Deterrent Disclosure

Stephen Glaeser† and Wayne R. Landsman

Kenan Flagler Business School, University of North Carolina at Chapel Hill

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ABSTRACT: We examine how product market competition affects the disclosure of innovation. Theory posits that product market competition can cause firms to increase their disclosure of innovation to deter product market competitors. Consistent with this reasoning, we find that patent applicants in more competitive industries voluntarily accelerate their patent disclosures, which are credibly disclosed via the United States Patent and Trademark Office. Our inferences are robust to using changes in industry-level import tariffs as sources of plausibly exogenous variation in product market competition in differences-in-differences designs. Consistent with patent disclosure deterring product market competitors, we find that timelier patent disclosures are more strongly associated with declines in the similarity of competitors’ products than are less timely patent disclosures. In total, our results suggest that product market competition increases patent disclosure timeliness, which is consistent with firms using the disclosure of innovation to deter product market competition.

Keywords: Voluntary disclosure, innovation, patents, competition

JEL classification: D23, G38, O30, O31, O33, O34, O38

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1. Introduction

We examine how product market competition affects the voluntary disclosure of innovation. Building on prior theory work, we predict that product market competition encourages the disclosure of innovation.\(^1\) Innovations provide firms with an efficiency or product advantage, and partial excludability, such as from patent protections, allows them partially to protect this advantage. Credibly communicating this advantage may cause potential competitors to avoid the innovator’s market and cause existing competitors to reduce their production or alter their products. Therefore, product market competition should encourage the disclosure of innovation.

Understanding when and why firms voluntarily disclose innovation is important to policy makers and academic research (e.g., Tegernsee Experts Group, 2012). Innovation is the central driver of economic growth because others can build on innovations, creating positive spillovers (e.g., Solow, 1957 and Romer, 1990). However, others cannot build on an innovation and no spillovers occur until the innovation is disclosed. The disclosure of innovation can also prevent the costly duplication of research efforts and can affect the allocation of capital because of information asymmetry around innovations (e.g., Aboody and Lev, 2000). However, prior academic work finds evidence that the disclosure of innovation can incur significant proprietary costs by providing enabling information to *technological* competitors (e.g., Ettredge et al., 2017; Cao et al., 2018).

Although technological and product market competition are correlated, they are distinct concepts.\(^2\) Technological competition is the competitive pursuit of innovations, which may be used in the innovator’s own product market, or licensed to competitors in its own or other product markets. Product market competition is the competitive pursuit of users or consumer spending in

\(^2\) Bloom et al., 2013; Ettredge et al., 2017; Cao et al., 2018; Bloom et al., 2018.
a given product market. For example, Apple and Intel are technological competitors as evidenced by their similar patenting activity, but are not product market competitors because Apple does not directly compete with Intel in the semiconductor product market. In contrast, Apple and Nokia are product market competitors in the smartphone product market. Theory suggests that technological competition will decrease the disclosure of innovation, while product market competition will increase the disclosure of innovation.\(^3\) Prior empirical work finds evidence of the former, and we contribute to the literature by documenting evidence of the latter.

To do so, we examine 193,937 successful patent applications filed by public firms with the U.S. Patent and Trademark Office (USPTO). All patent applications filed with the USPTO include a detailed description of how to recreate the innovation independently of the inventor. The USPTO publishes patent applications after a deadline of the earlier of 18 months after foreign filing and the decision date for applications seeking foreign protection, and the decision date for all others. However, applicants can choose to have the USPTO publish their applications prior to the publication deadline, credibly disclosing their innovation on a centralized repository monitored by competitors and investors (37 CFR § 1.219).\(^4\) We examine how product market competition affects this timing choice by comparing applications filed by applicants facing different degrees of product market competition (i.e., the unit of analysis is the patent application). Our focus on the timing of disclosure mirrors prior studies that examine manager earnings forecasts, which accelerate the disclosure of earnings information from the 10-K release date to the disclosure date.

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\(^4\) See, for example, Brown and Arshem (1993), Boulakia (2001), Kogan et al. (2017), Hegde et al. (2018) and Martens (2019). Brown and Arshem (1993) finds that 17% of visitors to Patent and Trademark Depository Libraries from 1991-92 used the patent information for legal, product, and market research, while 6% used the information for economic research. Boulakia (2001) describes the process of patent mapping by companies such as AT&T, IBM, and Lucent. Patent mapping allows the CEOs and VPs of these companies to “identify…future competitive threats” and “competitors that [they] didn’t know existed yet.”
Patent applications have several advantages as a setting to examine our research question. First, our data include the application date, the disclosure date, and the mandatory disclosure deadline for all patent applications. Because this information is revealed ex post, we are able to observe in-process applications that were not publicly disclosed at the time. This permits us to compare applicants that choose to disclose to those who choose not to. Second, each observation in our sample is a successful patent application, meaning that every applicant in our sample has successfully innovated and chosen to protect their innovation with a patent. Therefore, we are able to isolate applicants’ disclosure decisions from the underlying economics of successfully innovating and choosing patenting to protect that innovation. Third, patent examiners review patent applications for novelty and accuracy, and patent protections extend only to information disclosed in the application. When disclosed, patent applications are published by the USPTO on the USPTO website. Consequently, patent disclosures are highly credible (Long, 2002). Fourth, patents provide the right to exclude others from using the innovation. Therefore, patents match the assumption of excludability made by the theoretical models that motivate our predictions.

The final benefit of examining patenting applications is that doing so allows us to separately examine technological competition and product market competition. We use several features of the patent application setting to separate the effects of technological and product market competition. First, we follow Bloom et al. (2013) and Bloom et al. (2018) to construct a measure of technological competition based on competitors’ total R&D spending and comparative patenting activity across patent classes. Second, we construct a vector of patent class-by-year fixed effects. Third, we directly measure realized technological competition using the citations a patent receives. We include these fixed effects and measures of technological competition as controls throughout our analyses. Although our focus is on the effects of product market competition,
consistent with prior work we find technological competition discourages the disclosure of innovation (Cao et al., 2018).

We also use several approaches to measure product market competition. In our first set of analyses, we measure product market competition using industry concentration, separately measured with both U.S. Census data and public firm financial data (U.S. Department of Justice and Federal Trade Commission, 1993). We find that firms in industries that become less concentrated relatively accelerate their patent disclosures, which is consistent with product market competition encouraging the disclosure of innovation.

In our second set of analyses, we separately use changes in import tariffs and large import tariff decreases across different industries at different times as sources of variation in product market competition in differences-in-differences designs (e.g., Fresard, 2010; Huang et al., 2017). The intuition for this approach is that increases (decreases) in the tariff rate represent decreases (increases) in competition from foreign entrants. A strength of this approach is that Huang et al. (2017) presents evidence that tariff changes are plausibly exogenous with respect to firm disclosure choices (e.g., they are unexpected and not the result of lobbying; see also Fresard, 2010).

Consistent with our predictions, we find that both changes in tariff rates and large tariff decreases inverse increases in patent disclosure timeliness. We also examine whether firms affected by changes in tariff rates differentially change their disclosure behavior prior to the change (i.e., we conduct a parallel trends test). We find no evidence that firms respond to changes in tariff rates or large tariff decreases prior to the change, i.e., “treatment” and “control” firms exhibit parallel pre-treatment trends.

In our third set of analyses, we use a text-based measure of product market competition. We measure product market competition using managers’ perceptions of competition, as measured
by Li et al. (2012), and find that this measure also negatively relates to patent disclosure delays. In total, we find evidence that product market competition leads to timelier patent disclosure across multiple distinct measures of product market competition.

We conduct a variety of robustness tests and extensions, including re-estimating our main tests after controlling for patents values and excluding firms subject to Food and Drug Administration (FDA) oversight. Perhaps most notably, we document descriptive evidence that timelier patent disclosure is associated with decreases in the similarity of competitors’ products to those of the firm (Hoberg and Phillips, 2010, 2016). This evidence is consistent with patent disclosure successfully deterring product market competitors, and suggests deterrence is primarily responsible for the effect of product market competition on patent disclosure timeliness.

Our work contributes to the literature on voluntary disclosure by documenting evidence that product market competition causes timelier patent disclosure. In this regard, we also build on the literature that examines how firms respond to the threat of product market predation. For example, Bernard (2016) finds that firms avoid disclosures that could invite predation by product market competitors. In contrast, we find that firms use patent disclosures to discourage competition from product market rivals, which is consistent with firms “weaponizing” the disclosure of innovation in the face of competition (Ordover and Willig, 1981; Bloomfield, 2018; Bloomfield and Tuijn, 2018). Our focus on patent disclosures also answers the call of Leuz and Wysocki (2016) for more research on nontraditional disclosures. The disclosure of innovation is a particularly important nontraditional disclosure because the financial reporting system does not recognize investments in innovation as intangible assets.  

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5 We do not address whether the financial reporting system should or should not recognize these investments as assets. However, Hegde et al. (2018) and Martens (2019) find that investors trade based on the information in patent disclosures, suggesting patent disclosures may partially substitute for the recognition of innovative investments as intangible assets.
We also contribute to a growing literature that examines how firms trade off different types of disclosures (e.g., Glaeser, 2018; Heinle et al., 2018). In this regard, prior work that documents a positive effect of competition on voluntary disclosure, in particular Huang et al. (2017), is important. Huang et al. (2017) finds that significant tariff decreases reduce the quantity of voluntary earnings forecasts. In contrast, we find that significant tariff decreases increase the timeliness of patent disclosure. Together, our results highlight how the same economic force can affect different disclosures in very different ways, and suggest that both competition and disclosure are multidimensional constructs (Bloom et al., 2013; Cao et al., 2018; and Lee et al., 2019).

