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# Disclosure, Patenting, and Trade Secrecy

ARNOUD BOOT* AND VLADIMIR VLADIMIROV*

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Abstract

Patent applications often reveal proprietary information to competitors, but does such disclosure harm firms or also benefit them? We develop and empirically support a theory showing that when firms patent enhancements to incumbent, nondisruptive technologies, they can cooperate more easily on these technologies, increasing their profitability. The downside of cooperating on nondisruptive technologies is that the investment in and commitment to disruptive technologies decline. To improve their commitment to disruptive technologies, some firms rely more on trade secrecy. We provide empirical support for these predictions. We document that after a patent reform that made information about patent applications widely accessible, firms cooperate more and charge higher markups. Furthermore, the nature of patented innovation has changed, with the proportion of nondisruptive patents increasing substantially. Finally, while some firms start patenting more, others

*University of Amsterdam and CEPR

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patent less and rely more on trade secrecy, with the response depending on the attractiveness of firms' innovation prospects.

**JEL codes:** G31, G38, L41, M40, O31

**Keywords:** disclosure; patenting; trade secrecy; competition; cooperation; innovation; disruptive investments; breakthrough innovation

> *If the competition is investing heavily in patent protection in a specific technological field, a company may counter by investing in the development of similar, yet noninfringing technologies* — LexisNexis on the benefits of its patent filings monitoring service PatentInsight[1]

## 1. *Introduction*

Economists have long discussed how disclosure requirements affect firms' ability to stay innovative. While such requirements make firms more transparent to stakeholders and investors, disclosure can erode a firm's competitive edge by leaking information to current and potential new rivals (Verrecchia [1983], Healy and Palepu [2001], Leuz and Wysocki [2016]). Patent applications are a case in point: patent applications force firms to disclose a large amount of information about their R&D activities that could potentially benefit their rivals. Under current law, the content of patent applications becomes public 18 months after a patent filing, even though firms are not granted patent protection in about half of the cases (Carley, Hegde, and Marco [2015]). Yet, many large firms do not seem averse to such leakage of information. Pharma and biotech firms such as Eli Lilly, Pfizer, AstraZeneca, and Sanofi that rely heavily on patents publicly share even more information than is contained in patent filings through so-called "open innovation platforms." In tech, firms like IBM and Microsoft engage in open innovation by sharing research and technologies with external partners and the public. Major automotive manufacturers such as Tesla have also adopted open innovation approaches. The proclaimed objectives of such initiatives include helping the commercialization, adoption, and exploitation of innovations and cooperating on industry standards (Deloitte [2015]).

To better understand the link among these objectives, patent-related disclosure, and innovation, we analyze how a firm's choice between patenting and trade secrecy—the two standard choices for protecting intellectual property—affects opportunities for cooperation on nondisruptive technologies with rivals. By distinguishing between disruptive and nondisruptive innovation, we further show how such cooperation affects the pursuit

[1] See "https://www.lexisnexisip.com/resources/3-reasons-companies-should-monitor-competitors-patent-filings/ 3 Reasons Companies Should Monitor Competitors' Patent Filings " (LexisNexis, 2022).

of disruptive investments that could displace rivals and transform industries. To tackle these questions, we propose a theoretical framework and then offer empirical support for its predictions.

Our theoretical framework combines two main elements. First, firms with similar nondisruptive (incumbent) technologies repeatedly interact in the product market and can choose whether to patent improvements to these technologies rather than keep them a trade secret. The key difference between these two options we focus on is that patent applications signal to rivals what actions a firm is taking to improve its technologies. Second, next to their nondisruptive technology, the firms can also choose whether to pursue disruptive innovation that can cause other firms to become obsolete or unable to keep up. If the firm subsequently receives discouraging signals about the likelihood of the disruptive innovation succeeding, it can still decide to abandon it. That abandonment option helps the firm salvage some of the investment costs, but the prospect of wasted effort could demotivate the agents the firm needs to incentivize to work on making the investment successful.

A central element in the model is that firms can benefit from cooperating on nondisruptive technologies, provided they have not yet developed a disruptive technology capable of displacing their rivals. We focus on implicit cooperation, not involving explicit agreements with rivals. Examples of implicit cooperation include avoiding head-on competition via product differentiation, developing complementary aspects of technologies that improve their adoption by consumers, and openly sharing knowledge and data. The main challenge with implicit cooperation is that firms may have incentives to deviate and profit at their rivals' expense. Such deviations are difficult to detect because firms can only make noisy inferences about the other firms' actions.

Our first key result is that firms that choose to patent improvements to their nondisruptive technologies—rather than keep them as trade secrets — find it easier to sustain implicit cooperation and avoid head-on competition on those technologies. The leakage of information associated with patent applications ensures that there is a commonly observed history of signals around which firms can coordinate their actions. For example, related to the LexisNexis quote at the beginning, monitoring patent applications is informative about the type of R&D that firms are pursuing. This can be a useful signal of whether firms try to intensify head-on competition or avoid such competition, for example, by reducing the degree of overlap with rivals. In turn, this indicates what technologies rivals should focus on or stay away from. What particularly helps coordination is that patent applications reveal information regardless of whether a firm would subsequently like to withhold that information if its patent application is rejected. The resulting more complete history of signals makes it significantly easier for firms to cooperate on their nondisruptive technologies.

Our second result is that by enhancing opportunities for cooperation and increasing the profitability of nondisruptive technologies, patenting improvements to these technologies hinders the development of disruptive ones. Specifically, because cannibalizing nondisruptive technologies becomes less attractive when they are more profitable, firms invest less in disruptive technologies and more frequently abandon disruptive technologies they have invested in. The resulting erosion of commitment to disruptive investments further diminishes agents' incentives to work hard on making these investments successful. Intuitively, if agents know that the firm is likely to abandon a disruptive investment regardless of their effort, motivating these agents to work on that investment becomes more difficult, resulting in higher agency costs of motivating innovation.

Although these forces suggest that patenting firms will pursue more nondisruptive innovation at the expense of disruptive innovation, not all firms will choose to patent and seek cooperation on nondisruptive technologies. In particular, the potentially higher cost of motivating agents to work on disruptive innovation will drive some firms to establish a stronger commitment to such innovation by eschewing cooperation on nondisruptive technologies and relying more on trade secrecy. This is particularly relevant for firms with moderately attractive disruptive investment prospects, as these firms are most likely to receive ambiguous signals about whether to abandon a disruptive investment. Therefore, a stronger commitment to not abandoning disruptive innovation (when signals are ambiguous) significantly affects whether agents expect their efforts to be wasted, in turn significantly affecting agency costs. These considerations are less important for firms with marginally or very attractive investment prospects because such firms are more likely to receive clear-cut negative or positive signals about whether to abandon the disruptive investment. Hence, for these firms, agency costs depend little on whether they will abandon investment in case of ambiguous signals, and cooperating on their nondisruptive technologies overall benefits the firms.

A key feature of our model is that patent applications leak information to rivals. To provide empirical support for our theoretical predictions, we examine the passage of the American Inventors Protection Act (AIPA), which introduced precisely this feature to patent law in the United States by requiring firms to disclose patent applications after 18 months regardless of whether the patents are eventually granted. Prior to the AIPA, patent applications were kept confidential and became public only if patents were granted, which, according to our model, makes cooperation much more difficult. This legislation is considered important by prior work investigating the impact of disclosure on innovation, with the overall effects appearing very mixed. While some studies find a positive effect (Hegde, Herkenhoff, and Zhu [2023]), others find no effect (Saidi and Zaldokas [2021]) or an increase in innovation by rivals (Kim and Valentine [2021]). Our model can help explain such findings.

In line with our first main prediction, we document that the increase in information about patent applications after the AIPA has led to an increase in cooperation among firms more affected by the AIPA. To tackle the challenge of measuring the degree of cooperation among firms, we develop an index based on how often firms discuss cooperation relative to competition in their 10-K filings.[2] Further in line with our predictions that cooperation will increase firms' profitability, we document an increase in gross profits, markups, and operating margins among firms affected by the AIPA.

Supportive of our second main prediction, we also show that the AIPA has changed the nature of patented innovation, with nondisruptive patenting increasing dramatically after the introduction of the AIPA. This finding is based on a number of patent-level proxies for disruptive innovation, including various citation- and text-based measures that evaluate to what extent a patent represents a break from the past (Funk and Owen-Smith [2016], Kelly et al. [2021]).

We also provide support for our prediction that not all firms respond similarly to the AIPA, thus highlighting that focusing on patents as a measure of innovation is restrictive because it neglects that firms may keep their innovation activities a trade secret. To measure firms' reliance on trade secrecy in our empirical tests, we develop and externally validate (similar to Glaeser [2018]) an index based on how often firms discuss trade secrets relative to patenting in their 10-K filings. In line with our theory, we document that firms with moderately attractive disruptive investment opportunities react by patenting less and increasing their reliance on trade secrecy. We find the opposite for firms with marginally and highly attractive innovation opportunities. For all our difference-in-differences specifications, we provide evidence that the results are not explained by pre-existing differential trends.

Our paper is most closely related to prior work on the strategic use of patenting and the choice between patenting and trade secrecy (Hall et al., [2014], Glaeser [2018], Glaeser and Landsman [2021]). Two important findings in this literature are that: (1) firms consider patents an important source of information about what their rivals are working on; and (2) many firms patent for strategic reasons as a means of preventing others from innovating in that direction (Cohen, Nelson, and Walsh [2000], Cohen et al. [2002], Blind et al. [2006]). Hence, patents effectively signal to rivals which technologies to stay away from. Based on a similar reasoning, our paper's key point is that patenting nondisruptive technologies helps firms cooperate more efficiently or avoid head-on competition on these technologies. Our arguments and evidence are related to work showing that disclosure is instrumental for firms seeking implicit cooperation. In particular, prior studies have documented that firms appear to avoid head-on competition by implicitly cooperating on publicly sharing sensitive

[2] To externally validate that this index is a meaningful measure of cooperation, we exploit the cost-savings motivated closure of four of the seven regional Department of Justice (DOJ) offices in 2013, which has led to less antitrust oversight for firms in these regions (Ha, Ma, and Zaldokas [2024]). In line with theory, we show that our cooperation index increases for affected firms.

information about customers, contracts, and products (Bourveau, She, and Zaldokas [2020]). There is also evidence that tacit agreements are associated with firms disclosing more information in their revenue guidance, management forecasts, earning calls with analysts, and within industry associations (Bertomeu et al. [2020], Kepler [2021], Aryal et al. [2022], Pawliczek et al. [2022], Bushee et al. [2023]). Apart from discussing the role of patenting in facilitating implicit cooperation, we contribute to this literature by deriving novel predictions about how patenting nondisruptive technologies affects the incentives to pursue disruptive ones.

Our insight that disclosure can benefit firms by facilitating cooperation on overlapping nondisruptive technologies at the expense of investment in disruptive ones contrasts with much of prior theory in accounting and financial economics that predicts that disclosure (even if socially beneficial) harms firms' profitability by eroding their competitive advantage (Bhattacharya and Ritter [1983], Verrecchia [1983]). Despite the prominence of the latter argument, the evidence for it is mixed. Supportive of such reasoning, Berger, Choi, and Tomar [2024] show that reducing (cost) disclosure makes firms more profitable. Furthermore, Bernard [2016] shows that disclosure can guide entry by new rivals, and Aghamolla and Thakor [2022] find that firms affected by increased disclosure requirements reduce the size and risk of their project portfolios. Related, Breuer, Leuz, and Vanhaverbeke [2022] show that forcing firms to publicly disclose their financial statements leads to a decrease in both the profitability and innovation of small firms while an increase in those of larger firms. Indeed, size also matters in our setting because the cooperation benefit we model is arguably more relevant in industries with larger firms. On the positive side, there is evidence that higher disclosure standards are associated with more innovation in firms dependent on equity financing (Brown and Martinsson [2019]) and firms where disclosure can help reduce the performance-sensitivity of managerial turnover (Zhong [2018]). More generally, there is also evidence that disclosure improves financing and investment efficiency (Biddle, Hilary, and Verdi [2009], Fu, Kraft, and Zhang [2012]) and can have positive spillovers for competing firms (Shroff, Verdi, and Yost [2017]). Our theoretical and empirical results offer a new angle that complements and helps reconcile some of these contrasting findings while also explaining why and when some of these findings (such as the impact of patent disclosure on patent citations) reverse when considering how patent disclosure affects the nature of patented innovation.

## 2. *Model*

We start by developing the theory that underpins our hypotheses and then present evidence that supports these hypotheses in section 4. Two firms operate in an industry where their businesses overlap. All players are risk-neutral. Time is discrete and infinite, and the common discount factor is $\delta \in (0, 1)$. We introduce two key elements to this model that describe how firms compete through innovation. First, in every period of the game, the firms can choose whether to compete head-on in their overlapping businesses by pursuing *nondisruptive* innovation that improves their existing technologies. Second, firms can also pursue a *disruptive* investment opportunity that arrives with a positive probability at the beginning of each period. To concisely model that either none, both, or only one firm has such an investment opportunity, we assume that such investment opportunities arise only once for each firm. The disruptive investment requires a capital outlay of $K$, which the firm finances internally. Initially, we assume that both firms observe whether their counterpart makes a disruptive investment, but subsequently, we relax this assumption.

