Strategic Patenting Under Financial Disclosure Mandates

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Abstract

We examine how financial disclosure regulations influence firms' intellectual property (IP) protection strategies. While disclosure enhances transparency, it also exposes firms to competitive risks by revealing insights into their product market performance. Firms' strategic responses involve a trade-off between using patents to obtain legal protection and incurring the informational costs of patent disclosure. We develop a model of firms' patenting decisions that jointly embeds financial and patent disclosure. Our model predicts that increased financial transparency raises the risk of not patenting, compelling firms to lower their patenting threshold. This effect, which leads to more patent filings of lower average quality, dominates as long as financial and patent disclosures are substitutes or not strongly complementary. We test these predictions using the ASC 606 revenue disaggregation requirement. Using a difference-in-differences design, we find that affected firms file significantly more patents after the announcement, and the average quality of new patents declines. We also find that the effects are stronger for firms that historically rely more on patenting for protection and for firms with more opaque ex-ante information environments.

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1 Introduction

We examine how financial disclosure regulations shape firms' intellectual property (IP) protection strategies. By mandating the reporting of detailed financial and operational information, disclosure regulations enhance transparency but also expose firms to competitive risks (Bernard, 2016; Glaeser and Omartian, 2022). Although such disclosures do not reveal technological details, they provide competitors with valuable insights into a firm's business environment and product market success, potentially guiding rivals' entry and investment decisions.[1] This tension between transparency and the need to safeguard proprietary information raises an important question: how do financial disclosure mandates influence firms' intellectual property protection strategies? To address this question, it is important to distinguish firms' IP protection choices from firms' innovation outputs. While prior literature has examined how financial disclosure affects firms' innovation, typically using patents as a proxy for innovation output, we highlight that patents also encode protection choices. Consequently, the patenting decision is a distinct strategic margin that can respond to disclosure. Recognizing this dual role is essential for interpreting patent data and understanding how disclosure regulations shape firms' broader innovation outcomes.

In this paper, we study how firms adapt their patenting behavior—both in volume and quality—in response to increased transparency induced by disclosure regulations. We first develop a theoretical framework to address these questions. In our model, an incumbent firm observes the private value of an innovation and chooses whether to file a patent. The incumbent faces a competitor who makes two decisions: first, it chooses a search effort to discover the incumbent's market; second, if the search is successful, the competitor chooses a competition effort to capture a share of the incumbent's profits. If the incumbent firm does

[1] Firms frequently cite competitive harm when opposing disclosure mandates (Ettredge et al., 2000).

not patent, it keeps the innovation private. However, the incumbent then faces a baseline risk that the competitor will discover the market through market research and compete aggressively. Alternatively, the incumbent can choose to patent, which provides a legal "wall" that weakens the competitor's subsequent competition effort and protects a portion of the incumbent's profits. By filing a patent, the incumbent incurs fixed, administrative patenting costs. In addition, there is an informational cost: through patent disclosure, patenting makes the firm's market easier for the competitor to find.

The incumbent firm trades off these costs—direct fixed costs and indirect informational costs of patenting—against the benefit of legal protection from direct competition. We show that the optimal policy takes one of two forms, depending on firm-specific characteristics: a "never patent" policy or a "threshold" policy. When patent protection is too weak relative to the patent disclosure cost, the net benefit of patenting is always negative. Thus, these firms never patent and keep all innovations in secrecy. For other firms, where there is sufficient legal protection, the trade-off becomes positive for high-value innovations. We show that they only patent innovations with profit potential exceeding a certain threshold, while lower-value innovations remain unpatented.

Mandatory financial disclosure changes this trade-off by improving the baseline information environment. First, enhanced disclosure increases the relative benefit of *legal protection* offered by patenting, as the competitor's search effort under no patenting becomes cheaper and more effective. Second, mandatory disclosure alters the relative *informational cost* of patenting. If financial disclosure and patent disclosure are substitutes (i.e., they reveal overlapping information), then mandatory disclosure lowers the incremental cost of patent disclosure, reinforcing the incentive to patent. Conversely, if they are complements (e.g., financial data helps competitors interpret patent data), the patent disclosure becomes more informative and thus costlier for the incumbent. We show that for a wide range of cases—when patent disclosure and financial disclosure are substitutes, or when the complementarity is weak—financial disclosure regulations prompt firms to lower their patenting threshold. As a result, firms patent more, including lower-value innovations. Only when patent and financial disclosure are strong complements do firms increase their patenting threshold and patent less.

Our model focuses on the patenting decision conditional on innovation. We acknowledge that disclosure regulations can also affect innovation activities (e.g., Breuer et al., 2025; Azinovic-Yang, 2024). We expect that when transparency increases competitive pressure, firms adjust their protection strategy as a first line of defense because doing so is quicker and less costly than re-optimizing R&D. Shocks that are sufficiently large or persistent would start to alter underlying innovative effort (e.g., mandating public disclosure of financial statements from small, private firms). We interpret the disaggregation mandate under ASC 606 as a transparency shock that primarily operates through firms' protection strategies, with any change in the underlying innovation being a secondary effect. This perspective motivates both our theoretical setup and the empirical tests that follow.

In the second part of the paper, we test the predictions of our model. We use an empirical setting where there is a plausible exogenous increase in financial transparency for affected firms: the announcement of the Accounting Standards Codification (ASC) 606 revenue disaggregation requirements. ASC 606 mandates that public firms disaggregate revenues into categories reflecting the nature, amount, timing, and uncertainty of revenues and provide additional qualitative disclosures in the revenue footnotes.[2] The standard significantly expanded the volume and granularity of revenue information disclosed by firms (Hinson et al., 2024).

This granular disclosure provides competitors with valuable insights into how a firm

[2]Examples of categories include: type of good or service; geographical region; market or type of customer; type of contract; contract duration; timing of transfer of goods or services; and sales channels. See PWC (2025).

organizes its business and the composition of its revenue streams, making it easier to identify lucrative areas for competition. These competitive concerns were explicitly documented by the FASB in its "Basis for Conclusions" draft, where preparers expressed fears that the requirements could place them at a competitive disadvantage (ASU 2014-09). In the context of our model, we interpret this policy as improving the baseline information environment, which makes the competitor's search effort more effective.

We focus on the standard's announcement rather than its implementation to isolate the effects on strategic patenting from confounding effects of the disclosure itself (e.g., information spillover from peer disclosures, liquidity effects that could affect firms' investment decisions (Berger, 2011; Leuz and Wysocki, 2016)). Because firms learn the rules at announcement, they can begin adjusting their IP protection strategies even before disclosures appear in financial statements. We define treatment firms as those that began providing significantly more granular revenue disclosures under ASC 606. Although managers retain some discretion over the level of disaggregation, SEC review and comment-letter oversight enforced the standards effectively.[3] We discuss the exogeneity of this treatment and validation of our classification in Sections 3 and 4.2.

Using a difference-in-differences design, we investigate whether this shock to the information environment influences firms' patenting behavior. Our model predicts that, provided financial and patent disclosures are substitutes or weak complements, the mandate increases the relative benefit of patent protection by intensifying competitors' search efforts and competition, thereby prompting firms to file more patents. Consistent with this prediction, we find that firms impacted by the increased disclosure requirements file significantly more patents following the mandate announcement. Furthermore, our model predicts that

[3]For example, Hinson et al. (2024) documents a significant increase in revenue disaggregation after the implementation of ASC 606.

a lowered threshold will bring in "marginal" innovations that were previously not valuable enough to patent. We test this by examining patent quality and find evidence that the quality of patents filed by treated firms, measured by forward citations, deteriorated after the treatment year, indicating that newly filed patents are closer to the margin.[4]

Lastly, to test our model's assumption that this is a strategic shift in tendency to patent, not a change in innovation input, we examine whether the disclosure mandate altered innovation activities, using different measures of R&D investment. We find no significant change in R&D around the ASC 606 announcement. Our main results are also robust to controlling for R&D expenditure. Taken together, these findings provide additional support that the observed shift reflects a change in IP protection strategy, not a change in underlying innovation activity.

We test two cross-sectional implications of our model. First, we investigate heterogeneity in firms' existing IP strategies. Our model predicts two possible patenting strategies: a "never patent" policy and a "threshold" policy. Firms that historically rely on trade secrecy are an empirical proxy for firms in our model that use the "never patent" policy. As our model predicts, these firms are not at the active margin of the patenting decision.[5] For such firms, patent protection is relatively less attractive, and they instead rely more heavily on secrecy procedures, organizational routines, and contracting to mitigate leakage risk.[6] Using the trade secrecy measure from Glaeser (2018), we find weaker increases in patenting among firms that rely on trade secrecy.

[4]In supplementary analyses, we find consistent patterns in alternative patent quality measures. After ASC 606, treated firms' patents are less likely to fall in the top decile of the citation distribution, and the patents draw on a broader range of technological fields, but the subsequent influence is concentrated in a narrower set of technologies, making them less broadly impactful.

[5]In the context of our model, a marginal shock from the new disclosure mandate is unlikely to be large enough to flip a "never patent" firm into the patenting equilibrium.

[6]For example, patent protection is generally more effective for chemical compounds (as compositions of matter) than for algorithms.

Second, we test whether the effect of the shock varies with the ex-ante information environment. Our model predicts that the defensive patenting response will be strongest for firms that were initially most opaque. These firms experience the largest increase in transparency and thus in competitive threat when the new disclosure standards are imposed. Consistent with this prediction, we find that treated firms with a more opaque ex-ante information environment exhibit a significantly larger increase in patenting.

To validate and complement our main findings, we examine another empirical setting in which firms' competitive risks plausibly increased due to enhanced transparency: the segment reporting reform under Statement of Financial Accounting Standards (SFAS) 131. Issued in 1997, SFAS 131 mandated firms to report segments aligned with how management organizes and evaluates the business, rather than by pre-determined categories ("management approach"). It also expanded disclosure requirements for each segment. We examine the effect of SFAS 131 in an empirical design parallel to the ASC 606 setting. We find that affected firms increase patent applications around the announcement of SFAS 131, and these patents are of lower quality. However, the effects on both dimensions are smaller and less persistent than those of ASC 606. This attenuation is consistent with institutional differences: segment reporting is broader and coarser than product- or contract-level revenue disaggregation. In terms of our framework, SFAS 131 represents a smaller shock to the baseline information environment. The SFAS 131 results provide nuanced validation for our main findings and reinforce the mechanism that disclosure-driven transparency lowers firms' patenting thresholds and induces defensive filings near the margin.

Our paper makes several contributions. First, we provide a novel, tractable framework to analyze how a firm's information environment interacts with its choice of patenting. A key feature of our model is that it is one of the few to comprehensively integrate the two defining features of the patenting system: legal protection and patent disclosure, embedding them in a baseline information environment that governs competitors' ability to search. While prior work often focuses on just one of these dimensions, our framework allows us to examine how a change in the baseline information environment, such as that from a financial mandate, affects firms' strategic trade-off.[7] This model generates novel, testable predictions about firm responses, including key dimensions of heterogeneity that we subsequently test.

Second, our paper contributes to the growing accounting literature that examines how corporate disclosure affects innovations (see a review by Glaeser and Lang, 2024). Prior studies have documented mixed findings across settings.[8] Our framework offers a lens to organize these empirical findings. First, patent counts reflect both firms' innovation activity and their patenting strategy given an innovation (e.g., Breuer et al., 2025), and our framework and empirical setting explicitly disentangle these two. Second, holding innovation fixed, we demonstrate that patenting decisions represent a trade-off between the *legal protection* effect and the *informational cost* effect. Depending on which effect dominates, the strategic response can go in either direction.[9] Third, our framework highlights heterogeneous effects of disclosure regulations, depending on firms' baseline protection policies (e.g., "never patenting" vs. "threshold patenting"). This dependence on baseline policies helps reconcile why disclosure effects vary across different regulatory settings and sample compositions.

We also contribute to the literature on firms' strategic responses to proprietary concerns (e.g., Leuz, 2004; Glaeser and Omartian, 2022; Aghamolla and Thakor, 2022; Gao et al.,

[7] We are among the very few papers that study legal protection and patent disclosure jointly in one framework (e.g., Anton and Yao, 2004; Hopenhayn and Squintani, 2016). Previous studies have largely focused on one aspect of the two features (e.g., on patent disclosure: Hegde et al. (2023); Kim and Valentine (2021); Dyer et al. (2024); Boot and Vladimirov (2025); on legal protection: Schankerman (1998); Bhattacharya and Guriev (2006); Arora et al. (2008)).

[8] Examples are: the Sarbanes-Oxley Act (Allen et al., 2022), the EDGAR rollout (Dambra et al., 2024; Chang et al., 2024; Chawla, 2023), changes in revenue recognition rules (Cetin, 2023) and the extensive European reporting regulations (Breuer et al., 2025).

[9] Our analysis of the ASC 606 setting suggests that the legal protection effect dominates in that setting. Similarly, the findings of Breuer et al. (2025) on EU disclosure regulation are consistent with the legal protection effect. In contrast, the informational cost effect appears more salient in the EDGAR rollout setting (Chang et al., 2024).

2025). Much of this research has focused on how firms strategically manage their own disclosure in response to competitive threats, for example, withholding sensitive information or reducing granularity (Dedman and Lennox, 2009; Li et al., 2018; Glaeser, 2018). We move beyond reporting choices to document real strategic adjustments; we are among the few studies that link tangible defensive actions to disclosure mandates (e.g., Bernard et al., 2018).[10]

Finally, our framework has broader implications. It can be used to analyze not just financial disclosure, but also other events that change a firm's information environment. For instance, new mandates on sustainability or workplace safety reporting could similarly reveal sensitive operational information. Likewise, the proliferation of big data and advanced data analytics can make it easier for competitors to discover a firm's profitable markets. To the extent that these shocks increase competitive risks by improving baseline information environment, our model predicts they would have a similar effect on firms' IP protection trade-offs.

