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. We develop a model of strategic patenting 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, is predicted to dominate as long as financial and patent disclosures are substitutes or not strongly complementary. We test these predictions using the ASC 606's revenue disaggregation requirements. 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 dissemination 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 understanding how disclosure regulations shape firms' broader innovation and IP protection strategies.

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 profits. If the incumbent firm does not patent,

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

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 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—fixed patenting costs and heightened search risk from patent disclosure—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 (i.e. financial data helps competitors interpret patent data), the patent disclosure becomes more informative and thus costlier. 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 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 it 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). 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 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

[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).

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 Section 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 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

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

treatment year, indicating that newly filed patents are closer to the margin.

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, measured by 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 either the "never patent" policy or have a very high initial patenting threshold. As our model predicts, these firms are not at the active margin of the patenting decision. For such firms, secrecy procedures, organizational routines, and contracting already mitigate leakage risk, so the marginal benefit of adding a patent is smaller.[4] Using the trade secrecy measure from Glaeser (2018), we find weaker increases in patenting among firms that rely on trade secrecy.

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 previously most opaque. These firms experience the largest increase in competitive threat when the new disclosure standards are imposed. Consistent with this prediction, treated firms with a more opaque ex-ante information environment exhibit a significantly larger increase in patenting.

[4] 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 regime, nor will it substantially change the behavior of a firm whose threshold is already near the maximum.

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 competitor's 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 firm's strategic trade-off.[5] This model generates novel, testable predictions about firm

[5] 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

responses, including key dimensions of heterogeneity that we subsequently test.

Second, our paper contributes to the growing accounting literature that connects disclosure (and disclosure regulations) to innovation outcomes (see a review by Glaeser and Lang, 2024). Prior studies have documented mixed findings across settings like the Sarbanes-Oxley Act (Allen et al., 2022), the EDGAR rollout (Dambra et al., 2024; Chang et al., 2024), changes in revenue recognition rules (Cetin, 2023) and the extensive European reporting regulations (Breuer et al., 2025). Our framework offers a lens to organize these empirical findings in two key ways. First, we show that disclosure regulations can change firms' propensity to patent a given innovation, thereby altering patent counts even if the underlying innovation activity is unchanged. Second, the strategic response can go in either directions (more or less patenting), depending on whether the *legal protection* effect or the *informational cost* effect dominates.

We also contribute to the literature on firms' strategic responses to proprietary concerns. (e.g., Leuz, 2004; Glaeser and Omartian, 2022; Gao et al., 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, and are among the few papers that link tangible defensive actions to disclosure mandates (e.g., Bernard et al., 2018).[6]

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

Guriev (2006); Arora et al. (2008).)

[6]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 markets with a patenting option and demonstrate how financial reporting mandates influence firms' patenting behavior.

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.[7] After privately observing θ, the incumbent decides whether to patent 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.[8] First, firm j exerts a *search effort* $e_s \in [0, 1]$ to discover the product line and learn θ.[9] We normalize the discovery technology so that effort equals success probability: with probability e_s the search succeeds and j learns

[7] Many common probability distributions are log-concave (e.g., normal, exponential, and uniform distribution). A log-concave density function has a unimodal shape and other desirable properties (Bergstrom and Bagnoli, 2005).

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

[9] 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.)

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 information environment shaped by financial disclosure by the incumbent. A disclosure regulation that mandates granular 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 $C_c(e_c)$.[10] 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 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

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

Firm i faces the tradeoff 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

[10] 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.

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 $\eta_1 < \eta_0$.[11] If firm i chooses not to patent, it avoids both the fixed cost and the informational cost. Firm i's expected payoff is thus:

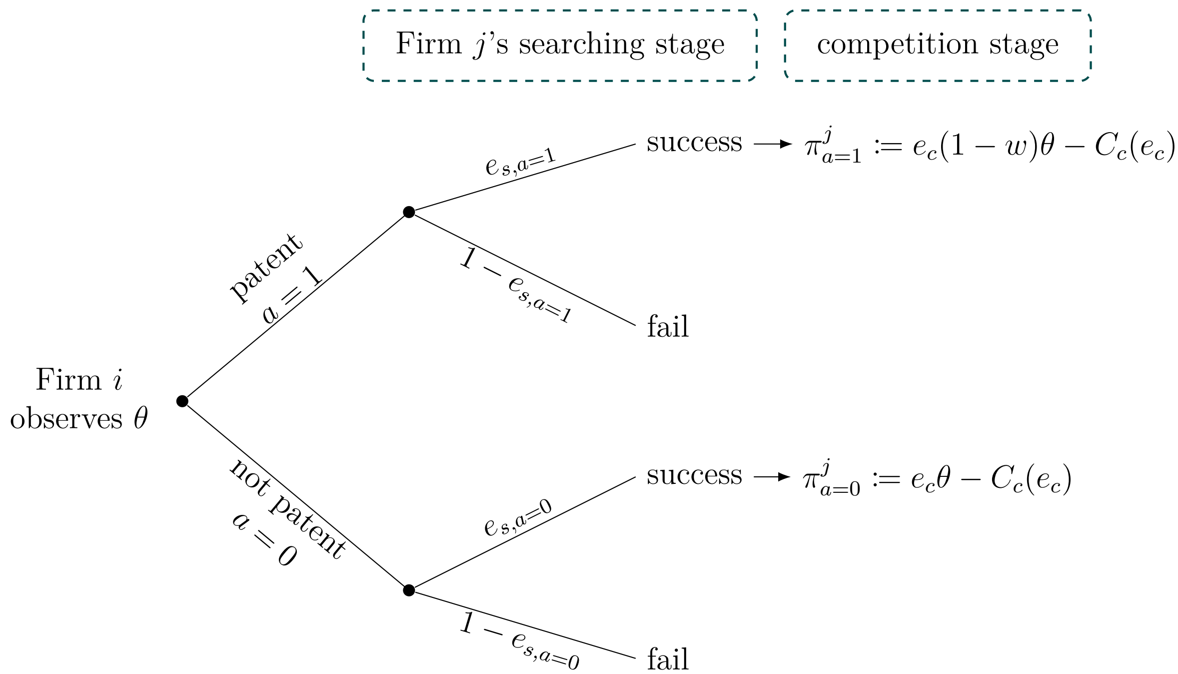
$$\left(1 - e^*_{s,a}\right)\theta + e^*_{s,a}(1 - e^*_{c,a})\theta - C_p a, \tag{2}$$

