sample Construction We start with USPTO's publicly available patent research dataset and restrict our sample to all regular utility patent applications filed between November 29, 2000 and December 31, 2005. We then remove observations for which important information, such as grant date or application date seemed erroneous or missing. For each patent, we calculate forward citations for the five-year and ten-year periods, excluding self-citations of the same patent owners and counting forward-citations from the disclosure date of patents (that is, 18-month publication date or grant date). For each patent, we identified the numbers

of product-innovation-related and process-innovation-related claims, provided by Ganglmair, Robinson and Seeligson (2022) using text-analysis-based classification. Finally, we bring in Compustat financial information for publicly-listed patentees by using the crosswalk between patent assignees and Compustat firms provided by Arora, Belenzon and Sheer (2021).

Table 1 presents the summary statistics for our sample.

Variable Definition. We define the disclosure date of a patent to be the earlier of its publication date and grant date date. If there is a parent application associated with the patent through continuations, the filing date of the patent is adjusted to that of the parent application (consistent with AIPA rules which require patent publication to occur 18 months from the application date of the earliest parent application). The publication gap of a patent is then defined to be the difference between its disclosure and filing dates, measured in months.

Descriptive Results. Figure 3 plots average patent quality for each monthly bin of publication lag and shows that higher-quality patents (measured by respectively the claims in the patents, 5-year forward citations and 10-year forward citations) are more likely to disclose early, particularly after controlling for technology categories (Panel B). Figure 4 further shows that the probability of late disclosure decreases with patent quality measured by forward citations across all technology fields. Only about 5 percent of the most important patents (i.e., those that are in the top 10th percentile of forward citations) prefer to delay disclosure in the Chemicals and Drugs and Medical fields, while about 15 percent delay disclosure in the Computers and Communications field.

IV Regressions and Model Estimation

IV.A Reduced-Form Regressions

To test the main prediction of our signaling model that high quality inventions are disclosed sooner, the first three columns of Table 2 regress the indicator for late publication on patent quality, controlling for observable characteristics of patent owners as well as CPC patent class, application year, and issue year fixed effects. Columns (4) to (6) of Table 2 look at how the log of publication gap correlates with patent quality, conditional on late publication. The estimates in this table together suggest that patents with higher *unobserved* quality (that cannot be explained by the firms' and patents' observable characteristics at the time of disclosure) are more likely to be disclosed early, both at the extensive and intensive margins, by small firms and firms with a large stock of previous patents.

Table 4 presents similar analyses using the Compustat sample, focusing on patents owned by publicly listed firms. Using this subsample of patents allows us to analyze the effect of various financial variables (e.g., capital and R&D expenses), available only for publicly listed firms, on disclosure strategy.

IV.B Model Estimation

Recall the model solution

$$\alpha(x) = \alpha_{\min}\left(1 + \frac{b}{a}x\right)^2$$

where α is the patent quality, x is the time left for copying, $\alpha_{\min}$ is the left bound of the distribution for α, and b/a captures the relative importance of gradual versus Eureka learning. To facilitate estimation of the model, we pick the five-year forward citation as the empirical counterpart of α and set the latest possible time for disclosure, T, to 100 months after patent application. It follows that x is the difference between T and the publication gap.

We use Nonlinear Least Squares to fit this quadratic equation and estimate two parameters, i.e. $\alpha_{\min}$ and b/a. Notice that a and b cannot be separately identified as only their *ratio* appears in the solution. Intuitively, a is the amount of Eureka knowledge that rivals can learn immediately upon the disclosure of a patent, whereas b measures how much more knowledge rivals can learn about the patent over time. The model only allows us to estimate the relative importance of the Eureka and gradual learning.

Table 6 presents the estimates of model parameters for the full sample and each of the six NBER technology classes. Table 7 presents heterogenous effects based on firm ownership, size, R&D intensity, and capital intensity. The last two columns of this table also explore heterogenous effect for product-innovation versus process-innovation patents. Patents that are considered to be product-innovation patents are those in which the majority of the claims relate to invention of new products.

Interestingly, b/a is estimated to be lower in Drugs and Medical where learning by competitors is gradual, and b/a is essentially zero in Computers and Communication where learning by rivals is more immediate (i.e., Eureka learning). This is consistent with our previous finding, evident from Figure 4, that the most important inventions in Computers and Communication are about thrice as likely as their counterparts in the Chemicals or Drugs and Medicine field to be disclosed early, at 18 months.

V Conclusion

We develop a theory of private information that explains the disclosure choices of inventors under competition. Our model predicts that high-quality inventors credibly signal the quality of their inventions by publishing their patents early. The model also provides a simple functional form to guide the estimation of the importance of learning over time (versus instantaneous learning) and quality thresholds across different industries and types of inventors.

Empirically, we find robust evidence for the central prediction of our signaling model that high-quality inventors publish sooner. Small inventors, those with lower investments in capital equipment, and R&D intensive firms seem to be particularly more likely to disclose their most important patents early. We also find that technology fields in which learning by competitors tends to be more gradual (e.g., Drugs and Medical) admit lower quality thresholds for disclosure, while fields in which learning is more immediate (e.g., Computers and Communication) are associated with higher quality thresholds for disclosure.

Our results inform policy discussions about the effect of patent disclosure provisions on innovation and competition. It also complements studies that document wide variation in the use of patents across different technology fields, by suggesting that at least some of the differences could be a result of how patent disclosures interact with the nature of learning in these fields.

Going forward, we plan to extend the model to understand the disclosure strategy of super-star inventors, and also to empirically estimate the economic value of patent disclosures through the stock market reactions they elicit.