2 Model

2.1 Setup

An incumbent firm i is endowed with an innovation that can be used to develop a new product line. The product line yields a baseline profit of θ, which is continuously distributed according to a distribution function F over $[\underline{\theta}, \overline{\theta}]$ with $0 < \underline{\theta} < \overline{\theta}$. We assume that F admits a log-concave density f.[11] After privately observing θ, the incumbent decides whether to patent

[10] In this respect, our framework is broadly related to studies that examine how disclosure and real decisions interact in various markets (e.g., Goldstein and Yang, 2019; Guttman and Meng, 2021; Matsuno, 2024). Specifically, we study disclosure in product market with a patenting option and demonstrate how financial reporting mandates influence firms' patenting behavior.

[11] Many common probability distributions are log-concave (e.g., normal, exponential, and uniform distributions). A log-concave density function has a unimodal shape and other desirable properties (Bergstrom

this invention. Let $a \in \{0,1\}$ denote the patenting decision, where $a = 1$ means patenting. When firm i chooses not to patent ($a = 0$), the firm keeps the innovation private. We denote the incumbent's patenting strategy by $\alpha : [\underline{\theta}, \overline{\theta}] \to \{0,1\}$.

An entrant firm j seeks to compete with firm i.[12] First, firm j exerts a *search effort* $e_s \in [0,1]$ to discover the product line and learn θ.[13] We normalize the discovery technology so that effort equals success probability: with probability e_s the search succeeds and j learns θ; with probability $1 - e_s$ it does not. The search effort is costly, and its cost is determined by both the information environment and the intensity of search. In particular, firm j incurs a search cost of $g(\eta)C_s(e_s)$, where C_s is a convex cost function and g is a smooth, increasing function. The parameter $\eta > 0$ captures the transparency of the information environment: a lower η corresponds to a more transparent environment, which makes search effort less costly. We interpret η as the overall information environment surrounding the incumbent. Both a financial disclosure regulation and the act of patent disclosure would decrease η.

If search is successful, the entrant firm j exerts a *competition effort* $e_c \in [0,1]$ to capture a share e_c of the baseline profit θ, at a convex cost of $C_c(e_c)$.[14] Competition efforts include engaging in advertisement campaigns, aggressive pricing strategies, and the development of substitutable products.

The payoff of firm j's competition effort depends on whether the innovation is protected by a patent. Following Abrams et al. (2013) and Argente et al. (2020), we model

and Bagnoli, 2005).

[12] We describe the model with a single entrant for simplicity. It represents the collective pressure of potential and incumbent competitors.

[13] In practice, typical search efforts include market research, competitive analysis, and consumer surveys, among other activities. By "discovering the product line," we mean that an entrant discovers a market with attractive opportunities (e.g., a market with growing consumer demand or a situation where the incumbent firm is struggling).

[14] Alternatively, e_c can be interpreted as the probability that firm j successfully displaces firm i. This reduced-form displacement technology can be microfounded in standard product-market models (e.g., Cournot with differentiation), where competition efforts translate into a share of the baseline profit.

patent protection as a "wall" of height $w \in (0, 1)$. Under patent protection, a competitor's substitutive product must differ sufficiently from the incumbent's. The "wall" parameter w captures the degree of differentiation required. When w is higher, the competitor can appropriate a smaller portion of the baseline profit for the same level of competition effort. When firm i does not patent, there is no protection wall. The payoff of the competition effort for firm j is thus

$$\pi_a^j(e_c, \theta, w) := e_c(1 - aw)\theta - C_c(e_c). \tag{1}$$

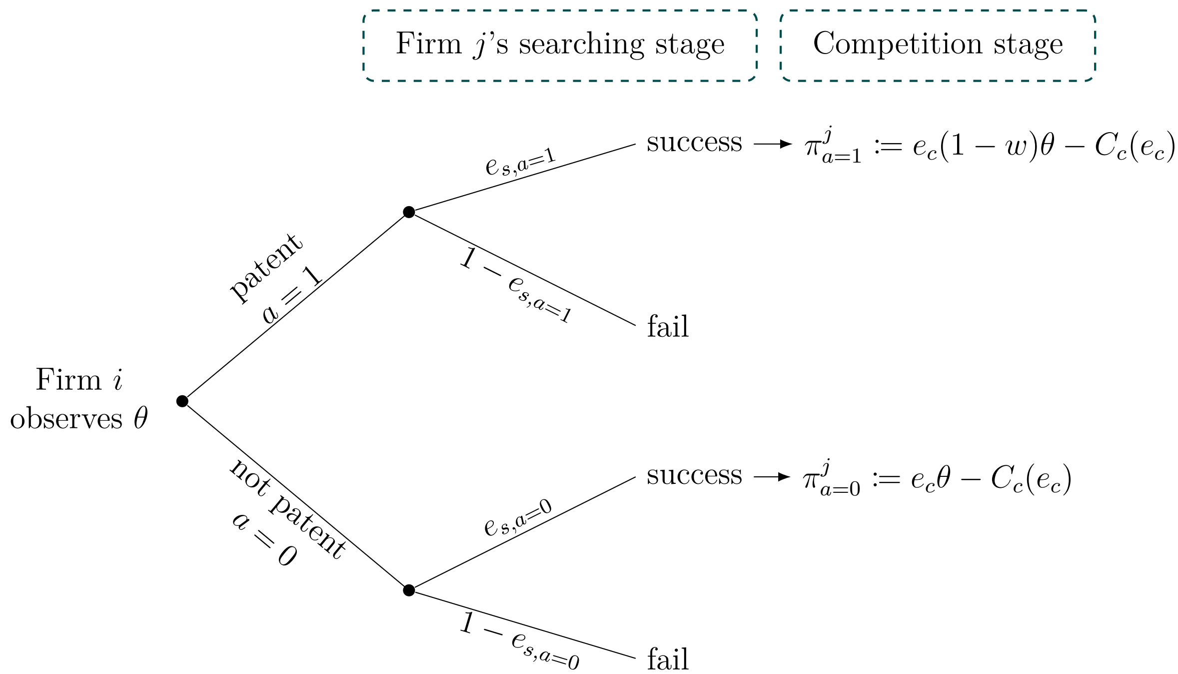
Firm i faces the trade-off between the legal protection provided by costly patenting and the intensified competition in the absence of a patent. If firm i chooses to patent, the innovation is protected by a patent wall of height w. Patenting involves two types of costs. First, there is a fixed cost, denoted by $C_p > 0$, which includes administrative fees, legal expenses, and other filing-related costs. Second, there is an indirect informational cost: as the patent system requires public disclosure about the invention, outsiders can learn technological know-how through the disclosed information. The patent disclosure requirement effectively reduces the information environment parameter from η_0 to $\eta_1 < \eta_0$.[15] If firm i chooses not to patent, it avoids both the fixed cost and the informational cost. Firm i's expected payoff is thus:

$$\left(1 - e_{s,a}^*\right)\theta + e_{s,a}^*\left[ae_{c,a}^* w + (1 - e_{c,a}^*)\right]\theta - C_p a, \tag{2}$$

where $e_{s,a}^*$ and $e_{c,a}^*$ are the equilibrium search effort and competition effort of firm j given firm i's patenting decision a, and $\eta_a = \eta_1$ if $a = 1$ and $\eta_a = \eta_0$ if $a = 0$. With probability $\left(1 - e_{s,a}^*\right)$, the entrant does not learn θ, and firm i receives the full baseline profit θ; with

[15] Patent disclosure may spur follow-up innovations, which could harm the filing firm's product market competition in the future (Kim and Valentine, 2021). The reduction in η represents the discounted sum of these future costs.

Figure 1: Sequence of events.



probability $e^*_{s,a}$, firm j learns θ and captures a fraction of the market, depending on the patenting decision and the degree of the legal protection. With patenting, firm j captures $(1-w)e^*_{c,a=1}$ of the market share, leaving the residual share of $1-(1-w)e^*_{c,a=1}$ to firm i. Without patenting, firm j captures the share $e^*_{c,a=0}$, leaving $1-e^*_{c,a=0}$ to firm i.

Figure 1 summarizes the timeline of the model. First, firm i privately observes an innovation outcome of value θ. The firm then decides whether to patent the innovation. Upon observing the patenting decision, the competitor, firm j, chooses a search effort e_s; with probability e_s, it learns θ and subsequently chooses a competition effort e_c. Finally, payoffs are realized according to (1) and (2).

Financial disclosure and patent disclosure

In the model, two types of disclosure play a central role. The first is financial disclosure, which determines the baseline transparency parameter η_0. A more transparent disclosure regime corresponds to a lower η_0. The second is the information contained in patent disclosure, captured by the change in $\eta_0 - \eta_1 > 0$. The interaction between these two information sources plays an important role. On the one hand, more transparent financial disclosure may substitute for patent disclosure. This occurs if the financial disclosure provides information that overlaps with patent disclosure. For example, if granular financial data already helps the competitor identify a profitable product line, then the incremental informational value of patent disclosure is diminished. On the other hand, financial disclosure may complement patent disclosure. This occurs if a competitor learns more about the focal firm by combining the two sources of information. To capture the substitutability/complementarity of information, we specify η_1 as an increasing function of η_0. The nature of their relationship is governed by the magnitude of this derivative:

Definition 1. We say that financial disclosure *substitutes* patent disclosure if $\frac{\partial \eta_1(\eta_0)}{\partial \eta_0} = 0$ and *complements* it if $\frac{\partial \eta_1(\eta_0)}{\partial \eta_0} > 0$.

Recall that η_0 denotes the information environment before patenting and η_1 the information environment after patent disclosure. In the substitute case, η_1 does not depend on η_0: once the firm patents, the information environment is pinned down at η_1 regardless of the starting level of financial transparency. Intuitively, this captures the situation where conditional on patenting, financial disclosure does not further change what competitors know. Patent disclosure is sufficiently informative, and additional financial disclosure is redundant. Since the firm's decision is whether to move from η_0 to η_1 by patenting, more transparent financial disclosure (i.e., a decrease in η_0) reduces the incremental effect of patent disclosure: the additional signal provided by patent disclosure, $\eta_0 - \eta_1$, shrinks. This reflects the idea that financial disclosure has already "done some of the work" of what patent disclosure would otherwise reveal. In the complement case, $\frac{\partial \eta_1(\eta_0)}{\partial \eta_0} > 0$, a more informative financial environment (a decrease in η_0) also makes the post-patent environment more informative (a lower η_1). In other words, combined patent and financial disclosure yields a more transparent overall information environment than patent disclosure alone.

Solution Concepts

We consider Perfect Bayesian Equilibrium (PBE). In particular, the competitor's belief upon the incumbent's patenting decision is determined by Bayes' law (as long as the decision is on the equilibrium path).

For the sake of exposition, throughout the main text, we assume that cost functions are quadratic in efforts:

$$C_s(e) = C_c(e) = \frac{k}{2}e^2,$$

where $k > 0$ is large enough so that the effort choices are interior. In the appendix, we prove the results for general cost functions.

2.2 Analysis

Competitor's Decisions

We solve the model backward and begin with firm j's decision at $t = 2$. If its search effort at $t = 1$ fails, then firm j has no choice to make at $t = 2$. If the search effort is successful, firm j chooses a competition effort e_c for each patenting decision $a \in \{0, 1\}$:

$$\max_{e_c \in [0,1]} \pi_a^j(e_c, \theta, w) = e_c(1 - aw)\theta - C_c(e_c).$$

Firm j's optimal competition effort solves the following first-order condition:

$$(1 - aw)\theta = \frac{\partial C_c}{\partial e_c}(e_c^*). \tag{3}$$

With quadratic costs, the competition effort choices are $e^*_{c,a} = k^{-1}(1-aw)\theta$. Since $w \in (0,1)$, we have $e^*_{c,a=0} > e^*_{c,a=1}$: in the absence of patent protection, firm j competes more aggressively. Furthermore, $e^*_{c,a=1}$ is decreasing in w: a higher degree of patent protection softens firm j's competition effort. If the patent protection is perfect, the competitor is excluded from the market (i.e., $\lim_{w\to 1} e^*_{c,a=1} = 0$). The corresponding payoff for firm j given the patenting decision a is

$$\pi^j_a(e^*_{c,a}, \theta, w) = \frac{(1-aw)^2\theta^2}{2k}.$$

At the search stage, firm j chooses a search effort e_s, anticipating the period-2 product market competition outcome. For each patenting decision a, firm j's optimal search effort e_s solves:

$$\max_{e_s} \; e_s \mathbb{E}[\pi^j_a(e^*_{c,a}, \theta, w) \mid \alpha(\theta) = a] - g(\eta_a) C_s(e_s),$$

and the optimal search effort given the patenting decision a is

$$e^*_{s,a} = \frac{(1-aw)^2 \mathbb{E}[\theta^2 \mid \alpha(\theta) = a]}{2k^2 g(\eta_a)}.$$

When firm j chooses a search effort, it forms a belief about the incumbent's invention θ based on the patenting decision. In particular, given a patenting strategy α, a patenting decision a signals that $\theta \in \{\theta \mid \alpha(\theta) = a\}$. For example, if firm i is more likely to patent when θ is high, then firm j revises its belief about θ upward: $\mathbb{E}[\theta^2 \mid \alpha(\theta) = 1] > \mathbb{E}[\theta^2 \mid \alpha(\theta) = 0]$. Beyond this signaling channel, firm i's patenting decision affects firm j's search effort through two additional channels. First, patent disclosure improves transparency and lowers the competitor's search cost (i.e., $\eta_1 < \eta_0$). This force intensifies firm j's search effort, all else equal. Second, patenting grants legal protection and reduces the competitor's expected profit at the competition stage. In turn, the competitor's expected return on search diminishes, which depresses its search effort. This legal protection effect is particularly strong when patent protection is strong (i.e., w is high).