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 probability $e^*_{s,a}$, firm j learns θ and captures a fraction $e^*_{c,a}$, leaving the residual share $1 - e^*_{c,a}$ 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).

[11] 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.



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_1 captures the information environment after patent disclosure. When η_1 is independent of η_0, more transparent financial disclosure (i.e., a decrease in η_0) makes patent disclosure incrementally less informative: 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 patent disclosure. Alternatively, if η_1 decreases with more financial disclosure (a decrease in η_0), then more transparent financial disclosure, combined with patent disclosure, yields a more transparent overall information environment.

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 a 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

$$\pi_a^j(e_{c,a}^*, \theta, w) = \frac{(1 - aw)^2\theta^2}{2k}.$$

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:

$$\max_{e_s} \; e_s\mathbb{E}[\pi_a^j(e_{c,a}^*, \theta, w) \mid \alpha(\theta) = a] - g(\eta_a)C_s(e_s),$$

and the optimal search effort 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)):

$$\Pi^i(a, \theta) := \max_{a \in \{0,1\}} (1 - e^*_s(a, \eta))\,\theta + e^*_s(a, \eta)(1 - e^*_c(a))\theta - C_p a.$$

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:

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

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 $1-w$) but it also makes firm j'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. *Define*

$$\overline{w} := 1 - \sqrt[3]{\frac{g(\eta_1)}{g(\eta_0)}\frac{\underline{\theta}^2}{\overline{\theta}^2}}, \quad \underline{w} := 1 - \sqrt[3]{\frac{g(\eta_1)}{g(\eta_0)}\frac{\mathbb{E}[\theta^2]}{\overline{\theta}^2}}.$$

such that an equilibrium satisfies the following:

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

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

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

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 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 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 lower η_0, i.e., a more transparent baseline information environment, 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 under financial disclosure mandates will patent more if the required financial disclosure and patent disclosure are substitutes, or if the complementarity is not too strong. The substitution case offers the clearest intuition. Greater transparency in financial disclosure raises the relative benefit of patenting, since keeping the innovation private becomes riskier. At the same time, the relative cost of patenting falls: some information has already been disclosed through financial reporting, which reduces the marginal informational cost of patenting. Alternatively, when the complementarity between financial and patent disclosure is sufficiently strong, a disclosure mandate can significantly raise the informational cost of patenting, leading 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 complements 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.[12] 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.[13] The new standard became effective for annual reporting periods beginning after December 15, 2017.[14] 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 in-

[12]See Welcome to Year 1 of ASC 606. Accessed 10/16/2024.

[13]See ASU 2014-09 REVENUE FROM CONTRACTS WITH CUSTOMERS (TOPIC 606). Accessed 10/03/2024.

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

tended 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.[15] The effectiveness of the revenue disaggregation mandate is also evidenced by academic studies. Hinson et al. (2024) found 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 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.

[15] 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).

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 final sample for the ASC 606 setting 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. A firm is classified as a "disaggregating firm" if it uses one of the XBRL tags for revenue disaggregation under ASC 606.[16] We construct a time-invariant treatment indicator $Treat_i$ equal to one for disaggregating firms (zero otherwise). Disaggregating firms constitute 69.4% of the sample.

To validate that our treatment classification captures a meaningful difference in firms'

[16]See Appendix B for further details.

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, $RevenueTags$, by parsing XBRL from both financial statements and footnotes, extracting tag names, values and periods.[17] We verify that our classification captures revenue disaggregation by showing that treated firms display a larger increase in $RevenueTags$ post-adoption. Figure 3 documents that treated firms show a pronounced increase in reported revenue items whereas non-disaggregating firms exhibit modest increase. For treated firms, the mean (median) $RevenueTags$ jumps from 15.9 (14) in 2017 to 27.5 (22) in 2018. In contrast, controls move from 9.5 (7) to 13.1 (8) in the same window. This gap persists in the post-adoption period, consistent with ASC 606 materially increasing revenue disaggregation among treated firms.

4.3 Patent-Related Variables

Our baseline 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, enabling 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 be cited (Hall et al., 2005). To address this issue, we analyze forward citations with CPC-class and grant-month fixed effects, and

[17] We exclude: (i) tags unrelated to revenue recognition, (ii) adjustment-type entries via dimension/member attributes, and (iii) remove clearly irrelevant items (e.g., "unearned revenues").

we scale each patent's citations by dividing by the CPC class × 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 patents per firm-year is 71.98 (3), indicating the data is highly skewed, which is typical for patent activity. In the typical firm-year, a patent receives on average about 2.37 citations and 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:

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

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

where the outcome variable $Y_{i,t}$ is different measures of the number of patent applications.

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 ($Post_t$) 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 fvariable 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: $Y_{i,t} = \#(Patents)_{i,t}$.[18] All specifications include fixed effects for the firm and year.