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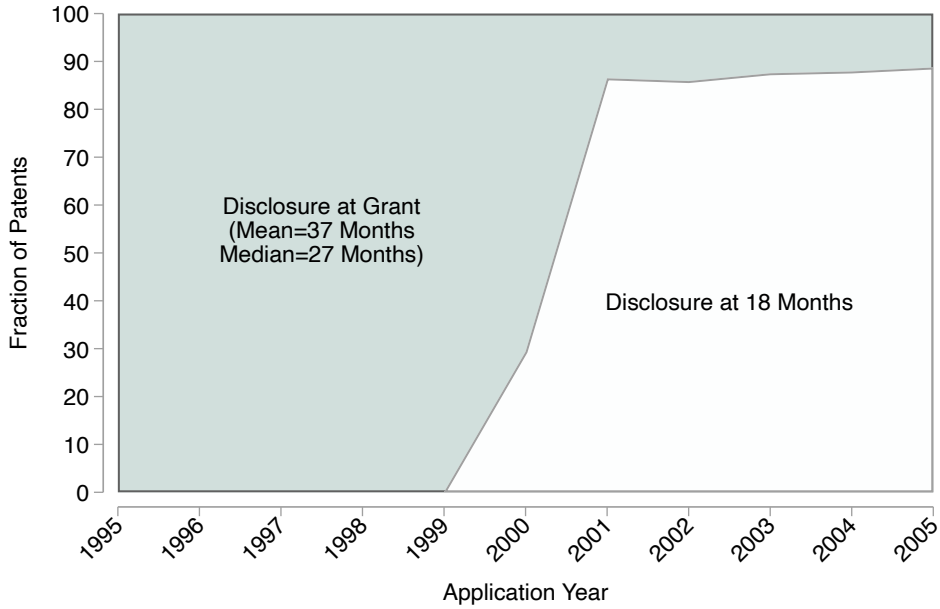
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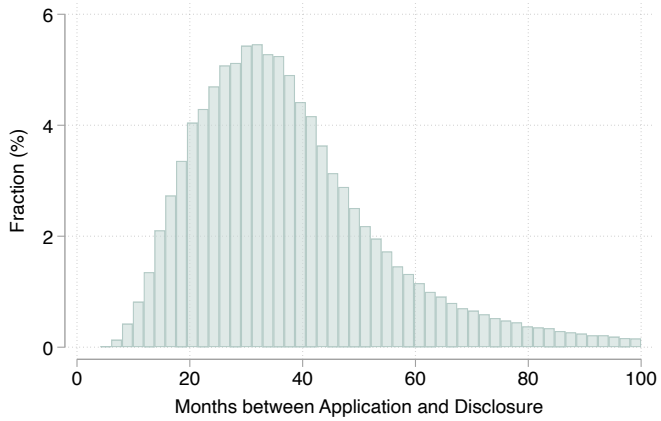
Figure 1: Publication Lag Since Application Date



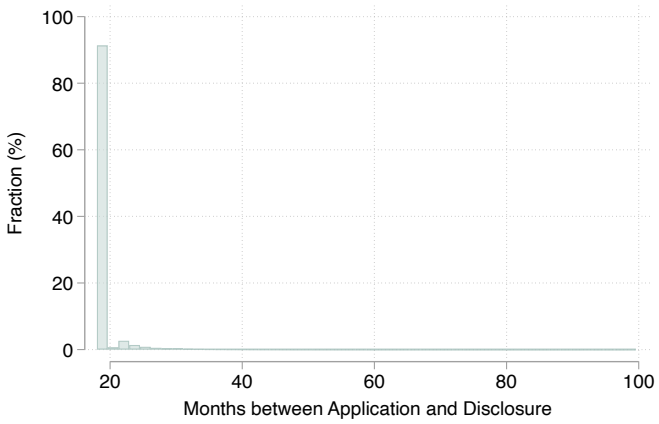
Notes: This figure plots the fraction of USPTO patent applications that are published at grant, versus those that are published at 18 months after application date. The figure uses the population of regular utility patent applications filed at the USPTO between 1995 and 2005. Patents with foreign priorities are excluded. All U.S. patent applications were published at grant prior to the American Inventors' Protection Act (AIPA). AIPA provided the choice of 18 month disclosure to patent applications filed on or after November 29, 2000.