Incumbent's Decisions

Having solved firm j's optimal search and competition effort, we now analyze firm i's patenting strategy at $t = 1$. Firm i solves the following objective (Equation (2)):

$$\max_{a\in\{0,1\}} \Pi^i(a, \theta) := \left(1 - e^*_{s,a}\right)\theta + e^*_{s,a}(ae^*_{c,a}w + 1 - e^*_{c,a})\theta - C_p a.$$

Denote by $\Delta(\theta)$ the net gain from patenting. We decompose $\Delta(\theta)$ into the direct cost component and the net benefit as a result of the entrant's search and competition effort:

$$\begin{aligned}\Delta(\theta) &= \Pi^i(1, \theta) - \Pi^i(0, \theta) \\ &= (e^*_{s,a=0}e^*_{c,a=0} - e^*_{s,a=1}e^*_{c,a=1}(1 - w))\theta - C_p \\ &= e^*_{c,a=0}\underbrace{\left[e^*_{s,a=0} - (1 - w)^2 e^*_{s,a=1}\right]}_{:=NB}\theta - C_p.\end{aligned} \tag{4}$$

The decomposition (4) illustrates the key economic forces that shape firm i's patenting decision. Patenting weakens the entrant's competition after discovery (the factor $(1 - w)^2$) but it also makes the entrant's search less costly due to patent disclosure $\eta_1 < \eta_0$. The term NB represents the net competitive benefit of patenting that arises from firm j's optimal search and competition responses to firm i's patenting decision. The competition effort without patenting, $e^*_{c,a=0}$, scales the economic stakes. Firm i patents if and only if $\Delta > 0$. The following proposition summarizes the incumbent's patenting strategy.

Proposition 1. *There exist $0 < \underline{w} < \overline{w} < 1$ such that an equilibrium satisfies the following:*

- *If $w > \overline{w}$, then firm i patents if and only if $\theta > \tau$ for some $\tau > 0$. With quadratic costs,* *the threshold solves*

$$\left(\frac{\mathbb{E}[\theta^2 \mid \theta < \tau]}{2g(\eta_0)} - \frac{(1-w)^4\mathbb{E}[\theta^2 \mid \theta > \tau]}{2g(\eta_1)}\right)\frac{\tau^2}{k^3} = C_p.$$

- *If $w < \underline{w}$, then firm i never patents.*

With quadratic costs, the cutoffs are given as follows:

$$\overline{w} := 1 - \sqrt[4]{\frac{g(\eta_1)}{g(\eta_0)}\frac{\underline{\theta}^2}{\overline{\theta}^2}}, \quad \underline{w} := 1 - \sqrt[4]{\frac{g(\eta_1)}{g(\eta_0)}\frac{\mathbb{E}[\theta^2]}{\overline{\theta}^2}}.$$

Proof. See the appendix. □

Depending on the level of protection that a patent can provide, the optimal strategy takes one of two forms: a "never patent" policy or a "threshold" policy. When patent protection is strong enough ($w > \overline{w}$), firm i patents when θ is sufficiently high (the "threshold" policy). In this equilibrium, when θ is low, the relative benefit of patent protection is small, so the firm chooses not to patent. The cutoff $\overline{w}$ depends on the information environment, specifically, the parameters η_0 and η_1. As patent disclosure becomes more informative (i.e, as $\eta_0 - \eta_1$ increases) the cutoff $\overline{w}$ rises. This result highlights a tension between the monopoly rights conferred by the patent and the information revealed through patent disclosure. As patent disclosure becomes more informative, stronger legal protection is required to make patenting worthwhile. Indeed, if legal protection is weak enough ($w < \underline{w}$), firm i never patents and hence the "never patent" policy.

The Role of Financial Disclosure Mandates

To examine how financial disclosure mandates influence firms' patenting strategy in our model framework, it's important to discuss the relation between the *new* financial disclosure regulation and patent disclosure. We consider the case $w > \overline{w}$, i.e., the threshold patenting policy.

Corollary 1. *A financial disclosure mandate (a decrease in η_0) affects the patenting threshold:*

- *If financial disclosure and patent disclosure are substitutes ($\frac{\partial \eta_1(\eta_0)}{\partial \eta_0} = 0$), or if the disclosures are complements ($\frac{\partial \eta_1(\eta_0)}{\partial \eta_0} > 0$) but the degree of complementarity is weak, patenting threshold τ decreases, i.e., firm i patents more.*
- *If financial disclosure and patent disclosure are complements and the degree of complementarity is strong, patenting threshold τ increases, i.e., firm i patents less.*

In our model, a new financial disclosure mandate represents a decrease in the baseline information environment parameter η_0, and it creates two competing effects on the firm's patenting trade-off. First, a more transparent baseline information environment (i.e., a lower η_0) leads to more intensive competitor search when the firm *does not* patent ($e^*_{s,a=0}$). As a result, keeping the innovation private becomes riskier; this effect lowers the patenting threshold τ (more patenting). Second, if financial disclosure and patent disclosure are complements, a decrease in η_0 also causes η_1 to decrease, which leads to more competitor search when the firm *does* patent ($e^*_{s,a=1}$). This effect raises the patenting threshold (less patenting), all else equal. The net result depends on which of these two effects dominates.

According to Corollary 1, the first effect dominates in a wide range of cases. Firms subject to financial disclosure mandates will patent more when financial and patent disclosures are substitutes, or when their complementarity is weak. The substitution case offers the clearest intuition. Greater transparency in financial disclosure raises the relative benefit of patent *legal protection*, since keeping the innovation private becomes riskier. At the same time, the relative *informational cost* of patenting falls: some of what a patent would reveal has already been disclosed through financial reporting, so the incremental information revealed by patenting is smaller. By contrast, when financial and patent disclosures are strong complements, the informational channel works in the opposite direction. Combining the two disclosures is substantially more revealing for rivals. In that case, the legal-protection benefit of patenting can be outweighed by the increase in the informational cost, and a disclosure mandate can lead to a net decrease in patenting.

The model also predicts how the value of patented innovations changes when firms patent more under financial reporting mandates.

Corollary 2. *Suppose financial and patent disclosure are substitutes or the complementarity is sufficiently small (i.e., τ decreases when η_0 decreases), the average value of patented inventions decreases when η_0 is lower, that is, $\mathbb{E}[\theta \mid \theta > \tau]$, is increasing in η_0.*

Corollary 2 highlights the selection effect driven by η_0. The intuition follows directly from Corollary 1. A higher τ implies that only inventions with greater value ($\theta > \tau$) are patented. Consequently, the pool of patented inventions becomes more selective, increasing the average value of a patented invention. Corollary 1 suggests that the patenting threshold τ decreases as η_0 decreases. When disclosure regulations enable competitors to search and imitate more easily, firm i patents less selectively, decreasing the average value of the patented innovations.

These findings illustrate how financial transparency affects firms' trade-offs when making strategic patenting decisions. In the empirical analyses below, we test the model's predictions and examine which theoretical channel dominates in practice.

3 Institutional Background

The main setting we utilize is the revenue disaggregation requirement under ASC 606, "Revenue from Contracts with Customers." Issued by the Financial Accounting Standards Board (FASB), it is widely regarded as one of the most significant accounting policy changes in the past decade.[16] The first exposure draft of the standard was issued in 2010 to solicit public comments, followed by extensive redeliberations based on feedback from various stakeholders. In May 2014, FASB issued the final version of the standard.[17] The new standard became effective for annual reporting periods beginning after December 15, 2017.[18] Since firms learned about the finalized mandates in mid-2014, they had ample time to respond and adjust.

ASC 606 imposed new disclosure requirements related to revenue. Among these, the mandate to disaggregate revenue had significant impacts. Companies are now required to disaggregate revenue into categories that reflect the nature, amount, timing, and uncertainty of revenue and cash flows arising from contracts with customers. This disaggregation is intended to provide users of financial statements with a clearer understanding of a company's various revenue streams and how they contribute to overall financial performance (Hinson et al., 2024).

Although companies have the flexibility to determine the methods and level of detail for disaggregation (ASC 606-10-55-91), regulators do enforce the revenue disaggregation requirement and require firms to provide justifications when their disaggregation is deemed insufficient. For example, Ford and Alphabet have received comment letters from the SEC asking them to justify how their revenue disaggregation fulfills the mandate.[19] The effectiveness of the revenue disaggregation mandate is also evidenced by academic studies. Hinson et al. (2024) find that more than half of the firms in their sample significantly increased the use of revenue-related tags in their financial statements following the implementation of ASC

[16]See Welcome to Year 1 of ASC 606 (`https://www.accountingtoday.com/opinion/welcome-to-year-one-of-asc-606`). Accessed 11/21/2025.

[17]See ASU 2014-09 REVENUE FROM CONTRACTS WITH CUSTOMERS (TOPIC 606) (`https://fasb.org/page/PageContent?pageId=/projects/recentlycompleted/revenue-recognition-summary.html`). Accessed 11/21/2025.

[18]For most of the firms, fiscal year 2018 marked the first year of ASC 606 adoption.

[19]See SEC Comment Letter to Alphabet (`https://www.sec.gov/Archives/edgar/data/1652044/000165204417000031/filename1.htm`) and SEC Comment Letter to Ford (`https://www.sec.gov/Archives/edgar/data/37996/000003799617000077/filename1.htm`).

606. This suggests that companies are largely complying with the disaggregation mandate.

The increased volume and salience of revenue disclosure impose proprietary costs on firms, exposing them to greater competitive risks (Beyer et al., 2010; Cetin, 2023). Disaggregated revenue information could inform (potential) competitors about the profitability and size of specific markets, as well as the disclosing firm's near-term strategies and product mix (Dedman and Lennox, 2009; Bernard et al., 2018; Berger et al., 2024). Figure 2 provides an example of how a company shifted from reporting revenue sources from two broad segments to disclosing seven categories of revenue sources.

4 Data

4.1 Sample Selection

Our sample consists of U.S.-listed firms. For the ASC 606 setting, the sample period is 2010–2021. We use 10-K filings from the SEC's EDGAR system to identify firms impacted by the disaggregation mandate. Financial statements data come from Compustat, stock prices and returns from CRSP, and patent-related data from the Kogan et al. (2017) patent database. We balance the panel over 2010–2021; this holds firm composition fixed and prevents entry/exit or sporadic reporting from mechanically shifting sample averages. Our main ASC 606 sample contains 9,696 firm–year observations for 808 unique firms.

To validate our main results in an independent setting, we assemble a second sample around the announcement of segment-reporting reform under SFAS 131. The sample period is 1993–2001. We construct outcomes and controls analogous to the ASC 606 setting. The SFAS 131 sample contains 12,897 firm–year observations for 1,433 unique firms.

4.2 Disaggregating Firms (Treatment Firms)

We define "disaggregating firms" as those that report revenue disaggregation under ASC 606 in their 10-K XBRL filings. Specifically, a firm is classified as a disaggregating firm if it uses one of the XBRL tags for revenue disaggregation under ASC 606.[20] We construct a time-invariant treatment indicator, $Treat_i$, which equal to one for disaggregating firms and zero otherwise. Control firms are those that do not use any of the XBRL tags for revenue disaggregatio. Our identification assumption is that treatment assignment is effectively exogenous in the sense that noncompliance with the mandate is limited and not systematically related to changes in patenting behavior. While the absence of disaggregation could, in principal, reflect noncompliance rather than a true lack of disaggregated revenue, SEC enforcement actions suggest that firms are unlikely to omit disaggregation when material revenue segmentation exists.[21]

To validate that our treatment classification captures a meaningful difference in firms' revenue disclosure, we examine whether disaggregating firms exhibit a larger pre-post increase in the number of reported revenue items than non-disaggregators. We construct a firm-year count of all revenue-related XBRL elements ($RevenueTags$) by parsing both financial statements and revenue footnotes and extracting tag names, values and periods.[22] If our classification captures revenue disaggregation, treated firms should display a larger increase in $RevenueTags$ after adoption. Figure 3 confirms this pattern: treated firms show a pronounced increase in reported revenue items, whereas non-disaggregating firms exhibit only a modest increase. For treated firms, the mean (median) $RevenueTags$ jumps from 15.9 (14) in 2017 to

[20] See Appendix A for further details.

[21] See SEC Comment Letter to Alphabet (`https://www.sec.gov/Archives/edgar/data/1652044/000165204417000031/filename1.htm`) and SEC Comment Letter to Ford (`https://www.sec.gov/Archives/edgar/data/37996/000003799617000077/filename1.htm`).

[22] We exclude: (i) tags unrelated to revenue recognition, (ii) adjustment-type entries via dimension/member attributes that simply restate the same underlying revenue amount, and (iii) clearly irrelevant items that do not pertain to current-period revenue performance (e.g., "unearned revenues").

27.5 (22) in 2018. In contrast, controls move from 9.5 (7) to 13.1 (8) over the same window. This gap persists in the post-adoption period, consistent with ASC 606 materially increasing revenue disaggregation among treated firms and validating our treatment classification.

4.3 Patent-Related Variables

Our main outcome is the number of patent applications at the firm-year level. We count patents based on their application year (instead of grant year) to align the timing of the firm's protection decision with the disclosure shock and to reduce truncation arising from heterogeneous grant lags. We include only those patents that are ultimately granted, allowing us to focus on patents that cleared examination.

To measure the quality of patents, we use the number of forward citations (Kogan et al., 2017; Glaeser and Lang, 2024). We measure the number of forward citations at the patent level rather than aggregating to the firm-year level. Forward citation counts are subject to truncation bias, as newer patents have had less time to accumulate citations (Hall et al., 2005). To address this issue, we analyze forward citations with CPC-class and grant-month fixed effects, and we scale each patent's citations by dividing by the CPC class $\times$ grant-month average.

4.4 Descriptive Statistics

Table 1 presents descriptive statistics for the main variables in our study—patenting activity, financial characteristics, and firms' R&D expenditure. Out of 9,696 firm-year observations (808 unique firms), 6,732 observations (561 firms) are classified as treated firms, while 2,964 observations (247 firms) serve as controls. The mean (median) number of patent applications per firm-year is 71.98 (3), indicating the data is highly skewed, which is typical for patent activity (Lerner and Seru, 2022). In the typical firm-year, a patent receives on average about 2.37 citations and a median of 1.90 citations. We also provide descriptive statistics for the subsample of treated firms that provide revenue disaggregation (Panel B) and control firms that do not (Panel C).