Figure 4 shows the dynamics of treatment effects for each year. We observe no statistically significant pre-trend prior to the 2014 announcement. The treatment effect exhibits an intuitive dynamic: treatment firms begin patenting at a significantly higher rate than their control, and this effect intensifies over time. The persistent upward trend after 2015 is consistent with the fact that the mandate is implemented in fiscal year 2018. Treated firms begin to adjust their strategy in anticipation of the mandate and then continue to do so as

[18] 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 B.1. Results are consistent with our main specifications.

implementation became certain.

Table 2 presents the regression estimates. Columns (1) and (2) report the average effect from Equation (5). Treatment firms—those that provided revenue disaggregation after ASC 606—exhibited a statistically significant increase in patent applications following the announcement of ASC 606. The coefficients are similar across the OLS specification and the negative binomial model. The magnitude of the effect is economically meaningful: on average, treatment firms increase their patenting rates by approximately 11.95% compared to control firms following the announcement of the mandate.[19]

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

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

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 analyze patent-level data and estimate the effect on forward citations (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 following specification.

$$\ln(\#\mathit{Citations})_{i,p,t} = \beta\,\mathit{Treat}_{i,p} \times \mathit{Post}_t + \Gamma\,\mathit{Controls}_{i,t} + \mathit{FE} + \epsilon_{i,t},$$

For citation-level regressions, we follow Hegde et al. (2023) and conduct patent-level analysis with fixed effects for CPC class and grant month to flexibly control for temporal and technological heterogeneity. We report results using log-transformed citation counts, both unscaled and scaled.

Table 3 presents the estimates for the DiD specifications with different fixed effect structures: Columns (1) and (3) for the average effect on log-transformed unscaled and scaled forward citations with CPC classification and grant month fixed effects, respectively, and

Column (2) and (4) show corresponding results adding firm fixed effects.

We observe that unscaled forward citations of patents filed by treatment firms decline by 10.85% after the announcement of the disaggregation rule (Column 1).[20] When firm fixed effects are included in Column (2), the decline attenuates to 6.92% but remains statistically significant.[21] Finally, using our fully-scaled measure (Column 4), which controls for all three fixed effects, we observe a statistically significant decrease in scaled citations. Across all specifications, the negative effect is statistically significant at the 99% level.

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 predominantly reliant on trade secrecy are an empirical proxy for firms in our model that are either in the "never patent" regime or have a very high initial patenting threshold. For these firms, the patenting decision is not at the active margin.

[20] $\exp(-0.1149) - 1 = -0.1085$
[21] $\exp(-0.0717) - 1 = -0.0692$

Therefore, a marginal shock from the new disclosure mandate is unlikely to be large enough to flip a "never patent" firm into the patenting regime or to substantially change the behavior of a firm whose threshold is already near the maximum. Moreover, shifting from "never patent" to threshold patenting policy would be costly, as it requires building administrative infrastructures 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 are 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 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 margin of the patenting decision and are thus less compelled to adjust their strategy. The absence of a significant response among these firms further validates our baseline findings: the observed increase in patenting is concentrated among firms for whom the patenting trade-off is at the margin.

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). 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. 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 shows that there will be 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 test this, we examine firms' innovation input by using R&D expenditure as the outcome variable in Equation (5) . As shown in Table 8, we find no significant change in the R&D investment of treatment firms after the revenue disaggregation announcement compared to control firms. This finding is also intuitive: adjusting a firm's patenting threshold is a direct and relatively fast response to a change in the information environment. Such an adjustment in IP strategy protects the firm's innovation pipeline, mitigating the need for a more costly change to its actual R&D investment. This finding confirms that the observed increase in patenting is likely a strategic shift in IP policy, not a change in innovation input.

We also rerun our main patent application and citation regressions while explicitly controlling for firms' R&D expenditure. The treatment effects, tabulated in Table B.2, are quantitatively similar. The findings reinforce the conclusion that the effect is driven by a strategic shift in IP protection policy rather than 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 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 confidence level 95%.[22]. 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 similar results.

We attribute this attenuation to critical differences in disclosure granularity between the two 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).[23] In contrast, under ASC 606, 3M's fiscal year 2019 10-K delineated 27 distinct product/service lines (e.g., oral care and drug delivery) within its segments, exposing previously obscured profitability metrics.[24] 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, which our model predicts would trigger 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 in-

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

[23] See 3M Inc. 10-K FY1997. Accessed 04/11/2025.

[24] See 3M Inc. 10-K FY2019. Accessed 04/11/2025.

formation 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.

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 lowers the threshold for patenting. As a result, firms patent more innovations as a defensive measure against competitive risks. This strategic shift in patenting behavior yields a lower average value of filed patents. Empirically, we exploit the announcement of the revenue disaggregation requirement of ASC 606 as a shock that increased firms' expectations of future competitive threats. We find that affected firms significantly increased their patent filings, while patent quality declined. These results support our model's predictions. We also find that the effect is muted for firms that predominantly rely on trade secrecy before the treatment. The findings are consistent with our model's prediction that these firms are not at the active margin of the patenting decision. Moreover, the treatment effect is strongest among firms with a more opaque ex-ante information environment. Lastly, we find no evidence that the affected firms significantly changed their R&D investment.

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' strategic IP management. While prior literature often uses patents as a proxy for innovation outcomes, we show that the patenting decision itself is a distinct strategic margin that responds to financial disclosure (Glaeser and Lang, 2024). Our study has important implications for policymakers, as it underscores how transparency causes equilibrium distortions in a competitive environment and patenting behavior.

Despite these insights, our study has limitations. While ASC 606 provides a valuable context, examining other disclosure regulations could enhance the generalizability of our findings. Future research could explore the long-term or aggregate effects of increased defensive patenting on market competition and subsequent innovation, providing a more comprehensive understanding of the implications of financial disclosure regulations.

References

Abrams, D. S., Akcigit, U., and Grennan, J. (2013). Patent Value and Citations: Creative Destruction or Strategic Disruption?