Figure 2: Publication Lag Since Application Date

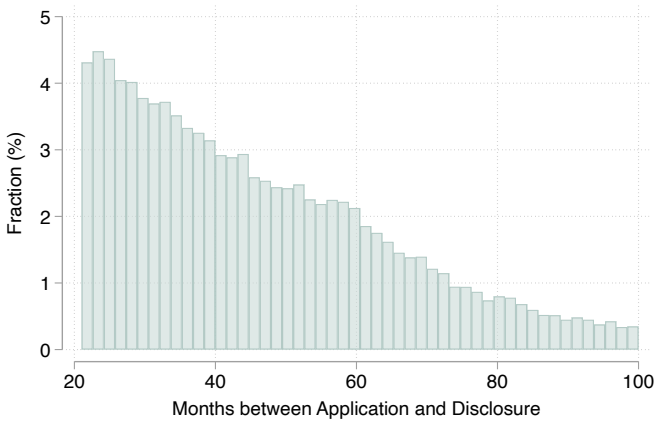
Panel A: Pre-AIPA



Panel B: Post-AIPA, Early-Disclosed



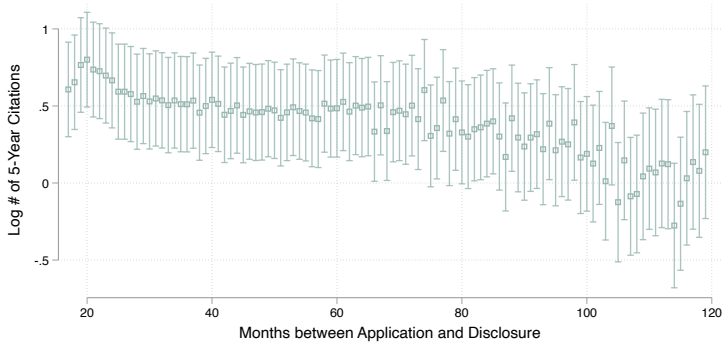
Panel C: Post-AIPA, Late-Disclosed



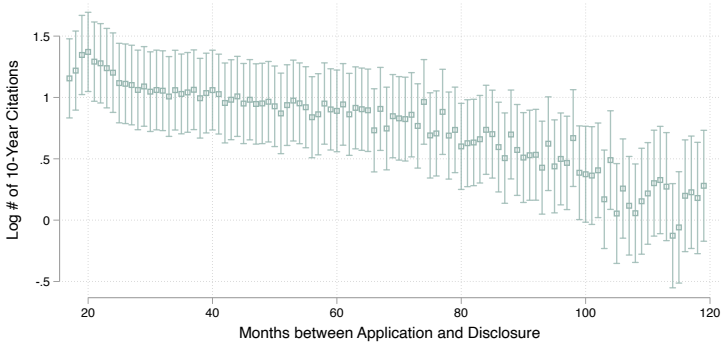
Notes: This graph plots the distribution of publication lags for three subsamples of regular utility patent applications filed at the USPTO between 1995 and 2005. Panel A focuses on patent applications filed before the American Inventors' Protection Act (AIPA). Panel B includes patent applications that were filed after the AIPA and disclosed at 18 months. Panel C covers patent applications filed after the AIPA with delayed disclosure. Patent applications with foreign priorities are excluded from the analysis. Before AIPA, all U.S. patent applications were published only upon grant. However, AIPA introduced the option for 18-month disclosure for applications filed on or after November 29, 2000.

Figure 3: Publication Lag and Patent Quality

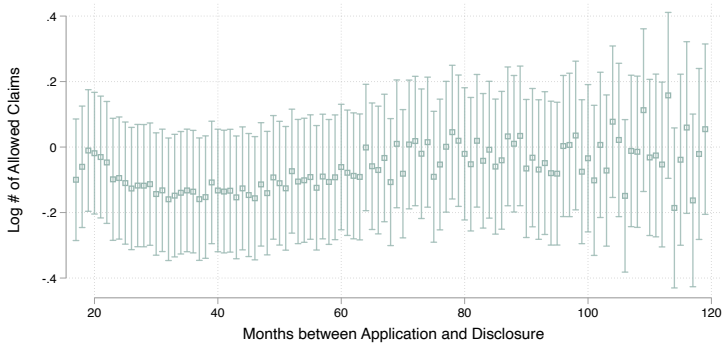
Panel A: 5-Year Citations



Panel B: 10-Year Citations



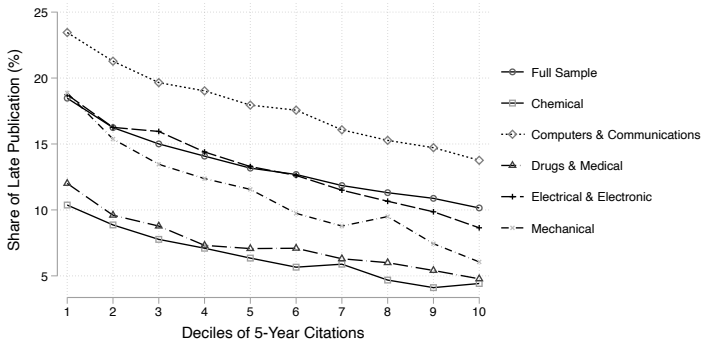
Panel C: Number of Claims



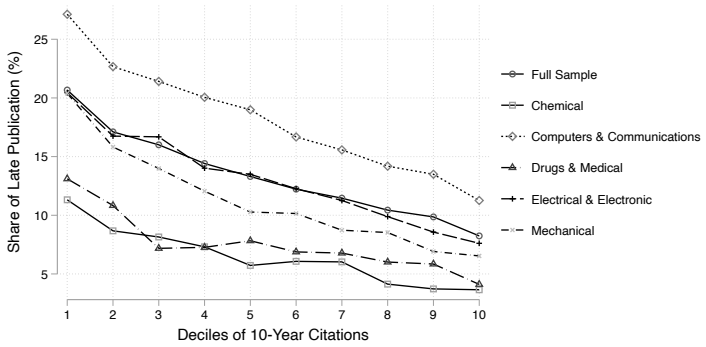
Notes: This graph plots the relationship between three measures of patent quality and publication lags. Specifically, it shows the average patent quality for each monthly bin of publication lags, after absorbing fixed effects for patent categories (i.e. CPC codes). Panel A measures patent quality using 5-year citations, Panel B uses 10-year citations, and Panel C relies on the number of claims. The sample includes all regular utility patent applications filed in the United States between November 29, 2000 and December 31, 2005, that had no equivalent foreign application and were granted before July 22, 2022.