5 Empirical Analysis

5.1 Financial Transparency and Patent Applications

In our empirical analysis, we first examine the 2014 announcement of the revenue disaggregation mandate (ASU 2014-09) as an exogenous shock to firms' future information environment. Foreseeing enhanced transparency and intensified competition, firms may adjust their patenting strategy to seek more legal protection, as our theoretical model predicts.

To test this prediction, we estimate the following difference-in-differences (DiD) specifications:

$$Y_{i,t} = \beta\, Treat_i \times Post_t + \Gamma\, Controls_{i,t} + FE + \epsilon_{i,t}, \tag{5}$$

$$Y_{i,t} = \sum_{t \neq 2014} \beta_t\, Treat_i \times Year_t + \Gamma\, Controls_{i,t} + FE + \epsilon_{i,t}, \tag{6}$$

where the outcome variable $Y_{i,t}$ is a measure of patenting activities.

We estimate (5) to evaluate the average effect of the new regulation and (6) to explore the dynamics of the treatment effects. As detailed in Section 4.2, we classify firms providing disaggregated revenue information post-implementation of ASC 606 as treatment firms ($Treat_i$). A distinct feature of our design is defining the post-period ($Year_t$) as starting in calendar year 2015, the first full year after the 2014 announcement, rather than at the 2018 implementation. This design allows us to isolate the strategic response to the anticipated competitive threat from other confounding real effects of the mandate's eventual implementation, such as improved liquidity or reduced cost of capital (Leuz and Wysocki, 2016; Goldstein et al., 2023).

We estimate Equations (5) and (6) using linear OLS and negative binomial regressions. The negative binomial estimation addresses concerns about the count nature and skewed distribution of patent applications. For the OLS regressions, we define the dependent variable as the logarithm of the number of patents plus one: $Y_{i,t} = \ln(\#(Patents)_{i,t} + 1)$. For the negative binomial regressions, we use the raw patent count: $Y_{i,t} = \#(Patents)_{i,t}$.[23] All specifications include fixed effects for the firm and year.

Figure 4 shows the dynamics of treatment effects by year. We observe no statistically significant pre-trend prior to the 2014 announcement. After 2014, the treatment effect follows an intuitive pattern: treatment firms begin patenting at a significantly higher rate than control firms, and this gap widens over time. The persistent upward trend after 2015 aligns with the disclosure mandate's implementation in fiscal year 2018. Treated firms appear to adjust their patenting strategy in anticipation of the mandate around 2017, continuing to do so as implementation became imminent.

Table 2 presents the regression estimates. Columns (1) and (2) report the average effect from Equation (5). Treated firms filed significantly more patent applications following the announcement. The estimates are similar across the OLS specification and the negative binomial model. The magnitude of the effect is economically meaningful: on average, treated firms increase their patenting rates by approximately 11.95% compared to control firms following the announcement of the mandate.[24]

Columns (3) and (4) shows the estimation results for different time periods. We bundle

[23] As a robustness check, we consider two modifications of the model: 1) We use $\ln(\#(Patents)_{i,t})$ instead of $\ln(1 + \#(Patents)_{i,t})$ as the outcome variable in the OLS estimation, and 2) We use a Poisson regression with raw count of patents as the outcome variable. The results are tabulated in Table C.1. Results are consistent with our main specifications.

[24] $\exp(0.1129) = 1.1195$

the years 2010–2013, 2015–2017, and 2018–2021, splitting the post-period into the anticipation window (2015–2017) and the post-implementation window (2018–2021). The results confirm the visual evidence from Figure 4, the treatment effect is positive in the initial anticipation window and becomes larger and more statistically significant after the mandate's implementation.

In summary, the findings are consistent with our theoretical prediction: the revenue disaggregation mandate enhanced transparency, prompting affected firms to patent more. Interpreted through our model (Corollary 1), this empirical result suggests that affected firms' competitive concern and the consequent incentive to seek legal protection through patenting dominate potential informational costs of patent disclosure. Therefore, we infer that the relationship between revenue disaggregation required by ASC 606 and patent disclosure is one of substitutes or weak complements.

5.2 Consequences for Patent Quality

We next examine whether the quality of patents filed by treated firms changed along with the increase in patenting rates. Our theoretical model (Corollary 2) predicts that the average quality of patented inventions should decrease due to strategic adjustments in response to enhanced transparency. In particular, our model suggests that the increase in patenting comes from lower-value, "marginal" inventions that were not worth patenting before the disclosure mandate. To test this prediction, we examine the effects on patent-level quality measures. Our primary quality measure is the number of forward citations each patent receives (Glaeser and Lang, 2024). To address the truncation issue of forward citations (Hall et al., 2005), we scale the number of forward citations by the grant-month average within the same CPC class.

We first examine the dynamics of the treatment effect. Figure 6 shows the application-month level treatment effects. Relative to control firms, the average forward citations for patents filed by treatment firms began to decline after around 2017, while no pre-trend is observed.

To examine the average change in patent quality, we estimate the patent-level DiD specifications using forward citations as the outcome variable. Table 3 reports the estimates. Columns (1) and (2) use the natural log of unscaled forward citations as the outcome variable. Columns (3) and (4) scale the outcome by cohort averages to address the truncation bias. Following Hegde et al. (2023), we include CPC class and grant-month fixed effects to control for temporal and technological heterogeneity. We report results that additionally include firm-fixed effects as well. We observe that the number of unscaled forward citations for patents filed by treatment firms declines by 10.85% following the announcement of the disaggregation rule (Column 1).[25] Controlling for firm fixed effects in Column (2), the decline attenuates to 6.92% but remains statistically significant.[26] Estimates using scaled forward citations are quantitatively similar, alleviating concerns about truncation bias.

We also examine whether our findings extend to alternative patent quality measures. Columns (1) and (2) of Table C.3 show that, after ASC 606 disaggregation mandate, treated firms' patents are significantly less likely to fall into the top decile of the forward citation distribution. Columns (3) and (4) document a modest increase in the dispersion of cited technology classes (i.e., patent originality), while Columns (5) and (6) show a decline in the dispersion of citing technology classes (i.e., patent generality).[27] These patterns suggest that, in the post-mandate period, patents filed by treated firms draw on a more diversified set of prior technologies but have a narrower, less generalizable technological impact.

[25] $\exp(-0.1149) - 1 = -0.1085$

[26] $\exp(-0.0717) - 1 = -0.0692$

[27] Following Trajtenberg et al. (1997), the originality measure is defined as one minus the Herfindahl index of cited technology classes, and the generality measure is defined analogously using citing classes.

Taken together with our citation results, this evidence is consistent with ASC 606 primarily encouraging additional, marginal recombinations of existing knowledge rather than broadly influential, path-breaking innovations.

These findings align with the predictions of our strategic patenting model. The enhanced transparency from the disaggregation mandate increased the perceived competitive risks of keeping the innovations private, making patenting a more attractive option. Affected firms thus started to patent inventions of lower value, for which the cost of patenting previously outweighed the benefits. Consequently, while firms increased their patenting rates, the average quality of patented inventions declined.

5.3 Cross-sectional Test: Different IP Protection Strategies

Our analyses so far show that firms generally respond to heightened competitive risks by filing more patents, often at the expense of average patent quality. However, this average pattern may obscure heterogeneity in firms' existing IP protection strategies.

Our theoretical model provides a prediction for this heterogeneity. The model generates two distinct forms of optimal patenting policy: a "never patent" policy and a "threshold" policy. We hypothesize that firms that rely heavily on trade secrecy are in a "never patent" equilibrium. For these firms, the patenting decision is not at the active margin. Therefore, a marginal shock from the new disclosure mandate is unlikely to be large enough to flip a "never patent" firm into the patenting equilibrium. Moreover, shifting from a "never patent" to a threshold patenting policy would be costly, as it requires building administrative infrastructure and adjusting organizational norms. Prior literature also suggests that firms vary in their reliance on patents versus trade secrecy (Cohen et al., 2000; Glaeser, 2018).

To assess whether and how heterogeneity in existing IP protection strategies affects firms' responses to competitive shocks, we conduct a cross-sectional analysis that splits firms based on their pre-shock reliance on trade secrecy. Following Glaeser (2018), we partition firms by whether they intensively discuss trade secrecy in their EDGAR filings. The variable *Pre TradeSecret* takes the value of 1 if the firm shows an above-median count of mentioning of trade secrecy in the pre-treatment period. We predict that these firms will be less responsive in patenting to the disaggregation mandates. We then incorporate this variable into our DiD specifications.

As shown in Table 4, we observe muted treatment effects of ASC 606 on patent filings among firms that historically relied on trade secrecy. Similarly, results in Table 5 indicate that for firms more reliant on trade secrecy, the quality of patents filed after treatment did not experience a significant decrease. These results are consistent with our model, suggesting that secrecy-oriented firms are not at the active margin of patenting decisions and are thus less compelled to adjust their strategy.

5.4 Cross-sectional Test: Ex-Ante Information Environment and Outside Monitoring

Our model predicts differential effects of disclosure regulation depending on the firm's ex-ante information environment. The disaggregation mandate (a decrease in η_0) represents a larger shock to a firm's competitive environment if that environment was opaque to begin with (i.e., had a high initial η_0).[28] A firm that is already highly transparent has less new, competitively sensitive information to reveal, so the change in its secrecy risk is small. Conversely, a firm that was previously opaque experiences the largest increase in its secrecy risk and should therefore have the strongest defensive patenting response.

We test this prediction by measuring each firm's ex-ante opacity using analyst following.

[28] More precisely, if the disclosure regulation induces a new baseline information environment of level η_0', then the improvement in transparency, measured by $\eta_0 - \eta_0'$, is greater when η_0 is higher.

We average the number of analysts covering the firm over the pre-period (2011 to 2014). To ensure that the measure captures firm-specific opacity rather than just size or industry norms, we residualize this measure: we remove the variation in coverage explained by firm size and by 2-digit NAICS industry fixed effects (Yu, 2008; Hong et al., 2000). We then flip the sign of the residual so that larger values denote greater opacity. For robustness, we also create a binary indicator for the most opaque group by flagging firms in the bottom tercile of the pre-period visibility distribution.

Table 6 shows the estimation results using patent applications as the outcome. The results support our model's predictions. Column (1) shows that firms with an opaque information environment before the treatment increase patenting significantly more after the ASC 606 announcement than less opaque firms. Column (2) shows similar results using the binary indicator for opacity. Table 7 shows the effect on patent quality. The decline in average patent quality post-ASC 606 is concentrated among firms that were more opaque ex ante.

The cross-sectional results are consistent with our model's predictions and provide further support for the view that the observed effect is not a broad sectoral trend, but a strategic response. The increase in patenting is concentrated among firms that are at the margin of patenting decisions and firms that experience the largest shock to their baseline information environment (the opaque firms).

5.5 Innovation Input

Our analysis so far has documented a strategic shift in firms' patenting behavior in response to enhanced transparency. Our theoretical framework characterizes this shift as a change in firms' propensity to patent, conditional on a given stream of innovations. To distinguish this mechanism from the alternative that firms changed their innovation activities, we now test whether the mandate affected innovation inputs, and whether our main patenting results persist after controlling for R&D.

To do so, we examine whether firms' innovation input measures change following the treatment, using the same empirical design as in Equation (5). We use R&D expenditure and R&D-related labor input as outcome variables and run DiD regressions analogous to our main patent specifications.[29] As shown in Table 8, we find no significant change in the R&D investment of treated firms after the revenue disaggregation announcement relative to control firms. One interpretation is that adjusting the patenting threshold is a direct and relatively fast response for protecting the innovation pipeline, mitigating the need for a more costly change to R&D in the case of a shock of the magnitude of ASC 606.

We also rerun our main patent application and citation regressions while explicitly controlling for firms' R&D expenditure. The treatment effects, tabulated in Table C.2, are quantitatively similar. These findings support the claim that the observed increase in patenting is likely a strategic shift in IP protection policy, not a change in underlying innovation activity.

5.6 Alternative Setting: SFAS 131

To validate the results and complement the main setting, we leverage another empirical setting: the segment reporting standard, SFAS 131. Implemented in 1997, the standard replaced SFAS 14 to address the mismatch between external reporting and internal management practices ("management approach"). The new standard expanded required disclosures to include inter-segment transactions, key expenses, and segment performance metrics, thereby aligning external reporting with internal governance. While this reform improved

[29] R&D expenditure is taken from the financial statements; R&D-related labor input variables are from Revelio Labs.

transparency and decision-usefulness for investors, it also heightened managers' concerns about revealing competitively sensitive information (Berger and Hann, 2007).

Through the lens of our model, both ASC 606 and SFAS 131 serve as shocks that make the firms' information environment more transparent, but their institutional details suggest a difference in magnitude. ASC 606's granular, product-level disclosures provide direct, actionable insights for rivals, representing a relatively large reduction in the baseline opacity. SFAS 131's broader, segment-level data represents a weaker, less precise information shock.

We follow prior literature (Berger and Hann, 2003; Cho, 2015) and define treatment firms as those that changed their segment disclosures upon the adoption of SFAS 131. We define treatment as beginning with the release of the initial exposure draft of SFAS 131 in January 1996. Upon this announcement, firms could reasonably anticipate the regulatory shift and begin adjusting their strategic behavior.

Results for this analysis are presented in Table 9. While the SFAS 131 estimates align directionally with our main findings (in Table 2), the economic magnitude and statistical significance are attenuated. Column (1) indicates that firms affected by SFAS 131 increased patent applications by 4.77% relative to control firms in the OLS model, a statistically significant effect at the 95% level.[30] This magnitude is approximately half of the treatment effect observed under ASC 606. The yearly treatment effects (Figure 5) show an upward trajectory in point estimates, but the increase is modest, with no statistically significant post-treatment coefficients at conventional levels. Negative binomial regressions in columns (2) and (4) yield quantitatively similar results.