Our work also has potential policy implications. Discussions by the heads of offices of and experts from the USPTO, the Japan Patent Office, the European Patent Office, and the patent offices of the UK, Denmark, Germany and France, suggests that regulators attempt to set patent disclosure deadlines by balancing the cost to individual inventors of revealing information to technological competitors against the positive externalities of patent disclosure (Tegernsee Experts Group, 2012). Our work can help inform regulators’ calculus by shedding light on when and why firms voluntarily accelerate their patent disclosures. This calculus has efficiency implications; the positive externalities of disclosed innovations are the central driver of growth in developed economies (e.g., Solow, 1957; Romer, 1990; Hall et al., 2010). The positive externalities of disclosed innovations suggests our focus on patent disclosures also answers the call of Leuz and Wysocki (2016) for more research examining settings that involve real effects of disclosure.

We organize the rest of the paper as follows. We provide background information on patenting, disclosure theory, and prior work in Section 2. We describe our research design in Section 3 and discuss our sample, data sources, and variable measurement in Section 4. We present
results in Section 5 and provide concluding remarks in Section 6.


2. Background and theoretical predictions

2.1 Patenting and patent disclosure

Patents provide the right to exclude others from the production or use of a novel device, process, apparatus, formula, or algorithm for a specified period. Patent offices issue patents to inventors after a patent examiner verifies the novelty and potential utility of the claimed item. Patent examiners frequently make requests to amend or revise the application. Applicant must either comply or object to these requests within six months. Patent examinations can be quite lengthy: an average of 34 months in our sample, with the longest examination lasting almost ten years.

The inventor can transfer or license the right embedded in the patent, usually to their employer, and can enforce the right only by the threat of, or an actual suit for, infringement damages or an injunction. The stated purpose of the patent system is to encourage invention and economic progress by providing inventors temporary monopoly rights in exchange for a public disclosure of how to recreate the innovation (e.g., Article 1, Section 8, Clause 8 of the U.S. Constitution).

The USPTO requires applicants also filing abroad to publish their application by the earlier of 18-months after filing abroad and the decision date, and requires all other applicants to disclose by the decision date. The USPTO also publishes applications not seeking foreign protection 18-months after filing unless requested otherwise. However, applicants can request at any time that

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6 This period is 20 years from the application filing date for U.S. utility patents and 14 years from the grant date for U.S. design patents.
7 “[The Congress shall have power] to promote the progress of science and useful arts, by securing for limited times to authors and inventors the exclusive right to their respective writings and discoveries.”
the USPTO publish their in-process application, after which the USPTO makes the application publicly available on the USPTO website. Applicants not seeking foreign protection can also choose to opt out of the 18-month disclosure.

When inventors disclose their proprietary knowledge has efficiency implications. Innovation is the central driver of growth in developed economies (e.g., Solow, 1957). Innovation contributes to growth because innovations are non-rival and produce technological spillovers, which increase the productivity and innovative ability of others (e.g., Romer, 1990; Bloom et al., 2013). More timely disclosure increases the speed of technological progress by allowing others to begin building on the inventor’s discovery sooner. Similarly, more timely disclosure reduces the potential for inefficient duplication of research efforts.

However, disclosure imposes costs on the innovator because other inventors can use the disclosed information in conjunction with their own research efforts to surpass the patented innovation in quality, or to invent around the patent. Consequently, some inventors view patent disclosures as the “greatest constraint on the effectiveness of patents” (Harabi, 1995). As a result, regulators balance the cost to individual inventors of revealing enabling information against the positive externalities of patent disclosure when setting patent disclosure deadlines. As the Tegernsee Heads, which consists of the heads of offices of and experts from the USPTO, the Japan Patent Office, the European Patent Office, explain:

“There are many policy considerations that underlie this balance. One such policy is to ensure that third party competitors have timely notice of new developments, so they can make informed decisions about, e.g., whether to continue pursuing a similar technology, or designing around the subject matter disclosed in the application. This, in turn, promotes a more effective allocation of research investments and a corresponding reduction in costly and time consuming litigation. Another underlying policy is to allow the inventor to make a suitably informed decision whether to continue seeking patent protection or to keep the information as a possible

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8 See, e.g., Horstmann et al., 1985; Grossman and Helpman, 1991; Scotchmer, 1991; O’Donoghue, 1998; Anton and Yao, 2004; Saidi and Zaldokas, 2017; Glaeser, 2018; Glaeser et al., 2019.
trade secret. 18-month publication also increases the efficiency of allocating patent rights by enabling an early assessment of prior art with respect to conflicting applications.”

Absent from the Tegernsee Heads’ discussion is a consideration of other potential benefits of the disclosure of innovation, including deterring product market competitors.

2.2 Competition and the disclosure of innovation

Anecdotal evidence suggests that firms disclose innovations to deter product market competitors. See, for example, Henry Ford’s disclosure of the moving assembly line (Arnold, 1914; Dalton, 1926; Hounshell, 1985; Hall et al., 2014), Microsoft’s product preannouncements (United States v. Microsoft, Civil Action 94-1564), and IBM’s disclosure of copper-dependent process in producing semi-conductors in place of aluminum (Harhoff et al., 2003).9

Building on this anecdotal evidence, Hughes and Pae (2015) presents a model in which an innovating firm has a choice of whether to disclose its innovation (see also Baker and Mezzetti, 2005; Jansen 2005, 2011). Disclosing is costly because doing so creates knowledge spillovers that can allow technological competitors to partially free ride. However, disclosing can also benefit the innovating firm by communicating its advantage to product market competitors and affecting their pricing or production decisions. Conceptually, this effect on competitors can occur because the product market competitor knows they cannot replicate a patented product innovation or because they know a patented process innovation lowers the disclosing firm’s cost of production.

We illustrate the theoretical relation between technological competition and the disclosure of innovation and between product market competition and the disclosure of innovation in Figure 1. Other things equal, the greater the intensity of product market competition, the greater the benefit of communicating an advantage from an innovation. In contrast, the greater the intensity

9 Deterrent disclosure even occurs in the natural world: Thomson’s gazelles use stotting as a credible, but costly, disclosure of their physical condition to deter predators (Fitzgibbon and Fanshawe, 1988).
of technological competition, the greater the cost of communicating information that about an innovation.\textsuperscript{10} Because the two types of competition are highly correlated, we hold the effect of technological competition fixed in our empirical analysis.

2.3 Prior empirical work

We build on the accounting literature that studies the disclosure of innovation.\textsuperscript{11} Broadly stated, this literature documents evidence that capital market concerns and a desire to protect proprietary information affects the disclosure of innovation. We contribute to this literature by examining how product market competition affects patent disclosure.

In this regard, we also build on prior empirical studies that examine the relation between product market competition and disclosure. This literature finds evidence of a negative relation or no relation between product market competition and disclosure (see Beyer et al., 2010 for a review). The weight of the evidence from this literature is consistent with product market competition discouraging disclosures that carry high proprietary costs with respect to competitors’ actions (e.g., competition discourages good news earnings forecasts that might encourage competitors to increase production; Verrechia, 1983; Clinch and Verrecchia, 1997). However, this prior work does not examine the relation between product market competition and the disclosure of innovation.

Importantly, the relation between product market competition and the disclosure of innovation is theoretically distinct from the relation between product market competition and other disclosures (Hughes and Pae, 2015). Therefore, our goal is not to examine the standard predictions about disclosure and competition through the lens of patent disclosures. Instead, our goal is to


\textsuperscript{11} See, e.g., Guo, et al., 2004; Jones, 2007; Merkley, 2014; Plumlee et al., 2015; Cao et al., 2018; Glaeser, 2018; Breuer et al., 2019; Chen et al. 2019; Huang et al., 2019.
examine a distinct theoretical prediction. Indeed, we find that product market competition causes an increase, rather than a decrease, in patent disclosure, as reflected by more timely voluntary disclosure.

In this regard, our work is related to the literature that finds that product competition encourages the disclosure of bad news (e.g., Li, 2010; Burks et al., 2017; Tomy, 2018). Our study differs because we study a good news disclosure that discourages entry by signaling forthcoming product market strength, whereas this prior work studies bad news disclosures that discourage entry by signaling poor product market conditions.

The study most closely related to our own is a concurrent working paper, Bloomfield and Tuijn (2018), which finds product market competition encourages voluntary capacity expansion disclosures. The primary difference between Bloomfield and Tuijn (2018) and our work is that we study the disclosure of innovation, while Bloomfield and Tuijn (2018) studies capacity expansion disclosures. Whereas capacity expansion disclosures represent a credible commitment to aggressive production schedules, the disclosure of innovation represents a credible signal of forthcoming product market strength.

Our study conceptually relates to the large literature on the determinants of innovation.12 We differ from this literature in that we study determinants of disclosing innovation, conditional on the existence of innovation, whereas this literature studies the determinants of successfully innovating. Prior work posits that innovation produces positive externalities that drive growth (e.g., Solow, 1957; Romer, 1990; Hall et al., 2010). These externalities occur because the disclosure of innovation allows others to begin building on the innovation and because public

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12 See, e.g., Aghion et al., 2005; Lerner et al., 2011; Hirshleifer et al., 2012; Aghion et al., 2013; Atanassov, 2013; He and Tian, 2013; Baranchuk et al., 2014; Chemmanur et al., 2014; Fang et al., 2014; Hsu et al., 2014; Seru, 2014; Tian and Wang, 2014; Cornaggia et al., 2015; Brav et al., 2016; Acharya and Xu, 2017; Agarwal et al., 2017; Balsmeier et al., 2017; Breuer et al., 2019; and Tsang et al., 2019.
disclosed) knowledge is nonrival (Romer, 1990). Consequently, understanding both what determines the creation of innovation and the disclosure of those innovations, is important to gaining a full understanding of the role innovation plays in growth.