**Disruptive Investment**. A typical example of a disruptive investment is investing in breakthrough innovation that could shake up the industry if it succeeds. Our model of disruptive investments incorporates two key features common to such models (Aghion and Tirole [1994], Manso [2011]).

First, the firm learns about the success probability of the disruptive investment opportunity over time. Specifically, if the firm invests in period $t$, then at the interim date of that period, $\tau_t = 0.5$, the firm observes a nonverifiable state $\theta_i$, which corresponds to the probability of the investment's success. At this point, the firm has the option to exit and recoup $L$ by liquidating the investment.[3]

Second, if the firm decides to undertake the disruptive investment, it needs to employ an agent to carry it out. The advantage of employing the agent is that if the agent exerts effort, the probability of state $\theta_i$ changes from $q^0_{\theta_i}$ to $q^e_{\theta_i}$, with $\Delta_{\theta_i} := q^e_{\theta_i} - q^0_{\theta_i}$ denoting the difference. Specifically, effort increases the probability of success, $\sum_{\Theta} \Delta_{\theta_i}\theta_i > 0$, but comes at a nonmonetary cost $c$ to the agent. Throughout, we assume that investing is worth it only if a firm's agent exerts effort. The state realization $\theta_i$ is drawn independently for each firm $i$ and is also observable to the agent but not to outsiders. With more than two state realizations of $\theta_i$, the option to abandon the disruptive investment at the intermediate date will affect the agent's effort incentives. To capture this effect on effort, we assume that $\theta_i \in \Theta = \{0, \theta_M, \theta_G\}$, with $0 < \theta_M < \theta_G < 1$. We assume three state realizations, but our analysis generalizes to *any* number of states higher than two.

If a firm successfully develops a disruptive investment while its competitor does not, the disruptive firm takes over the market. We assume that the rival firm's cash flows are reduced to zero, and it exits the market, while the disruptive firm realizes an expected cash flow of $x_m$ in all remaining

[3] Modeling the choice between exploration of new ideas and exploitation of old ones as such a so-called "bandit" problem follows a long tradition in accounting and financial economics (Weitzman [1979], Manso [2011], Chen, Liang, and Petrov [2023], Baldenius and Yang [2023]).

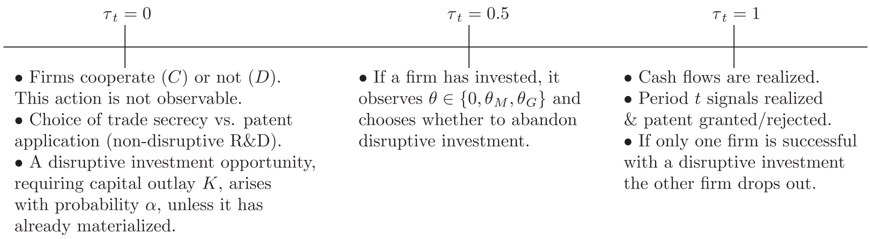


FIG. 1.—Timeline of a period.

periods.[4] Therefore, pursuing disruptive investments is inherently risky, but success may result in a monopoly status. In contrast, if neither firm successfully develops the disruptive technology or both successfully develop it, neither firm manages to become disruptive. In this case, the firms' expected cash flows depend on whether they compete or cooperate on their overlapping nondisruptive technologies. Endogenizing how this choice interacts with disruptive and nondisruptive innovation is the central novelty of our model. In what follows, we explain the difference between cooperation and competition. Figure 1 summarizes the timeline of a period.

**Cooperation and Competition on Nondisruptive Innovation**. When both firms, $i = \{1, 2\}$, have access to the same production technology, their expected cash flows depend on the nondisruptive technological choices $a_{it}, a_{jt} \in A = \{C, D\}$ the firms take in a period. These actions—"cooperate," action $C$, and "not cooperate," action $D$—refer to whether a firm focuses its *nondisruptive* innovation on modifying its existing technology to reduce the degree of overlap or intensify the rivalry with the other firm. These technological choices are neither observable nor verifiable to outsiders and, thus, cannot be contracted upon. The actions taken by a firm give rise to a privately observed signal, $y_{it} \in \{S, F\}$, whether the improvements to the firm's technology make it sufficiently different to that of its rival, where the distribution over the possible signals in the period is $\pi\left(\cdot | a_{it}, a_{jt}\right)$. Given an action profile $a = \left(a_{it}, a_{jt}\right)$, a firm's expected cash flows in a period are given by

$$x_{a_{it}a_{jt}} := \sum_{y_{it} \in Y} g_i\left(a_{it}, y_{it}\right)\pi\left(y_{it} | a_{it}, a_{jt}\right),$$

where $g$ stands for the firm's (nondisruptive) production function, given the firm's action $a_{it}$ and the realization of the firm-specific signal $y_{it}$. Example 1 in appendix A offers a concrete illustration of how cooperation affects cash flows. Each firm seeks to maximize the average discounted sum of its expected cash flows. We restrict attention to cases in which

$$x_{DC} > x_{CC} > x_{DD} \geq x_{CD}. \tag{1}$$

[4] Although we do not explicitly model this, we interpret $x_m$ as the average expected cash flow, accounting for the possibility that a new firm may enter the market and catch up with the new technology.

The interpretation of (1) is that the expected cash flows when both firms cooperate are higher than when no firm cooperates, and deviating from cooperation benefits the deviator at the expense of the firm that cooperates. Our formulation of the stage game is very general because assumption (1) can be micro-founded with most variations of standard models of competition such as Cournot or Bertrand. Throughout the analysis, we focus on pure strategies, but we also discuss the robustness of the results when allowing for mixed strategies. As standard, we assume that the firms' strategies do not depend on irrelevant information. That is, a firm's strategy depends only on its current posterior beliefs about the other firm's history of actions and signals and not on how the firm has reached these posterior beliefs.

If firms do not cooperate (i.e., take the deviation action, $D$), they compete. Notably, any potential advantage of not cooperating is only temporary because it only affects the payoff in the respective period. To achieve a permanent advantage, a firm must undertake a *disruptive* investment, which we model separately as described above.

**Disclosure: Patenting Versus Trade Secrecy**. At the beginning of each period, before observing signal $y_{it}$, each firm can choose whether it wants that signal to be observable to all at the end of the period. We interpret this choice as the firm's choice between a patent application and trade secrecy—arguably, in line with the fact that the leakage of information to rivals is one of the key distinguishing features between a patent application and trade secrecy. If the firm chooses to file a patent application, it provides information about its technology, which translates into a verifiable signal revealing $y_{it}$ at the end of the period. We assume that a patent is approved if and only if the improvements to a firm's nondisruptive technology successfully differentiates the firm from its rival ($y_{it} = S$). If the firm chooses trade secrecy, its signal $y_{it}$ remains its private information.

Our assumption that a patent application effectively commits the firm to disclose signal $y_{it} \in \{S, F\}$ at the end of the period regardless of its realization can be motivated by two stylized facts. First, about half of patent applications are rejected, indeed leaving substantial uncertainty for the firm about whether its technology will be seen as sufficiently different from that of its rivals. Second, the average delay between patent application and grant decision is, on average, more than two years, while patent applications become public after 18 months regardless of whether they are subsequently granted (see for details section 4). Thus, a patent application effectively commits most firms to disclose both the content and the decision on that application.

Finally, note that firms in our setting are indifferent about whether to patent their *disruptive* innovation because such an innovation displaces the other firm, leaving no area of overlap and no scope for cooperation. That said, our model can be extended to consider the entry of a new firm that catches up with the disruptive technology, with that technology becoming the new area of overlap, leading to the same strategic considerations.

## 3. Patenting, Cooperation, and Disruptive Investment

**Interpretation of Cooperation and Competition**. We interpret the cooperation action $C$ as whether firms focus their nondisruptive R&D on modifying their *nondisruptive* products and services to reduce the degree of overlap with other firms. For example, firms may modify different aspects of a technology, with one firm focusing on the software and the other on the hardware. Conversely, an example of action $D$ is when two companies in the smartphone industry try to improve the same feature of their technology (e.g., a touchscreen display), thereby intensifying competition for customers who value that feature. Another interpretation of action $C$ is when firms focus their research on developing complementary aspects of a new technology that has already been discovered and can be pursued by both firms. Examples include improvements to green mobility or new-generation drugs, which consumers will adopt more broadly if more firms work on improving different aspects of the technology. Action $D$ may correspond, then, to focusing research on improving nongreen technologies or, respectively, already established drugs to temporarily benefit from undermining the other firm's efforts.

### 3.1 PATENTING NONDISRUPTIVE INNOVATION AND COOPERATION

Solving the model backward, we start with the case in which neither firm has a disruptive investment opportunity (i.e., both firms' investments have either succeeded, failed, or been abandoned) and show the distinct value of opting for patent applications over trade secrecy. Subsequently, we study the case where firms can cooperate on their existing technology while simultaneously competing by pursuing a disruptive investment.

**Why Patenting Helps Cooperation**. When neither firm has a disruptive investment opportunity, the main choices they face are whether or not to cooperate and whether or not to apply for patents for their nondisruptive innovation (which effectively forces them to disclose $y_{it}$). However, maintaining cooperation is difficult because the firms' actions are not observable. In particular, if one firm intends to cooperate, it is optimal for the other not to do so, as its expected cash flow from not cooperating, $x_{DC}$, is higher than that from cooperating, $x_{CC}$. The only Nash equilibrium of the stage game is that both firms do not cooperate.

In light of this problem, patenting improvements to the nondisruptive technology is beneficial in that it results in the disclosure of the signals $y_{it}$, which can help the firms support a cooperative equilibrium. Though actions remain unobservable and signals only allow for noisy inferences about these actions, committing to disclosing these signals through patenting offers a commonly observed history of signals around which the firms can coordinate their follow-up actions. Specifically, there is a perfect public equilibrium (PPE) in which both firms cooperate in period $t$ and continue to cooperate in period $t+1$ if and only if both firms file for a patent and the resulting disclosed signals are above a certain threshold indicating cooperation.[5] The argument is standard: there is a PPE in which both firms cooperate in period $t$ and cooperate in period $t+1$ if they are successful in period $t$ (i.e., $y_{it}, y_{jt} = S$). Lack of success by one of the firms (i.e., $y_{it} = F$ or $y_{jt} = F$) triggers non-cooperation in all future periods. As non-cooperation is the Nash equilibrium of the stage game, the action profile $(D, D)$ is a self-enforcing (i.e., incentive-compatible and credible) threat for any $\delta$. In turn, the action profile $(C, C)$ can be enforced if the benefit from continued cooperation is higher than that from deviation, which confers a one-period advantage but leads to abandonment of cooperation thereafter. (Readers less familiar with this argument can refer to Example 1 in appendix A.)

**Why Trade Secrecy Hampers Cooperation**. To highlight the role of patenting in helping firms support cooperation, we now show that the above simple argument breaks down if firms do not patent but choose trade secrecy, in which case their signals remain private.[6] At first sight, the basic problem when signals are private is the same: we need to determine the firms' beliefs about the continuation strategies (and thus, private histories) of their counterparties, conditional on their own private histories. The concept of PPE (e.g., Green and Porter [1984]) that we applied for the case of patenting dramatically simplifies this problem by conditioning strategies only on commonly observable signals, which allows for a recursive formulation of equilibrium payoffs. However, this approach cannot be applied when signals are private because then there is no commonly observable history of signals around which to align actions. The result is a stark difference in predictions (all proofs are in appendix A).

**Lemma 1.** *When signals remain firms' private information, firms cannot support a cooperative equilibrium.*

To illustrate the intuition, suppose that both firms choose trade secrecy and are thus not forced to disclose $y_{it}$. Consider the following sequential equilibrium candidate. Firm $i$ cooperates in period $t$ and cooperates again in period $t+1$ if and only if its private signal is $y_{it} = S$. That is, unlike with patenting, the firms can only rely on their own signals.

The problems with conditioning actions only on private signals are that (1) monitoring cooperation is more difficult (as inferences about actions are based on fewer signals) and (2) the threat to punish deviations by abandoning cooperation following signals indicating deviations is less credible (not self-enforcing). The first point is obvious. To see the latter, suppose that a firm that chooses trade secrecy observes a signal that should trigger abandoning cooperation. That firm now faces a dilemma:

[5] In a PPE, the firms' strategies in every period depend only on the public history (i.e., disclosed signals) and not on the firms' private history (i.e., information about their prior actions).

[6] In practice, positive R&D spending not accompanied by patenting could help outsiders infer that a firm is relying on trade secrecy. Firms also typically have to discuss trade secrecy in their 10-K filings (section 4).

abandoning cooperation will harm not only the other firm, but also itself. What is more, the firm anticipates that a signal indicating that the other firm has deviated must be wrong. Indeed, as both firms cooperate in the proposed candidate equilibrium, the only (equilibrium) explanation for such a signal is that it is due to bad luck rather than deviation by the other firm. Therefore, the firm will neglect its signal and continue cooperating.[7] That makes supporting a cooperative equilibrium impossible because the lack of a credible threat to abandon cooperation will invite deviations from cooperation. It is straightforward to extend the argument to the case in which only one firm relies on trade secrecy.