We attribute this attenuation to differences in disclosure granularity between the two

[30] $\exp(0.0466) = 1.0477$

standards. The 3M Inc. example is illustrative: under SFAS 131, 3M's fiscal year 1997 10-K disclosed just three broad segments (Industrial and Consumer; Life Sciences; and Corporate/Unallocated).[31] In contrast, under ASC 606, 3M's fiscal year 2019 10-K reported 27 distinct product/service lines (e.g., oral care and drug delivery) within its segments, exposing previously obscured profitability metrics.[32] This attenuation is consistent with our framework. Because segment reporting is broader and coarser than ASC 606, it represents a smaller shock to the baseline information environment. Our model predicts that such a smaller shock triggers a weaker strategic response.

Moreover, we find consistent evidence for the effects on patent quality. Results in Table 10 indicate that SFAS 131-affected firms exhibit statistically significant declines in both scaled and unscaled forward citations at the 1% confidence level, though the economic magnitudes are again attenuated relative to ASC 606. This attenuation mirrors the pattern for patent applications in subsection 5.1, reinforcing the conclusion that disclosure granularity modulates firms' strategic responses. The dynamic effects in Figure 7 also show a more delayed response, with citation declines materializing only 2–3 years post-treatment.

The attenuated effects on both quantity and quality are consistent with our proposed mechanism: SFAS 131's broader segment definitions expose less competitively sensitive information than ASC 606's product-level disaggregation. Collectively, these results support the predictions of our model and highlight that the extent to which financial reporting mandates affect firms' IP protection strategy depends on the specificity and usefulness of the required disclosure.

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[31] See 3M Inc. 10-K FY1997 (`https://investors.3m.com/financials/sec-filings/content/0000066740-98-000002/0000066740-98-000002.pdf`). Accessed 04/11/2025.

[32] See 3M Inc. 10-K FY2019 (`https://investors.3m.com/financials/sec-filings/content/0001558370-20-000581/0001558370-20-000581.pdf`). Accessed 04/11/2025.

6 Conclusion

In this study, we investigate how financial disclosure regulations affect firms' strategic patenting behavior. Our theoretical model predicts that, as long as the newly required financial disclosure and patent disclosure are not strong complements, increased transparency raises the risk of keeping innovations private and lowers the threshold for patenting. As a result, firms optimally respond by filing more patents as a defensive measure against competitive risks, which in turn lowers the average value of filed patents. Empirically, we exploit the announcement of the ASC 606 revenue disaggregation requirement as a shock to firms' information environment and competitive exposure. Using a difference-in-differences design, we find that affected firms significantly increase their patent filings following the announcement, while the patent quality declines. These results support our model's predictions. We also find that the response is muted for firms that historically rely more on trade secrecy, in line with the model prediction that such firms are less likely to be at the active margin of the patenting decision. Moreover, the treatment effect is strongest among firms with a more opaque ex-ante information environment, where the transparency shock is larger. Lastly, we find no evidence of a significant change in R&D investment for treated firms, supporting our interpretation that the main adjustment occurs in IP protection strategy rather than in underlying innovative effort.

We complement and validate our main findings using the SFAS 131 segment reporting mandate as an alternative empirical setting. The estimated treatment effects are consistent with the ASC 606 setting, but the magnitude of the effects are attenuated. This result aligns with the broader nature of the disclosure mandated by SFAS 131 compared to ASC 606.

Our findings contribute to the literature by highlighting how disclosure regulations can influence firms' IP strategies. While prior literature often uses patents as a proxy for innovation outcome, we show that the patenting decision itself is a distinct strategic margin that responds to financial disclosure. Our analysis also helps interpret previous mixed empirical findings by emphasizing the joint roles of legal protection and informational costs, and how their balance depends on the degree of substitutability or complementarity between financial and patent disclosures. Future research could examine other regulatory settings and explore the long-term and aggregate effects of defensive patenting on market competition, follow-on innovation, and welfare.

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Figure 2: An Example of Impact of Revenue Disaggregation Requirement

The table below provides revenue by segment for each of the last three years. See section titled “Segment Information” in Company Overview and Note 22, “Segment Information” to the Consolidated Financial Statements for further information about each of our segments.

(In Millions)	**2013**	2012	2011
Industrial Process	**$ 1,107.4**	$ 955.8	$ 766.7
Motion Technologies	**721.8**	626.2	634.4
Interconnect Solutions	**395.5**	375.7	417.8
Control Technologies	**278.2**	277.1	285.5
Eliminations	**(6.0)**	(7.0)	(18.8)
Revenue	**$ 2,496.9**	$ 2,227.8	$ 2,085.6

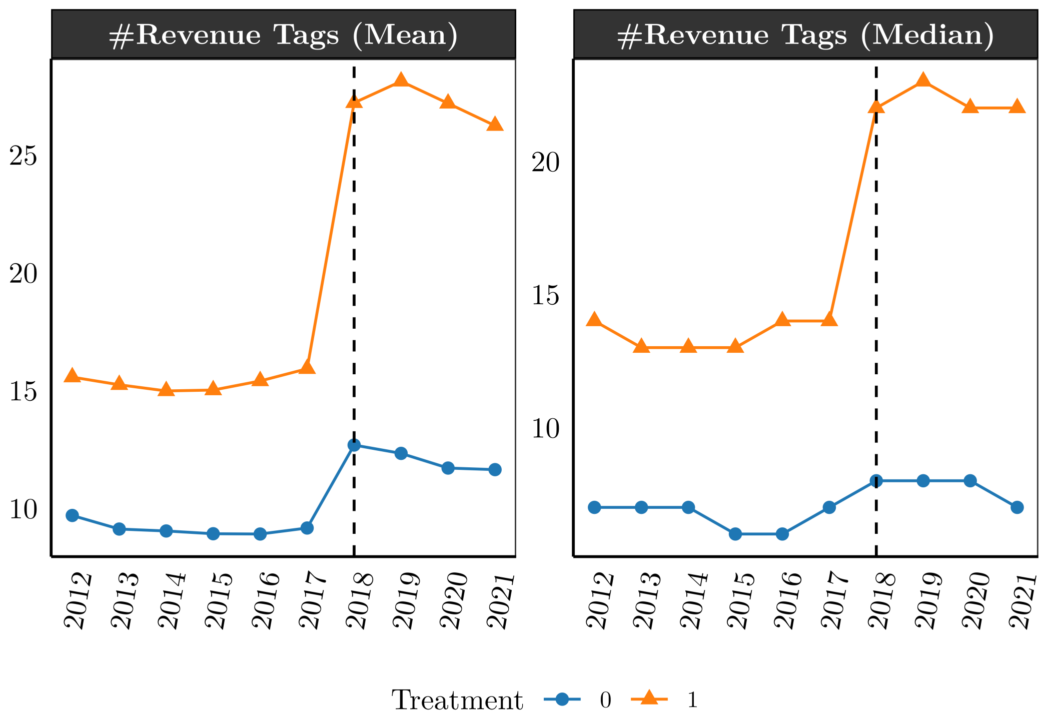
NOTE 4
REVENUE

The following table represents our revenue disaggregated by product category for the years ended December 31, 2018, 2017, and 2016:

For the Year Ended December 31, 2018	Motion Technologies	Industrial Process	Connect & Control Technologies	Eliminations	Total
Vehicle components	$ 1,100.8	$ —	$ —	$ (0.2)	$ 1,100.6
Industrial pumps	—	598.7	—	—	598.7
Aerospace & defense components	8.5	—	369.5	—	378.0
Oil & gas pumps and components	—	228.4	39.6	—	268.0
Industrial components and other	12.6	—	237.5	(2.5)	247.6
Rail components	152.2	—	—	—	152.2
Total	$ 1,274.1	$ 827.1	$ 646.6	$ (2.7)	$ 2,745.1
For the Year Ended December 31, 2017					
Vehicle components	$ 1,023.0	$ —	$ —	$ (0.2)	$ 1,022.8
Industrial pumps	—	560.0	—	—	560.0
Aerospace & defense components	9.6	—	348.0	—	357.6
Oil & gas pumps and components	—	247.2	34.2	—	281.4
Industrial components and other	7.3	—	223.4	(3.3)	227.4
Rail components	136.1	—	—	—	136.1
Total	$ 1,176.0	$ 807.2	$ 605.6	$ (3.5)	$ 2,585.3
For the Year Ended December 31, 2016					
Vehicle components	$ 915.4	$ —	$ —	$ (0.4)	$ 915.0
Industrial pumps	—	566.0	—	(0.3)	565.7
Aerospace & defense components	7.6	—	350.6	—	358.2
Oil & gas pumps and components	—	264.1	26.0	—	290.1
Industrial components and other	6.0	—	219.7	(3.7)	222.0
Rail components	54.4	—	—	—	54.4
Total	$ 983.4	$ 830.1	$ 596.3	$ (4.4)	$ 2,405.4

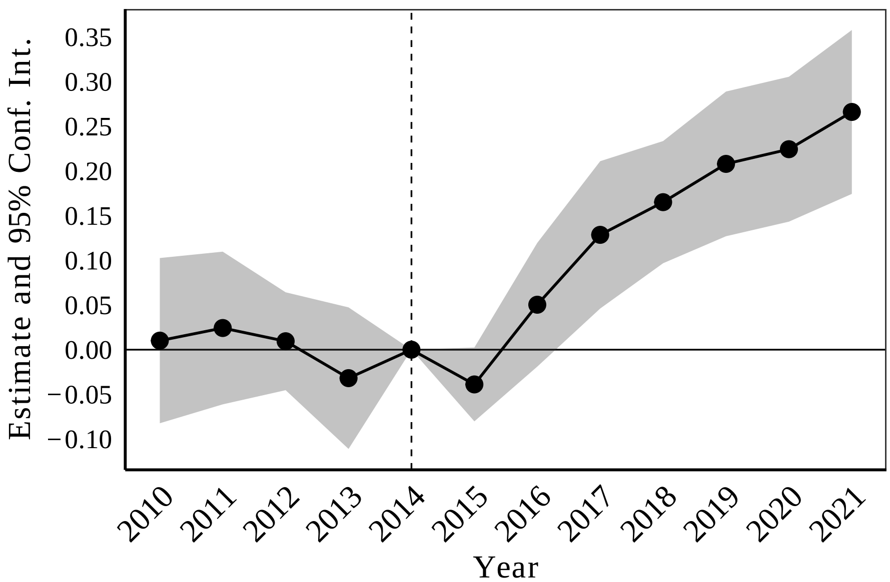
Note: ITT Inc. is a manufacturing company that produces specialty components for the aerospace, transportation, energy, and industrial markets. ITT Inc. was only disclosing broad segments in 2013. In 2018, it further disaggregated revenue sources under each of the categories and retrospectively disaggregated for years 2017 and 2016.

Figure 3: The Number of Revenue Tags



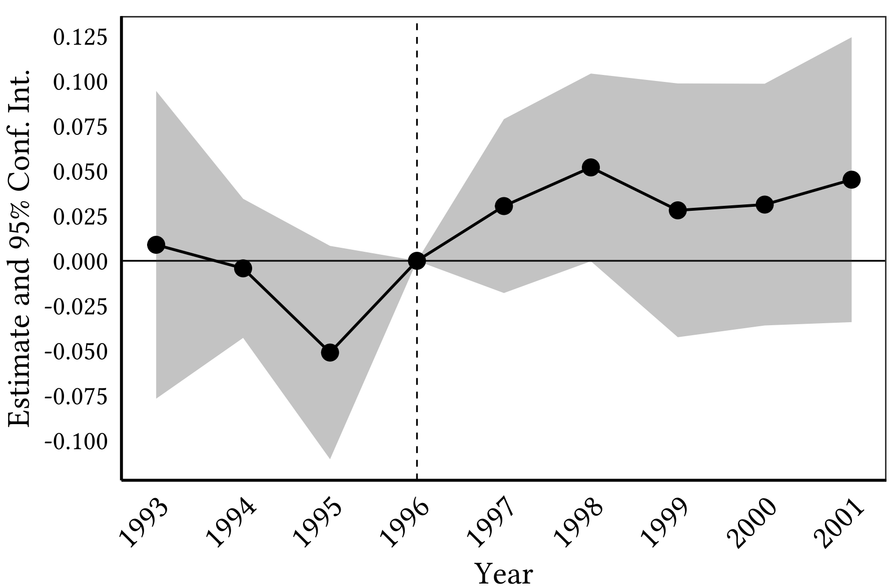
Note: The figure plots the mean and median number of numerical revenue tags around the implementation of ASC 606 in 2018. The period of analysis starts from 2012 because XBRL rolled out to all firms around 2012. The revenue tags are counted allowing for duplicates since same tag name could be used to tag different numbers in the disaggregated revenue. We remove revenue tags that pertain to other periods, tags that are unrelated to revenues (e.g. deferred revenue), duplicate tags with same numeric value, and adjustments to ensure that we capture items that belong to the performance of the entity.