Allen, A., Lewis-Western, M. F., and Valentine, K. (2022). The Innovation and Reporting Consequences of Financial Regulation for Young Life-Cycle Firms. *Journal of Accounting Research*, 60(1):45–95.

Anton, J. J. and Yao, D. A. (2004). Little Patents and Big Secrets: Managing Intellectual Property. *The RAND Journal of Economics*, 35(1):1–22.

Argente, D., Baslandze, S., Hanley, D., and Moreira, S. (2020). Patents to Products: Product Innovation and Firm Dynamics. *SSRN Electronic Journal*.

Arora, A., Ceccagnoli, M., and Cohen, W. M. (2008). R&D and the patent premium. *International Journal of Industrial Organization*, 26(5):1153–1179.

Azinovic-Yang, L. (2024). Innovation and Welfare Impacts of Disclosure Regulation: A General Equilibrium Approach.

Berger, P. G. (2011). Challenges and Opportunities in Disclosure Research—A Discussion of 'the Financial Reporting Environment: Review of the Recent Literature'. *Journal of Accounting and Economics*, 51(1):204–218.

Berger, P. G., Choi, J. H., and Tomar, S. (2024). Breaking it Down: Economic Consequences of Disaggregated Cost Disclosures. *Management Science*, 70(3):1374–1393.

Berger, P. G. and Hann, R. (2003). The Impact of SFAS No. 131 on Information and Monitoring. *Journal of Accounting Research*, 41(2):163–223.

Berger, P. G. and Hann, R. N. (2007). Segment profitability and the proprietary and agency costs of disclosure. *The Accounting Review*, 82(4):869–906.

Bergstrom, T. and Bagnoli, M. (2005). Log-Concave Probability and Its Applications. *Economic Theory*, 26:445–469.

Bernard, D. (2016). Is the risk of product market predation a cost of disclosure? *Journal of Accounting and Economics*, 62(2):305–325.

Bernard, D., Burgstahler, D., and Kaya, D. (2018). Size Management by European Private Firms to Minimize Proprietary Costs of Disclosure. *Journal of Accounting and Economics*, 66(1):94–122.

Beyer, A., Cohen, D. A., Lys, T. Z., and Walther, B. R. (2010). The financial reporting environment: Review of the recent literature. *Journal of Accounting and Economics*, 50(2):296–343.

Bhattacharya, S. and Guriev, S. (2006). Patents vs. Trade Secrets: Knowledge Licensing and

Spillover. *Journal of the European Economic Association*, 4(6):1112–1147.

Boot, A. and Vladimirov, V. (2025). Disclosure, Patenting, and Trade Secrecy. *Journal of Accounting Research*, 63(1):5–56.

Breuer, M., Leuz, C., and Vanhaverbeke, S. (2025). Reporting Regulation and Corporate Innovation. *Journal of Accounting and Economics*, 80(1):101769.

Cetin, F. M. (2023). The Real Effects of Accounting on Innovation: Evidence from Asc 606.

Chang, Y.-C., Tseng, K., and Yu, T.-W. (2024). Access to Financial Disclosure and Knowledge Spillover. *The Accounting Review*, 99(5):147–170.

Cho, Y. J. (2015). Segment Disclosure Transparency and Internal Capital Market Efficiency: Evidence from SFAS No. 131. *Journal of Accounting Research*, 53(4):669–723.

Cohen, W. M., Nelson, R. R., and Walsh, J. P. (2000). Protecting Their Intellectual Assets: Appropriability Conditions and Why U.S. Manufacturing Firms Patent (or Not).

Dambra, M., Mihov, A., and Sanz, L. (2024). Unintended Real Effects of EDGAR: Evidence from Corporate Innovation. *The Accounting Review*, 99(6):75–99.

Dedman, E. and Lennox, C. (2009). Perceived Competition, Profitability and the Withholding of Information About Sales and the Cost of Sales. *Journal of Accounting and Economics*, 48(2):210–230.

Dyer, T. A., Glaeser, S., Lang, M. H., and Sprecher, C. (2024). The effect of patent disclosure quality on innovation. *Journal of Accounting and Economics*, 77(2):101647.

Ettredge, M., Kwon, S. Y., and Smith, D. B. (2000). The Effect of SFAS No. 131 on Numbers of Reported Business Segments.

Gao, H., Shroff, N., and Zhang, P. (2025). Sanctions Paradox: Do US Export Restrictions Hurt Domestic Innovation? *Available at SSRN 5373282*.

Glaeser, S. (2018). The Effects of Proprietary Information on Corporate Disclosure and Transparency: Evidence from Trade Secrets. *Journal of Accounting and Economics*, 66(1):163–193.

Glaeser, S. and Lang, M. (2024). Measuring Innovation and Navigating Its Unique Information Issues: A Review of the Accounting Literature on Innovation. *Journal of Accounting and Economics*, page 101720.

Glaeser, S. and Omartian, J. D. (2022). Public Firm Presence, Financial Reporting, and the Decline of U.S. Manufacturing. *Journal of Accounting Research*, 60(3):1085–1130.

Goldstein, I. and Yang, L. (2019). Good Disclosure, Bad Disclosure. *Journal of Financial Economics*, 131(1):118–138.

Goldstein, I., Yang, S., and Zuo, L. (2023). The Real Effects of Modern Information Technologies: Evidence from the EDGAR Implementation. *Journal of Accounting Research*, 61(5):1699–1733.

Guttman, I. and Meng, X. (2021). The Effect of Voluntary Disclosure on Investment Inefficiency. *The Accounting Review*, 96(1):199–223.

Hall, B. H., Jaffe, A., and Trajtenberg, M. (2005). Market Value and Patent Citations. *The RAND Journal of Economics*, 36(1):16–38.