In summary, the lack of a commonly observed history of signals—reported regardless of whether firms find it ex post optimal to do so—impedes the monitoring of cooperation and makes the threat of abandoning cooperation less credible, both of which are crucial impediments to sustaining cooperative equilibria. Based on Lemma 1 and the preceding discussion, our first main prediction is:

**Proposition 1.** *Patenting the improvements to nondisruptive technologies allows firms to support cooperative equilibria on such technologies. The firms cannot achieve the same outcome if either one relies on trade secrecy.*

**Information Spillovers**. Although our model is stylized and the assumptions behind it are stark, we argue in the online appendix that the main message of Proposition 1 is robust to relaxing many of these assumptions. Here, we want to discuss an alternative interpretation of the cooperative action $C$. Thus far, we have assumed that patent applications were important only to the extent that they enforced the disclosure of signals indicative of the firms' actions. An *alternative* form of cooperation with rivals is when firms share knowledge (as in our pharma example in the Introduction), which can help firms avoid duplication of research efforts and could help them coordinate on common standards on complementary technologies. Patenting now plays two roles: it is both a signal of what knowledge firms have gained (which is indicative of whether they are cooperating), and the information contained in patents is a useful complement to the data and knowledge that firms cooperate on sharing. This role of patenting is related to arguments in the literature that patents cause "information spillovers" that benefit rivals. However, while prior work has discussed the *harm* for disclosing firms, which can be avoided through trade secrecy, our new angle is to highlight the *benefit* of patenting as a means of facilitating cooperation on disclosing information.[8]

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[7] The firm will find it rational to stop cooperating in period $t+1$ only if it expects its rival to do the same. However, the firm's signal does not affect its expectation of whether its rival will stop cooperating because (in an equilibrium in which both firms cooperate) the two firms' signals are independent.

[8] By revealing more of the firm's information endowment, patenting can also make it easier to support unraveling equilibria where firms reveal information voluntarily about their

### 3.2 IMPACT ON DISRUPTIVE INVESTMENT

Proposition 1 discussed the case in which the firms do not have disruptive opportunities. Next, we formalize the idea that firms may cooperate on their nondisruptive technology while simultaneously competing by making disruptive investments aimed at displacing rivals. Here, we analyze the case in which only one firm has a disruptive investment opportunity, as most of the intuition can be derived from this case. In the online appendix, we extend our analysis to the case in which both firms can invest.

Let firm $i$ be endowed with a disruptive investment opportunity while the other firm has none (it has tried and failed). The question is how cooperating on nondisruptive innovation interacts with firm $i$'s incentive to pursue disruptive innovation. Clearly, for the other firm, the option to cooperate with firm $i$ on its existing nondisruptive technologies is always beneficial, so it will patent its nondisruptive innovation (Proposition 1).

**The Firm's Investment and Contracting Problem**. Suppose that firm $i$ wants to pursue the disruptive investment at the beginning of period $t$, which requires hiring and motivating an agent.[9] To undertake the investment opportunity, the firm offers the agent a contract that specifies control rights over the disruptive investment's continuation and cash flow rights that may depend on the observable outcomes. Without loss of generality, we assume that the contract offers the agent a payment of $w_A$ in case the investment is abandoned, $w_m$ if it succeeds and the firm takes over the market as a monopolist, and $w$ if the investment is unsuccessful. This contract results in an expected payoff for the agent of

$$U = \sum_{\theta_i \in \Theta} q^e_{\theta_i}\big((\theta_i w_m + (1-\theta_i)w)\mathbf{1}_{\theta_i} + w_A\big(1 - \mathbf{1}_{\theta_i}\big)\big), \tag{2}$$

where $\mathbf{1}_{\theta_i}$ is an indicator function taking the value of one if the investment is continued after the realization of state $\theta_i$ at the intermediate date, and zero if it is abandoned. As standard, we normalize the agent's outside option to zero, so $U - c$ can be interpreted as the agent's agency rent.

activities (Milgrom [1981], Dye [1985]). See Bertomeu et al. [2021] and Bertomeu and Liang [2015] and the references therein for other effects of voluntary disclosure. In general, supporting cooperative equilibria entirely based on voluntary disclosure is hard, but voluntary disclosure can help by complementing the information that firms are forced to disclose by filing patent applications (for more details, see the online appendix).

[9] Note that if firm $i$ chooses not to invest in period $t$, it will also not invest in later periods because it will face the same problem in all these periods. Thus, firm $i$ either invests immediately when its investment opportunity arises or does not invest at all.

Firm $i$'s present value from investing net of its payments to the agent is higher than the outside option of not investing if

$$V_I := \sum_{\theta_i \in \Theta} q^e_{\theta_i} \left( \left( \theta_i \frac{x_m}{1-\delta} + (1-\theta_i)\mathrm{E}x \right) \mathbf{1}_{\theta_i} + (L + \mathrm{E}x)\left(1 - \mathbf{1}_{\theta_i}\right) \right)$$
$$- K - U \geq \frac{v^{pat}}{1-\delta}, \tag{3}$$

where $v^{pat}$ is the firm's (average) expected payoff in a period in which both firms patent and cooperate on their nondisruptive technologies; $\mathrm{E}x = \frac{v^{pat}}{1-\delta}$ is the expected discounted payoff when cooperation starts in period $t$; and $\mathrm{E}x = x_{DD} + \frac{\delta v^{pat}}{1-\delta}$ if firm $i$ chooses trade secrecy in period $t$, with cooperation starting in period $t+1$ after the disruptive innovation has failed or has been abandoned. The outside option on the right-hand side of (3) is $\frac{v^{pat}}{1-\delta}$ because the firm is better off patenting and cooperating with its rival in their overlapping businesses if it does not invest (Proposition 1).

Once the investment is started, the firm and the agent observe at the interim date of the period the investment's probability of success $\theta_i$. The investment is continued (i.e., $\mathbf{1}_{\theta_i} = 1$) if doing so creates more joint surplus for both parties, compared to liquidating the investment and continuing with the nondisruptive technologies:

$$\theta_i \frac{x_m}{1-\delta} + (1-\theta_i)\mathrm{E}x \geq L + \mathrm{E}x \Longleftrightarrow \frac{x_m}{1-\delta} \geq \frac{L}{\theta_i} + \mathrm{E}x. \tag{4}$$

The firm's objective is to maximize $V_I$ by optimally designing $\{w, w_m, w_A\}$ and allocating the continuation control right at the intermediate date, anticipating that continuation decisions other than those given by (4) will be renegotiated. Without loss of generality, assume that the firm has all bargaining power in such renegotiations. Furthermore, the contract is maximized subject to the incentive constraint that ensures the agent exerts effort:

$$\sum_{\theta_i \in \Theta} \left(q^e_{\theta_i} - q^0_{\theta_i}\right)\left((\theta_i w_m + (1-\theta_i)w)\mathbf{1}_{\theta_i} + w_A\left(1 - \mathbf{1}_{\theta_i}\right)\right) \geq c. \tag{5}$$

**Impact of Patenting Nondisruptive Innovation on Disruptive Investment and Trade Secrecy**. Cooperation opportunities (facilitated through patenting) increase the profitability of the firm's existing business, which encumbers the pursuit of disruptive investment. First, as is well-known, a more-valuable existing business makes firms more reluctant to pursue investments that cannibalize that business. Specifically, condition (3) becomes more difficult to satisfy if the difference between $v^{pat}$ and $x_{DD}$ increases.

Second, conditional on undertaking the disruptive investment, the firm is more likely to abandon it if its nondisruptive technology is more valuable. Formally, the state realization, $\theta_i$, needs to be higher for continuing the investment opportunity to be worth it (i.e., for condition (4) to be satisfied).

We can equivalently express this statement in terms of the expected profit from a successful disruptive investment, $\frac{x_m}{1-\delta}$. In particular, observe that if

$$\frac{x_m}{1-\delta} \in \left(X', X''\right), \text{ where } \begin{cases} X' := & \frac{L}{\theta_M} + x_{DD} + \delta \frac{v^{pat}}{1-\delta} \\ X'' := & \frac{L}{\theta_M} + \frac{v^{pat}}{1-\delta} \end{cases}, \tag{6}$$

condition (4) is satisfied for states $\{\theta_M, \theta_G\}$ if the firm chooses trade secrecy but only for state $\theta_G$ if the firm chooses to patent the improvement to its nondisruptive technology. That is, there is an "ambiguous" state $\theta_M$ in which the continuation decision crucially depends on the firm's commitment to the disruptive technology. In turn, this commitment endogenously depends on whether the firm chooses patenting or trade secrecy.

The choice between patenting and trade secrecy is, indeed, not trivial because it affects both the firm's investment in disruptive innovation and the agency costs associated with motivating agents to pursue such innovation. In particular, the higher probability of ex post abandonment affects the agent's ex ante incentives to exert effort in making the investment successful. On the positive side, when contracts are optimally structured to pay agents more if the investment is continued, a higher probability of abandonment creates stronger incentives to exert effort. However, there is also a countervailing "wasted effort" effect. Specifically, when the agent's effort increases the probability not only of states in which the investment is continued, but also in which the investment is abandoned, the agent's effort is partially wasted. In our model, this occurs if $\Delta_{\theta_M} > 0$, that is, when effort increases the probability of the intermediate "ambiguous" state $\theta_M$, and the investment is abandoned in that state.[10] The prospect of such abandonment makes it harder to incentivize effort. If this wasted-effort effect is sufficiently strong, the agent needs to be promised higher compensation ("agency rent") to exert effort, reducing the "piece of the pie" remaining for the firm. In such cases, the firm may prefer opting for trade secrecy, as this helps it pursue the disruptive investment at a lower cost.

**Proposition 2.** *Suppose that only firm i can make a disruptive investment and that both firms patent and cooperate on their nondisruptive technologies. Then: (1) Firm i is less likely to pursue the disruptive investment, and, conditional on pursuing it, the firm is more likely to abandon it. (2) Firm i would make a higher expected profit when choosing trade secrecy if and only if the disruptive investment opportunity is moderately attractive,* $\frac{x_m}{1-\delta} \in (X', X'')$, *and the wasted effort effect is sufficiently strong—that is, there is a threshold* $\Delta^*_{\theta_M}$ *such that* $\Delta_{\theta_M} > \Delta^*_{\theta_M}$.

**Illustrating the Difference in Agency Rent**. Because the agency costs associated with motivating innovation are widely considered to be a first-order problem for organizations trying to motivate innovation (Manso [2011]), and as they can affect the choice between patenting and trade secrecy, we

[10] With two states, there is no notion of an "intermediate state" explaining why the wasted effect does not arise. However, this problem is present whenever there are more than two states.

illustrate how cooperation opportunities affect these costs in a bit more detail.[11] Suppose the agent is only paid if the firm's investment is successful but not otherwise (i.e., $w_A = w = 0$). By standard arguments, the incentive constraint (5) will bind, implying that if the firm continues the investment only in state $\theta_G$, it must hold that $w_m = \frac{c}{\Delta_{\theta_G}\theta_G}$. Hence, the expected payment to the agent, net of the effort cost, $c$, is

$$q^e_{\theta_G}\theta_G w_m - c = \frac{q^0_{\theta_G}}{\Delta_{\theta_G}}c. \tag{7}$$

Instead, if the firm continues the investment in states $\{\theta_M, \theta_G\}$, from (5), it will hold that $w_m = \frac{c}{\sum_{\theta_i\in\{\theta_M,\theta_G\}}\Delta_{\theta_i}\theta_i}$. Hence, the expected payment to the agent, net of the effort cost, is

$$\sum_{\theta_i\in\{\theta_M,\theta_G\}} q^e_{\theta_i}\theta_i w_m - c = \frac{\sum_{\theta_i\in\{\theta_M,\theta_G\}} q^0_{\theta_i}\theta_i}{\sum_{\theta_i\in\{\theta_M,\theta_G\}}\Delta_{\theta_i}\theta_i}c. \tag{8}$$

The right-hand sides of expressions (7) and (8) correspond to the agency rent the firm needs to pay the agent to exert effort. The difference between (7) and (8) is positive if only if $\Delta_{\theta_M} > \frac{q^0_{\theta_M}\Delta_{\theta_G}}{q^0_{\theta_G}}$. Thus, for moderately attractive investment opportunities, $\frac{x_m}{1-\delta} \in (X', X'')$—where the continuation decision in state $\theta_M$ differs between patenting and trade secrecy—trade secrecy will entail lower agency costs if the wasted-effort effect is strong. If $\Delta_{\theta_M}$ is sufficiently larger than $\frac{q^0_{\theta_M}\Delta_{\theta_G}}{q^0_{\theta_G}}$, the lower agency rent under trade secrecy can compensate for the fact that the expected cash flows under trade secrecy are lower and make trade secrecy preferable.