3. Research design

3.1 Baseline model

Our baseline model compares the timing of voluntary disclosure by patent applicants facing different levels of product market competition:

\[
\text{Patent Disclosure Delay}_{i,j,t} = \beta_0 + \beta_1 \text{Product Market Competition}_{i,t} - 1 + \gamma X_{i,t-d} + \eta Y_{j,t} + \text{IndustryFE} + \text{PatentClass} \times \text{ApplicationYearFE} + \varepsilon_{i,j,t},
\]

where \( i \) indexes patent applicants (i.e., \( i \) indexes individual firms), \( j \) indexes patent applications, and \( t \) indexes application years. All patent applicant variables are measured as of the most recent fiscal year prior to the patent application filing (the \( t-d \) subscript refers to the applicants’ most recent fiscal year end prior to the patent filing).\(^{13}\) Patents Disclosure Delay is one of two measures of the length of time the applicant delays disclosure, which we describe in section 4.2. Product Market Competition is one of several measures of product market competition, which we describe in section 4.3. Based on our discussion in section 2.2, we predict that more intense product market competition will lead to more timely patent disclosure.

\( X \) is a vector of the following time-varying patent applicant controls. External Capital Dependence is capital expenditures plus R&D expenditures minus operating activities net cash flow, divided by capital expenditures plus R&D expenditures (Rajan and Zingales, 1998). Blockholders is the number of shareholders listed on Thomson-Reuters with 5% or more

\(^{13}\) For example, for a firm with a December fiscal year-end filing an application on April 3, 2003, we measure the patent applicant variables as of December 31, 2002.
ownership of the firm. *Leverage* is the book value of total debt, divided by the book value of total assets. *Ln*(Equity Market Value) is the natural logarithm of the market value of the firm’s equity. *Loss* is an indicator equal to one if net income is negative. *Market to Book* is the ratio of the market value of assets to the book value of assets. *R&D* is R&D expenditures scaled by total assets. Missing values of R&D are replaced with zeroes. *Missing R&D* is an indicator set equal to one if data on R&D expenditures is missing (Koh and Reeb, 2015). *Return* is the buy and hold return over the prior fiscal year. *Return on Assets* is income before extraordinary items scaled by the book value of assets. *Sigma(Returns)* is the standard deviation of monthly returns. We make no predictions regarding the coefficients on these control variables.

We include several controls for technological competition to isolate the effect of product market competition. First, we include realized knowledge spillovers, *Ln*(Technological Competition 1), in the vector of patent application controls, *Y*. *Ln*(Technological Competition 1) is the natural logarithm of one plus the number of citations the patent receives.

Second, we include *Ln*(Technological Competition 2) in the vector *X*. Bloom et al. (2018) calculates Technological Competition 2 as the potential knowledge spillovers from patenting activity.¹⁴ Bloom et al. (2018) first calculates the Jaffe (1986) measure of technological proximity:

\[
Technological Proximity_{i,j} = \frac{(T_i T'_j)}{(T_i T'_i)^{1/2} (T_j T'_j)^{1/2}},
\]

where *T* is the vector of firm *i* or *j*’s share of patenting activity across USPTO patent classes over the period 1970 to 2006. Technological Proximity measures the degree of technological overlap between two firms and ranges from 0 to 1. Technological Competition 2 is the pool of potential knowledge spillovers for firm *i* in year *t*:

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¹⁴ We thank the authors of Bloom et al. (2013) and Bloom et al. (2018) for making the data publicly available on Nicholas Bloom’s website: [https://people.stanford.edu/nbloom/](https://people.stanford.edu/nbloom/).
\[ \text{Technological Competition}_{i,t} = \sum_{j \neq i} \text{Technological Proximity}_{i,j} \times R&D \text{ Stock}_{j,t} \]

R&D Stock is calculated from current and historical R&D spending using the perpetual inventory method assuming a 15% depreciation rate (Hall et al., 2005). We divide Technological Competition 2 by 100,000 and take the natural logarithm to ease interpretation.

Third, we include a vector of indicators for each National Bureau of Economic Research (NBER) patent class in each application year (PatentClass x ApplicationYearFE). Consequently, our tests compare patent applications filed in the same patent class in the same year. Therefore, these indicators control for all knowledge spillovers that are common within a patent class. Conceptually, patent class by year fixed effects serve as controls for technological competition in the same manner that industry by year fixed effects serve as controls for product market competition.

We expect firms to delay their patent disclosures more when technological competition is more intense, i.e., we predict a positive relation between Patent Disclosure Delay and both Technological Competition 2 and \( \ln(\text{Technological Competition 1}) \). However, we note that the inclusion of PatentClass x ApplicationYearFE and multiple measures of technological competition may reduce the power of our tests to detect a relation between technological competition and Patent Disclosure Delay. We make these research design choices because our goal is to control for technological competition, not document its effect.

3.2 Differences-in-differences models

Eq. (1) measures the relation between product market competition in the most recent prior fiscal year and patent disclosure delays. A potential concern with interpreting the results of estimating Eq. (1) is that Hughes and Pae (2015) contend firms use patent disclosure to affect competition. Hence, the relation between the two may be endogenous. We attempt to address this
concern directly in Eq. (1) by using measures of competition that precede firms’ disclosure choices. Nonetheless, we use an additional approach to address this and other potential endogeneity concerns. Specifically, we estimate the following generalized differences-in-differences specification:

\[
\text{Patent Disclosure Delay}_{i,j,t} = \beta_0 + \beta_1 \text{Tariff Measure} + \gamma' X_{i,t-d} + \eta' Y_{j,t} + \text{FirmFE} + \text{PatentClass} \times \text{ApplicationYearFE} + \epsilon_{i,j,t}
\]  

(2)

Eq. (2) is identical to Eq. (1), except that we replace IndustryFE with FirmFE and replace Product Market Competition with Tariff Measure. Tariff Measure is one of two measures of firm exposure to tariffs on foreign competitors, which we also describe in section 4.3. The inclusion of FirmFEs mean that Eq. (2) effectively estimates the relation between changes in Tariff Measure and changes in Patent Disclosure Delay.

We follow Huang et al. (2017) and interpret changes in tariff rates as a source of variation in product market competition that is plausibly exogenous with respect to disclosure choices. The intuition for this approach is that tariffs are a significant trade barrier that reduce foreign competitors’ potential profits in the domestic market. Because tariffs are levied on the value of the good, and not the profit on the good, even seemingly small changes in tariffs significantly discourage foreign competitors (Fresard, 2010).

The effect of changes in tariff rates can identify the effect of changes in competition only if the differences-in-differences assumptions are satisfied. One of the main differences-in-differences assumptions is the parallel trends assumption. We explicitly test for evidence of pre-existing differential trends around changes in tariff rates by estimating the following generalized differences-in-differences specification:

\[
\text{Patent Disclosure Delay}_{i,j,t} = \beta_0 + \beta_1 \text{Tariff Measure}_{t} + \beta_2 \text{Tariff Measure}_{t+1} + \epsilon_{i,j,t}
\]
\[ B_3 \text{Tariff Measure}_{i,t+2} + \beta_4 \text{Tariff Measure}_{i,t+3} + \gamma X_{i,t-d} + \eta Y_{j,t} + \text{FirmFE} + \text{PatentClass} \times \text{ApplicationYearFE} + \epsilon_{i,j,t} \] (3)

Eq. (3) is identical to Eq. (2), except that we include three leads of Tariff Measure. The coefficient estimates on these leads measure the degree to which the disclosure choices of firms that experience a change in tariff rates in the future differ prior to the change. Statistically insignificant and economically small coefficient estimates would suggest that these firms did not behave differently prior to the change in the tariff rate, and would support the validity of the parallel trends assumption.

A second assumption necessary for causal inference, including from differences-in-differences specifications, is the Stable Unit Treatment Value Assumption (SUTVA). SUTVA requires that the treatment status of one firm does not affect other firms’ potential outcomes (see Glaeser and Guay, 2017 and Armstrong et al., 2018 for discussions of SUTVA in the context of accounting research). In our setting, SUTVA requires that firms' decisions to accelerate their patent disclosures in response to product market competition does not affect the patent disclosure decisions of other firms not exposed to the same level of competition.

SUTVA is often a concern in studies of innovation because of the presence of knowledge spillovers. For example, knowledge spillovers imply that the patenting rates of treatment firms can affect the patenting rates of control firms (Glaeser, 2018). However, this is less of a concern in our setting because we do not examine patenting rates, but instead examine disclosure decisions conditional on filing a patent. Additionally, we include controls for knowledge spillovers and indicators for each patent class in each year, which should mitigate the influence of potential knowledge spillovers. In total, we expect SUTVA to be satisfied in our setting.
4. Sample and descriptive statistics

4.1 Sample

Our sample begins with all successful patent applications filed with the USPTO after the American Inventors Protection Act (AIPA) became effective on November 29, 2000.\textsuperscript{15} We examine the post-AIPA period because of data constraints and because the AIPA introduces the 18-month disclosure deadline for applicants seeking foreign protection. We require non-missing data on all control variables and tariff rates in all tests. We follow Hall et al. (2001) and remove the final three years of the patent database (2008-2010) from the sample to address potential truncation bias in patent applications and citations resulting from patent applications appearing in the database only after their grant. We also remove observations where the disclosure deadline is within 180 days of the application filing date to ensure applicants face a meaningful disclosure choice (we present evidence in Table 9 that our results are not sensitive to this choice). Our final sample consists of 193,937 patent applications filed between November 29, 2000 and December 31, 2006.

We focus on successful applications because unsuccessful applications may never be disclosed. It is unclear how to measure nondisclosure empirically, or whether unsuccessful and successful applications are comparable. Focusing on successful applications also allows us to isolate applicants’ disclosure decisions from the underlying economics of successfully patenting. Nonetheless, it is unlikely that the exclusion of unsuccessful patent applications presents a serious sampling issue because the USPTO granted between 89% and 98% of applications each year of our sample period (Cotropia et al., 2014).