Hegde, D., Herkenhoff, K., and Zhu, C. (2023). Patent Publication and Innovation. *Journal of Political Economy*, 131(7):1845–1903.

Hinson, L. A., Pündrich, G. P., and Zakota, M. (2024). The Decision-Usefulness of ASC 606 Revenue Disaggregation. *The Accounting Review*, 99(3):225–258.

Hong, H., Lim, T., and Stein, J. C. (2000). Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies. *The Journal of Finance*, 55(1):265–295.

Hopenhayn, H. A. and Squintani, F. (2016). Patent Rights and Innovation Disclosure. *The Review of Economic Studies*, 83(1):199–230.

Kim, J. and Valentine, K. (2021). The Innovation Consequences of Mandatory Patent Disclosures. *Journal of Accounting and Economics*, 71(2-3):101381.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2):665–712. Publisher: Oxford Academic.

Leuz, C. (2004). Proprietary Versus Nonproprietary Disclosures: Evidence from Germany. In *The Economics and Politics of Accounting: International Perspectives on Trends, Policy, and Practice*. Oxford University Press.

Leuz, C. and Wysocki, P. D. (2016). The Economics of Disclosure and Financial Reporting Regulation: Evidence and Suggestions for Future Research. *Journal of Accounting Research*, 54(2):525–622.

Li, Y., Lin, Y., and Zhang, L. (2018). Trade Secrets Law and Corporate Disclosure: Causal Evidence on the Proprietary Cost Hypothesis. *Journal of Accounting Research*, 56(1):265–308.

Matsuno, S. (2024). Disclosure, Signaling, and First-Mover (Dis)advantage. *Available at SSRN: https://ssrn.com/abstract=4985567*.

PWC (2025). Chapter 33: Revenue and contract costs.

Schankerman, M. (1998). How Valuable is Patent Protection? Estimates by Technology Field. *The RAND Journal of Economics*, 29(1):77–107.

Yu, F. F. (2008). Analyst coverage and earnings management. *Journal of Financial Economics*, 88(2):245–271.

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

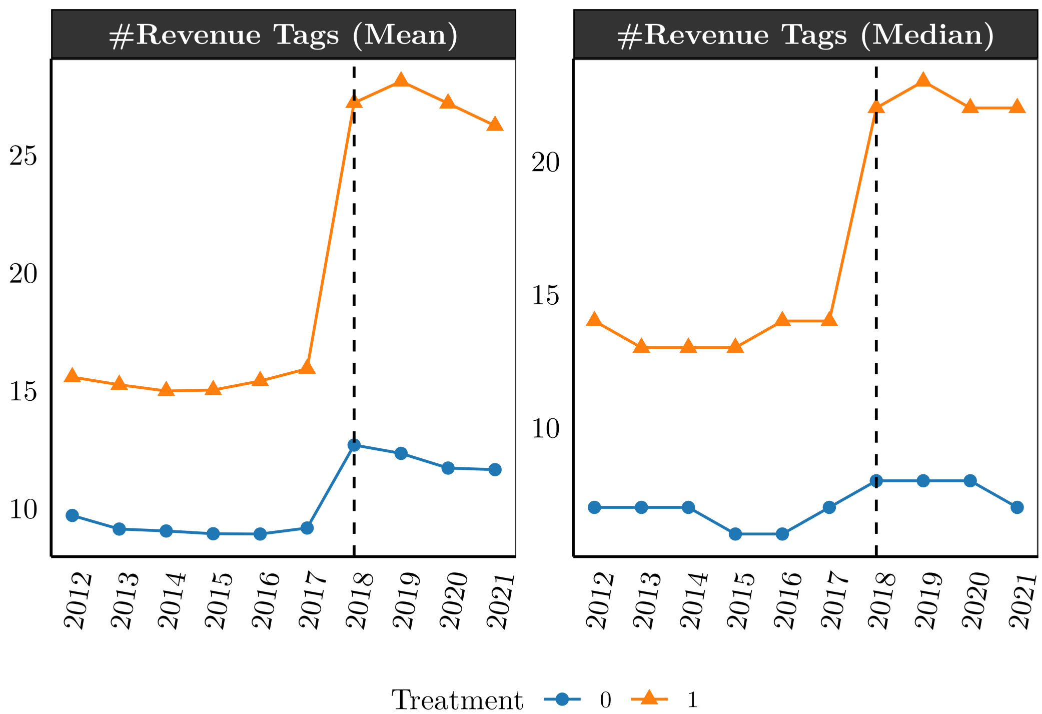
NOTE 4
REVENUE

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

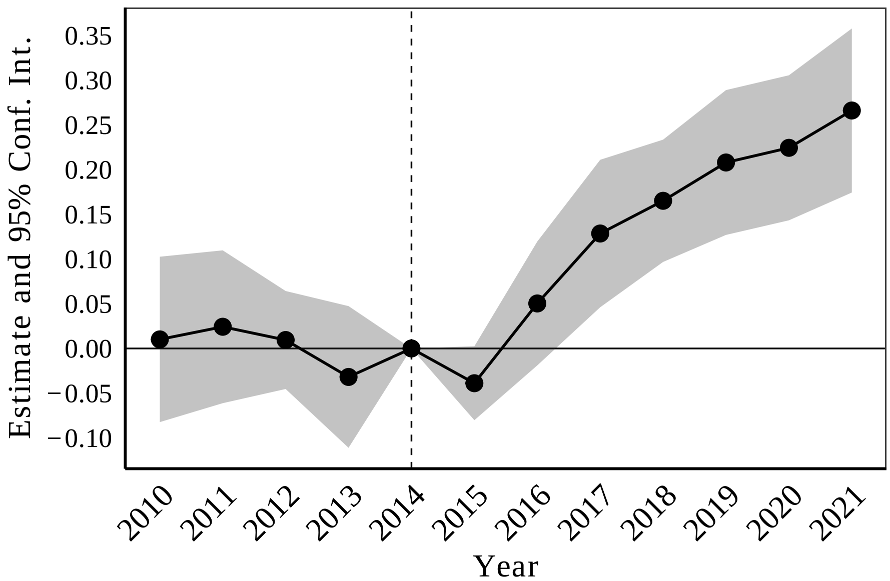
Note: ITT Inc. is a manufacturing company that produces specialty components for the aerospace, transportation, energy, and industrial markets. ITT Inc. was only disclosing broad segments in 2013. In 2018, it further disaggregated revenue sources under each of the categories and retrospectively disaggregated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