If, instead, the continuation decision under patenting and trade secrecy is the same, there will be no difference in agency rent, and the higher profitability brought about by patenting and cooperating will always dominate (despite the negative implications for disruptive investment). This is the case outside of the intermediate region $(X', X'')$. In particular, patenting and cooperating is preferable if the disruptive investment is highly attractive, $\frac{x_m}{1-\delta} \geq X''$. In this case, the firm is unlikely to abandon investment regardless of whether it chooses patenting or trade secrecy for its nondisruptive innovation (in both cases, it continues in states $\{\theta_M, \theta_G\}$). Thus, the agency costs are the same, but patenting improvements to its nondisruptive technology benefits the firm because it offers the opportunity to cooperate on that technology. Patenting and cooperating also dominate at the other extreme, that is, $\frac{x_m}{1-\delta} \leq X'$, where the disruptive investment is marginally attractive. In this case, the continuation decision is again the same (the

[11] A common feature between our model and Manso [2011] is that the firm can learn over time about its disruptive investment opportunity and abandon it. However, while Manso emphasizes the importance of tolerance for early failure and reward for long-term success in lowering the agency costs associated with motivating innovation, our key innovation is to study how the opportunities to cooperate with rivals interact with such agency costs.

firm continues only in state $\theta_G$), and the opportunities to cooperate on the firms' existing nondisruptive technologies are even more valuable.[12]

## 4. Hypotheses and Empirical Tests

Our theory provides a new angle on the real effects of patenting disclosure requirements. In particular, our model shows that making patent applications public information before the decision on these applications facilitates cooperation on nondisruptive innovation, which in turn affects firms' incentives to pursue disruptive innovation. In what follows, we provide supportive evidence for our theory by examining the passage of the AIPA, which introduced precisely this feature to U.S. patent law. Before the passage of the AIPA, information about patents only became available after they were granted, which was, on average, more than two years following application. The AIPA forced firms to make such information public after 18 months, even for patents that were not eventually granted. As only about 50% of patents are typically approved (Carley, Hegde, and Marco [2015]), the earlier disclosure of patent applications, regardless of their subsequent approval, has led to the disclosure of information that would not have occurred otherwise. The law was enacted in November 1999 and affected patent applications starting in November 2000.

The key source of variation we exploit is that the AIPA affected some industries more than others, as there is wide-ranging variation in the time it took to approve patents in different industries in the pre-AIPA period. The idea is that industries with longer lags between patent application and grant date were more strongly affected by the passage of the AIPA. That allows us to construct a continuous treatment variable that is defined as the median time from patent application to grant date for the industry. For a more detailed description of the institutional background surrounding the AIPA and its suitability as a shock to firms' patenting information environment, we refer to Johnson and Popp [2003], Graham and Hegde [2015], and Hegde, Herkenhoff, and Zhu [2023].

Apart from the fact that the AIPA closely maps to our modeling framework, it is interesting to consider this legislation because prior studies of its impact have produced results that seem hard to reconcile. In particular, some papers demonstrate that stricter patenting disclosure regulations increase patent citations (Hegde, Herkenhoff, and Zhu [2023]). Others

[12] The negative effect on agency costs is less pronounced if multiple firms simultaneously pursue disruptive investments (see online appendix). With such rivalry, cooperation puts commitment to disruptive investment less at risk because the firms feel pressure to invest for fear of being left behind. Moreover, disclosure can help firms transition from cooperating on their existing technologies to cooperating on their new technologies. As in our pharma and biotech example, cooperation could then broaden the adoption of the new technologies (e.g., via common standards) or spur innovation by suppliers and customers (Gnyawali, He, and Madhavan [2006], Bushee, Keusch, and Kim-Gina [2023]).

report no effect on the level of patenting (Saidi and Zaldokas [2021]). Further complicating the interpretation of legislations such as the AIPA, studies of closely related legislations have shown that mandating more disclosure leads to fewer innovating firms producing the same level of innovation (Breuer, Leuz, and Vanhaverbeke [2022]). There is also evidence that the AIPA has led to information spillovers that benefit rivals (Kim and Valentine [2021]), but these findings are not accompanied by evidence that firms forced to disclose more are actually harmed. In what follows, we discuss how our model and empirical evidence can reconcile and expand on such mixed findings.

### 4.1 HYPOTHESES

Following Proposition 1, we predict that the passage of the AIPA—which corresponds to how we model patenting in our model—has benefited firms by making it easier to cooperate on nondisruptive technologies, in turn leading to higher profitability, markups, and operating margins.[13] As we have argued in the context of Proposition 1, cooperation is more difficult to achieve when firms have more leeway to keep information about patent applications private, which corresponds more closely to the pre-AIPA regime.

*H1*: Making information about patent applications more widely available allows firms to engage in more cooperation. This enables firms to charge higher markups, resulting in higher profitability and operating margins.

Our second main prediction is that by making it easier for firms to cooperate on overlapping nondisruptive technologies, the AIPA will change the nature of *patented* innovation (Proposition 2). Several direct effects all go in the same direction. First, the AIPA will lead to an increase in patenting of nondisruptive technologies because that helps firms cooperate better and avoid head-on competition on such technologies. The same would not apply to disruptive innovation, as the overlap and possibilities for cooperation are missing. Second, as nondisruptive technologies become more profitable, investing in disruptive ones becomes less attractive. Furthermore, when firms invest in a disruptive technology, they are more likely to abandon it if they receive mediocre signals about its prospects.[14]

[13] As we have argued, examples of the benefit of forcing firms to disclose more information about their patent applications include that it becomes easier for firms to avoid head-on competition by improving their products to reduce the overlap with other firms. Furthermore, it can help firms improve complementary aspects of a technology to increase its adoption, avoid duplication of research efforts, or converge faster on common standards. All of this can help firms maintain higher profits on new and old technologies for longer, which should be reflected in higher markups.

[14] Cooperation opportunities are typically considered more relevant for larger firms because they have a larger impact on the market as a whole, and small firms have more to gain

*H2*: Making information about patent applications more widely available changes the nature of patented innovation, leading to the patenting of more nondisruptive innovation.

A key element of our paper is that focusing only on *patented* innovation can be misleading because it neglects that firms can choose trade secrecy over patenting. Indeed, we show that the erosion in commitment to disruptive innovation can increase the agency costs associated with motivating such innovation, especially for firms with moderately attractive disruptive investment opportunities (Proposition 2). If these agency costs are sufficiently large, such firms may choose to increase their reliance on trade secrecy and patent less as a means of improving their commitment to disruptive innovation.

*H3*: (1) Making information about patent applications more widely available will lead to an increase in patenting and a decrease in trade secrecy in firms with marginally or very attractive disruptive investment opportunities. These effects will be weaker for firms with moderately attractive disruptive investment opportunities. (2) Among firms with moderately attractive disruptive opportunities, those that do not benefit from the cooperation opportunities opened up by the AIPA will not increase their patenting and may even decrease it while relying more on trade secrecy.

### 4.2 RESEARCH DESIGN

In what follows, we explain in detail how we test H1–H3. We start by explaining how we collect information on the relevant variables, for which we provide definitions and descriptive statistics in table 1. We list all data sources we use in table 7. Data on public firms come from Compustat and the firms' SEC 10-K filings. Patent data come from the USPTO's database, where we use Kogan et al. [2017] crosswalk to match patents to Compustat firms.

***4.2.1. Proxies for Cooperation and Markups.*** **Profitability and Markups**. We calculate profitability as gross profits scaled by sales as in Berger, Choi, and Tomar [2024]. Operating margins are defined as in Grullon, Larkin, and Michaely [2019] as operating income before depreciation minus depreciation (i.e., EBIT) scaled by sales. Markups are calculated as $\frac{sale_{it}}{cogs_{it}}$ where $sale_{it}$ and $cogs_{it}$ are firm-level sales and cost of goods sold. Focusing on markups is interesting, as it shows whether firms can sell at higher prices compared to their variable costs of production. The use of firm fixed effects should mitigate concerns that differences in fixed costs may drive differences in

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from deviating. Indeed, our evidence is based on public firms, which are typically much larger than nonpublic firms. Related, Breuer et al. [2020] find that stricter reporting standards benefit innovative large firms, but the effect is the opposite for small firms.

**TABLE 1**
*Summary Statistics*

| | Mean | Median | SD | N |
|---|---|---|---|---|
| Cooperation index | 0.322 | 0.289 | 0.199 | 58,342 |
| Profitability | −0.161 | 0.359 | 3.613 | 101,059 |
| Ln(markup) | 0.476 | 0.442 | 0.791 | 100,484 |
| Ln(operating margin) | −2.246 | −2.152 | 1.040 | 67,292 |
| Trade secrecy index | 0.141 | 0.000 | 0.263 | 58,511 |
| Ln(patents) | 0.306 | 0.000 | 0.766 | 117,856 |
| Ln(delay) | 6.659 | 6.653 | 0.175 | 108,072 |
| SG&A/sales | 0.762 | 0.266 | 2.386 | 80,239 |
| Ln(sales) | 4.443 | 4.502 | 2.676 | 101,048 |
| Industry ln(sales) | 4.350 | 4.081 | 1.592 | 117,837 |
| Similarity | 10.813 | 2.382 | 21.945 | 63,136 |
| Ln(citations) | 2.198 | 2.079 | 1.003 | 458,507 |
| Ln(3-year citations) | 0.876 | 0.693 | 0.732 | 487,360 |
| Ln(5-year citations) | 1.417 | 1.386 | 0.859 | 487,360 |
| Ln(7-year citations) | 1.748 | 1.609 | 0.916 | 487,360 |
| Ln(10-year citations) | 1.967 | 1.946 | 0.974 | 487,360 |
| Destabilizing/consolidating index 5 year post grant | 0.371 | 0.025 | 2.347 | 484,584 |
| Destabilizing/consolidating index 10 year post grant | 0.984 | 0.091 | 6.383 | 487,042 |
| Forward/backward similarity top 5% | 0.133 | 0.000 | 0.339 | 487,302 |
| Forward/backward similarity top 10% | 0.216 | 0.000 | 0.412 | 487,302 |

This table shows the summary statistics for the main variables used in the analysis. $Cooperation\ index$ is an index based on how many times a firm's 10-K filing with the SEC mentions phrases related to cooperation relative to cooperation or competition. $Profitability$ is gross profit scaled by sales. $Ln(markup)$ is defined as the natural logarithm of the ratio of sales to cost of goods sold. $Ln(operating\ margin)$ is the natural logarithm of operating income before depreciation minus depreciation scaled by sales. $Trade\ secrecy\ index$ is an index based on how many times a firm's 10-K filing with the SEC mentions phrases related to trade secrecy relative to trade secrecy or patenting. $Ln(patents)$ is the natural logarithm of one plus the number of patents a firm produces in a given year. $Ln(delay)$ measures the median days between the filing date and the grant date across all patents granted in the same four-digit SIC industry between 1996 and 2000. $SG\&A/sales$ is sales, general, and administrative expenses over sales. $Ln(sales)$ is the natural log of sales, adjusted to inflation (base year 2004). $Similarity$ is the Hoberg and Phillips [2016] total similarity score. $Ln(citations)$ is the natural logarithm of one plus the number of forward citations of a patent until the year 2020. $Ln(n-year\ citations)$ is the natural logarithm of one plus the $n$-year forward citations of a patent. The attractiveness of innovation is the mean market value of patents produced between 1996 and 2000 by firms in the same four-digit SIC industry. $Destabilizing/consolidating\ index\ n\ year\ post\ grant$ is a patent-level consolidation and disruption index, measuring whether follow-up patents in the $n$ years post a patent's grant date cite a focal patent more than its predecessors. $Forward/backward\ similarity\ top\ n\%$ is an indicator variable showing whether a patent can be classified as a breakthrough innovation based on its textual commonality with preceding and follow-up innovation.

markups because it is unlikely that the fixed costs of firms systematically change around the AIPA.

**Cooperation**. A bigger challenge is identifying firms that pursue cooperation. To the best of our knowledge, there is no commonly used measure of cooperation. Therefore, we propose one based on the firms' SEC filings. In particular, we extract all available 10-K filings from the SEC's EDGAR database. For each firm $i$ and filing period $t$, we search for phrases related to competition, cooperation, and collaboration. We then count all instances in a 10-K filing of words related to competition ($\#competition_{it}$)

and cooperation and collaboration ($\#cooperation_{it}$) and construct an index of cooperation, defined as

$$Cooperation\ index_{it} = \frac{\#cooperation_{it}}{\#cooperation_{it} + \#competition_{it}}. \tag{9}$$

Note that by construction, this index is bounded between zero and one, with higher values indicating more discussions of cooperation relative to competition in the firms' 10-K filings. We construct this measure for all available SEC EDGAR filings for the period of 1995–2023. To link SEC filings to Compustat, we use the historical linking tables between CIK numbers and gvkey provided by WRDS. Our sample starts in 1995 since SEC EDGAR's coverage starts in 1994 but is very sparse for that year. The advantage of our cooperation measure is that it is widely available, as regulation S-K requires firms to discuss actions (such as cooperations and collaborations) and risks (such as competition) that could meaningfully impact firm value and investors' investment decisions. The disadvantage is that the language firms use in their 10-K filings is highly standardized, exhibiting little variation across years.