\textsuperscript{15} We thank the authors of Kogan et al. (2017) for making this data available on Noah Stoffman’s website: http://iu.box.com/patents.
We also focus on patent applications made by public firms to ensure the necessary data to calculate controls. Consequently, our results may not generalize to the behavior of private applicants, abandoned patent applications, or unpatented innovations (Glaeser and Guay, 2017). However, we believe that our theoretical foundations should help assuage these concerns. Moreover, the vast majority of R&D is conducted by public firms, and we believe public firms’ successful patent disclosures are inherently interesting and economically important.\footnote{E.g., Hirschey et al. (2012), Kogan et al. (2017) Kim (2018) and Valentine (2018).}

4.2 Disclosure measures

We use two measures of patent disclosure timeliness. Our focus on the timeliness of disclosure mirrors prior work that examines voluntary manager forecasts (see Hirst et al., 2008 for a review). Manager forecasts serve to accelerate news from the 10-K or 10-Q release date to the forecast date. Similarly, voluntary patent disclosures serve to accelerate information about the existence and nature of innovations from the mandatory disclosure date to the voluntary disclosure date.

By studying the timeliness of patent disclosures, we document firms’ responses along an intensive margin of disclosure. Firms may also respond along extensive margins, e.g., firms may change how they protect their innovations with secrecy or patenting (Glaeser et al., 2019). An advantage of studying firms’ responses along an intensive margin is that doing so allows us to observe firms with information they could disclose, but choose not to (i.e., we can compare applicants who choose to credibly disclose today, to those who choose to delay disclosure). In contrast, it is difficult, if not impossible, to disentangle extensive margin responses, such as the decision to rely on trade secrecy, from a failure to innovate (Glaeser et al., 2019).
Both of our measures of patent disclosure timeliness reflect the degree to which applicants delay disclosure, and are therefore inverse measures of timeliness. The first is $\ln(Days\ to\ Actual\ Disclosure)$ which is calculated as the natural logarithm of the number of days between the patent application date and the date the USPTO publicly discloses the application, less 14 weeks for USPTO processing. Figure 2 presents the frequency histogram of $Days\ to\ Actual\ Disclosure$. The two most frequent disclosure choices are disclosing fairly early in the application process (the first spike) and at the 18 month deadline for firms that file abroad concurrently with the U.S. application (the second spike).

We include $\ln(Days\ to\ Latest\ Possible\ Disclosure)$ as a control when using $\ln(Days\ to\ Actual\ Disclosure)$ as the dependent variable. $\ln(Days\ to\ Latest\ Possible\ Disclosure)$ is the natural logarithm of the number of days until the applicant must disclose their application.\footnote{The application disclosure deadline is the earlier of 18-months in days following the foreign filing date and the approval date for applications seeking foreign protection, and the approval date for all others. We obtain data on foreign protection and priority dates from the USPTO research datasets: https://www.uspto.gov/learning-and-resources/electronic-data-products/historical-patent-data-files; https://www.uspto.gov/learning-and-resources/electronic-data-products/patent-examination-research-dataset-public-pair; https://www.uspto.gov/learning-and-resources/ip-policy/economic-research/research-datasets.} Figure 3 presents the frequency histogram of $Days\ to\ Latest\ Possible\ Disclosure$. The large spike represents applicants seeking foreign protection around the same period that they file with the USPTO, and who therefore must publish 18 months after filing, at the latest. We remove observations where $Days\ to\ Actual$ disclosure is negative or exceeds $Days\ to\ Latest\ Possible\ Disclosure$. Our second measure of the degree to which applicants delay disclosure is $Percentage\ Disclosure\ Delay$, which we calculate as $Days\ to\ Actual\ Disclosure$ divided by $Days\ to\ Latest\ Possible\ Disclosure$.\footnote{While applicants likely have some foresight regarding $Days\ to\ Latest\ Possible\ Disclosure$, this foresight is imperfect when the disclosure deadline is the decision date. For example, the USPTO provides data useful for estimating $Days\ to\ Latest\ Possible\ Disclosure$, such as the backlog of unexamined applications, but does not commit to a decision date (https://www.uspto.gov/dashboards/patents/main.dashxml). As a result, $Percentage\ Disclosure\ Delay$ likely measures disclosure decisions with error. However, any measurement error in $Percentage\ Disclosure\ Delay$ is unlikely to be correlated with product market competition, and therefore only serves to attenuate our empirical estimates of the association between product market competition and disclosure timeliness.}
**Percentage Disclosure Delay** ranges from zero to one and is increasing in the degree to which the firm delays disclosure (e.g., values of one suggest the firm delays disclosure as long as possible and discloses only when required to do so). Figure 4 presents the frequency histogram of **Percentage Disclosure Delay**. The histogram highlights that patent applicants wait until the mandatory deadline to disclose for slightly over 10% of patent applications. The histogram also highlights that there is a great deal of variation in disclosure choices.

### 4.3 Product market competition measures

We examine several measures of product market competition because our view is that no measure perfectly encapsulates all dimension of product market competition (e.g., competition from foreign entrants, competition from existing competitors, etc.). We take the natural logarithm of our competition measures when possible because we expect the effect of competition on patent disclosure to be proportional.

We use industry concentration as our first measure of product market competition because the U.S. Department of Justice and the Federal Trade Commission explicitly view increases in industry concentration as anti-competitive decreases in product market competition (U.S. Department of Justice and Federal Trade Commission, 2010).\(^{19}\) \(\text{Ln(Compustat Concentration Ratio)}\) is the natural logarithm of the Herfindahl-Hirschman Index of industry concentration for firms in the Compustat database. We calculate the Herfindahl-Hirschman Index as the sum of the squared market share of each publicly traded company in a particular four-digit SIC code in a given year. We calculate market share using the sales of a particular company divided by the total sales of the four-digit SIC code.

\(^{19}\) Studies of voluntary disclosure that use industry concentration measured using public firm financial data to reflect product market competition include Bamber and Cheon, 1998; Botosan and Stanford, 2005; Verrecchia and Weber, 2006; and Berger and Hann, 2007. Ali et al., 2014 use U.S. Census data.
Ln(Compustat Concentration Ratio) may measure industry concentration with error because it does not include private firms (Lang and Sul, 2014). Consequently, we follow Ali et al. (2014) and Keil (2017) and additionally measure industry concentration using U.S. Census data that includes both public and private firms. Following Ali et al. (2014) and Keil (2017), ln(Census Concentration Ratio) is the natural logarithm of the sum of the squared market share of the 50 largest public and private companies in a six-digit NAICS industry (or all the public and private companies if there are fewer than 50).20 Again following prior work, we apply the 2002 and 2007 Census values to the five years centered on the census date.

We also use changes in tariff rates as a source of plausibly exogenous variation in product market competition. We first measure tariff rates using the ad valorem most favored nation tariff rate recorded by the United States International Trade Commission (USITC), or Tariff Rate.21 Figure 5 presents the application-level frequency histogram of the non-zero tariff rate changes affecting 67,884 in-sample applications. The histogram suggests that there is a great deal of variation in tariff rate changes, and that changes can be substantial. In our empirical tests, we use ln(1-Tariff Rate). We examine 1-Tariff Rate, rather than Tariff Rate, so that we can take the natural logarithm. 1-Tariff Rate corresponds to the fraction of the pre-tariff value of goods that importers retain.

Additionally, we follow Fresard (2010) and Huang et al. (2017) and measure tariff changes using an indicator for the period after significant reductions in tariff rates that do not subsequently reverse, of Post Significant Tariff Decrease. A strength of this measure is that it is unlikely that

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20 We thank Jan Keil for making this data publicly available on his website: https://sites.google.com/site/drjankeil/data. We divide his values by 100 to ease interpretation.
21 Available at, e.g., https://www.usitc.gov/tariff_affairs/documents/tariff_data/tariff_database_2000.txt. The USITC tracks tariff rates by harmonized tariff schedule eight-digit merchandise categories (HTS8 industries). We use the concordance developed by Pierce and Schott (2012) to average HTS8 industry tariffs at the four-digit SIC level. We thank the authors of Pierce and Schott (2012) for making the data available on Peter Schott’s website: http://faculty.som.yale.edu/peterschott/sub_international.htm.
affected firms lobby to decrease tariffs on foreign competitors, suggesting this measure ameliorates any concern that firm lobbying biases our results.

Finally, we use a fifth, text-based, measure of product market competition. $\text{Ln}(\text{Manager Perception of Competition})$ is the natural logarithm of the number of occurrences of competition-related words per 1,000 total words in the 10-K (Li et al., 2012).22

### 4.4 Descriptive statistics

Table 1 presents sample descriptive statistics. In-sample applications must be disclosed an average of 949 days after filing. Applicants choose to accelerate their application on average; in-sample applications are disclosed an average of 371 days after filing. The mean of $\text{Percentage Disclosure Delay}$ is 41%, suggesting applicants accelerate their disclosure by slightly more than half the possible delay. The standard deviation of $\text{Percentage Disclosure Delay}$ is 29%, indicating that there is a great deal of variation in applicant disclosure choices (see also Figure 4).23 $\text{Post Significant Tariff Decrease}$ is rarer than general tariff rate changes (1,466 patent applications are affected by significant tariff decreases, compared to 67,884 patent applications affected by any tariff rate change).

### 5. Results

#### 5.1 Competition and patent disclosure delays

Table 2 presents the results of estimating Eq. (1) with $\text{ln(Compustat Concentration Ratio)}$ as our measure of product market competition in columns (1) and (3) and with $\text{ln(Census}$

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22 We thank the authors of Li et al. (2012) for making these data publicly available on Feng Li’s website: http://webuser.bus.umich.edu/feng/competition_sasdata.zip.