Figure 3: The Number of Revenue Tags



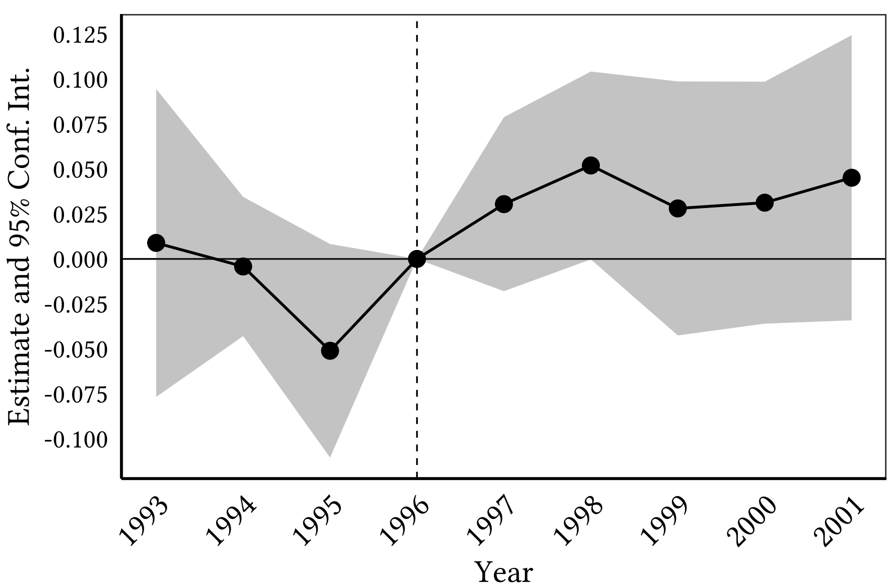
Note: The figure plots the mean and median number of numerical revenue tags around the implementation of ASC 606 in 2018. The period of analysis starts from 2012 because XBRL rolled out to all firms around 2012. The revenue tags are counted allowing for duplicates since same tag name could be used to 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)



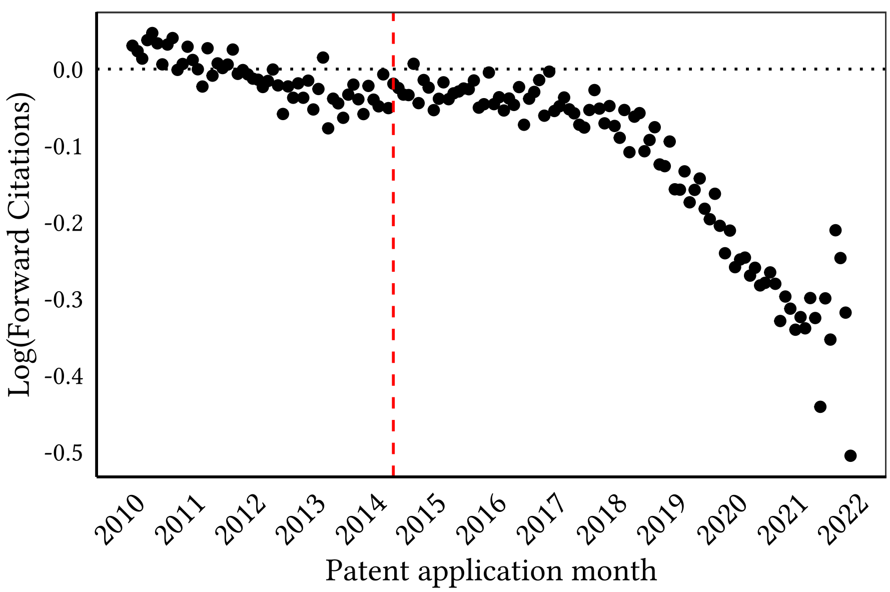
Note: The figure shows the OLS estimates of the DiD coefficients of the regression $\ln(\#Patents + 1)_{i,t} = \sum_{t\neq 2014} \beta_t \, Treat_i \times Post_t + \Gamma \, Controls_{i,t} + \alpha_i + \gamma_c + \epsilon_{i,t}$, where α_i and γ_c are firm and CPC class fixed effects. The model is estimated 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 $\ln(\#Patents + 1)_{i,t} = \sum_{t\neq 2014} \beta_t \, Treat_i \times Post_t + \Gamma \, Controls_{i,t} + \alpha_i + \gamma_c + \epsilon_{i,t}$, where α_i and γ_c are firm and CPC class 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)