Figure 4: Late Publication Decision and Patent Quality

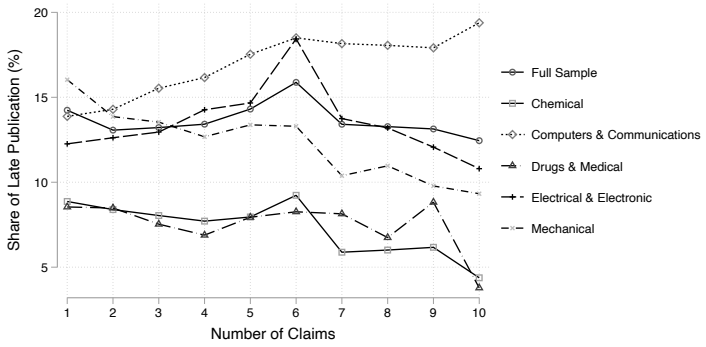
Panel A: 5-Year Citations



Panel B: 5-Year Citations

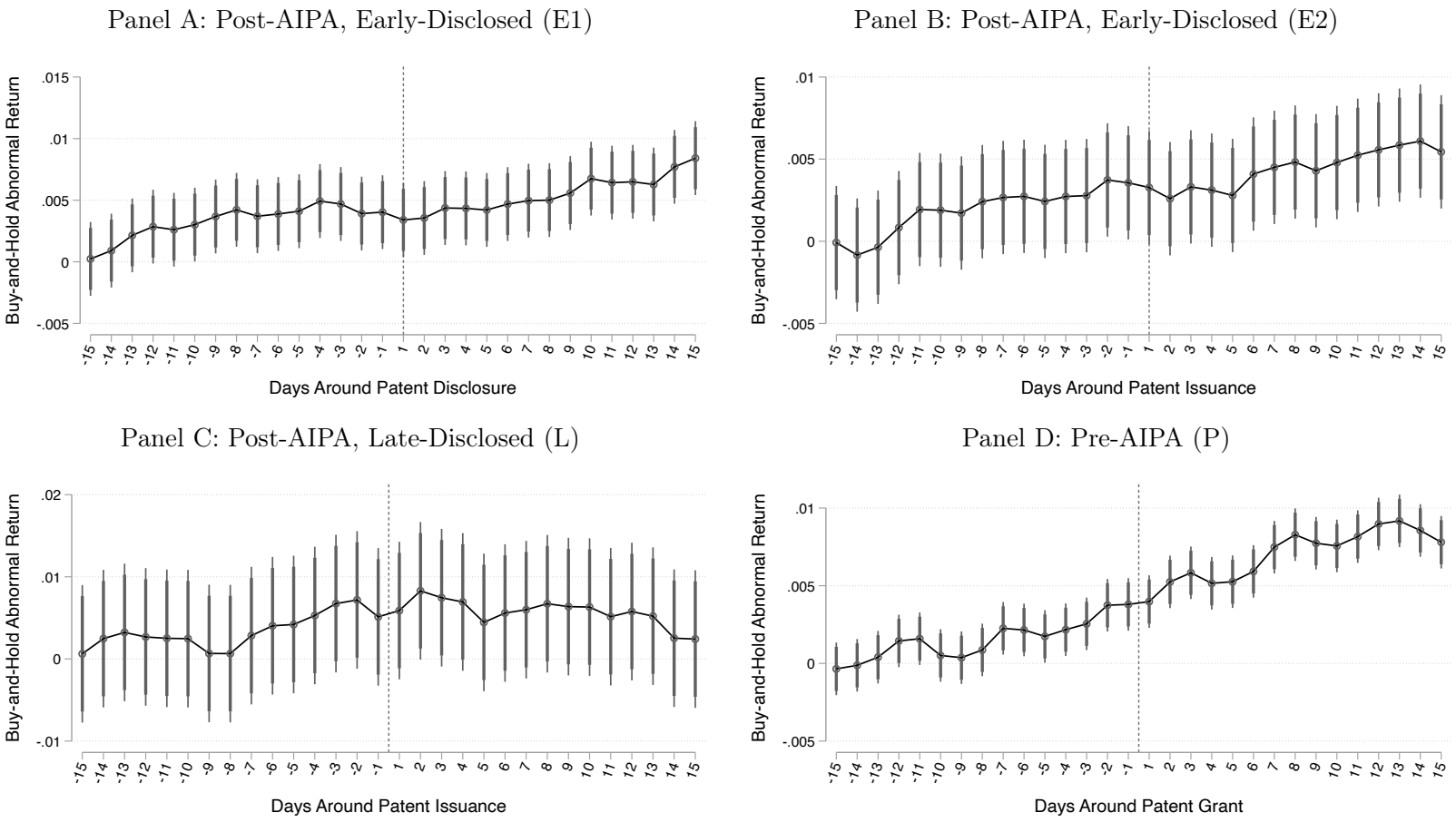


Panel C: 5-Year Citations



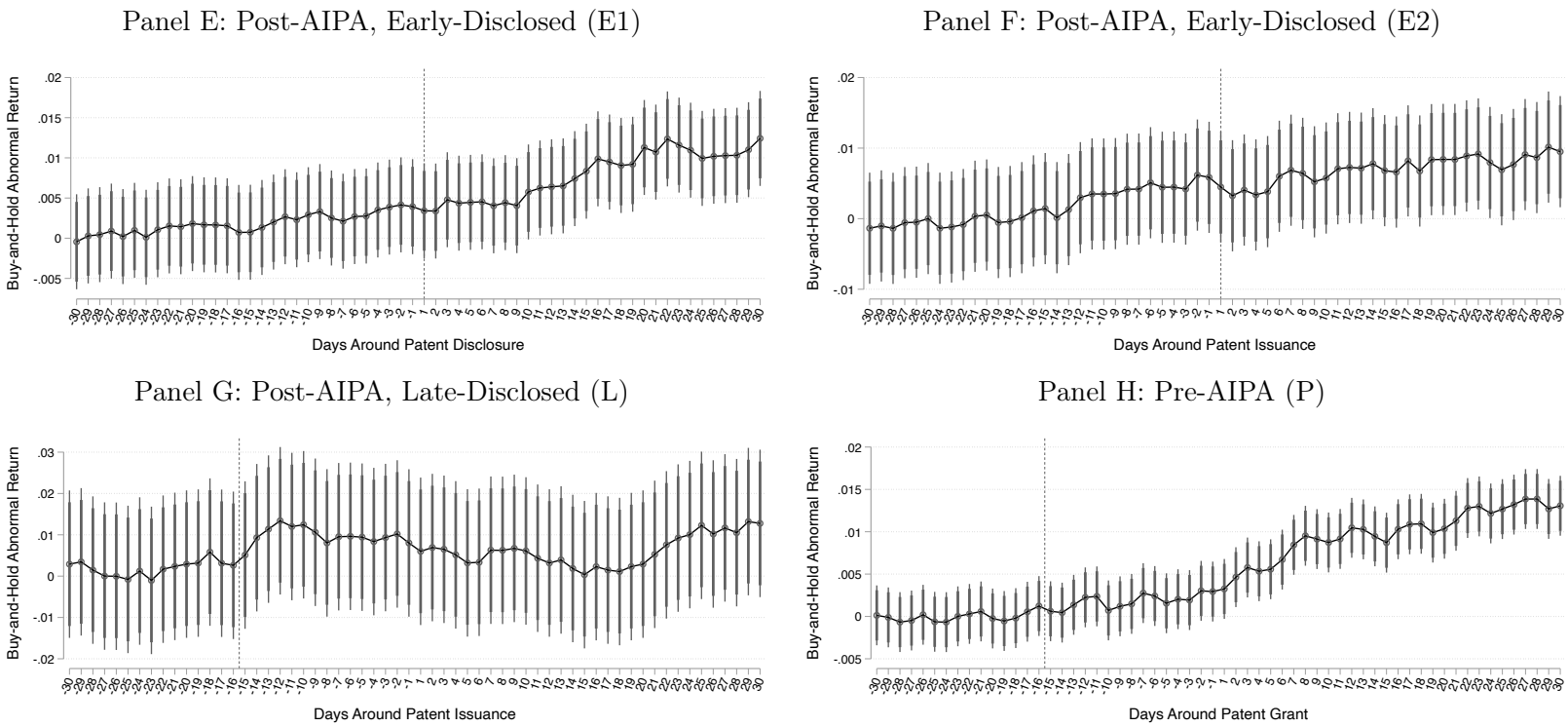
Notes: This figure plots the share of late-disclosed patents across deciles of patent quality for five different NBER patent classes. Panel A measures quality using 5-year forward citations, Panel B uses 10-year forward citations, and Panel C relies on the number of claims. Self-citations, where the citing and cited patents share common assignees, are excluded from the analysis. The sample includes all utility patent applications filed in the United States between November 29, 2000, and December 31, 2005, that were published before July 22, 2022.