To externally validate that the cooperation index (9) meaningfully captures the importance of cooperation relative to competition for firms, we verify that the index increases in situations in which firms are more likely to cooperate. For this purpose, we consider the closure of four of the DOJ's seven regional offices in 2013. These regional offices were responsible for monitoring local product markets. The closure of these offices was motivated by cost-cutting, and it led to a sharp drop in antitrust case filings (Ha, Ma, and Zaldokas [2024]). The economic force that we exploit is that a higher probability of antitrust lawsuits and a breakdown of future cooperation reduces the expected profitability of cooperation, making deviation from cooperation more profitable. Thus, when enforcement is stricter, supporting cooperation becomes more difficult not only due to the direct effect that antitrust enforcement is more likely to break up implicit cooperation and collusion, but also due to the indirect effect that the threat of such breakups makes supporting cooperative equilibria more difficult. In turn, these two channels also mean that laxer antitrust enforcement following the closure of the DOJ's regional offices makes supporting cooperation more attractive. In appendix B.1, we discuss the institutional background behind these closures in more detail and show that they have led to a statistically and economically significant increase in our cooperation index among affected firms (see table B.1 and figure B.1).

*4.2.2. Identifying Patent Disruptiveness.* To measure the disruptiveness of patents, we use three different sets of measures. As standard, we consider forward citations (3-year, 5-year, 7-year, 10-year, and all forward citations) as one measure of a patent's importance. As an alternative measure of patent disruptiveness, we use the network-based measures proposed by Funk and Owen-Smith [2016]. Funk and Owen-Smith [2016] identify a patent as being more innovative if follow-up patents start citing this paper more than its predecessors. Intuitively, the idea is that such patents represent a break from past ways of thinking. As another set of alternative measures for patent disruptiveness, we use the measures proposed by Kelly et al. [2021], which are not based on patent citations. To construct their measures, Kelly et al. [2021] measure the textual similarity among all pairs of patents to quantify commonality in the topical content. A patent is then defined as important if it is distinct from prior patents (i.e., it is novel) but similar to future patents (i.e., it is impactful). For more details on how the variables are constructed and where the data can be downloaded, see table 7.

*4.2.3. Identifying Firms Pursuing Trade Secrecy.* Similar to the challenge of identifying firms pursuing cooperation, to the best of our knowledge, there is no standard way of measuring firms' reliance on trade secrecy. Nearly all empirical work on trade secrecy is based on self-reported survey measures. One main notable exception is Glaeser [2018], who constructs a trade secrecy measure based on 10-K filings. Specifically, Glaeser [2018] searches all 10-K filings for references to trade secrets and constructs a dummy variable, taking the value of one if a firm discusses trade secrecy in its 10-K filing. To circumvent the issue that a dummy variable for trade secrecy is sticky and shows little variation within firms over time—which is a problem for our regression specifications featuring firm fixed effects—we construct a trade secrecy index following the intuition of our cooperation index. In particular, we count the number of references to patents and firms' patenting activities ($\#patenting_{it}$) and trade secrecy ($\#trade\ secrecy_{it}$) and construct a trade secrecy index, defined as

$$Trade\ secrecy\ index_{it} = \frac{\#trade\ secrecy_{it}}{\#trade\ secrecy_{it} + \#patenting_{it}}, \tag{10}$$

which is, again, by construction between zero and one, with higher values indicating that firms discuss trade secrecy more relative to patenting in their 10-K filings.[15]

To externally validate that our trade secrecy index (10) is a meaningful measure of firms' reliance on trade secrecy, we follow Glaeser [2018] and test whether this index increases when U.S. states pass legislation that makes it easier for firms to protect trade secrets. The legislations we exploit are the staggered adoptions of the Uniform Trade Secrets Act (UTSA), the Inevitable Disclosure Doctrine (IDD), and staggered changes to the enforcement of noncompete agreements across U.S. states. We explain these legislations in detail in appendix B.2, where we also present and discuss our empirical results validating our trade secrecy index (see table B.2). In particular, we show that our measure of trade secrecy increases when legislation makes trade secrecy more attractive to firms.

[15] When we convert our continuous variable to a dummy, taking the value of one whenever our index is strictly positive, we replicate almost perfectly Glaeser's [2018] trade secrecy dummy variable.

*4.2.4. Difference-in-Differences Specification.* To test H1 and H3, we estimate the following difference-in-differences specification for the years 1996–2005

$$Y_{it} = \alpha + \beta_1 Post_t \times Treatement_s + \gamma X_{it} + \nu_i + \mu_t + \varepsilon_{it}, \tag{11}$$

where the dependent variable $Y_{it}$ is one of the following variables: (1) cooperation index, the natural log of $\#cooperation_{it}$ or $\#competition_{it}$; (2) gross profits, the natural logarithm of markups or operating margins; (3) trade secrecy index or the natural logarithm of the number of patents produced by the firm $i$ in year $t$. To study how the AIPA has affected the nature of patented innovation (H2), we modify (11) as

$$Y_{jit} = \alpha + \beta_1 Post_t \times Treatement_s + \gamma X_{it} + \nu_i + \eta_{tc} + \varepsilon_{jit}, \tag{12}$$

where $Y_{jit}$ is one of the patent-level measures of patent disruptiveness for a patent $j$ produced by firm $i$ in period $t$ discussed above. In specification (11), we include firm and year fixed effects, and in specification (12), we consider firm and patent technology subclass × year fixed effects.[16]

Our theory predicts that making patent applications public information affects the firms' industry equilibrium. Thus, in equation (11), the treatment variable, $Treatement_s$, is defined at the industry level, as we are interested in how firms respond to a shock that affects all firms in the same industry. Specifically, $Treatement$ is the logarithm of the median number of days between patent application and grant dates for the respective four-digit SIC industry over the five years leading to the year 2000. Our prediction is that firms in industries with longer delays in the approval of their submitted patents will be more affected by the passage of the AIPA. $Post_t$ is a dummy variable that takes the value of one in the four years following the passage of the act and zero in the four preceding years. The main coefficient of interest in all specifications is $\beta_1$.

To investigate the differential impact of the AIPA on firms with marginally, moderately, and very attractive disruptive investment opportunities (H3), we split the sample into three terciles depending on the market value of patents produced in the same four-digit SIC code industry over the last five years. The rationale is that industries that produce patents in the lowest tercile are likely to have less attractive investment opportunities (corresponding to $\frac{x_m}{1-\delta} \leq X'$), whereas industries in the highest tercile should have the most attractive investment opportunities ($\frac{x_m}{1-\delta} \geq X'$). Firms in the middle tercile should correspond to the firms with moderately attractive

[16] We do not include $Treatment$ as a separate variable, as it is absorbed by the firm fixed effects. We include year fixed effects instead of a dummy $Post$ for the post-AIPA years, as that improves precision and provides a better fit of the model. Specifically, this specification does not assume that all firms in the treatment (or untreated) group have the same average $Y$; and it allows the intercept to vary for each firm. Furthermore, it does not assume that a common change in $Y$ around the event is a simple change in level; it allows a common change in $Y$ to vary by year.

investment opportunities in our model ($\frac{x_m}{1-\delta} \in (X', X'')$). To proxy for the market value of new patents, we use the variable $Tsm$, which is defined by equation (10) in Kogan et al. [2017] and made available by the authors. This variable represents the sum of the dollar value of patents produced by a firm in a given year, scaled by firm size. The dollar value of patents is calculated based on the firm's stock market reaction to the patents' announcements. For every industry, we take the average over the five years before the introduction of the AIPA. As market reactions to patent announcements should capture the expected profit from a new technology, this measure appears to be a good proxy for the expected profitability of innovation.

$X_{it}$ is a vector of firm-level control variables that includes firm size, defined as $\ln(sale)$ in 2004 dollar prices and sales, general, and administrative costs scaled by sales. The regressions control for firm and year fixed effects, as well as the median size of firms in the industry. Following Bertrand, Duflo, and Mullainathan [2004], we choose the most conservative level of clustering of standard errors, which is at the four-digit industry SIC level in our setting. Table 1 offers an overview of the main variables of interest.[17]

The key identifying assumption for the results is parallel trends. To support the premise behind our difference-in-differences model that the results are not explained by pre-existing differential trends, we estimate and plot the coefficients from the following firm- and patent-level models

$$Y_{it} = \alpha + \sum_t \beta_t (Treatement_s \times \mathbf{1}_t) + \gamma X_{it} + \nu_i + \mu_t + \varepsilon_{it}, \qquad (13)$$

$$Y_{jit} = \alpha + \sum_t \beta_t (Treatement_s \times \mathbf{1}_t) + \gamma X_{it} + \nu_i + \eta_{tc} + \varepsilon_{jit}, \qquad (14)$$

where $\mathbf{1}_t$ is an indicator that equals 1 if the event time is $t$. The omitted category is the first year in the sample window. That is, all estimates of $\beta_t$ are relative to this period.

### 4.3 HYPOTHESIS 1: IMPACT OF AIPA ON COOPERATION, MARKUPS, AND OPERATING MARGINS

We start with investigating H1, which characterizes the effect of the AIPA on cooperation and profitability. In table 2, we show that the AIPA has led to a significant increase in the cooperation index among firms that are more affected by the legislation. In particular, an increase in delay between

[17] In specifications (11) and (12), we do not include a lagged dependent variable because we have firm fixed effects. The problem with including a lagged dependent variable is easiest to see with OLS. Suppose that one estimates $y_{i,t} = a + b_1 y_{i,t-1} + b_2 x_{i,t} + v_{i,t}$, where $v_{it} = f_i + u_{i,t}$ but $y_{i,t-1} = a + b_1 y_{i,t-2} + b_2 x_{i,t-1} + f_i + u_{i,t-1}$. Thus, $y_{i,t-1}$, and the composite error, $v_{i,t}$, are positively correlated because both contain $f_i$, and we would get an omitted variable bias. Similarly, if we include fixed effects (and we do a within transformation), the lagged mean of $y$, which will now be on the right-hand side of the model, will always be negatively correlated with the demeaned error $u$.

**TABLE 2**
*Effect of AIPA on Cooperation*

| | Cooperation Index All Firms (1) | Ln(#cooperation) All Firms (2) | Ln(#competition) All Firms (3) |
|---|---|---|---|
| Treatment × post | 0.042*** | 0.158*** | −0.064 |
| | (0.015) | (0.056) | (0.045) |
| SG&A/sales | 0.001 | 0.017*** | 0.016*** |
| | (0.001) | (0.005) | (0.004) |
| Ln(sales) | −0.007** | 0.064*** | 0.098*** |
| | (0.003) | (0.009) | (0.011) |
| Industry ln(sales) | −0.002 | −0.019 | −0.011 |
| | (0.003) | (0.013) | (0.009) |
| Firm FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 40,608 | 40,651 | 40,651 |
| Adjusted $R^2$ | 0.575 | 0.627 | 0.674 |

This table shows changes in cooperation in the years around the enactment of the AIPA based on the difference-in-differences specification (11). *Cooperation index* is an index based on how many times a firm's 10-K filing with the SEC mentions phrases related to cooperation relative to cooperation or competition. *Ln(#cooperation)* is the log of the number of times a firm's 10-K filing with the SEC mentions phrases related to cooperation. *Ln(#competition)* is the log of the number of times a firm's 10-K filing with the SEC mentions phrases related to competition. *Treatment* is the log of the median difference in days between the filing date and the grant date across all patents granted in the same four-digit SIC industry between 1996 and 2000. *Post* is a dummy variable equal to 1 for the years following the enactment of the AIPA. The control variables are firm and median industry *Ln(sales)*, which is the natural log of sales, adjusted to inflation (base year 2004), and *SG&A/sales*, which is sales, general, and administrative expenses over sales. These variables are winsorized at 1%. Robust standard errors clustered at the four-digit SIC level are in parentheses. ** and *** indicate that the coefficient is statistically significant at the 5% and 1% levels, respectively.

patent application and grant date in the respective industry leads to a significant increase both in the number of times firms mention cooperation in their 10-Ks and in the cooperation index. Notably, the increase in the cooperation index comes entirely from firms that mention cooperation more frequently (model (2)). In model (3) of table 2, we show that the number of instances firms mention competition is unchanged. In terms of economic significance, a 1% increase in delay leads to a roughly 0.15% increase in phrases related to cooperation. This is quite significant, given that much of the language in firms' 10-Ks is highly standardized and exhibits little variation within firms. In figure 2, we plot the coefficients from our treatment dynamics regressions and show that patent delay has no differential impact between treatment and control firms before the enactment of the AIPA, with the difference showing up after the year 2000. The gray area in this picture corresponds to the period between November 1999 and November 2000, when the AIPA had already been voted on but was still not in effect. Perhaps unsurprisingly, there is already an increase in the cooperation index in this anticipatory period.