23 We identify 32% of applications as seeking foreign protection (i.e., where Foreign Protection = 1). Although we examine different samples, our 32% rate is similar to the 25% rate for domestic applicants in Johnson and Popp (2001), the 18.7% rate for litigated and matched applications in Graham and Harhoff (2014), and the 28.5%–43.4% for U.S. large inventors in different technology fields post-AIPA in Graham and Hegde (2015).
Concentration Ratio) as our measure of product market competition in columns (2) and (4). Columns (1) and (2) present results using ln(Days to Actual Disclosure) as the dependent variable, and columns (3) and (4) present results using Percentage Disclosure Delay.

The results in column (1) suggest that a 1% increase in product market competition is associated with a 0.21% decrease in the time until patent disclosure \((t\text{-statistic} = 1.74)\). The results in column (2) suggest that a 1% increase in product market competition results in a 0.67% decrease in the time until patent disclosure \((t\text{-statistic} = 3.23)\). The results in column (3) suggest that a 1% increase in product market competition results in a 0.10 percentage point decrease in the delay until disclosure \((t\text{-statistic} = 2.11)\). The results in column (4) suggest that a 1% increase in product market competition results in a 0.27 percentage point decrease in the delay until disclosure \((t\text{-statistic} = 3.73)\). The larger coefficient estimate on ln(Census Concentration Ratio) suggests that including private firms in the measure significantly reduces attenuating measurement error. Together, the results in Table 2 are consistent with increases in product market competition, as measured by decreases in industry concentration, resulting in decreases in patent disclosure delays.

We turn to the control variables for technological competition. We examine coefficient estimates when including the full sample (i.e., in columns (1) and (3)). The coefficient estimate on ln(Technological Competition 1) in column (1) suggests that a 1% increase in realized technological competition results in a 0.05% increase in the number of days until patent disclosure \((t\text{-statistic} = 4.49)\). The results in column (3) suggest that a 1% increase in technological competition results in a 0.026 percentage point increase in the delay until disclosure \((t\text{-statistic} = 3.95)\). Together, these results suggest that disclosure delays are increasing in the degree of technological competition, as measured by patent citations.
In contrast, there is no relation between ln(*Technological Competition 2*) and disclosure delays, as evidenced by small and statistically insignificant coefficient estimates in both columns (1) and (3). However, we caution readers against interpreting the insignificant and small coefficient as evidence that technological competition does not affect disclosure for two reasons. First, the inclusion of Patent Class x Year fixed effects may reduce the power to detect an effect of ln(*Technological Competition 2*). Second, the inclusion of ln(*Technological Competition 1*) in the regression, itself a measure of technological competition, further reduces the power to detect an effect of ln(*Technological Competition 2*).

5.2 Competition and patent disclosure delays, differences-in-differences

Table 3 presents the results of estimating Eq. (2) with ln(*1-Tariff Rate*) as a source of variation in product market competition in columns (1) and (3), and *Post Significant Tariff Decrease* as a source of variation in product market competition in columns (2) and (4). Columns (1) and (2) present results using ln(*Days to Actual Disclosure*) as the dependent variable, and columns (3) and (4) present results using *Percentage Disclosure Delay*.

The results in column (1) suggest that a 1% tariff decrease results in a 0.9% decrease in the delay until patent disclosure (*t*-statistic = –5.60). The results in column (2) suggest that firms accelerate their disclosures by 19.6% following a significant tariff decrease (*t*-statistic = –4.33). The results in column (3) suggests that a 1% decrease in the tariff rate results in a 0.32 percentage point decrease in the delay until disclosure (*t*-statistic = –2.85). The results in column (4) suggest that significant tariff decreases result in a 7.9 percentage point decrease in the delay until disclosure (*t*-statistic = –5.71). Taken together, the results suggest changes in product market competition cause inverse changes in patent disclosure delays.
Most of the coefficient estimates on control variables that are statistically significant in Table 2 are largely statistically insignificant in Table 3. This is possibly because these control variables are largely time-invariant, such that little variation remains after including the firm fixed effects. An exception is the coefficient on ln(Technological Competition 1), which remains statistically significant (t-statistics ranging from 4.34 to 4.64). This result highlights that technological competition discourages disclosure, which is consistent with the assumptions of Hughes and Pae (2015) and explains why patent applicants do not always disclose, despite the product market benefits of patent disclosure (e.g., Cao et al., 2018).

5.3 Competition and patent disclosure delays, text-based measure of competition

Table 4 presents the results of estimating Eq. (1) with ln(Manager Perception of Competition) as an alternative measure of product market competition. Columns (1) and (2) present results respectively using ln(Days to Actual Disclosure) and Percentage Disclosure Delay as the dependent variable. For the sake of parsimony, we do not report coefficient estimates or test statistics for control variables. The results in column (1) suggest that a 1% increase in the manager’s perception of competition results in a 0.04% decrease in the delay until disclosure (t-statistic = –3.26). The results in column (2) suggest that a 1% increase in the manager’s perception of competition results in a 0.01 percentage point decrease in the delay until disclosure (t-statistic = –2.43). Taken together, the results in Table 4 suggest that our inferences are robust to measuring competition using an alternative, text-based measure of competition.

5.4 Competition and patent disclosure delays, differences-in-differences parallel trends

Table 5 presents the results of estimating Eq. (3) repeating the sequence of dependent and independent variables from Table 3. Additionally, we include measures of tariff rates in each of the next three years in all columns. We find no evidence that firms respond to changes in future
tariff rates prior to the change, i.e., we find no evidence of differential pre-treatment trends. In particular, none of the 12 coefficient estimates on future tariff rates are statistically significantly different from zero. More importantly, the coefficients estimates themselves do not seem to suggest a progressively larger negative relation between changes in disclosure and future changes in tariff rates, prior to the change.

5.5 Patent disclosure and subsequent competitor behavior

The results discussed so far suggest that firms respond to product market competition by speeding their disclosure of innovation. If firms do so to deter product market competitors, then competitors should avoid the disclosing firm’s product market. In turn, this should decrease the similarity between the firm’s products and those of their product market competitors. Alternatively, if firms respond to product market competition by speeding their disclosure of innovation to market their innovations to competitors (royalty seeking), then competitors should license the firm’s innovation (Hegde and Luo, 2017). In turn, this should increase the similarity between the firm’s products and those of their product market competitors. Consequently, how the timeliness of the disclosure of innovation affects product similarity can reveal firms’ primary motivation for disclosing their innovations.

To examine how timelier disclosure of innovation affects product market similarity, we estimate the following specification:

\[
\ln(\text{Product Similarity}_{i,j,i,t+3}) = \beta_0 + \beta_1 \ln(\text{Days Since Disclosure}_{i,j,t}) + \gamma' X_{i,t-d} + \eta' Y_{j,t} \\
+ \text{Firm FE} + \text{Patent Class x Application Year FE} + \varepsilon_{i,j,t} \tag{4}
\]

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\[24\] Firms can seek reasonable royalties for infringement occurring between publication and grant (35 U.S.C. § 154(d)), although such rights are “rarely asserted or granted” (Dowd and Crotty, 2016) and “highly unusual” (Millemann, 2016).
where $\ln(Days \text{ } Since \text{ } Disclosure)$ is the natural logarithm of the number of days between the patent approval date and the patent disclosure date, and Product Similarity is a measure of the similarity between the patent filing firm’s products and those of its competitors. We measure Product Similarity three years after the first 10-K filing subsequent to the patent approval date to allow sufficient time for competitors to change their production decisions.

We use three measures of Product Similarity. First, $\ln(Product \text{ } Similarity)$ is the cosine similarity between the firm’s 10-K product descriptions and that of its competitor, averaged over all competitors (Hoberg and Phillips, 2010, 2016). The second and third measures, $\ln(Product \text{ } Similarity \text{ } IC \text{ } 25)$ and $\ln(Product \text{ } Similarity \text{ } SIC)$, are similarly constructed, but averaged over the 25 most similar competitors and all competitors in the same four-digit SIC industry, respectively.

The results suggest that a 1% increase in the time since disclosure is associated with a 0.016% to 0.021% decrease in the similarity of competitors’ products ($t$-statistics of $-1.84$ to $-2.15$). This finding provides additional support that the positive relation between disclosure timeliness and product market competition is attributable, at least in part, to disclosing firms’ desire to deter product market competitors. However, we note that the results do not rule out the possibility that other economic forces are at work, including the incentive to disclose early to gain patent royalties. Nonetheless, finding that product similarity decreases rather than increases when patent disclosure is timelier suggests that deterrence plays a more prominent role than royalty seeking.

5.6 Extensions

5.6.1 Excluding industries regulated by the Food and Drug Administration

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25 We thank the authors of Hoberg and Phillips (2010, 2016) for making the data available on their website: http://hobergphillips.tuck.dartmouth.edu/.
The FDA requires regulated firms to disclose results from clinical trials. To the extent that clinical trial disclosures occur before the patent applications, it is possible that our prior results could understate the effect of product market competition on the timeliness of patent disclosure. Therefore, we estimate Eqs. (1) and (2), after removing firms potentially regulated by the FDA (those firms in Fama-French 48 industries 2, 3, 4, 5, 12, and 13). The results, presented in Table 7, are largely similar to the results reported in Tables 2 and 3 (absolute value of $t$-statistics of 1.80 to 4.90).

5.6.2 Controlling for patent values

Product market competition may affect the value of innovation (e.g., Aghion and Griffith, 2008). If more valuable innovations are more or less likely to be disclosed earlier, then changes in the value of innovations may represent an alternative channel through which product market competition could affect the timeliness of patent disclosure. We examine this alternative mechanism by modifying Eqs. (1) and (2) to include the value of individual patents. We follow Kogan et al. (2017) and measure patent values using the stock market’s assessment of the patent value ($Patent\ Value$). The results, presented in Table 8, are similar to those reported in Tables 2 and 3 (absolute value of $t$-statistics of 1.75 to 5.70). We also find little evidence that $Patent\ Value$ is related to the timeliness of patent disclosure (the coefficient estimate on $Patent\ Value$ is statistically insignificant in all columns).