Figure 5: Stock Market Response to Patent Events



Notes: This figure presents coefficient estimates from event study regressions around four patent events. The shaded areas represent the 95% and 90%confidence intervals. The buy-and-hold abnormal return reflects the excess return from holding the stock relative to the CRSP Index. The event window spans 15 days before to 15 days after each event. On the 15th day post-event, the coefficient estimates are $\beta_{E1} = 0.0084$, $\beta_{E2} = 0.0054$, $\beta_L = 0.0024$, and $\beta_P = 0.0078$, satisfying the inequality $\beta_{E1} + \beta_{E2} > \beta_P > \beta_L$.

Figure 5: Stock Market Response to Patent Events



Notes: This figure presents coefficient estimates from event study regressions around four patent events. The shaded areas represent the 95% and 90%confidence intervals. The buy-and-hold abnormal return reflects the excess return from holding the stock relative to the CRSP Index. The event window spans 30 days before to 30 days after each event. On the 30th day post-event, the coefficient estimates are $\beta_{E1} = 0.0124$, $\beta_{E2} = 0.0095$, $\beta_L = 0.0128$, and $\beta_P = 0.0131$, satisfying the inequality $\beta_{E1} + \beta_{E2} > \beta_P > \beta_L$.

Table 1: Summary Statistics

Variable	Obs	Mean	SD	Median	P5	P95
Panel A: Patent Characteristics						
Pub Gap (Months)	1980481	34.05	21.81	27.53	15.9	75.39
5-Year Citations	1980481	8.87	17.36	4	0	34
10-Year Citations	1980481	16.92	36.44	7	0	66
N Allowed Claims	1980481	17.64	16.35	15	3	42
Frac Product Claims	1980481	64.04	47.99	100	0	100
Panel B: Patent Owner Characteristics (at Patent Level)						
Small Firm Dummy	1980447	.25	.43	0	0	1
Public Firm Dummy	1980481	.28	.45	0	0	1
N Past Patents	1765440	4458.5	8681.61	486	0	22542
Assets	552587	39927.87	85148.2	11773.65	140.95	140247.7
Employment	551935	76.92	98.85	39.02	.35	296.69
R&D Expenses	549107	.45	.46	.2	0	1
Revenue	552586	25222.77	36559.65	11206.19	73.19	115033.6
Capital	552470	15176.78	25574.01	5679.18	33.61	73637.18
Panel C: Patent Owner Characteristics (at Owner Level)						
Small Firm Dummy	153872	.59	.49	1	0	1
Public Firm Dummy	153873	.05	.22	0	0	0
N Past Patents	153873	165.28	1790.18	1	0	119
Assets	7473	23040.81	73650.6	2312.29	12.62	91732
Employment	7415	40.64	72.71	10.07	.06	177.05
R&D Expenses	7337	.66	.44	1	0	1
Revenue	7472	13132.46	28828.87	1909.15	3.71	84328.73
Capital	7471	8424.75	21531.69	920.83	2.64	39379.45

Notes: This table shows summary statistics for the analysis sample constructed in Section III. Panel A summarizes variables that describe patent characteristics, and Panel C those that describe patent owner characteristics.

Table 2: Publication Lag and Patent Quality

	Extensive: Late Pub Dummy			Intensive | Late Publication: Log Pub Gap		
	(1)	(2)	(3)	(4)	(5)	(6)
Log 5-Year Citations	-0.023***			-0.036***		
	(0.000)			(0.001)		
Log 10-Year Citations		-0.031***			-0.047***	
		(0.000)			(0.001)	
Log Allowed Claims			0.000			-0.015***
			(0.001)			(0.001)
Public Firm Dummy	0.072***	0.073***	0.070***	0.066***	0.066***	0.066***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Small Firm Dummy	0.002	0.003**	0.001	-0.009***	-0.007**	-0.013***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Log Past Patents	-0.016***	-0.017***	-0.016***	-0.008***	-0.009***	-0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	407044	407044	407044	132781	132781	132781
CPC FE	Yes	Yes	Yes	Yes	Yes	Yes
Appl Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Iss Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents regression results that describe how patent disclosure decisions are related to patent quality and other characteristics. Columns (1) to (3) uses a dummy variables that equals one if the patent opts for disclosure at granting as dependent variable. Columns (4) to (6) uses the log publication gap in months as dependent variable, conditional on opting for disclosure at granting. Fixed effects for each application year, issue year, and CPC code are included. Standard errors are reported in parentheses. *** indicates significance at the 0.01 level, ** at 0.5, and * at 0.1.