Figure 4: Effect on the Number of Patent Applications (ASC 606)



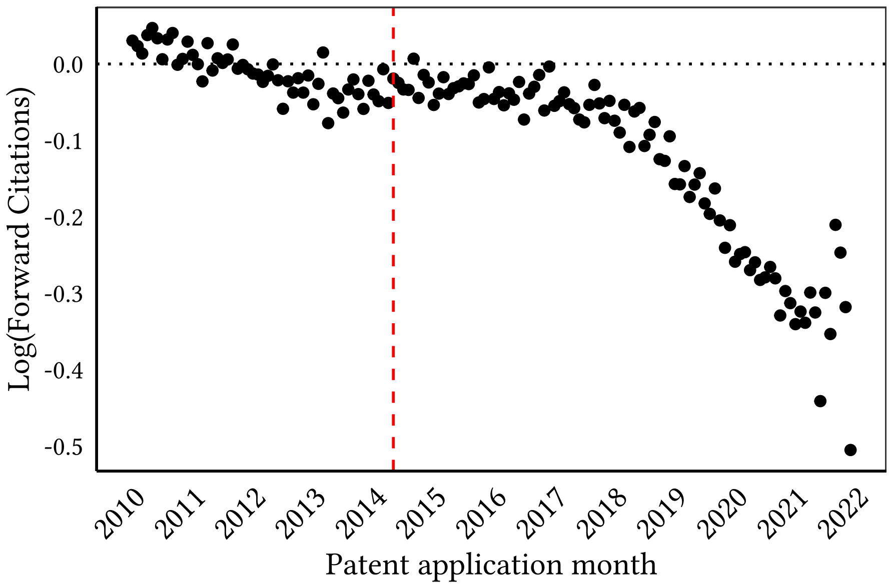
Note: The figure shows the OLS estimates of the DiD coefficients of the regression $\ln(\#Patents + 1)_{i,t} = \sum_{t \neq 2014} \beta_t Treat_i \times Year_t + \Gamma Controls_{i,t} + \text{FE} + +\epsilon_{i,t}$, where α_i and γ_c are firm and year fixed effects. The model is estimated with ASC 606 sample. The shaded region indicates the 95% confidence interval.

Figure 5: Effect on the Number of Patent Applications (SFAS 131)



Note: The figure shows the OLS estimates of the DiD coefficients of the regression $\ln(\#Patents + 1)_{i,t} = \sum_{t \neq 1996} \beta_t Treat_i \times Year_t + \Gamma Controls_{i,t} + FE + \epsilon_{i,t}$, where the fixed effects FE includes CPC Class, grant month, and firm fixed effects. The model is estimated with SFAS 131 sample. The shaded region indicates the 95% confidence interval.

Figure 6: The Effects on Forward Citations (ASC 606)

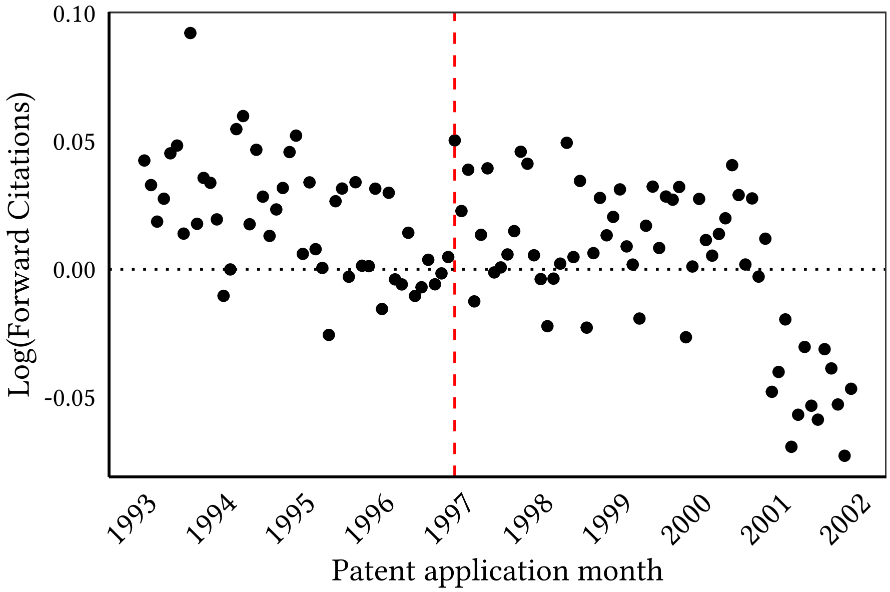


Note: The figure plots the application-month average of the log of scaled forward citations for treatment firms relative to control firms. Each point corresponds to a coefficient β from the regression:

$$y_{i,p,t} = \sum_{m} \beta_m \cdot Treat_i \cdot \mathbb{1}\{t = m\} + \Gamma Controls_{i,t} + FE + \varepsilon_{i,t},$$

where m denotes an application month of firm i's patent p. The fixed effects FE includes CPC Class, grant month, and firm fixed effects. The model is estimated with the ASC 606 sample.

Figure 7: The Effects on Forward Citations (SFAS 131)



Note: The figure plots the application-month average of the log of scaled forward citations for treatment firms relative to control firms. Each point corresponds to a coefficient β_m from the regression:

$$y_{i,p,t} = \sum_m \beta_m \cdot Treat_i \cdot \mathbb{1}\{t = m\} + \Gamma Controls_{i,t} + FE + \varepsilon_{i,t},$$

where m denotes an application month of firm i's patent p. The fixed effects FE includes CPC Class, grant month, and firm fixed effects. The model is estimated with the SFAS 131 sample.

Table 1: Summary Statistics

Panel A: Summary Statistics

	Obs	Mean	SD	p10	p25	p50	p75	p90
Treat	9,696	0.6943	0.4607	0.0000	0.0000	1.0000	1.0000	1.0000
R&D	9,696	0.0836	0.1839	0.0000	0.0031	0.0303	0.0999	0.2038
#Patent	9,696	71.9837	355.9484	0.0000	0.0000	3.0000	19.0000	94.0000
#unscaled citation	9,696	2.3696	10.0642	0.0000	0.0000	0.1333	1.9000	5.3333
cash	9,696	0.1674	0.1696	0.0207	0.0544	0.1158	0.2152	0.3774
leverage	9,696	0.5153	0.3442	0.1754	0.3215	0.4975	0.6623	0.8164
size	9,696	7.4722	2.4508	4.1303	5.6541	7.4915	9.2174	10.7001
MTB	9,696	3.5569	58.1824	0.8944	1.4806	2.4882	4.3198	8.2089
ROA	9,696	-0.0123	0.2747	-0.1976	-0.0098	0.0413	0.0833	0.1359

Panel B: Summary Statistics for ***Treat = 1***

	Obs	Mean	SD	p10	p25	p50	p75	p90
R&D	6,732	0.0742	0.1310	0.0000	0.0026	0.0293	0.0958	0.1843
#Patent	6,732	64.2704	353.3273	0.0000	0.0000	3.0000	18.0000	82.0000
#unscaled citation	6,732	2.2498	7.8746	0.0000	0.0000	0.1093	2.0000	5.5789
cash	6,732	0.1539	0.1461	0.0193	0.0521	0.1129	0.2056	0.3436
leverage	6,732	0.5168	0.2638	0.1895	0.3338	0.5075	0.6701	0.8233
size	6,732	7.4570	2.2778	4.3540	5.8154	7.4911	9.0388	10.5146
MTB	6,732	3.4867	47.2548	1.0039	1.5831	2.5923	4.5227	8.3953
ROA	6,732	0.0040	0.2108	-0.1430	-0.0015	0.0431	0.0836	0.1351

Panel C: Summary Statistics for ***Treat = 0***

	Obs	Mean	SD	p10	p25	p50	p75	p90
R&D	2,964	0.1049	0.2664	0.0000	0.0035	0.0330	0.1146	0.2702
#Patent	2,964	89.5027	361.2800	0.0000	0.0000	3.0000	24.0000	115.0000
#unscaled citation	2,964	2.6416	13.8001	0.0000	0.0000	0.1719	1.6895	4.8519
cash	2,964	0.1980	0.2104	0.0257	0.0595	0.1253	0.2488	0.4767
leverage	2,964	0.5117	0.4790	0.1565	0.3029	0.4712	0.6483	0.8024
size	2,964	7.5067	2.8044	3.7395	5.2487	7.5006	9.7880	11.5652
MTB	2,964	3.7165	77.4835	0.7432	1.2333	2.2389	3.9613	7.5807
ROA	2,964	-0.0493	0.3795	-0.3264	-0.0351	0.0369	0.0826	0.1374

Note: Table 1 presents descriptive statistics. Panel A comprises 9,696 firm-year observations from 808 firms. Of these, 6,732 observations (561 firms) are for firms subject to the disaggregation disclosure regulation (Panel B), and 2,964 observations (247 firms) are for firms not subject to the regulation (Panel C). *R&D* is scaled by lagged total assets.

Table 2: The Effects on Patent Applications (ASC 606)

	ln(1+#Patent) (1) OLS	#Patent (2) Neg. Bin.	ln(1+#Patent) (3) OLS	#Patent (4) Neg. Bin.
Treat × Post 2015	0.1129	0.1221		
	(0.0411)	(0.0605)		
Years 2010-2013 × Treat			0.0101	-0.0103
			(0.0425)	(0.0443)
Years 2015-2017 × Treat			0.0314	0.0209
			(0.0325)	(0.0554)
Years 2018-2021 × Treat			0.1886	0.2083
			(0.0479)	(0.0869)
Controls	✓	✓	✓	✓
Within R^2	0.01620		0.01805	
Observations	9,696	9,696	9,696	9,696
Year fixed effects	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓

Note: $Treat$ is a dummy variable taking value of 1 for disaggregating firms defined as in subsection 4.2, and $Post2015$ is a dummy variable taking value of 1 for years of and after 2015. Control variables include $leverage$, ROA, $cash$, MTB, $size$. Standard errors in parentheses are clustered at the two-digit NAICS level.

Table 3: The Effects on Forward Citations (ASC 606)

	ln(#unscaled citation)		ln(#scaled citation)	
	(1)	(2)	(3)	(4)
Treat	0.1767		0.0954	
	(0.0048)		(0.0019)	
Post 2015	0.0699	0.0648	0.0100	0.0094
	(0.0111)	(0.0100)	(0.0048)	(0.0041)
Treat × Post 2015	-0.1149	-0.0717	-0.0168	-0.0029
	(0.0083)	(0.0070)	(0.0037)	(0.0034)
Controls	✓	✓	✓	✓
Within R^2	0.01324	0.00587	0.01079	0.00115
Observations	697,929	697,869	667,955	667,890
CPC Class fixed effects	✓	✓	✓	✓
Grant Month fixed effects	✓	✓	✓	✓
Firm fixed effects		✓		✓

Note: $Treat$ is a dummy variable taking value of 1 for disaggregating firms defined as in subsection 4.2, and *Post2015* is a dummy variable taking value of 1 for years of and after 2015. Unscaled citations are the number of forward citations, and scaled citations are unscaled citations by grant-month average in each of the CPC classes. Control variables include $leverage$, ROA, $cash$, MTB, $size$. Standard errors are clustered at the grant month level separately for the treatment and control groups. The forward citations are measured from the granting date, while the panel data is organized by filing year.

Table 4: The Effects on Patent Applications:
Cross Section by Different IP Protection Strategies (ASC 606)

	ln(1+#patent) (1) OLS	#patent (2) Neg. Bin.
Treat × Post2015	0.2174	0.1794
	(0.0559)	(0.0669)
Treat × Post2015 × Pre TradeSecret	-0.2229	-0.1245
	(0.0556)	(0.0533)
Post2015 × Pre TradeSecret	0.1084	0.0903
	(0.0591)	(0.0515)
Controls	✓	✓
Within R^2	0.01808	
Observations	9,696	9,696
Year fixed effects	✓	✓
Firm fixed effects	✓	✓

Note: *Treat* is a dummy variable taking the value of 1 for disaggregating firms defined as in subsection 4.2, and *Post2015* is an indicator equal to one for years 2015 and onward. *Pre TradeSecret* is an indicator equal to one for firms with above-median count of the mentions of trade secrecy in the pre-treatment period. Control variables include *leverage*, *ROA*, *cash*, *MTB*, *size*. Standard errors, reported in parentheses, are clustered at the two-digit NAICS level. The regression includes year and firm fixed effects as indicated.

Table 5: The Effects on Forward Citations:
Cross Section by Different IP Protection Strategies (ASC 606)

	ln(#unscaled citation)		ln(#scaled citation)	
	(1)	(2)	(3)	(4)
Treat × Post2015	-0.1412	-0.1423	-0.0183	-0.0362
	(0.0114)	(0.0097)	(0.0058)	(0.0049)
Treat × Post2015 × Pre TradeSecret	0.1471	0.1779	0.0582	0.0843
	(0.0151)	(0.0124)	(0.0095)	(0.0079)
Treat	0.1990		0.1093	
	(0.0075)		(0.0037)	
Treat × Pre TradeSecret	-0.1777		-0.0936	
	(0.0125)		(0.0065)	
Post2015	0.0930	0.0806	0.0222	0.0170
	(0.0121)	(0.0107)	(0.0051)	(0.0043)
Post2015 × Pre TradeSecret	-0.1387	-0.1032	-0.0714	-0.0493
	(0.0125)	(0.0099)	(0.0076)	(0.0063)
Pre TradeSecret	0.1916		0.0971	
	(0.0121)		(0.0060)	
Controls	✓	✓	✓	✓
Within R^2	0.01448	0.00634	0.01142	0.00134
Observations	697,929	697,869	667,955	667,890
CPC Class fixed effects	✓	✓	✓	✓
Grant Month fixed effects	✓	✓	✓	✓
Firm fixed effects		✓		✓

Note: $Treat$ is a dummy variable taking the value of 1 for disaggregating firms defined as in subsection 4.2, and $Post2015$ is a dummy variable taking the value of 1 for years of and after 2015. *Pre TradeSecret* is an indicator equal to one for firms with an above-median count of the mentioning of trade secrecy in the pre-treatment period. Unscaled citations are the number of forward citations, and scaled citations divide unscaled citations by grant-month average in each of the CPC class. Control variables include *leverage*, ROA, *cash*, MTB, *size*. Standard errors are clustered at the grant month level separately for the treatment and control groups. The forward citations are measured from the granting date, but the panel data is organized by filing year.