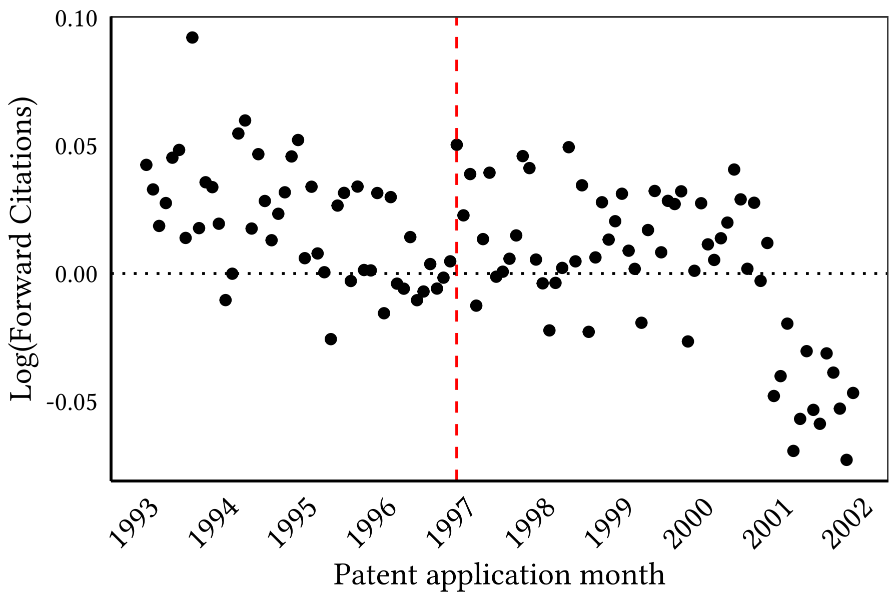


Note: The figure plots the application-month average of the log of scaled forward citations for treatment firms relative to control firms. Each point corresponds to a coefficient β from the regression:

$$y_{i,t} = \sum_{m} \beta_m \cdot \mathit{Treat}_i \cdot \mathbb{1}\{t = m\} + \Gamma\, \mathit{Controls}_{i,t} + \alpha_i + \gamma_c + \varepsilon_{i,t},$$

where m denotes an application month, and α_i and γ_c are firm and CPC class 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:

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

where m denotes an application month and α_i and γ_c are firm and CPC class 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
Treatment	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
Number of Patents	9,696	71.9837	355.9484	0.0000	0.0000	3.0000	19.0000	94.0000
Number of Citations	9,696	2.3696	10.0642	0.0000	0.0000	0.1333	1.9000	5.3333
Cash Holdings	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
Market-to-Book	9,696	0.0036	0.0582	0.0009	0.0015	0.0025	0.0043	0.0082
Return On Asset	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
Number of Patents	6,732	64.2704	353.3273	0.0000	0.0000	3.0000	18.0000	82.0000
Number of Citations	6,732	2.2498	7.8746	0.0000	0.0000	0.1093	2.0000	5.5789
Cash Holdings	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
Market-to-Book	6,732	0.0035	0.0473	0.0010	0.0016	0.0026	0.0045	0.0084
Return On Asset	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
Number of Patents	2,964	89.5027	361.2800	0.0000	0.0000	3.0000	24.0000	115.0000
Number of Citations	2,964	2.6416	13.8001	0.0000	0.0000	0.1719	1.6895	4.8519
Cash Holdings	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
Market-to-Book	2,964	0.0037	0.0775	0.0007	0.0012	0.0022	0.0040	0.0076
Return On Asset	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, 6,731 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 a dummy variable taking the value of 1 for years of and after 2015. *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 mentioning 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 *Post*2015 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* 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. Information opacity (*Opaque*) is constructed in the *pre-treatment* window (2011–2014): for each firm, we compute its average number of covering analysts over this period and exclude firms with no coverage. The continuous *Opaque* is the negative, standardized residual from regressing pre-period analyst coverage on firm size with 2-digit NAICS industry fixed effects (larger values indicate more opaque relative to size- and industry-peers); the binary *Opaque* equals 1 for firms in the bottom tercile of that 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*. Standard errors, reported in parentheses, are clustered at the two-digit NAICS level. The regressions include year and firm fixed effects as indicated.

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* 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. Information opacity (*Opaque*) is constructed in the *pre-treatment* window (2011–2014): for each firm, we compute its average number of covering analysts over this period and exclude firms with no coverage. The continuous *Opaque* is the negative, standardized residual from regressing pre-period analyst coverage on firm size with 2-digit NAICS industry fixed effects (larger values indicate more opaque relative to size- and industry-peers); the binary *Opaque* equals 1 for firms in the bottom tercile of that 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*. Standard errors, reported in parentheses, are clustered at the two-digit NAICS level. The regressions include year and firm fixed effects as indicated.

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

	R&D (1)	R&D' (2)
Treat × Post 2015	-0.0009	0.0002
	(0.0048)	(0.0059)
Controls	✓	✓
Within R^2	0.02796	0.02713
Observations	9,696	7,777
Year fixed effects	✓	✓
Firm fixed effects	✓	✓

Note: This table shows the effect of ASC 606 announcement on R&D expenditure. *R&D* is scaled by lagged total assets. In Column (1), the outcome variable *R&D* replaces missing values as 0. In Column (2), the outcome variable R&D′ do not replace missing values by 0. Control variables include *leverage*, *ROA*, *cash*, *MTB*, *size*. Standard errors in parenthesis are clustered at 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 × Post	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 taking value of 1 for disaggregating firms defined as in subsection 4.2, and *Post* is a dummy variable taking value of 1 for years after 1996. Control variables include *leverage*, *ROA*, *cash*, *MTB*, *size*. Standard errors in parenthesis are clustered at 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)	
Post	-0.0182	0.0163	-0.0092	0.0038
	(0.0122)	(0.0124)	(0.0050)	(0.0050)
Treat × Post	-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 taking value of 1 for disaggregating firms defined as in subsection 4.2, and *Post* 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 Proofs for Section 2

A.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.