5.6.3 Including all early-deadline applications

Table 9 reports the results from estimating Eqs. (1) and (2) after including the 524 observations in which the firm’s disclosure deadline falls within 180 days of the patent filing date. We find similar results as those reported in Tables 2 and 3 (absolute value of $t$-statistics of 1.77 to 5.80).
6. Conclusion

We document the effect of product market competition on the disclosure of innovation. We find that firms relatively accelerate their patent disclosures when facing more intense product market competition. Our inferences are largely unchanged across multiple measures of product market competition, and when using changes in tariff rates as a source of plausibly exogenous variation in product market competition. In total, our results suggest that product market competition increases the speed of patent disclosure, consistent with firms “weaponizing” the disclosure of innovation to deter product market competitors. Our work contributes to the literature on voluntary disclosure and firms’ responses to product market competition by documenting the relation between product market competition and the voluntary disclosure of innovation. Our work may also inform the regulatory debate on mandatory patent disclosure deadlines by shedding light on when and why firms voluntarily accelerate their patent disclosures.
References


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Huang, S., Ng, J., Ranasinghe, T., & Zhang, M. Do innovative firms communicate more? Evidence from the relation between patenting and management earnings forecasts. Working paper.


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Appendix A. Variable Definitions

Patent variables

**Days Since Disclosure**
The number days of between the disclosure of a patent filing and the patent application decision date.

**Days to Latest Possible Disclosure**
The number of days until the patent application must be published (the earlier of 18-months after filing abroad for applications seeking foreign protection and the patent decision date, and the patent decision date for all others).

**Days to Actual Disclosure**
The number of days until the USPTO publishes the patent filing, either at the request of the applicant or because the disclosure deadline passes, less 14 weeks for publication delays.

**ln(Technological Competition 1)**
The natural logarithm of one plus the number of citations the patent receives.

**Patent Value**
The value of the patent, in tens of millions of dollars, as calculated by Kogan et al. (2017) using the stock market reaction to the patent’s approval.

**Percentage Disclosure Delay**
The number of days until the disclosure of a patent filing, divided by the number of days until the latest possible disclosure.

Firm variables

**Blockholders**
The number of shareholders listed on Thomson Reuters with 5% or more ownership of the firm.

**External Capital Dependence**
Capital expenditures plus R&D expenditures minus operating activities net cash flow, divided by capital expenditures plus R&D expenditures (Rajan and Zingales, 1998).

**Leverage**
Book value of total debt, divided by book value of total assets.

**ln(Census Concentration Ratio)**
The natural logarithm of the sum of the squared market share of the 50 largest public and private companies in the industry if there are fewer than 50. Market share is calculated as the sales of a particular company divided by the total sales of the six-digit NAICS industry. Compiled from 2002 and 2007 U.S. Census data by Keil (2017) and applied to the five years centered on the census date. See also Ali et al. (2014).

**ln(Compustat Concentration Ratio)**
The natural logarithm of the sum of the squared market share of each publicly traded company in a particular four-digit SIC code in a given year. Market share is calculated as the sales of a particular company divided by the total Compustat sales of the SIC code.

**ln(Manager Perception of Competition)**
The natural logarithm of the number of occurrences of competition-related words per 1,000 total words in the 10-K, as calculated by Li et al. (2012).

**ln(Equity Market Value)**
The natural logarithm of the market value of the firm’s equity.

**ln(Product Similarity)**
The average cosine similarity between the 10-K product descriptions of the firm and all competitors, as calculated by Hoberg and Phillips (2010, 2016).

**ln(Product Similarity IC 25)**
The average cosine similarity between the 10-K product descriptions of the firm and its 25 closest competitors, as calculated by Hoberg and Phillips (2010, 2016).

**ln(Product Similarity SIC)**
The average cosine similarity between the 10-K product descriptions of the firm and all competitors in the same four-digit SIC industry, as calculated by Hoberg and Phillips (2010, 2016).

**Loss**
An indicator equal to one if net income is negative.

**Market to Book**
Market value of assets to book value of assets.
### Missing R&D
An indicator equal to one if data on R&D spending is missing.

### Post Significant Tariff Decrease
Indicator equal to one in the year of an in-sample significant tariff decrease and thereafter. Significant tariff decreases occur if the three-digit SIC level tariff decreases relative to the prior year by more than three times the median tariff rate decrease from 1995-2011 and is not preceded or followed by a tariff increase greater than 80% of the reduction. Compiled by Huang et al. (2017, Table 1, pp. 189-190).

### R&D
R&D expenditures scaled by total assets. Missing values of R&D are replaced with zeroes.

### Return
Buy and hold return over the fiscal year.

### Return on Assets
Income before extraordinary items scaled by total assets.

### sigma(Returns)
The standard deviation of monthly returns.

### Tariff Rate
The most favored nation ad valorem tariff rate. Eight-digit U.S. harmonized tariff schedule rates are averaged to four-digit SIC levels following the industry concordance developed by Pierce and Schott (2012).

### Technological Competition 2
*Technological Competition* 2 begins with the Jaffe (1986) measure of technological proximity:

\[
Technological\ Proximity_{i,j} = \frac{(T_i T'_j)}{(T_i T'_i)^{1/2} (T'_j T'_j)^{1/2}}
\]

where \( T \) is the vector of firm \( i \) or \( j \)'s share of patenting activity across each USPTO patent class over the period 1970 to 2006. *Technological Proximity* measures the degree of technological overlap between two firms and ranges from 0 to 1. *Technological Competition* 2 is the pool of potential knowledge spillovers for firm \( i \) in year \( t \):

\[
Technological\ Competition_{i,t} = \sum_{j \neq i} Technological\ Proximity_{i,j} \times R&D\ Stock_{j,t}
\]

*R&D Stock* is calculated from current and historical R&D spending using the perpetual inventory method assuming a 15% depreciation rate (Hall, Jaffe, Trajtenberg, 2005). We divide *Technological Competition* 2 by 100,000 to ease interpretation. Calculated by Bloom et al. (2013, 2018).
This figure presents a graphical representation of the different types of competition, and how they theoretically affect the disclosure of innovation.

**Technological Competition:** competition for new ideas or ways of doing things (e.g., Apple vs Intel).

**Product Market Competition:** competition for users or sales (e.g., Apple vs Nokia).
Figure 2
This figure presents the frequency histogram of the days until patent disclosure.

Figure 3
This figure presents the frequency histogram of the days until the latest possible patent disclosure.
Figure 4
This figure presents the frequency histogram of the days until patent disclosure divided by the days until the latest possible disclosure.

Figure 5
This figure presents the frequency histogram of the application-level non-zero tariff rate changes affecting 67,884 in-sample applications.
Table 1
Descriptive statistics

This Table presents descriptive statistics for our sample. The main sample is constructed from all successful patent applications filed with the USPTO from November 29, 2000 (post-AIPA) to December 31, 2006, intersected with CRSP and Compustat (stock price and accounting data). The final sample consists of 193,937 patent applications.

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<th>Observations</th>
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<th>75th</th>
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<td>0.00</td>
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<td>1062.00</td>
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</table>

| Firm variables:                               |              |        |        |       |        |       |
| Blockholders                                  | 193,937      | 0.78   | 1.20   | 0.00  | 0.00   | 1.00  |
| Census Concentration Ratio                    | 145,138      | 0.86   | 0.12   | 0.83  | 0.90   | 0.91  |
| In(Census Concentration Ratio)                | 145,138      | -0.16  | 0.17   | -0.76 | -0.11  | -0.09 |
| Compustat Concentration Ratio                 | 193,937      | 0.27   | 0.22   | 0.10  | 0.19   | 0.34  |
| In(Compustat Concentration Ratio)             | 193,937      | -1.60  | 0.75   | -2.31 | -1.67  | -1.09 |
| External Capital Reliance                     | 193,937      | 0.04   | 0.70   | -0.32 | 0.10   | 0.43  |
| Leverage                                      | 193,937      | 0.18   | 0.15   | 0.05  | 0.15   | 0.26  |
| ln(Equity Market Value)                       | 193,937      | 9.73   | 1.50   | 8.94  | 9.95   | 10.71 |
| Loss (% of firm-years)                        | 193,937      | 20%    | .      | .     | .      | .     |
| Manager Perception of Competition             | 81,056       | 0.57   | 0.55   | 0.21  | 0.40   | 0.67  |
| ln(Manager Perception of Competition)         | 81,056       | -0.95  | 0.89   | -1.57 | -0.93  | -0.40 |
| Market to Book                                | 193,937      | 1.87   | 1.80   | 0.65  | 1.20   | 2.60  |
| Missing R&D                                    | 193,937      | 1%     | .      | .     | .      | .     |
| Post Significant Tariff Decrease              | 193,937      | 1%     | .      | .     | .      | .     |
| Product Similarity                            | 88,909       | 0.03   | 0.01   | 0.02  | 0.03   | 0.04  |
| ln(Product Similarity)                        | 88,909       | -3.63  | 0.47   | -3.88 | -3.57  | -3.31 |
| Product Similarity IC 25                      | 84,478       | 0.03   | 0.02   | 0.02  | 0.03   | 0.04  |
| ln(Product Similarity IC 25)                  | 84,478       | -3.57  | 0.57   | -3.81 | -3.46  | -3.19 |
| Product Similarity SIC                        | 75,965       | 0.04   | 0.02   | 0.03  | 0.04   | 0.05  |
| ln(Product Similarity SIC)                    | 75,965       | -3.33  | 0.66   | -3.59 | -3.18  | -2.90 |
| R&D                                           | 193,937      | 0.07   | 0.04   | 0.04  | 0.07   | 0.10  |
| Return                                        | 193,937      | 0.06   | 0.52   | -0.27 | -0.02  | 0.25  |
| Return on Assets                              | 193,937      | 0.04   | 0.10   | 0.01  | 0.04   | 0.09  |
| sigma(Returns)                                | 193,937      | 0.13   | 0.07   | 0.07  | 0.11   | 0.17  |
Table 1, continued
Descriptive statistics