Table 3 further presents how the AIPA has affected gross profits, operating margins, and markups. In line with H1, we find that there is a

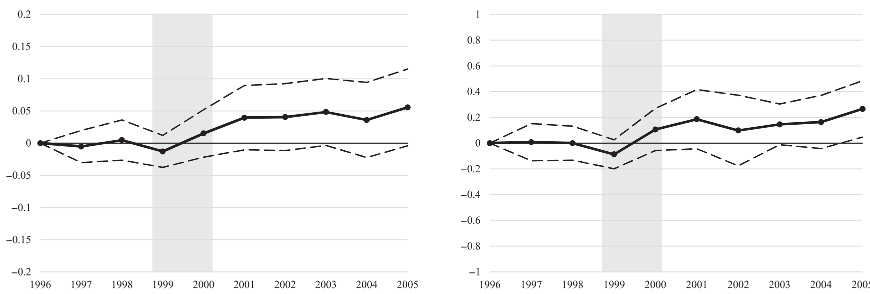



FIG. 2.—Effect of AIPA on cooperation. This figure shows changes in cooperation in the years around the enactment of the AIPA in 2000. The estimates $\beta_t$ and their 90% confidence intervals are from the difference-in-differences specification (13). *Cooperation index* is an index based on how many times a firm's 10-K filing with the SEC mentions phrases related to cooperation relative to cooperation or competition. *Ln(#cooperation)* is the log of the number of times a firm's 10-K filing with the SEC mentions phrases related to cooperation. *Treatment* is the log of the median difference in days between the filing date and the grant date across all patents granted in the same four-digit SIC industry between 1996 and 2000. *Post* is a dummy variable equal to 1 for the years following the enactment of the AIPA. The control variables are firm and median industry *Ln(sales)*, which is the natural log of sales, adjusted to inflation (base year 2004), and *SG&A/sales*, which is sales, general, and administrative expenses over sales. These variables are winsorized at 1%. Robust standard errors are clustered at the four-digit SIC level.

significant increase in all three variables. In terms of economic significance, a 1% increase in patent delay leads to a 0.4% increase in markups and a 0.8% increase in operating margins.[18] Notably, these findings are in stark contrast to the standard argument that more disclosure harms innovative firms (Bhattacharya and Ritter [1983]). We believe these insights are important, as they highlight that within the same settings in which prior work has documented spillover effects to rivals, disclosing firms are actually not harmed. Thus, while spillover effects are certainly important in practice (see also our results on spillovers in the online appendix), we need to expand existing theory to explain why stricter disclosure mandates have led to higher gross profits, markups, and operating margins. Our paper offers a step in this direction.[19]

[18] Note that taking the log of operating margins drops all firms with negative earnings (but this is not a problem for markups, which are all positive, and profitability, where we do not take the log). We find qualitatively similar results when we take the inverse hyperbolic sine transformation instead of the logs, which also helps deal with extreme values and has an interpretation similar to that of logs, that is, the coefficient can be interpreted as the percentage increase in operating margins when delay increases by 1%. As is perhaps intuitive, the effects are driven primarily by firms with positive earnings that are arguably more likely to be incumbents that can benefit from cooperation.

[19] In untabulated regressions, we further verify that the effects on profitability, markups, and operating margins come primarily from firms more similar to other firms. To measure similarity to other firms, we use Hoberg and Phillips [2016] total similarity score.

TABLE 3
*Effect of AIPA on Profitability, Markups, and Operating Margins*

| | Profitability | Ln(markups) | Ln(operating margins) |
|---|---|---|---|
| | All Firms | All Firms | All Firms |
| | (1) | (2) | (3) |
| Treatment × post | 0.251*** | 0.356** | 0.776*** |
| | (0.068) | (0.175) | (0.294) |
| SG&A/sales | −0.210*** | −0.051*** | −4.037*** |
| | (0.026) | (0.004) | (0.443) |
| Ln(sales) | 0.070*** | 0.012 | 0.039** |
| | (0.024) | (0.009) | (0.019) |
| Industry ln(sales) | 0.011 | −0.003 | −0.019 |
| | (0.018) | (0.019) | (0.033) |
| Firm FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 66,414 | 66,010 | 43,151 |
| Adjusted $R^2$ | 0.479 | 0.723 | 0.696 |

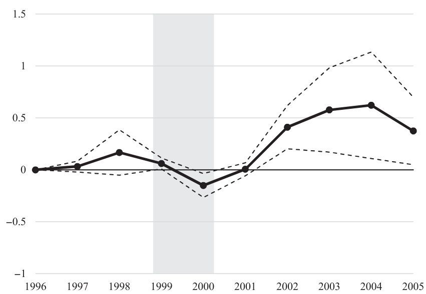
This table shows changes in markups in the years around the enactment of the AIPA based on the difference-in-differences specification (11). *Profitability* is defined as gross profit scaled by sales. *Ln(markup)* is the natural log of *markup*, where *markup* is defined as the ratio of sales to cost of goods sold. *Ln(operating margins)* is the natural logarithm of operating income scaled by sales. *Treatment* is the log of the median difference in days between the filing date and the grant date across all patents granted in the same four-digit SIC industry between 1996 and 2000. *Post* is a dummy variable equal to 1 for the years following the enactment of the AIPA. The control variables are firm and median industry *Ln(sales)*, which is the natural log of sales, adjusted to inflation (base year 2004), and *SG&A/sales*, which is sales, general, and administrative expenses over sales. These variables are winsorized at 1%. Robust standard errors clustered at the four-digit SIC level are in parentheses. ** and *** indicate that the coefficient is statistically significant at the 5% and 1% levels, respectively.

In figure 3 (and figure C.1 in the online appendix), we further show that the increase in gross profits, markups, and operating margins started after 2001. Notably, this is consistent with the idea that implicit cooperation initiated at the end of 2000 or in 2001 will need at least "one period" to show up in financial results.

### 4.4 HYPOTHESIS 2: IMPACT OF AIPA ON NATURE OF PATENTS

Next, we turn to H2 and investigate how the AIPA has changed the nature of *patented* innovation. We start by looking at how the AIPA affects the number of forward citations in industries with longer patent delays. In table 4, we document a sharp drop in patent citations across the board for all measures of forward citations. In model (1), a 1% increase in patent delay leads to a roughly 0.8% drop in patent citations. This decrease in patent citations is in line with H2, which predicts that firms will patent more of their nondisruptive innovation as a means of cooperating on nondisruptive technologies. In figure 4 (and figure C.2 in the online appendix), we show that the drop in patent citations affects patents produced after the AIPA comes into force.

In table 5, we estimate model (12) for a number of other proxies of patent disruptiveness. The same picture emerges when we look at the breakthrough innovation measures by Funk and Owen-Smith [2016] and Kelly



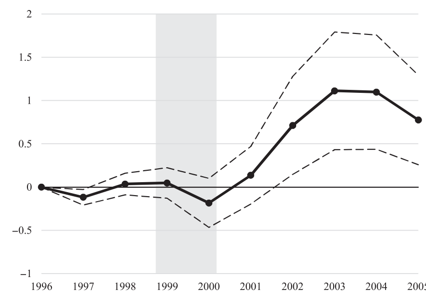




FIG. 3.—Effect of AIPA on markups and operating margins. This figure shows changes in gross profits and markups in the years around the enactment of the AIPA. The corresponding figure for gross profits is contained in the online appendix (figure C.1 in the online appendix). The estimates $\beta_t$ and their 90% confidence intervals are from the difference-in-differences specification (13). The dependent variable in panel A is $Ln(markup)$, and it is defined as the log of the ratio of sales to cost of goods sold. The dependent variable in panel B is $Ln(operating\ margins)$, where $operating\ margins$ is defined as operating income before depreciation minus depreciation scaled by sales. $Treatment$ is the log of the median difference in days between the filing date and the grant date across all patents granted in the same four-digit SIC industry between 1996 and 2000. *Post* is a dummy variable equal to 1 for the years following the enactment of the AIPA. The control variables are firm and median industry $Ln(sales)$, which is the natural log of sales, adjusted to inflation (base year 2004), and $SG\&A/sales$, which is sales, general, and administrative expenses over sales. These variables are winsorized at 1%. Robust standard errors are clustered at the four-digit SIC level.

et al. [2021] that analyze whether follow-up patents are more likely to start citing a patent rather than its predecessors, as well as whether a patent is distinct from prior patents but similar to future patents. Our treatment dynamics regressions that we plot in figure 5 (and figure C.3 in the online appendix) yield further support for these insights and H2.

The key insight from table 5 is that the AIPA has changed the nature of *patented* innovation, leading to less cited and less disruptive patents. To proxy for the counterfactual of what patented innovation would have looked like without the AIPA, our identification strategy relies on comparing firms more affected by the AIPA with firms less affected by the AIPA. It is interesting to contrast this approach to Hegde, Herkenhoff, and Zhu's [2023] identification strategy, which compares an invention patented in the United States with the *same* invention patented in Europe, where an AIPA-like regime was already in place. The identification assumption is that U.S. inventors primarily consider U.S. patent filings and do not pay attention to patent filings (for the same inventions) in Europe. The authors find that the AIPA has led to an increase in patent citations of a patent filed in the United States relative to its twin counterpart in Europe. The interpretation of this result is very different from ours. Hegde, Herkenhoff, and Zhu's [2023] identification strategy does not consider how the AIPA has changed the nature of patented innovation, as it takes a patented invention as given.

TABLE 4
*Effect of AIPA on Patent Citations*

| | Ln(citations) | | | | |
|---|---|---|---|---|---|
| | All | 3 Years | 5 Years | 7 Years | 10 Years |
| | (1) | (2) | (3) | (4) | (5) |
| Treatment × post | −0.780*** | −0.513*** | −0.594*** | −0.667*** | −0.746*** |
| | (0.138) | (0.108) | (0.148) | (0.157) | (0.147) |
| SG&A/sales | 0.000 | 0.002 | 0.005 | 0.004 | 0.003 |
| | (0.007) | (0.004) | (0.006) | (0.007) | (0.007) |
| Ln(sales) | −0.025** | (0.022) | −0.024** | −0.023** | −0.027*** |
| | (0.010) | (0.013) | (0.012) | (0.010) | (0.010) |
| Industry ln(sales) | −0.014 | −0.014* | −0.015 | −0.015 | −0.013 |
| | (0.010) | (0.008) | (0.010) | (0.009) | (0.010) |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Technology subclass-year FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 416,286 | 416,286 | 416,286 | 416,286 | 416,286 |
| Adjusted $R^2$ | 0.280 | 0.148 | 0.175 | 0.204 | 0.263 |

This table shows changes in patent citations in the years around the enactment of the AIPA, based on the difference-in-differences specification (12). The dependent variable is the natural logarithm of one plus the number of forward citations of a patent for different windows. In table C.1 in the online appendix, we present the corresponding Poisson regressions, where the dependent variable is the number of citations instead of the log of one plus the number of citations. $Treatment$ is the log of the median difference in days between the filing date and the grant date across all patents granted in the same four-digit SIC industry between 1996 and 2000. *Post* is a dummy variable equal to 1 for the years following the enactment of the AIPA. The control variables are firm and median industry $Ln(sales)$, which is the natural log of sales, adjusted to inflation (base year 2004), and $SG\&A/sales$, which is sales, general, and administrative expenses over sales. These variables are winsorized at 1%. Robust standard errors clustered at the four-digit SIC level are in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

Instead, the interpretation is that conditional on patenting a specific invention (and, thus, holding the nature of innovation fixed), that invention experiences an increase in patent citations in jurisdictions that start disclosing patent applications sooner. Therefore, our results and those of Hegde, Herkenhoff, and Zhu [2023] do not contradict but complement each other, as they highlight very different effects of the AIPA on innovation.

### 4.5 HYPOTHESIS 3: NONMONOTONE IMPACT OF AIPA ON PATENTING AND TRADE SECRECY

A limitation of focusing on patented innovation is that it suffers from a selection problem, as it can only deliver insights about how the nature of *patented* innovation has changed. And for all firms that choose to patent, our model predictions are the same—there will be an increase in nondisruptive patents. However, our model also predicts that the AIPA will affect the level of patenting and firms' use of trade secrecy. What is more, the impact can differ in direction across different types of firms.