Table 3: Publication Lag and Patent Quality

	Extensive: Late Pub Dummy			Intensive | Late Publication: Log Pub Gap		
	(1)	(2)	(3)	(4)	(5)	(6)
Log 5-Year Citations	-0.0219***			-0.0345***		
	(0.0005)			(0.0009)		
Log 5-Year Citations × Small Firm Dummy	-0.0051***			-0.0064***		
	(0.0009)			(0.0016)		
Log 10-Year Citations		-0.0299***			-0.0447***	
		(0.0004)			(0.0009)	
Log 10-Year Citations × Small Firm Dummy		-0.0045***			-0.0068***	
		(0.0008)			(0.0015)	
Log Allowed Claims			0.0058***			-0.0080***
			(0.0008)			(0.0017)
Log Allowed Claims × Small Firm Dummy			-0.0190***			-0.0212***
			(0.0015)			(0.0029)
Small Firm Dummy	0.0144***	0.0171***	0.0678***	0.0061	0.0136**	0.0612***
	(0.0026)	(0.0029)	(0.0056)	(0.0048)	(0.0054)	(0.0105)
Log Past Patents	-0.0164***	-0.0166***	-0.0157***	-0.0081***	-0.0087***	-0.0071***
	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0004)	(0.0004)
Public Firm Dummy	0.0720***	0.0727***	0.0697***	0.0660***	0.0657***	0.0653***
	(0.0013)	(0.0013)	(0.0013)	(0.0025)	(0.0025)	(0.0026)
N	407044	407044	407044	132781	132781	132781
CPC FE	Yes	Yes	Yes	Yes	Yes	Yes
Appl Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Iss Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents regression results that describe heterogeneous effects of patent quality on disclosure decisions. Columns (1) to (3) uses a dummy variables that equals one if the patent opts for disclosure at granting as dependent variable. Columns (4) to (6) uses the log publication gap in months as dependent variable, conditional on opting for disclosure at granting. Fixed effects for each application year, issue year, and CPC code are included. Standard errors are reported in parentheses. *** indicates significance at the 0.01 level, ** at 0.5, and * at 0.1.

Table 4: Publication Lag and Patent Quality—Compustat Sample

	Extensive: Late Pub Dummy						Intensive | Late Publication: Log Pub Gap					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log 5-Year Citations	-0.0284***			-0.0641***			-0.0384***			-0.0491***		
	(0.0006)			(0.0023)			(0.0012)			(0.0039)		
Log 5-Year Citations × Small Firm Dummy	-0.0068***						-0.0141***					
	(0.0023)						(0.0038)					
Log 5-Year Citations × Log Capital				0.0040***						0.0012**		
				(0.0002)						(0.0005)		
Log 10-Year Citations		-0.0365***			-0.0830***			-0.0467***			-0.0596***	
		(0.0006)			(0.0021)			(0.0011)			(0.0036)	
Log 10-Year Citations × Small Firm Dummy		-0.0085***						-0.0160***				
		(0.0022)						(0.0036)				
Log 10-Year Citations × Log Capital					0.0052***						0.0014***	
					(0.0002)						(0.0004)	
Log Allowed Claims			-0.0021*			0.0023			-0.0189***			-0.0191***
			(0.0011)			(0.0043)			(0.0022)			(0.0073)
Log Allowed Claims × Small Firm Dummy			-0.0211***						-0.0201***			
			(0.0045)						(0.0071)			
Log Allowed Claims × Log Capital						-0.0007						-0.0002
						(0.0005)						(0.0008)
Small Firm Dummy	-0.0812***	-0.0681***	-0.0290*	-0.0973***	-0.0927***	-0.1061***	-0.0268**	-0.0084	-0.0026	-0.0645***	-0.0607***	-0.0755***
	(0.0074)	(0.0084)	(0.0167)	(0.0037)	(0.0037)	(0.0037)	(0.0119)	(0.0133)	(0.0263)	(0.0061)	(0.0061)	(0.0062)
Log Past Patents	-0.0257***	-0.0260***	-0.0251***	-0.0258***	-0.0260***	-0.0251***	-0.0157***	-0.0164***	-0.0141***	-0.0157***	-0.0164***	-0.0141***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Log Capital	-0.0114***	-0.0114***	-0.0111***	-0.0213***	-0.0275***	-0.0088***	-0.0008	-0.0009	-0.0009	-0.0037***	-0.0052***	-0.0002
	(0.0005)	(0.0005)	(0.0005)	(0.0008)	(0.0009)	(0.0018)	(0.0009)	(0.0009)	(0.0009)	(0.0014)	(0.0015)	(0.0031)
Log R&D Expenses	0.0102***	0.0103***	0.0103***	0.0103***	0.0104***	0.0103***	0.0019***	0.0018**	0.0027***	0.0020***	0.0019**	0.0027***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0007)	(0.0007)	(0.0008)	(0.0007)	(0.0007)	(0.0008)
N	208879	208879	208879	208879	208879	208879	63556	63556	63556	63556	63556	63556
CPC FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Appl Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Iss Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Notes: This table presents regression results that describe heterogenous effects of patent quality on disclosure decisions using the Compustat sample, which includes all patents filed by public firms. Columns (1) to (3) uses a dummy variables that equals one if the patent opts for disclosure at granting as dependent variable. Columns (4) to (6) uses the log publication gap in months as dependent variable, conditioinal on opting for disclosure at granting. Fixed effects for each application year, issue year, and CPC code are included. Standard errors are reported in parentheses. *** indicates significance at the 0.01 level, ** at 0.5, and * at 0.1.