This Table presents descriptive statistics for our sample. The main sample is constructed from all successful patent applications filed with the USPTO from November 29, 2000 (post-AIPA) to December 31, 2006, intersected with CRSP and Compustat (stock price and accounting data). The final sample consists of 193,937 patent applications.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Observations</th>
<th>Mean</th>
<th>Std</th>
<th>25th</th>
<th>Median</th>
<th>75th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firm variables, continued:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tariff Decrease (nonzero subsample)</td>
<td>25,282</td>
<td>-1.8%</td>
<td>2.0%</td>
<td>-2.4%</td>
<td>-1.2%</td>
<td>-0.1%</td>
</tr>
<tr>
<td>Tariff Increase (nonzero subsample)</td>
<td>42,602</td>
<td>1.7%</td>
<td>1.9%</td>
<td>0.1%</td>
<td>1.5%</td>
<td>2.4%</td>
</tr>
<tr>
<td>Tariff Rate</td>
<td>193,937</td>
<td>0.7%</td>
<td>1.5%</td>
<td>0%</td>
<td>0%</td>
<td>0.3%</td>
</tr>
<tr>
<td>ln(1 − Tariff Rate)</td>
<td>193,937</td>
<td>-0.01</td>
<td>0.01</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>R&amp;D Spillovers</td>
<td>193,937</td>
<td>40.19</td>
<td>16.54</td>
<td>4.74</td>
<td>27.93</td>
<td>41.35</td>
</tr>
<tr>
<td>ln(Technological Competition 2)</td>
<td>193,937</td>
<td>3.58</td>
<td>0.54</td>
<td>3.33</td>
<td>3.72</td>
<td>3.97</td>
</tr>
</tbody>
</table>
Table 2

Competition and patent disclosure delays

This Table presents OLS regressions of patent disclosure choices as a function of product market competition. All variables are as defined in Appendix A. \( t \)-statistics appear in parentheses and are based on standard errors clustered by industry and date. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail). Sample descriptive characteristics are found in Table 1.

<table>
<thead>
<tr>
<th>Variable:</th>
<th>( \ln(\text{Days to Disclosure}) )</th>
<th>Percentage Disclosure Delay</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \ln(\text{Compustat Concentration Ratio}) )</td>
<td>0.214* (1.74)</td>
<td>0.102** (2.11)</td>
</tr>
<tr>
<td>( \ln(\text{Census Concentration Ratio}) )</td>
<td>. (3.23)</td>
<td>. (3.73)</td>
</tr>
<tr>
<td>Blockholders</td>
<td>0.060*** (7.04)</td>
<td>0.028** (2.54)</td>
</tr>
<tr>
<td>( \ln(\text{Market Value}) )</td>
<td>-0.000 (-0.03)</td>
<td>-0.003 (-0.30)</td>
</tr>
<tr>
<td>Loss</td>
<td>0.057* (1.70)</td>
<td>0.037 (1.19)</td>
</tr>
<tr>
<td>Market to Book</td>
<td>-0.003 (-0.21)</td>
<td>-0.018*** (-2.65)</td>
</tr>
<tr>
<td>Missing R&amp;D</td>
<td>0.002 (0.02)</td>
<td>-0.046 (-0.51)</td>
</tr>
<tr>
<td>( \ln(\text{R&amp;D}) )</td>
<td>2.073*** (5.60)</td>
<td>2.257*** (7.84)</td>
</tr>
<tr>
<td>Return</td>
<td>-0.036 (-1.42)</td>
<td>0.005 (0.21)</td>
</tr>
<tr>
<td>( \ln(\text{Return on Assets}) )</td>
<td>0.342** (2.06)</td>
<td>0.423*** (2.61)</td>
</tr>
<tr>
<td>( \ln(\text{Technological Competition 2}) )</td>
<td>-0.094 (-0.88)</td>
<td>-0.172 (-1.38)</td>
</tr>
<tr>
<td>( \ln(\text{Days to Latest Possible Disclosure}) )</td>
<td>0.874*** (13.86)</td>
<td>0.842*** (14.32)</td>
</tr>
<tr>
<td>Patent Class x Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Industry Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Adjusted R(^2)</td>
<td>0.315</td>
<td>0.305</td>
</tr>
</tbody>
</table>
### Table 3

**Competition and patent disclosure delays, differences-in-differences**

This Table presents OLS regressions of patent disclosure choices as a function of industry-level tariffs. All variables are as defined in Appendix A. \( t \)-statistics appear in parentheses and are based on standard errors clustered by industry and date. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail). Sample descriptive characteristics are found in Table 1.

<table>
<thead>
<tr>
<th>Variable:</th>
<th>( \ln(\text{Days to Disclosure}) )</th>
<th>( \ln(\text{Market Value}) )</th>
<th>( \text{Percentage Disclosure Delay} )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(3)</td>
<td>(2)</td>
</tr>
<tr>
<td>( \ln(1 - \text{Tari}f \text{ Rate}) )</td>
<td>-0.923*** (-5.60)</td>
<td>-0.015 (-3.61)</td>
<td>-0.320*** (-2.85)</td>
</tr>
<tr>
<td>( \text{Post Significant Tari}f \text{ Decrease} )</td>
<td>-0.179*** (-4.33)</td>
<td>-0.179*** (-4.33)</td>
<td>-0.079*** (-5.71)</td>
</tr>
<tr>
<td>( \text{Blockholders} )</td>
<td>-0.013*** (-2.67)</td>
<td>-0.013*** (-2.67)</td>
<td>-0.004 (-1.43)</td>
</tr>
<tr>
<td>( \text{External Capital Reliance} )</td>
<td>-0.021* (-1.77)</td>
<td>-0.022* (-1.86)</td>
<td>-0.006 (-1.47)</td>
</tr>
<tr>
<td>( \text{Leverage} )</td>
<td>-0.001 (-0.01)</td>
<td>-0.012 (0.82)</td>
<td>0.039 (0.35)</td>
</tr>
<tr>
<td>( \ln(\text{Technological Competition 1}) )</td>
<td>0.035*** (4.35)</td>
<td>0.014* (1.17)</td>
<td>0.014* (1.83)</td>
</tr>
<tr>
<td>( \ln(\text{Market Value}) )</td>
<td>-0.015 (-0.36)</td>
<td>-0.015 (-0.37)</td>
<td>-0.011 (-0.68)</td>
</tr>
<tr>
<td>( \text{Loss} )</td>
<td>0.026 (1.17)</td>
<td>0.028 (1.27)</td>
<td>0.014* (1.73)</td>
</tr>
<tr>
<td>( \text{Market to Book} )</td>
<td>0.006 (0.88)</td>
<td>0.007 (0.95)</td>
<td>0.000 (0.14)</td>
</tr>
<tr>
<td>( \text{Missing R&amp;D} )</td>
<td>-0.044 (-0.68)</td>
<td>-0.037 (-0.57)</td>
<td>-0.016 (-0.81)</td>
</tr>
<tr>
<td>( \text{R&amp;D} )</td>
<td>0.101 (0.15)</td>
<td>0.094 (0.14)</td>
<td>0.083 (0.30)</td>
</tr>
<tr>
<td>( \text{Return} )</td>
<td>-0.008 (-0.69)</td>
<td>-0.008 (-0.67)</td>
<td>-0.001 (-0.15)</td>
</tr>
<tr>
<td>( \text{Return on Assets} )</td>
<td>-0.059 (-0.67)</td>
<td>-0.052 (-0.58)</td>
<td>0.004 (0.14)</td>
</tr>
<tr>
<td>( \text{sigma(Returns)} )</td>
<td>-0.070 (-0.67)</td>
<td>-0.073 (-0.67)</td>
<td>0.012 (0.30)</td>
</tr>
<tr>
<td>( \ln(\text{Technological Competition 2}) )</td>
<td>-0.248 (-1.48)</td>
<td>-0.257 (-1.56)</td>
<td>-0.070 (-1.14)</td>
</tr>
<tr>
<td>( \ln(\text{Days to Latest Possible Disclosure}) )</td>
<td>0.808*** (13.56)</td>
<td>0.808*** (13.53)</td>
<td>-</td>
</tr>
<tr>
<td>( \text{Patent Class x Year Fixed Effects} )</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>( \text{Firm Fixed Effects} )</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>( \text{Observations} )</td>
<td>193,937</td>
<td>193,937</td>
<td>193,937</td>
</tr>
</tbody>
</table>
| \( \text{Adjusted R}^2 \)          | 0.400                                  | 0.400                          | 0.325                                    | 0.325
Table 4

Competition and patent disclosure delays, text-based measure of competition

This Table presents OLS regressions of patent disclosure choices as a function of an alternative, text-based measure of product market competition. Controls are included in both columns, except \( \ln(\text{Days to Latest Possible Disclosure}) \) which is only included in column (1). All variables are as defined in Appendix A. \( t \)-statistics appear in parentheses and are based on standard errors clustered by industry and date. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail). Sample descriptive characteristics are found in Table 1.