To test H3, we analyze the impact of the AIPA on the number of patents produced by firms and firms' reliance on trade secrecy. Similar to prior work (Saidi and Zaldokas [2021]), we find that the average effect of the

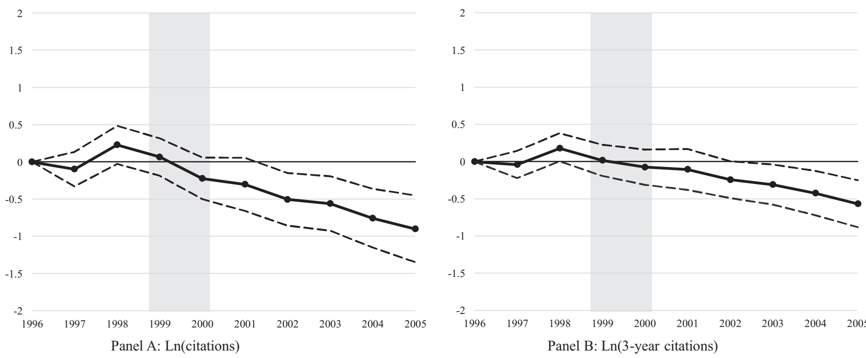



FIG. 4.—Effect of AIPA on patent citations. This figure shows changes in innovation in the years around the enactment of the AIPA. The estimates $\beta_t$ and their 90% confidence intervals are from the difference-in-differences specification (14). The dependent variable is the log of one plus the number of forward citations of a patent. Panel A plots all forward citations, and panel B plots the three-year forward citations. Figure C.2 in the online appendix contains the corresponding figures for the five-, seven-, and ten-year forward citations. $Treatment$ is the log of the median difference in days between the filing date and the grant date across all patents granted in the same four-digit SIC industry between 1996 and 2000. $Post$ is a dummy variable equal to 1 for the years following the enactment of the AIPA. The control variables are firm and median industry $Ln(sales)$, which is the natural log of sales, adjusted to inflation (base year 2004), and $SG\&A/sales$, which is sales, general, and administrative expenses over sales. These variables are winsorized at 1%. Robust standard errors are clustered at the four-digit SIC level.

AIPA on the number of patents produced by firms is insignificant.[20] However, in line with H3, table 6 shows that this average conceals a lot of variation across different types of firms. In particular, we document that the enactment of the AIPA has led to an increase in patenting in the lowest and highest tercile of investment attractiveness. By contrast, there is a decrease in patenting in the middle tercile.

The results for trade secrecy are nearly the mirror image of those of patenting. Similar to patenting, there is no effect on trade secrecy when we look at all firms in the sample. However, table 6 shows that there is a significant increase in our trade secrecy index for firms in the middle tercile and a significant decrease for firms in the highest tercile (there is no effect in the lowest tercile). Thus, as predicted by our model, pooling the firms from all terciles can distort the conclusions about how the AIPA has affected firms' incentives to pursue patenting and trade secrecy because the effect across different types of firms can be opposite.[21]

[20] Note, however, that the average effect is positive and significant in our Poisson regressions specifications (see Table C.2 in the online appendix).

[21] We also run the regressions with $Ln(\#trade\ secrecy_{it})$ and $Ln(\#patenting_{it})$ as dependent variables and find that the increase in the trade secrecy index in the middle tercile primarily comes from firms mentioning fewer phrases related to patenting in their 10-K filings. Simi-

**TABLE 5**
*Effect of AIPA on Patent Disruptiveness*

| | Disruptive Innovation | | | |
|---|---|---|---|---|
| | Destabalizing/Consolidating Index | | Forward/Backward Similarity | |
| | 5 Year Post Grant (1) | 10 Years Post Grant (2) | Top 5% (3) | Top 10% (4) |
| Treatment × post | −1.086*** | −2.381*** | −0.281*** | −0.328*** |
| | (0.305) | (0.700) | (0.048) | (0.083) |
| SG&A/sales | −0.030* | (0.021) | −0.007* | (0.004) |
| | (0.015) | (0.042) | (0.004) | (0.004) |
| Ln(sales) | −0.059** | −0.161** | −0.016** | (0.011) |
| | (0.030) | (0.069) | (0.008) | (0.010) |
| Industry ln(sales) | 0.001 | −0.029 | 0.001 | 0.002 |
| | (0.016) | (0.036) | (0.004) | (0.005) |
| Firm FE | Yes | Yes | Yes | Yes |
| Technology subclass-year FE | Yes | Yes | Yes | Yes |
| Observations | 414,361 | 416,072 | 416,286 | 416,286 |
| Adjusted $R^2$ | 0.026 | 0.034 | 0.380 | 0.388 |

This table shows changes in disruptive patents in the years around the enactment of the AIPA based on the difference-in-differences specification (12). In models (1) and (2), the dependent variable is *Destabilizing/consolidating index n year post grant*, which is a patent-level consolidation and disruption index, measuring whether follow-up patents in the *n* years post a patent's grant date cite a focal patent more than its predecessors. In models (3) and (4), the dependent variable is *Forward/backward similarity top n%*, which is an indicator variable showing whether a patent can be classified as a breakthrough innovation based on its textual commonality with preceding and follow-up innovation. *Treatment* is the log of the median difference in days between the filing date and the grant date across all patents granted in the same four-digit SIC industry between 1996 and 2000. *Post* is a dummy variable equal to 1 for the years following the enactment of the AIPA. The control variables are firm and median industry *Ln(sales)*, which is the natural log of sales, adjusted to inflation (base year 2004), and *SG&A/sales*, which is sales, general, and administrative expenses over sales. These variables are winsorized at 1%. Robust standard errors clustered at the four-digit SIC level are in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

Overall, these results highlight the importance of studying the impact of the AIPA not only at the patent level, but also in conjunction with the impact on trade secrecy. The results in figures C.4 and C.5 in the online appendix support the premise that the results are not explained by pre-existing trends. What is notable is that similar to our cooperation index (and unlike markups), patenting and trade secrecy were—as expected—quicker to adapt. Once again, this could be explained by the fact that AIPA was already passed in 1999, allowing forward-looking firms to adjust their patenting activities.

## 4.6 ROBUSTNESS AND DISCUSSIONS

We perform a battery of robustness tests and find similar results when choosing different event windows, sample splits, defining industries at the

larly, the increase in the highest tercile primarily comes from firms mentioning more phrases related to patenting in their 10-K filings.

**TABLE 6**

*Effect of AIPA on Patenting and Trade Secrecy*

| | Ln(patents) | | | | Trade Secrecy Index | | | |
|---|---|---|---|---|---|---|---|---|
| | All | Attractiveness | | | All | Attractiveness | | |
| | Firms | Low | Moderate | High | Firms | Low | Moderate | High |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Treatment × post | 0.063 | 0.048** | −0.223*** | 0.411** | 0.010 | 0.023 | 0.095*** | −0.163*** |
| | (0.090) | (0.021) | (0.078) | (0.180) | (0.032) | (0.031) | (0.027) | (0.042) |
| SG&A/sales | 0.003** | 0.001 | 0.003 | 0.005 | −0.002** | −0.002 | −0.002 | −0.003*** |
| | (0.002) | (0.001) | (0.002) | (0.003) | (0.001) | (0.003) | (0.002) | (0.001) |
| Ln(sales) | 0.027*** | 0.015*** | 0.030*** | 0.033** | −0.004 | −0.005 | −0.002 | −0.006* |
| | (0.007) | (0.004) | (0.008) | (0.013) | (0.003) | (0.006) | (0.006) | (0.003) |
| Industry ln(sales) | 0.003 | 0.001 | −0.005 | 0.001 | 0.002 | 0.000 | 0.006 | 0.005 |
| | (0.009) | (0.005) | (0.012) | (0.020) | (0.005) | (0.006) | (0.005) | (0.009) |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 66,414 | 22,195 | 19,486 | 24,540 | 40,651 | 14,194 | 12,441 | 13,892 |
| Adjusted $R^2$ | 0.914 | 0.891 | 0.913 | 0.917 | 0.413 | 0.327 | 0.285 | 0.590 |

This table shows changes in patenting and trade secrecy in the years around the enactment of the AIPA based on the difference-in-differences specification (11). The dependent variable in models (1)–(4) is the natural logarithm of one plus the number of patents produced by a firm in a year. Table C.2 in the online appendix contains the corresponding Poisson regressions where the dependent variable is the number of patents rather than the log of one plus the number of patents. The dependent variable in models (5)–(8) is *Trade secrecy index*, which is defined in (10). To proxy for the attractiveness of innovation, we use the market value of patents (provided by Kogan et al., 2017), produced between 1996 and 2000 in the same four-digit SIC industry. Models (2), (3), (4), (6), (7), and (8) split the sample depending on whether a firm is in the lowest, middle, or highest tercile according to this measure in the year 2000. *Treatment* is the log of the median difference in days between the filing date and the grant date across all patents granted in the same four-digit SIC industry between 1996 and 2000. *Post* is a dummy variable equal to 1 for the years following the enactment of the AIPA. The control variables are firm and median industry *Ln(sales)*, which is the natural log of sales, adjusted to inflation (base year 2004), and *SG&A/sales*, which is sales, general, and administrative expenses over sales. These variables are winsorized at 1%. Robust standard errors clustered at the four-digit SIC level are in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

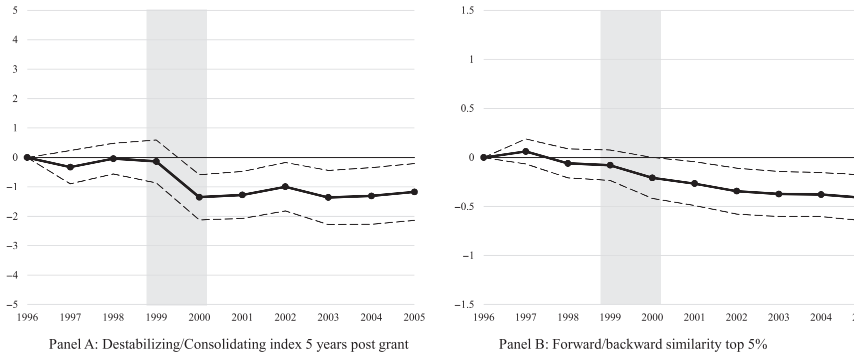



FIG. 5.—Effect of AIPA on patent disruptiveness. This figure shows changes in various measures of patenting innovativeness in the years around the enactment of the AIPA. The estimates $\beta_t$ and their 90% confidence intervals are from the difference-in-differences specification (14). *Destabilizing/consolidating index* 5 *year post grant* is a patent-level consolidation and disruption index, measuring whether follow-up patents in the $n$ years post a patent's grant date cite a focal patent more than its predecessors. *Forward/backward similarity top* 5% is an indicator variable showing whether a patent can be classified as a breakthrough innovation based on its textual commonality with preceding and follow-up innovation. Figure C.3 in the online appendix contains the corresponding figures for *Destabilizing/consolidating index* 10 *year post grant* and *Forward/backward similarity top* 10%. *Treatment* is the log of the median difference in days between the filing date and the grant date across all patents granted in the same four-digit SIC industry between 1996 and 2000. *Post* is a dummy variable equal to 1 for the years following the enactment of the AIPA. The control variables are firm and median industry $Ln(sales)$, which is the natural log of sales, adjusted to inflation (base year 2004), and $SG\&A/sales$, which is sales, general, and administrative expenses over sales. These variables are winsorized at 1%. Robust standard errors are clustered at the four-digit SIC level.

three-digit (rather than four-digit) SIC code level, and restricting attention to industries that produce more patents. A robustness question that is perhaps worth discussing in more detail relates to our choice to follow the standard practices in the literature on innovation. This literature has recently faced the criticism that innovation proxies, based on the natural logarithm of one plus a variable introduces a bias in regression results, with the recommendation being to use Poisson regressions without taking logs. Furthermore, the literature has been criticized for insufficiently accounting for spillover effects. In the online appendix, we show that our results are robust when accounting for such considerations (tables C.1– C.2).