Table 6: The Effects on Patent Applications:
Cross Section by Information Environment (ASC 606)

	ln(#patent)	
	(1) Continuous Opaque	(2) Binary Opaque
Treat × Post2015	0.1095	0.0162
	(0.0510)	(0.0549)
Treat × Post2015 × Opaque	0.2304	0.2510
	(0.0786)	(0.1042)
Post2015 × Opaque	-0.1300	-0.1769
	(0.0489)	(0.0792)
Controls	✓	✓
Within R^2	0.0254	0.0196
Observations	9,336	9,336
Year fixed effects	✓	✓
Firm fixed effects	✓	✓

Note: *Treat* equals 1 for disaggregating firms (see subsection 4.2); *Post2015* equals 1 for years of and after 2015. Unscaled citations are the number of forward citations, and scaled citations are unscaled citations by grant-month average in each of the CPC classes. Information opacity (*Opaque*) is constructed in the pre-treatment window (2011–2014). For each firm, we compute its average number of covering analysts during this period and exclude firms with no coverage. The continuous *Opaque* is the negative, standardized residual from a regression of pre-period analyst coverage on firm size, including 2-digit NAICS industry fixed effects. Larger values indicate greater opacity relative to size- and industry-level peers. The binary *Opaque* equals 1 for firms in the bottom tercile of the residual distribution. Column (1) reports the triple-difference specification using the continuous *Opaque*; Column (2) repeats the analysis using the binary *Opaque*. Control variables include $leverage$, ROA, $cash$, MTB, $size$. Fixed effects include year and firm fixed effects. Standard errors, reported in parentheses, are clustered at the two-digit NAICS level.

Table 7: The Effects on Forward Citations:
Cross Section by Information Environment (ASC 606)

	Continuous Opaque				Binary Opaque			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln(#unscaled citation)		ln(#scaled citation)		ln(#unscaled citation)		ln(#scaled citation)	
Treat × Post2015 × Opaque	−0.0272	−0.0820	−0.0112	−0.0353	−0.2280	−0.2840	−0.0975	−0.1170
	(0.0038)	(0.0039)	(0.0021)	(0.0022)	(0.0206)	(0.0205)	(0.0118)	(0.0121)
Treat × Post2015	−0.0453	−0.0392	0.0114	0.0016	0.0045	0.0634	0.0276	0.0499
	(0.0083)	(0.0078)	(0.0046)	(0.0045)	(0.0105)	(0.0084)	(0.0060)	(0.0051)
Post × Opaque	0.0493	0.0613	0.0200	0.0233	0.1820	0.2040	0.0667	0.0795
	(0.0031)	(0.0029)	(0.0017)	(0.0014)	(0.0133)	(0.0110)	(0.0065)	(0.0056)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Within R^2	0.0199	0.0077	0.0149	0.0017	0.0198	0.0073	0.0141	0.0016
Observations	697,462	697,411	667,505	667,449	697,462	697,411	667,505	667,449
CPC Class fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Grant Month fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
Firm fixed effects		✓		✓		✓		✓

Note: *Treat* equals 1 for disaggregating firms (see subsection 4.2); *Post2015* equals 1 for years of and after 2015. Unscaled citations are the number of forward citations, and scaled citations are unscaled citations by grant-month average in each of the CPC classes. The continuous and binary information opacity (*Opaque*) variables used here are the same opacity measures reported in Table 6. Columns (1)–(4) reports the triple-difference specification using the continuous *Opaque*; Columns (5)–(8) repeats the analysis using the binary *Opaque*. Control variables include *leverage*, *ROA*, *cash*, *MTB*, *size*. Standard errors are clustered at the grant month level separately for the treatment and control groups. The forward citations are measured from the granting date, while the panel data is organized by filing year.

Table 8: The Effects on R&D (ASC 606)

	R&D (1)	R&D' (2)	%R&D Wages (3)	%R&D Headcounts (4)
Treat × Post2015	-0.0009	0.0002	-0.0004	-0.0006
	(0.0048)	(0.0059)	(0.0013)	(0.0014)
Controls	✓	✓	✓	✓
Within R^2	0.02796	0.02713	0.00130	0.00122
Observations	9,695	7,777	8,940	8,940
Year fixed effects	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓

Note: This table reports the effect of the ASC 606 announcement on firms' R&D input. In columns (1) and (2), the dependent variable is R&D expenditure scaled by lagged total assets. Column (1) treats missing R&D observations as zero, while column (2) restricts the sample to firm-years with non-missing R&D. In columns (3) and (4), R&D input is measured using labor-based proxies from Revelio Labs: column (3) uses the share of the firm's total wage bill paid to R&D employees, and column (4) uses the share of the firm's workforce employed in R&D roles. Control variables include *leverage*, *ROA*, *cash*, *MTB*, *size*. Standard errors in parentheses are clustered at the two-digit NAICS level.

Table 9: The Effects on Patent Applications (SFAS 131)

	ln(1+#patent) (1) OLS	#patent (2) Neg. Bin.	ln(1+#patent) (3) OLS	#patent (4) Neg. Bin.
Treat × Post1996	0.0466	0.1045		
	(0.0193)	(0.0350)		
Years 1993-1995 × Treat			-0.0154	-0.0727
			(0.0207)	(0.0316)
Years 1997-1999 × Treat			0.0368	0.0388
			(0.0249)	(0.0465)
Years 2000-2001 × Treat			0.0382	0.0370
			(0.0304)	(0.0437)
Controls	✓	✓	✓	✓
Within R^2	0.03888		0.03898	
Observations	12,897	11,511	12,897	11,511
Year fixed effects	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓

Note: *Treat* is a dummy variable equal to 1 for firms that changed their reported segment definitions upon adopting SFAS 131 (Cho, 2015). *Post*1996 is a dummy variable equal to 1 for years after 1996. Control variables include *leverage*, *ROA*, *cash*, *MTB*, *size*. Standard errors in parentheses are clustered at the two-digit NAICS level.

Table 10: The Effects on Forward Citations (SFAS 131)

	ln(#unscaled citation)		ln(#scaled citation)	
	(1)	(2)	(3)	(4)
Treat	0.1090		0.0398	
	(0.0084)		(0.0032)	
Post1996	-0.0182	0.0163	-0.0092	0.0038
	(0.0122)	(0.0124)	(0.0050)	(0.0050)
Treat × Post1996	-0.0424	-0.0364	-0.0194	-0.0175
	(0.0096)	(0.0099)	(0.0036)	(0.0038)
Controls	✓	✓	✓	✓
Within R^2	0.01367	0.00193	0.01294	0.00187
Observations	371,839	371,675	371,571	371,406
CPC Class fixed effects	✓	✓	✓	✓
Grant Month fixed effects	✓	✓	✓	✓
Firm fixed effects		✓		✓

Note: $Treat$ is a dummy variable equal to 1 for firms that changed their reported segment definitions upon adopting SFAS 131 (Cho, 2015). $Post1996$ is a dummy variable taking the value of 1 for years of and after 1996. Unscaled citations are the number of forward citations, and scaled citations divide unscaled citations by grant-month average in each of the CPC classes. Control variables include $leverage$, ROA, $cash$, MTB, $size$. Standard errors are clustered at the grant month level separately for the treatment and control groups. The forward citations are measured from the granting date, but the panel data is organized by filing year.

Appendix

A Variable Definitions

Variable	Definition and Source
Financial Reporting Regulation Variables	
Treat (ASC 606)	Dummy variable taking the value of 1 if a firm uses one of the XBRL tags for revenue disaggregation under ASC 606, and zero otherwise. (EDGAR)
Treat (SFAS 131)	Dummy variable taking the value of 1 if a firm changed their segment disclosures upon the adoption of SFAS 131 as defined in Cho (2015), and zero otherwise. (EDGAR)
RevenueTags	Count of revenue-related XBRL tags used to report revenue disaggregation under ASC 606, excluding adjustments and irrelevant items. (EDGAR)
Patent and R&D Variables	
#Patent	Number of patent applications in each year that are ultimately granted, measured at the firm-year level. (USPTO)
$\ln(1 + \#Patent)$	The natural logarithm of *#Patent* plus one. (USPTO)
ln(#*unscaled citation*)	The natural logarithm of patent-level forward citations. (USPTO)
ln(#*scaled citation*)	The natural logarithm of patent-level forward citations scaled by grant-month and CPC class average. (USPTO)
Pre TradeSecret	Dummy variable taking the value of 1 if the firm shows an above-median count of mentioning “trade secret” or “trade secrecy” in 10-K filings in the pre-ASC606 period. (EDGAR)

Opaque	Measure of the pre-ASC606 information environment based on analyst coverage. For each firm, we compute the average number of analysts following the firm over 2011–2014 and regress this average on firm size and 2-digit NAICS industry fixed effects. The continuous opacity measure is defined as the negative of the residual from this regression, so that larger values indicate lower analyst coverage than predicted by size and industry (greater opacity). We also construct a binary indicator equal to 1 for firms in the top (most opaque) tercile of this continuous measure, and 0 otherwise. (I/B/E/S, COMPUSTAT)
R&D	R&D expenditure scaled by lagged total assets with missing values replaced with zero. (COMPUSTAT)
R&D′	R&D expenditure scaled by lagged total assets with missing values dropped. (COMPUSTAT)
%R&D Wages	The share of a firm's total wage bill paid to R&D employee. (Revelio Labs)
%R&D Headcounts	The share of the firm's workforce employed in R&D roles (Revelio Labs)
$Tail10$	Indicator equal to 1 if a patent's forward citation count (as defined above) is at or above the 90th percentile of the citation distribution among all patents filed in the same application year; 0 otherwise. This captures whether a patent lies in the upper tail of the citation distribution within its filing cohort. (USPTO)
Dispersion in cited classes (originality)	Patent-level index capturing the technological breadth of a patent's knowledge base. For each patent i, let s_{ij} denote the share of its backward citations that go to patents in 3-digit technology class j, and define $\textit{Dispersion in cited classes}_i = 1 - \sum_j s_{ij}^2$, so higher values indicate that the cited prior art is spread across many technology classes rather than concentrated in a single field. (USPTO)

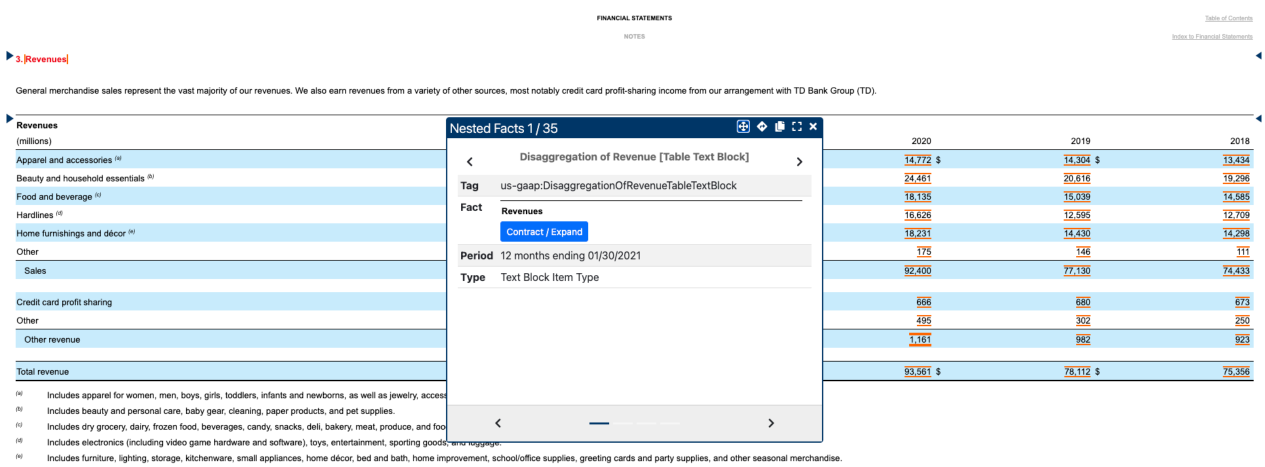
Dispersion in citing classes (generality)	Patent-level index capturing the technological breadth of a patent's subsequent impact. For each patent i, let s_{ij} denote the share of its forward citations that come from citing patents in 3-digit technology class j, and define $\textit{Dispersion in citing classes}_i = 1 - \sum_j s_{ij}^2$, so higher values indicate that the patent is cited by follow-on inventions in many different technology classes rather than being used within a single field. (USPTO)
Control Variables	
Cash	A firm's cash holdings computed as cash and short-term investments divided by total asset ($Cash$ = CHE/AT). CHE is Compustat cash and short-term investments; AT is total assets. (COMPUSTAT)
Leverage	Leverage computed as a firm's total liability divided by total assets ($Leverage$ = LT/AT), where LT is total liabilities and AT is total assets. (COMPUSTAT)
Size	The natural logarithm of a firm's total asset ($size = \ln(\text{AT})$). AT is total assets. (COMPUSTAT)
ROA	A firm's return on asset computed as net income divided by total asset (ROA = NI/AT), where NI is net income and AT is total assets. (COMPUSTAT)
MTB	Market-to-Book ratio computed as a firm's market value divided by its book value of equity ($MTB = (\text{PRCC\_F} \times \text{CSHO})/(\text{AT} - \text{LT})$), where PRCC_F is the fiscal year-end share price, CSHO is common shares outstanding, AT is total assets, and LT is total liabilities. (COMPUSTAT)

Revenue Tags To identify disaggregating firms, we extract non-numeric XBRL elements that contain terms related to revenue disaggregation. We extract these tags from EDGAR Data files by a regular expression. We first identify disaggregating firms using standardized tags names in taxonomy in our sample year which represents line items ('DisaggregationOfRevenueLineItems') or table text blocks ('DisaggregationOfRevenueTableTextBlock') that pertain to disaggregation. To account for company-specific variations in tag names, we use the following regular expression:

```
[data["tag"].str.contains(r'(Disaggregation\w*Revenue\w*|Disaggregat\w+Revenue\w*)',
regex=True, case=False, na=False)]
```

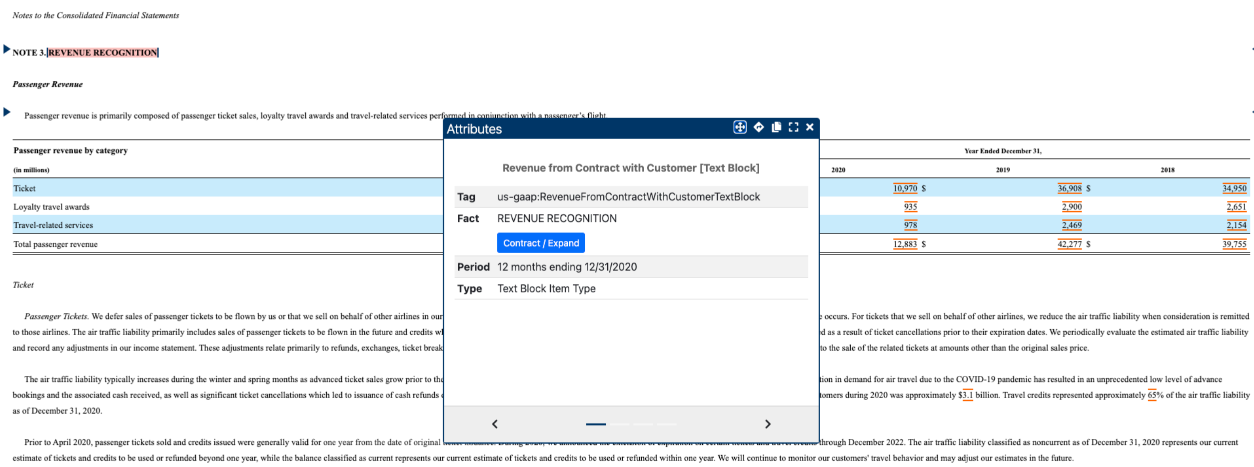
We filter the extracted tags by excluding those unrelated to revenue (e.g., "Unearned Revenue"), those from prior fiscal years, and those representing adjustments by identifying axis and member attributes. This filtering approach captures only the disaggregation-related revenue tags pertinent to the fiscal year under analysis.