A.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:

$$\mathbb{E}[\pi^j_a(e^*_c(\theta, aw), \theta, w) \mid a] = \frac{\partial C_s}{\partial e_s}(e^*_s, \eta_a).$$

For the competitor's belief $\mu \in \Delta([\underline{\theta}, \overline{\theta}])$, define $A(\theta, \mu_a) := e^*_{s,a=0}(\mu_1)e^*_{c,a=0} - e^*_{s,a=1}(\mu_0)e^*_{c,a=1}$, 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 $w \to 1$, from the first-order condition (3), the competitor does not exert any effort: $\lim_{w\to 1} e^*_{c,a=0} = 0$. In this case, $A(\theta, \mu_a) = e^*_{s,a=0}(\mu_1)e^*_{c,a=0}$ 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 benefit of the patenting disappears, so $\lim_{w\to 0} A(\theta, \mu_a) = 0$. In this case, $\Delta(\theta) < 0$ regardless of θ, so the incumbent never patents.[25] 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

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

By the implicit function theorem, we have

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

Therefore, when $\rho = 0$, we have $\frac{\partial \tau}{\partial \eta_0} > 0$. When $\rho > 0$, we have $\frac{\partial^2 \tau}{\partial \rho \partial \eta_0} < 0$, so $\frac{\partial \tau}{\partial \eta_0} > 0$ can be negative when ρ is large enough.

[25]To support this equilibrium, let the competitor's off-path belief assign probability one to the highest value $\overline{\theta}$ in the off-path event of patenting.

A.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

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

Since inside of the bracket term, 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

$$X > \frac{\underline{\theta}^2}{2g(\eta_0)} - (1-w)^3\frac{\overline{\theta}^2}{2g(\eta_1)}.$$

Therefore, $X > 0$ if

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

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

Next,

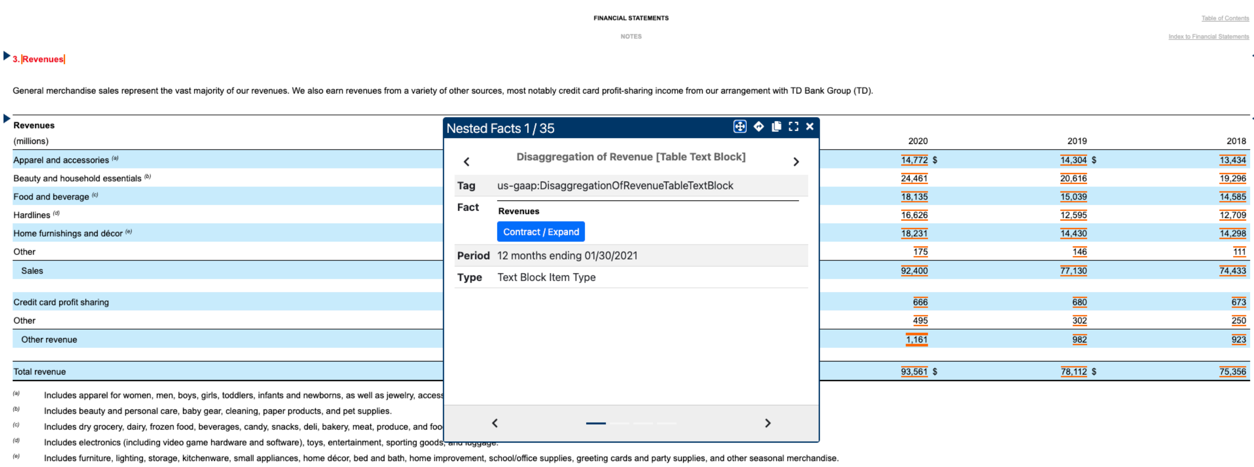
B Data and Variable Constructions

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 using python. 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 a regular expression:

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

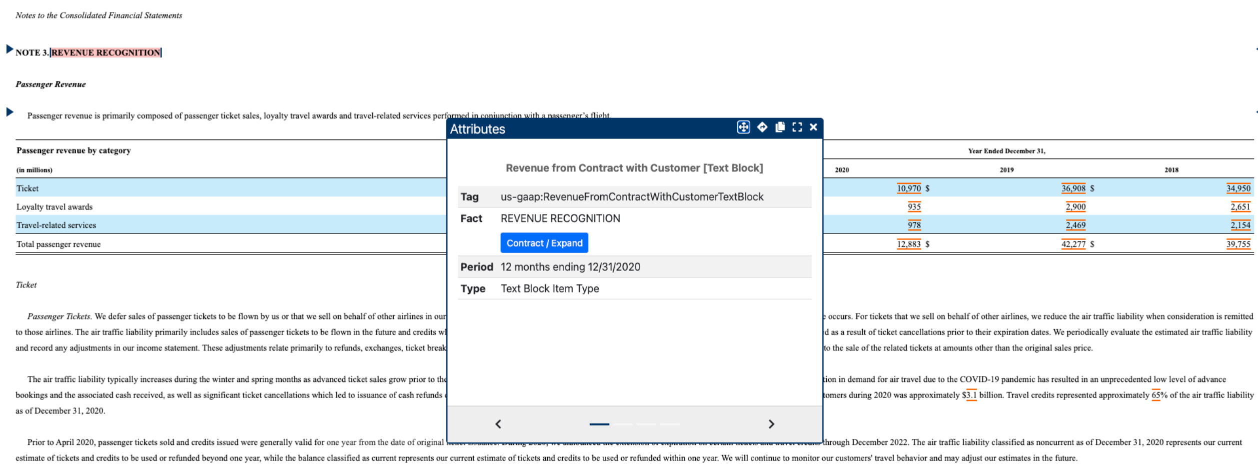
To ensure relevance, we filter the extracted tags by excluding those unrelated to revenue (e.g., "Unearned Revenue"), those from prior fiscal years, and those representing adjustments by identifying axis and member attributes. This filtering approach captures only the disaggregation-related revenue tags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

Figure B.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 'DisaggregationOfRevenueTable-TextBlock'.

Figure B.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'.

Table B.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 B.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 B.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 parenthesis are clustered at two-digit NAICS level.