<table>
<thead>
<tr>
<th>Variable: ( \ln(\text{Manager Perception of Competition}) )</th>
<th>( \ln(\text{Days to Actual Disclosure}) )</th>
<th>( \text{Percentage Disclosure Delay} )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>( \ln(\text{Manager Perception of Competition}) )</td>
<td>-0.037***</td>
<td>-0.013**</td>
</tr>
<tr>
<td></td>
<td>(-3.26)</td>
<td>(-2.43)</td>
</tr>
<tr>
<td>Controls?</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Patent Class x Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Firm Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>81,056</td>
<td>81,056</td>
</tr>
<tr>
<td>Adjusted ( R^2 )</td>
<td>0.206</td>
<td>0.168</td>
</tr>
</tbody>
</table>
Table 5

Competition and patent disclosure delays, differences-in-differences parallel trends

This Table presents OLS regressions of patent disclosure choices as a function of industry-level tariffs and industry-level tariffs in each of the next three years. Controls are included in both columns, except \(\ln(Days\ to\ Latest\ Possible\ Disclosure)\) which is only included in columns (1) and (2). All variables are as defined in Appendix A. \(t\)-statistics appear in parentheses and are based on standard errors clustered by industry and date. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail). Sample descriptive characteristics are found in Table 1.

<table>
<thead>
<tr>
<th>Variable:</th>
<th>ln(Days to Disclosure)</th>
<th>Percentage Disclosure Delay</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>ln(1 - Tariff Rate)</td>
<td>-0.747***</td>
<td>.</td>
</tr>
<tr>
<td></td>
<td>(-7.29)</td>
<td>.</td>
</tr>
<tr>
<td>ln(1 - Tariff Rate(_{t+1}))</td>
<td>1.024</td>
<td>.</td>
</tr>
<tr>
<td></td>
<td>(1.45)</td>
<td>.</td>
</tr>
<tr>
<td>ln(1 - Tariff Rate(_{t+2}))</td>
<td>0.241</td>
<td>.</td>
</tr>
<tr>
<td></td>
<td>(0.78)</td>
<td>.</td>
</tr>
<tr>
<td>ln(1 - Tariff Rate(_{t+3}))</td>
<td>0.513</td>
<td>.</td>
</tr>
<tr>
<td></td>
<td>(0.65)</td>
<td>.</td>
</tr>
<tr>
<td>Post Significant Tariff Decrease</td>
<td>.</td>
<td>-0.181**</td>
</tr>
<tr>
<td></td>
<td>.</td>
<td>(-2.19)</td>
</tr>
<tr>
<td>Post Significant Tariff Decrease(_{t+1})</td>
<td>.</td>
<td>-0.053</td>
</tr>
<tr>
<td></td>
<td>.</td>
<td>(-0.58)</td>
</tr>
<tr>
<td>Post Significant Tariff Decrease(_{t+2})</td>
<td>.</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>.</td>
<td>(0.28)</td>
</tr>
<tr>
<td>Post Significant Tariff Decrease(_{t+3})</td>
<td>.</td>
<td>0.051</td>
</tr>
<tr>
<td></td>
<td>.</td>
<td>(0.47)</td>
</tr>
</tbody>
</table>

Controls? | Yes | Yes | Yes | Yes |
Patent Class x Year Fixed Effects | Yes | Yes | Yes | Yes |
Firm Fixed Effects | Yes | Yes | Yes | Yes |
Observations | 193,937 | 193,937 | 193,937 | 193,937 |
Adjusted R\(^2\) | 0.400 | 0.400 | 0.325 | 0.325 |
Table 6
Patent disclosure and subsequent competitor behavior

This Table presents OLS regressions of the similarity of the competitors’ products to the firms’ products after patent issuance as a function of firms’ patent disclosure choices during the patent application process. All variables are as defined in Appendix A. t–statistics appear in parentheses and are based on standard errors clustered by industry and date. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two–tail). Sample descriptive characteristics are found in Table 1.

<table>
<thead>
<tr>
<th>Variable:</th>
<th>ln(Product Similarity)</th>
<th>ln(Product Similarity IC 25)</th>
<th>ln(Product Similarity SIC)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>ln(Days Since Disclosure)</td>
<td>-0.016* (1.84)</td>
<td>-0.021** (-2.15)</td>
<td>-0.020** (-2.00)</td>
</tr>
<tr>
<td>Controls?</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Patent Class x Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Firm Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>88,909</td>
<td>84,478</td>
<td>75,965</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.676</td>
<td>0.579</td>
<td>0.647</td>
</tr>
</tbody>
</table>
Table 7
Excluding industries regulated by the Food and Drug Administration

This Table repeats the results of Table 2 (columns 1, 2, 5, and 6) and Table 3 (columns 3, 4, 7, and 8) after excluding firms operating in industries that can be regulated by the FDA (Fama-French 48 industries 2, 3, 4, 5, 12, and 13). Controls are included in all columns, except $\ln(\text{Days to Latest Possible Disclosure})$ which is only included in columns (1)-(4). All variables are as defined in Appendix A. $t$-statistics appear in parentheses and are based on standard errors clustered by industry and date. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail). Sample descriptive characteristics are found in Table 1.

| Variable: | $\ln(\text{Days to Disclosure})$ | $\%\text{ Disclosure Delay}$ |  |  |  |  |  |  |
|-----------|-------------------------------|-----------------------------|  |  |  |  |  |  |
|           | (1)                           | (2)                         | (3) | (4) | (5) | (6) | (7) | (8) |
| $\ln(\text{Compustat Concentration Ratio})$ | 0.232*                        | .                           | .   | .   | 0.107** | . | . | . |
|           | (1.80)                        | .                           | .   | .   | (2.13) | . | . | . |
| $\ln(\text{Census Concentration Ratio})$ | .                            | 0.756***                    | .   | .   | .   | 0.289*** | . | . |
|           | .                            | (3.51)                      | .   | .   | .   | (4.01) | . | . |
| $\ln(1 - \text{TariOFF Rate})$ | .                            | -1.031***                   | .   | .   | .   | .   | -0.344*** | . |
|           | .                            | (-3.39)                     | .   | .   | .   | .   | (-2.68) | . |
| $\text{Post Significant Tariff Decrease}$ | .                            | .                           | -0.167*** | . | . | . | -0.074*** |
|           | .                            | (-3.98)                     | .   | .   | .   | .   | . | (-4.90) |
| Controls? | Yes                          | Yes                         | Yes | Yes | Yes | Yes | Yes | Yes |
| Patent Class x Year Fixed Effects | Yes                          | Yes                         | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm Fixed Effects | Yes                          | Yes                         | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 178,754                       | 130,274                     | 178,754 | 178,754 | 178,754 | 130,274 | 178,754 | 178,754 |
| Adjusted $R^2$ | 0.325                         | 0.316                       | 0.407 | 0.407 | 0.177 | 0.192 | 0.324 | 0.324 |
### Table 8

Controlling for patent values

This Table repeats the results of Table 2 (columns 1, 2, 5, and 6) and Table 3 (columns 3, 4, 7, and 8). Prior controls are included in all columns, except ln(Days to Latest Possible Disclosure) which is only included in columns (1)-(4). Controls for the value of the patent are included in all columns. All variables are as defined in Appendix A. $t$–statistics appear in parentheses and are based on standard errors clustered by industry and date. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two–tail). Sample descriptive characteristics are found in Table 1.

<table>
<thead>
<tr>
<th>Variable:</th>
<th>ln(Days to Disclosure)</th>
<th>Percentage Disclosure Delay</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>ln(Compustat Concentration Ratio)</td>
<td>0.216*</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(1.75)</td>
<td>-</td>
</tr>
<tr>
<td>ln(Census Concentration Ratio)</td>
<td>.</td>
<td>0.694***</td>
</tr>
<tr>
<td></td>
<td>.</td>
<td>(3.25)</td>
</tr>
<tr>
<td>ln(1 - Tariff Rate)</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td></td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>Post Significant Tariff Decrease</td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td></td>
<td>.</td>
<td>.</td>
</tr>
<tr>
<td>Patent Value</td>
<td>-0.004</td>
<td>-0.008</td>
</tr>
<tr>
<td></td>
<td>(-0.48)</td>
<td>(-1.33)</td>
</tr>
<tr>
<td>Controls?</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Patent Class x Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Firm Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.315</td>
<td>0.306</td>
</tr>
</tbody>
</table>
Table 9
Including early-deadline applications

This Table repeats the results of Table 2 (columns 1, 2, 5, and 6) and Table 3 (columns 3, 4, 7, and 8), after including observations where the disclosure deadlines falls within 180 days of the patent filing. Prior controls are included in all columns, except ln(Days to Latest Possible Disclosure) which is only included in columns (1)-(4). All variables are as defined in Appendix A. t-statistics appear in parentheses and are based on standard errors clustered by industry and date. ***, **, and * denote statistical significance at the 0.01, 0.05, and 0.10 levels (two-tail). Sample descriptive characteristics are found in Table 1.

<table>
<thead>
<tr>
<th>Variable</th>
<th>ln(Days to Disclosure)</th>
<th>Percentage Disclosure Delay</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4) (5)</td>
<td>(6) (7) (8)</td>
</tr>
<tr>
<td>ln(Compustat Concentration Ratio)</td>
<td>0.218*</td>
<td>0.103**</td>
</tr>
<tr>
<td></td>
<td>(1.77)</td>
<td>(2.14)</td>
</tr>
<tr>
<td>ln(Census Concentration Ratio)</td>
<td>.</td>
<td>0.687***</td>
</tr>
<tr>
<td></td>
<td>.</td>
<td>(2.14)</td>
</tr>
<tr>
<td>ln(t - Tariff Rate)</td>
<td>.</td>
<td>-0.921***</td>
</tr>
<tr>
<td></td>
<td>.</td>
<td>(-5.41)</td>
</tr>
<tr>
<td>Post Significant Tariff Decrease</td>
<td>.</td>
<td>-0.181***</td>
</tr>
<tr>
<td></td>
<td>.</td>
<td>(-4.44)</td>
</tr>
<tr>
<td>Controls?</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Patent Class x Year Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Firm Fixed Effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>194,461</td>
<td>194,461</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.320</td>
<td>0.324</td>
</tr>
</tbody>
</table>

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