Table 5: Publication Lag and Patent Quality - NBER Categories

	Extensive: Late Pub Dummy		
	(1)	(2)	(3)
Chemical × Log 5-Year Citations	-0.0531***		
	(0.0012)		
Computers&Communications × Log 5-Year Citations	-0.0059***		
	(0.0006)		
Drugs&Medical × Log 5-Year Citations	-0.0478***		
	(0.0010)		
Electrical&Electronic × Log 5-Year Citations	-0.0163***		
	(0.0008)		
Mechanical × Log 5-Year Citations	-0.0423***		
	(0.0012)		
Others × Log 5-Year Citations	-0.0547***		
	(0.0012)		
Chemical × Log 10-Year Citations		-0.0589***	
		(0.0010)	
Computers&Communications × Log 10-Year Citations		-0.0182***	
		(0.0006)	
Drugs&Medical × Log 10-Year Citations		-0.0513***	
		(0.0009)	
Electrical&Electronic × Log 10-Year Citations		-0.0272***	
		(0.0007)	
Mechanical × Log 10-Year Citations		-0.0497***	
		(0.0010)	
Others × Log 10-Year Citations		-0.0584***	
		(0.0010)	
Chemical × Log Allowed Claims			-0.0242***
			(0.0013)
Computers&Communications × Log Allowed Claims			0.0155***
			(0.0011)
Drugs&Medical × Log Allowed Claims			-0.0237***
			(0.0014)
Electrical&Electronic × Log Allowed Claims			0.0061***
			(0.0012)
Mechanical × Log Allowed Claims			-0.0153***
			(0.0013)
Others × Log Allowed Claims			-0.0282***
			(0.0013)
Small Firm Dummy	-0.1146***	-0.1114***	-0.1178***
	(0.0037)	(0.0037)	(0.0037)
Log Past Patents	-0.0192***	-0.0203***	-0.0211***
	(0.0005)	(0.0005)	(0.0005)
Log Capital	-0.0203***	-0.0197***	-0.0175***
	(0.0004)	(0.0004)	(0.0005)
Log R&D Expenses	-0.0011***	-0.0006*	0.0007**
	(0.0003)	(0.0003)	(0.0004)
N	207788	207788	207788
Appl Year FE	Yes	Yes	Yes
Iss Year FE	Yes	Yes	Yes

Notes: This table presents regression results that describe heterogeneous effects of patent quality on disclosure decisions by NBER categories. The LHS variables equals one if the patent opts for disclosure at granting as dependent variable. Fixed effects for each application year and issue year are included. Standard errors are reported in parentheses. *** indicates significance at the 0.01 level, ** at 0.5, and * at 0.1.

Table 6: Estimates of Model Parameters by NBER Technology Classes

	Full Sample	Chemical	Computers and Communications	Drugs and Medical	Electrical and Electronic	Mechanical	Others
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\alpha_{\min}$	7.0661***	4.3936***	11.1666***	3.0728***	5.2100***	5.6037***	4.4082***
	(0.2696)	(0.6256)	(0.5343)	(0.7227)	(0.4895)	(0.6288)	(0.4544)
b/a	0.0030***	0.0032***	0.0018***	0.0181***	0.0044***	0.0010	0.0029***
	(0.0003)	(0.0011)	(0.0003)	(0.0036)	(0.0008)	(0.0008)	(0.0008)
N	435534	41241	138095	42665	86269	58575	63280

Notes: This table presents NLS estimates for equation 8. $\alpha_{\min}$ is the model parameter that captures the lowest quality type of patents. The ratio b/a corresponds to the relative importance of gradual learning versus Eureka learning. The first row runs NLS for the full sample, whereas the second to the last row runs NLS for subsamples that correspond to each NBER technology class. Standard errors are reported in parentheses. *** indicates significance at the 0.01 level, ** at 0.5, and * at 0.1.

Table 7: Estimates of Model Parameters — Heterogeneous Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	All	Public		Small		R&D Intensive		Capital Intensive		Innovation Type	
		0	1	0	1	0	1	0	1	Process	Product
$\alpha_{\min}$	7.066***	8.245***	6.323***	6.605***	8.677***	6.037***	6.811***	5.619***	6.346***	6.352***	7.442***
	(0.270)	(0.376)	(0.399)	(0.313)	(0.540)	(0.561)	(0.572)	(0.498)	(0.637)	(0.409)	(0.354)
b/a	0.003***	0.001***	0.005***	0.004***	0.001**	0.006***	0.003***	0.006***	0.004***	0.005***	0.002***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
N	435534	241281	194253	296629	138899	97129	97022	98287	95865	167450	268084

Notes: This table presents NLS estimates for equation 8. $\alpha_{\min}$ is the model parameter that captures the lowest quality type of patents. The ratio b/a corresponds to the relative importance of gradual learning versus Eureka learning. The first columns uses the full sample. The second to third columns use two subsamples for patents that are filed by private versus public firms. Coumns (3) to (9) are based on subsamples defined in a similar way but based on wether the patent is filed by a large versus small firms, less versus more R&D intensive firms, and less versus more capital intensive firms. The last two columns use subsamples for process-innovation patents and product-innovation patents, respectively. Standard errors are reported in parentheses. *** indicates significance at the 0.01 level, ** at 0.5, and * at 0.1.

A Appendix: Proof of Proposition 1

The incumbent's criterion (4) simplifies to

$$U(\alpha, \hat{\alpha}, x) = \alpha D(\alpha) - \omega(x, \hat{\alpha})\,\alpha\,[D(\alpha) - D(\alpha + \delta(x))]$$

The multiplicative constant α cancels and the criterion is

$$\max_x \{D(\alpha) - \omega(x, \hat{\alpha})\,[D(\alpha) - D(\alpha + \delta(x))]\}$$

Then the probability of entry is

$$\omega(x, \hat{\alpha}) = (a + bx)\,(\hat{\alpha} + a + bx)^{-\beta}.$$

Then the incumbent maximizes

$$\begin{aligned} \frac{U(\alpha, \hat{\alpha}, x)}{\alpha} &= (a + bx)\,(\hat{\alpha} + a + bx)^{-\beta}\,(\alpha + a + bx)^{-\beta} \\ &\quad + \left(1 - (a + bx)\,(\hat{\alpha} + a + bx)^{-\beta}\right)\alpha^{-\beta} \end{aligned} \tag{21}$$

That is,

$$\frac{U(\alpha, \hat{\alpha}, x)}{\alpha} - \alpha^{-\beta} = (a + bx)\,(\hat{\alpha} + a + bx)^{-\beta}\left((\alpha + a + bx)^{-\beta} - \alpha^{-\beta}\right) \equiv \hat{U}(\alpha, \hat{\alpha}, x) \tag{22}$$

A.A The case $\beta = 1$.