Figure A.1: Example of standardized tag - Table Text Block



Note: This is a part of a firm's 10-K filing for the fiscal year of 2020. If you click on the tags, you can observe Attributes of the tags. The name of the tag that this pop-up shows is 'DisaggregationOfRevenueTableTextBlock'.

Figure A.2: Example of non-standardized tag - Table Text Block



Note: This is a part of a firm's 10-K filing for the fiscal year of 2020. If you click on the tags, you can observe the Attributes of the tags. The name of the tag that this pop-up shows is 'RevenueFromContractWithCustomerTextBlock'.

B Proofs for Section 2

B.1 Additional Details of the Model

Assumption on Cost Functions

We assume that the cost functions $C = C_s, C_c$ are continuously differentiable, strictly convex, strictly increasing, and satisfy the following boundary conditions:

$$\lim_{e \to 0} \frac{\partial C}{\partial e}(e) = 0, \quad \lim_{e \to 1} \frac{\partial C}{\partial e}(e) > \overline{\theta}.$$

These conditions ensure that the optimal efforts are interior.

Relationships between Financial and Patent Disclosure

For convenience, we parameterize the relationship between the information environment parameters η_1 and η_0 as follows:

$$\eta_1(\eta_0) = \underline{\eta} + \rho(\eta_0 - \underline{\eta}),$$

where $\underline{\eta} < \eta_0$ and $\rho \in [0, 1)$. When $\rho = 0$, the two types of disclosure are substitutes. When $\rho > 0$, disclosures are complements, with a higher ρ indicating stronger complementarity.

B.2 Proofs

We first prove the results for general cost functions and distributions. We then provide the analysis of the quadratic-cost example discussed in the main text.

Proof of Proposition 1

First, we characterize the competitor's optimal efforts for a general cost function. At the competition stage, firm j's optimal competition effort solves the first-order condition (3). With the optimal competition effort $e^*_{c,a}$, at the search stage, firm j's optimal search effort solves the following first-order condition:

$$\mathbb{E}[\pi_a^j(e_c^*(\theta, aw), \theta, w) \mid a] = g(\eta_a)\frac{\partial C_s}{\partial e_s}(e_s^*, \eta_a).$$

For the competitor's belief $\mu \in \Delta([\underline{\theta}, \overline{\theta}])$, define $A(\theta, \mu_a) := e^*_{s,a=0}(\mu_0)e^*_{c,a=0} - e^*_{s,a=1}(\mu_1)e^*_{c,a=1}(1-w)$, where the search efforts are written as a function of the belief μ. Now (4) can be rewritten as

$$\Delta(\theta) = A(\theta, \mu_a)\theta - C_p.$$

By definition, firm i patents if and only if $\Delta(\theta) \geq 0$. Note that $e^*_{s,a}$ is independent of θ and that $e^*_{c,a}$ is increasing in θ.

When $w \to 1$, the competitor does not exert any effort given patenting: $\lim_{w\to 1} e^*_{c,a=1} = 0$ from the first-order condition (3). In this case, $A(\theta, \mu_a) = e^*_{s,a=0}(\mu_0)e^*_{c,a=0}$ is increasing in θ, because $e^*_{c,a=0}$ is increasing in θ and $e^*_{s,a=0}$ is independent of θ.

Since A is continuous in θ, there exists $\overline{w} < 1$ such that A is increasing in θ for any $w > \overline{w}$. Consequently, for such w, the function $\Delta(\theta)$ is increasing in θ, and any equilibrium takes the form of a threshold strategy: firm i patents if and only if $\theta > \tau$ for some $\tau > 0$. Define

$$h(\tau) := A(\tau, \mu_a(\tau))\tau - C_p,$$

where $\mu_a(\tau)$ is the competitor's belief induced by the threshold strategy with cutoff τ. The equilibrium threshold τ solves $A(\tau, \mu_a(\tau))\tau = C_p$.

Next, we consider the no-patent case. As w tends to zero, the competition efforts converges to the same value regardless of the patenting decision, so

$$\lim_{w\to 0} A(\theta,\mu_a) = \lim_{w\to 0}(e^*_{s,a=0}(\mu_0) - e^*_{s,a=1}(\mu_1))e^*_{c,a}|_{w=0}$$

Let the competitor's off-path belief assign probability one to the highest value $\overline{\theta}$ in the off-path event of patenting. With $w \to 0$, the search efforts $e^*_{s,a}$ depends on the patenting decision only through the competitor's belief μ_a. Thus under the above off-path belief, we have $\Delta(\theta) < 0$ for all θ, and the incumbent never patents. Since A is continuous in w, there is $\underline{w}$ such that the firm never patents for any $w < \underline{w}$.

Proof of Corollary 1

Let τ be the equilibrium threshold. Observe that

$$\frac{\partial h}{\partial \eta_0} = \underbrace{\frac{\partial e^*_{s,a=0}}{\partial \eta_0} e^*_{c,a=0}}_{<0} \tau + \rho \frac{\partial h}{\partial \eta_1}, \quad \frac{\partial h}{\partial \eta_1} = -(1-w)\frac{\partial e^*_{s,a=1}}{\partial \eta_1} e^*_{c,a=1}\tau > 0$$

By the implicit function theorem, we have

$$\frac{\partial \tau}{\partial \eta_0} = -\frac{\frac{\partial e^*_{s,a=0}}{\partial \eta_0} e^*_{c,a=0}\tau + \rho \frac{\partial h}{\partial \eta_1}}{\partial h / \partial \tau}.$$

Define the cutoff complementarity ρ^* by

$$\rho^* := \left(-\frac{\partial e^*_{s,a=0}}{\partial \eta_0} e^*_{c,a=0}\tau\right) \Bigg/ \frac{\partial h}{\partial \eta_1} > 0.$$

Then, $\frac{\partial \tau}{\partial \eta_0}$ is negative when $\rho > \rho^*$

B.3 Quadratic Cost Example

Suppose that $C_c(e) = C_s(e) = ke^2/2$, as in the main text. The competition and search efforts are derived by solving the first-order conditions:

$$e^*_{c,a} = \frac{(1-aw)\theta}{k}, \quad e^*_{s,a} = \frac{(1-aw)^2\mathbb{E}[\theta^2 \mid a]}{2k^2 g(\eta_a)}.$$

Using these, we obtain

$$\Delta(\theta) = \underbrace{\left[\frac{\mathbb{E}[\theta^2 \mid a=0]}{2g(\eta_0)} - \frac{(1-w)^4\mathbb{E}[\theta^2 \mid a=1]}{2g(\eta_1)}\right]}_{:=X} \frac{\theta^2}{k^3} - C_p.$$

Since the term inside the bracket, denoted by X, is independent of θ, the function Δ is increasing in θ if $X > 0$. When $w \to 1$, clearly $X > 0$. When $w < 1$, observe that

$$X > \frac{\underline{\theta}^2}{2g(\eta_0)} - (1-w)^4 \frac{\overline{\theta}^2}{2g(\eta_1)}.$$

Therefore, $X > 0$ if

$$(1-w)^4 < \frac{g(\eta_1)}{g(\eta_0)} \frac{\underline{\theta}^2}{\overline{\theta}^2}.$$

This expression reduces to $w > \overline{w}$, where $\overline{w}$ is defined in Proposition 1.

Next, consider a no-patent equilibrium: the incumbent's strategy is $\alpha(\theta) \equiv 0$. Let the competitor's off-path belief assign probability one to $\theta = \overline{\theta}$, so we have $\mathbb{E}[\theta^2 \mid a = 1] = \overline{\theta}^2$. Since $\theta > 0$, a no-patent equilibrium can be supported if $X < 0$ given this off-path belief. Since $\mathbb{E}[\theta^2 \mid a] = \mathbb{E}[\theta^2]$, the condition $X < 0$ reduces to

$$(1-w)^4 > \frac{g(\eta_1)}{g(\eta_0)} \frac{\mathbb{E}[\theta^2]}{\overline{\theta}^2}.$$

This expression reduces to $w < \underline{w}$, where $\underline{w}$ is defined in Proposition 1.

C Additional Tables

In this section, we present additional estimation results.

Table C.1: The Effects on Patent Applications (ASC 606)

	ln(#Patent)		#Patent	
	(1)	(2)	(3)	(4)
	OLS	OLS	Poisson	Poisson
Treat × Post 2015	0.0899		0.0504	
	(0.0269)		(0.0594)	
Years 2010-2013 × Treat		-0.0310		-0.0164
		(0.0479)		(0.0491)
Years 2015-2017 × Treat		-0.0080		0.0349
		(0.0462)		(0.0745)
Years 2018-2021 × Treat		0.1383		0.0411
		(0.0662)		(0.0588)
Controls	✓	✓	✓	✓
Within R^2	0.03087	0.03246		
Observations	6,536	6,536	9,696	9,696
Year fixed effects	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓

Note: This table reports robustness checks for Table 2. Columns (1) and (2) show the estimates after dropping observations with zero patent applications and using the log of total patents, rather than computing ln(1 + total number of patents). Columns (3) and (4) present the results from Poisson regressions.

Table C.2: The Effects on Patent Applications with R&D control (ASC 606)

	ln(1+#Patent) (1) OLS	#Patent (2) Neg. Bin.	ln(1+#Patent) (3) OLS	#Patent (4) Neg. Bin.
Treat × Post 2015	0.1129	0.1225		
	(0.0411)	(0.0613)		
Years 2010-2013 × Treat			0.0103	-0.0101
			(0.0428)	(0.0442)
Years 2015-2017 × Treat			0.0318	0.0225
			(0.0325)	(0.0553)
Years 2018-2021 × Treat			0.1886	0.2079
			(0.0479)	(0.0876)
R&D	0.0319	0.1740	0.0274	0.1647
	(0.0756)	(0.1853)	(0.0757)	(0.1863)
Controls	✓	✓	✓	✓
Within R^2	0.01623		0.01808	
Observations	9,696	9,696	9,696	9,696
Year fixed effects	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓

Note: This table replicates Table 2 and Table C.1 but with *R&D* included as a control. R&D is scaled by lagged total assets, with missing R&D set to 0. Results are similar when observations with missing R&D are dropped. The other control variables include *leverage*, *ROA*, *cash*, *MTB*, *size*. Standard errors in parentheses are clustered at the two-digit NAICS level.

Table C.3: The Effects on Alternative Patent Quality (ASC 606)

	Tail10		Dispersion in cited classes (originality)		Dispersion in citing classes (generality)	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post 2015	0.0005	-0.0167	0.0081	0.0058	-0.0185	-0.0137
	(0.0028)	(0.0034)	(0.0015)	(0.0017)	(0.0016)	(0.0015)
Controls	✓	✓	✓	✓	✓	✓
Within R^2	0.0147	0.0094	0.0101	0.0007	0.0071	0.0009
Observations	697,929	697,869	609,920	609,857	609,920	609,857
CPC Class fixed effects	✓	✓	✓	✓	✓	✓
Grant Month fixed effects	✓	✓	✓	✓	✓	✓
Firm fixed effects		✓		✓		✓

Note: This table examines the effect of ASC 606 on alternative measures of patent quality. The variable $Tail10$ is a patent-level indicator equal to 1 if a patent's forward citation count is at or above the 90th percentile of the citation distribution among all patents filed in the same year, and 0 otherwise. For each patent i, *Dispersion in cited classes (originality)* is measured as $1 - \sum_j s_{ij}^2$, where s_{ij} is the share of its *backward* citations that go to patents in 3-digit technology class j (i.e., one minus the Herfindahl index of the cited classes). For each patent i, *Dispersion in citing classes (generality)* is measured as $1 - \sum_j s_{ij}^2$, where s_{ij} is the share of its *forward* citations that come from citing patents in 3-digit technology class j (i.e., one minus the Herfindahl index of the citing classes). Control variables include *leverage*, ROA, *cash*, MTB, *size*. Standard errors in parentheses are clustered at the two-digit NAICS level.