If $\beta = 1$, we have

$$\omega(x, \hat{\alpha}) = \frac{a + bx}{\hat{\alpha} + a + bx} = \frac{1}{1 + \hat{\alpha}/(a + bx)} < 1$$

$$U(\alpha, \hat{\alpha}, x) = \frac{1}{1 + \hat{\alpha}/(a + bx)}\frac{\alpha}{\alpha + a + bx} + \left(1 - \frac{1}{1 + \hat{\alpha}/(a + bx)}\right) \times 1$$

The criterion simplifies to

$$\begin{aligned}\hat{U}(\alpha,\hat{\alpha},x)-1 &= \frac{1}{1+\hat{\alpha}/(a+bx)}\left(\frac{\alpha}{\alpha+a+bx}-1\right)\\ &= \frac{-1}{1+\hat{\alpha}/(a+bx)}\frac{a+bx}{\alpha+a+bx}=\frac{-(a+bx)^2}{(\hat{\alpha}+a+bx)(\alpha+a+bx)}\end{aligned}$$

or to minimize

$$\frac{(a+bx)^2}{(\hat{\alpha}+a+bx)(\alpha+a+bx)}=(a+bx)^2(\hat{\alpha}+a+bx)^{-1}(\alpha+a+bx)^{-1} \tag{23}$$

The single-crossing property is proved in the last Appendix.

A.A.1 FOC for the case $\beta = 1$

The criterion is

$$\hat{U}(\alpha,\hat{\alpha},x)\equiv(a+bx)^2(\hat{\alpha}+a+bx)^{-1}(\alpha+a+bx)^{-1}$$

The FOC is

$$\hat{U}_3(\alpha,\hat{\alpha},x)+\hat{U}_2(\alpha,\hat{\alpha},x)\frac{d\hat{\alpha}}{dx}=0$$

Evaluated at $\hat{\alpha}=\alpha$ the ODE reads

$$\begin{aligned}\frac{d\alpha}{dx} &= -\frac{\hat{U}_3(\alpha,\alpha,x)}{\hat{U}_2(\alpha,\alpha,x)}=\frac{2b(\alpha+a+bx)}{a+bx}-b-\frac{b(\alpha+a+bx)}{(\alpha+a+bx)}\\ &= \frac{2b(\alpha+a+bx)}{a+bx}-2b=2b\left(\frac{\alpha+a+bx}{a+bx}-1\right)\\ &= 2b\frac{\alpha}{a+bx}\end{aligned} \tag{24}$$

The ODE in (24) has the general solution

$$\alpha(x)=C(a+bx)^2. \tag{25}$$

To get C we use the weakest type, $\alpha_{\min}$ who would set $x = 0$, so that $\alpha_{\min} = Ca^2$, which implies

$$C = \frac{\alpha_{\min}}{a^2} \tag{26}$$

Substituting from (26) into (25) we get (8)

A.A.2 Single crossing property when $\beta = 1$

The single-crossing property (Mailath, 1987) requires that the ratio of the derivatives

$$\hat{U}_3(\alpha, \hat{\alpha}, x) / \hat{U}_2(\alpha, \hat{\alpha}, x)$$

is strictly monotone in α. Using the expression in (23) which we reproduce here,

$$\hat{U}(\alpha, \hat{\alpha}, x) \equiv (a + bx)^2 (\hat{\alpha} + a + bx)^{-1} (\alpha + a + bx)^{-1}$$

$$\hat{U}_2 = -(a + bx)^2 (\hat{\alpha} + a + bx)^{-2} (\alpha + a + bx)^{-1}$$

$$\begin{aligned}\hat{U}_3 = {} & 2b(a + bx)(\hat{\alpha} + a + bx)^{-1}(\alpha + a + bx)^{-1} \\ & - b(a + bx)^2 (\hat{\alpha} + a + bx)^{-2} (\alpha + a + bx)^{-1} \\ & - b(a + bx)^2 (\hat{\alpha} + a + bx)^{-1} (\alpha + a + bx)^{-2}.\end{aligned}$$

Then the following ratio should be monotone in α:

$$\frac{\hat{U}_3}{\hat{U}_2} = \frac{2b(\hat{\alpha} + a + bx)}{-(a + bx)} + b + \frac{b(\hat{\alpha} + a + bx)}{(\alpha + a + bx)},$$

and α enters only in the denominator of the third term – so the ratio $\frac{\hat{U}_3}{\hat{U}_2}$ is indeed strictly decreasing in α for all x.

B Proof of Proposition 2

Proof. Define

$$\tilde{\alpha} \equiv q(\alpha, k). \tag{27}$$

Then the only way α and k enter the model is through $\tilde{\alpha}$. Eqs. (4) and (5) become

$$U(\tilde{\alpha}, x) = \omega(x, \tilde{\alpha})\,\tilde{\alpha} D(\hat{\alpha} + \delta(x)) + (1 - \omega(x, \hat{\alpha}))\,\tilde{\alpha} D(\tilde{\alpha}) \tag{28}$$

and then

$$\tau(\tilde{\alpha}) = \arg\max_x U\left(\tilde{\alpha}, \tau^{-1}(x), x\right) \quad \text{for all } \tilde{\alpha}. \tag{29}$$

The challenger still learns linearly

$$\delta(x) = a + bx$$

and then

$$\tilde{\alpha}(x) = \tilde{\alpha}_{\min}\left(1 + \frac{b}{a}x\right)^2. \tag{30}$$

for $x \in \left[0, \frac{a}{b}\left(\sqrt{\frac{\tilde{\alpha}_{\max}}{\tilde{\alpha}_{\min}}} - 1\right)\right]$. Inverting (8), we get (17). □