As a closing remark, we should note that our evidence is based on public firms, essentially all of which are large relative to the vast majority of private firms in the economy. Indeed, our theory primarily applies to firms above a critical size level, at which cooperation with rivals becomes a relevant consideration. This implies that the effects we document for public firms may not be present in the case of small or private firms. For such firms, the costs of patent disclosure (both direct and indirect, such as being preyed on by larger firms) are likely to be larger (Acikalin et al. [2023]). Indeed, Breuer,

TABLE 7
*Variable Definitions and Sources of Data*

| Variable | Definition | Source |
|---|---|---|
| Text-based variables (Sep-Dec 2023): | | |
| Cooperation index | #cooperation/(#cooperation + #competition) #cooperation is the number of phases related to cooperation in a firm's 10-K; #competition is the number of phases related to competition in a firm's 10-K | 10-K filings from SEC EDGAR https://www.sec.gov/edgar/search-and-access |
| Trade secrecy index | #trade secrecy/(#trade secrecy + #patenting) #trade secrecy is the number of phases related to trade secrecy in a firm's 10-K; #patenting is the number of phases related to patenting in a firm's 10-K | 10-K filings from SEC EDGAR https://www.sec.gov/edgar/search-and-access |
| Similarity | Text-based measure of how similar a firm's products and services are to those of other firms, corresponds to variable tnic3simm from Hoberg and Phillips (2016) | Hoberg and Phillips data library https://hobergphillips.tuck.dartmouth.edu/ (based on firm's 10-K filings in SEC EDGAR) |
| Variables used in validation of cooperation and trade secrecy indexes (Sep 2023 - Jan 2024): | | |
| Change in Distance | Log of the difference in miles between the firm's headquarter and the DOJ's local office responsible for the oversight of firms in the same ZIP code before and after 2013 | ZIP codes of firms and DOJ offices come from Ha, Ma, and Zaldokas' (2024) data appendix: https://data.mendeley.com/datasets/t9cmfb8vcj/1 |
| IDD | Indicator taking the value of one after a state-level adoption of the Inevitable Disclosure Doctrine | Table 1 in Klasa, Oritz Molina, Serfling (2018) |
| USTA | Indicator taking the value of one after a state-level adoption of the Uniform Trade Secrets Act | Appendix A in Glaeser (2018) |
| Weak Enforcement | Garmaise' (2011) index of the enforcement of noncompete agreements times negative one. The changes to this index come from Kini et al. (2018) | Table A.1 in Garmaise (2011), Appendix B in Kini, Williams, Yin (2021) |

(*Continued*)

TABLE 7—(*Continued*)

| Variable | Definition | Source |
|---|---|---|
| Patents and citations data (Sep 2023): | | |
| Patents, citations, delay | Number of patents produced by a firm; the number of patent citations a firm receives in a year; delay between patent application and grant date in days. | Kogan, Papanikolaou, Seru, Stoffmann (2017) https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data |
| Forward/backward similarity top n% | Indicator variable of whether the ratio of textual similarity between a patent and follow-up/preceding patents is in the top n%. Corresponds to break_p95_rrfsim05 and break_p90_rrfsim010 in Kelly et al. (2021) | Kelly, Papanikolaou, Seru, Taddy (2021) https://github.com/KPSS2017/Measuring-Technological-Innovation-Over-the-Long-Run-Extended-Data |
| Destabilizing/consolidating index n year post grant | An index reflecting whether follow-up patents are more likely to start citing the focal patent instead of its predecessors; defined by equation (4) in Funk and Owen-Smith (2016). | Funk and Owen-Smith (2016), http://russellfunk.org/cdindex/data.html |
| Tsm | Sum of the dollar value of patents produced by a firm in a given year, scaled by firm size. The dollar value of patents is calculated based on the firm's stock market reaction to the patents' announcement. Defined by equation (10) in Kogan et al. (2017) | Kogan, Papanikolaou, Seru, Stoffmann (2017) https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data |
| Accounting and inflation data (Aug 2022): | | |
| Markups | sale/(cost of goods sold) | Compustat |
| Operating margins | (operating income before depreciation minus depreciation) / sales | Compustat |
| Sales, SG&A, Total assets | Sales, SG&A, Total assets from firms' annual reports | Compustat |
| CPI index | CPI index, used for the calculation of log(sale), deflated at 2004 prices | https://fred.stlouisfed.org/series/CPIAUCSL#0 |

Leuz, and Vanhaverbeke [2022] find that disclosure harms profitability in small firms despite the effect being positive for large ones. Such findings underscore the importance of firm size when studying the multifaceted effects of disclosure and suggest avenues for future research.

At a basic level, we have shown that the AIPA has impacted various outcomes that were likely not anticipated when the legislation was passed and have not been considered by prior work studying this reform. We have further shown that interpreting the results from prior empirical work on the AIPA may be misleading. Indeed, we have shown that the directional effect of the AIPA on patenting and trade secrecy differs depending on the attractiveness of innovation.[22] Furthermore, as in the case of patent citations, the impact of the reform and its interpretation crucially depends on the identification strategy and, thus, on the relevant counterfactual. Taken together, the evidence supports H1–H3 and illustrates the value of interpreting the evidence through the lens of theory. Yet we see these results as the starting rather than the end point of the discussion. In particular, on the empirical side, it would be interesting to test the model's predictions and assumptions more comprehensively. Furthermore, one may enrich the analysis by relying on better empirical measures, different identification strategies, evidence from different countries, incorporating large private firms, or resorting to structural estimation. On the theory side, it would also be interesting to expand our model to analyze welfare implications or consider alternative models that offer complementary explanations for our empirical findings.

## 5. *Conclusion*

In this paper, we show that making information about patent applications more widely available helps firms cooperate on nondisruptive technologies by establishing a commonly observed history of signals around which firms can align their actions. The cooperation we have in mind can range from avoiding head-on competition in such nondisruptive technologies to sharing knowledge and data that could broaden the adoption of technologies that are no longer disruptive but would gain from broader adoption when firms introduce further complementary improvements to these technologies.

Cooperating on nondisruptive technologies, however, leads to less investment in disruptive technologies. Furthermore, when firms invest in disruptive technologies, they are more likely to abandon them. In turn, the resulting lack of commitment to disruptive innovation increases the agency costs related to motivating agents to work hard on such innovation. All these effects undermine the pursuit of disruptive innovation.

Despite the negative impact on disruptive innovation, the opportunities to cooperate on nondisruptive technologies make firms at least weakly better off. However, the choice of whether to actually make use of these opportunities (through patenting) is still not trivial. In particular, we show

[22] Further motivating the importance of accounting for nonmonotone effects, Baldenius and Yang [2023] show theoretically that there is a nonmonotone relationship between disclosure and innovation also in the context of intra-firm communication between a firm's CEO and its board.

that firms with moderately attractive investment prospects suffer most from a lack of commitment to disruptive innovation. Thus, to improve their commitment, these firms might rely more on trade secrecy and less on patenting.

We support our model's predictions by providing new evidence related to the passage of the AIPA. This legislation made information about patent applications more widely available by forcing firms to disclose their patent applications after 18 months, regardless of whether the patents were eventually granted. The latter is decided, on average, after more than two years, with about half of patent applications being rejected. In line with our predictions about the benefits of patenting and cooperation, the evidence is that the AIPA has led to more cooperation across firms. Furthermore, it has led to higher gross profits, markups, and operating margins. The AIPA has also affected the nature of *patented* innovation, with the proportion of nondisruptive patenting experiencing a pronounced increase. Finally, the evidence supports our model predictions that firms with moderately attractive innovation opportunities have reacted by relying more on trade secrecy and less on patenting, while for firms with marginally and very attractive innovation opportunities, the effect is the opposite. Overall, our paper highlights the multi-faceted impact of patent disclosure on innovation and the choice between patenting and trade secrecy.

As a concluding remark, it is worth mentioning that our model could be recast to address how the choice between going public, which is associated with significant information disclosure, and staying private affects innovation. Applied to that context, our model could shed light on why empirical findings that going public leads to more exploitation of existing ideas rather than the development of new ones (Bernstein [2015], Gao, Hsu, and Li [2018]) go hand in hand with findings that large, primarily public, firms have amassed significant market power over the last decades (De Loecker, Eeckhout, and Unger [2020]). In particular, our analysis suggests that the more stringent disclosure requirements for public firms may facilitate more coordination among these firms, thus affecting their innovation. Such alternative applications of our model might be worth considering in future research.

## APPENDIX A: OMITTED PROOFS

**Example A.1.** ***Example of How Cooperation Affects Cash Flows and a PPE can be Supported***. *Suppose that the technology outcome corresponds to whether a firm has succeeded (S) or failed (F) in successfully modifying its existing products to differentiate itself from its rival. Let the probabilities of successfully differentiating be* $\pi\ (S|C, C) = \pi\ (S|D, C) = \pi$ *and* $\pi\ (S|D, D) = \pi\ (S|C, D) = 0$. *Conditional on successfully differentiating, each firm has a probability* $\rho$ *of being commercially successful, which allows it to charge a price of* $p$ *above the firms' unit cost of pro-*

*duction k, resulting in a markup of* $\left(p-k\right)/k>0$.[23] *If both firms are commercially successful, each firm can sell a quantity of* $\frac{d}{2}$, *resulting in net cash flows of* $\frac{d}{2}\left(p-k\right)$. *However, if only firm i is commercially successful, firm* i*'s product will dominate in that period, and it can sell a quantity of d, resulting in net cash flows of* $d\left(p-k\right)$. *Note that this creates incentives not to cooperate. Finally, if a firm has not successfully differentiated its technology or is not commercially successful, it cannot charge a price above k, resulting in zero profits. Thus, if both firms cooperate, their expected payoffs are* $x_{CC}=\left(\pi^{2}\left(\rho^{2}\frac{1}{2}+\rho\left(1-\rho\right)\right)+\pi\left(1-\pi\right)\rho\right)d\left(p-k\right)$; *if one firm deviates from cooperation, its expected payoff is* $x_{DC}=\pi\rho d\left(p-k\right)$, *while that of the other firm is* $x_{CD}=0$; *if neither firm cooperates, the expected payoffs are* $x_{DD}=0$.

*Based on this setting, we now illustrate when cooperation of the sort described in subsection 4.1 can be supported as a PPE. Cooperation leads to a higher expected payoff than deviating if:*[24]

$$\begin{aligned} v^{pat} &= (1-\delta)\left(\pi^{2}\left(\rho^{2}\frac{1}{2}+\rho(1-\rho)\right)+\pi(1-\pi)\rho\right)d\left(p-k\right) \\ &\quad + \pi^{2}\delta v^{pat} \geq (1-\delta)\pi\rho d\left(p-k\right). \end{aligned} \tag{A.1}$$

*Condition (A.1) is satisfied if the firms sufficiently value future cooperation, that is,* $\delta\geq\frac{\rho}{2\pi}$. ▲

*Proof of Lemma* 1. We show that when signals are not disclosed, the only equilibrium that can be sustained is the repetition of the Nash equilibrium of the stage game after all histories. As the only equilibrium of the stage game is $(D, D)$, the result follows.

Consider a strategy profile $\sigma=\left(\left(\sigma_{1t}\right)_{t=1}^{\infty},\left(\sigma_{2t}\right)_{t=1}^{\infty}\right)$ for the two firms with $\sigma_i^t: H_i^t\rightarrow A_i$, where a private history of player $i$ is an element $h_i^t=\left(y_{i0},a_{i0},\ldots,y_{it},a_{it}\right)\in H_i^t$ and $A_i=\{C,D\}$. By convention, we have that $H^0=\{\varnothing\}$. We refer to the two players as player $i$ and player $j$ and take the first period of cooperation to be $t=0$. Observe that for all $y_{j0}, y_{i0}$ it holds that the probability that firm $j$ has played an out-of-equilibrium action $a_{j0}\neq\sigma_{j0}\left(\varnothing\right)$ and has received signal $y_{j0}$ is simply $\mathbb{P}\left(a_{j0},y_{j0}|\sigma_{i0}\left(\varnothing\right),y_{i0}\right)=0$, as out-of-equilibrium actions have a probability of zero on the equilibrium path. This probability is independent of firm $i$'s signal realization $y_{i0}$ or strategy $\sigma_{i0}$.

[23] Note that if $\rho=1$, the firm's commercial success would be perfectly informative of the outcome $y$, so the choice of whether to disclose $y$ would be irrelevant if the firm's commercial success (e.g., cash flows) is observable. Furthermore, note that if $\pi=1$, the firm's signal would be perfectly informative of the firm's action, thus, making it possible to condition on the firms' actions.

[24] We follow the convention of normalizing the firms' expected payoffs by multiplying them by $(1-\delta)$. This normalization implies that the repeated game payoffs are comparable to the stage game payoffs. Intuitively, the infinite constant stream of 1 utils has a value of 1. Note that there are also other PPEs in this setting, where low signals trigger non-cooperation for finitely many periods.

Furthermore, given that the signals are drawn independently for each firm, in a pure strategies equilibrium, the probability that firm $j$ plays its equilibrium strategy $\sigma_{j0}$ and observes signal $y_{j0}$ given that firm $i$ plays its equilibrium action $\sigma_{i0}$ is also independent of firm $i$'s signal $y_{i0}$. Overall, as firm $i$'s signal $y_{i0}$ does not affect its belief about firm $j$'s private history $h_j^0 = (y_{j0}, a_{j0})$, the continuation strategy of firm $i$ induced by its strategy in $t = 0$, given the history in $t = 0$, must be independent of its signal $y_{i0}$. A symmetric argument applies for firm $j$: the continuation strategy of firm $j$ induced by its strategy in period 0, given the history in $t = 0$, must be independent of its signal $y_{j0}$. This means that expected continuation payoffs based on the signal in $t = 0$ do not affect firm $i$'s strategy $\sigma_i(\varnothing)$ in $t = 0$. As the same holds for firm $j$, the strategy profile $\sigma(\varnothing)$ must constitute a Nash equilibrium of the stage game in $t = 0$. Proceeding by induction, we can extend the argument to all remaining periods. □

*Proof of Proposition* 1. The argument follows from the discussion in the main text and lemma 1. As the firms can only support a cooperative equilibrium if both firms patent, they will choose to patent when trying to cooperate. □

*Proof of Proposition* 2. In what follows, we compute and compare the firm's maximum expected payoff under both patenting and trade secrecy. Suppose that $\frac{x_m}{1-\delta} \in (X', X'')$. That is, the continuation condition (4) is satisfied for $\{\theta_M, \theta_G\}$ if the firm chooses trade secrecy, but only for $\theta_G$ if it chooses patenting and cooperation. As discussed in the main text, in all remaining cases, patenting and cooperation dominate. As outsiders cannot distinguish between signals showing states $\theta_M$ and $\theta_G$, the control right to continue the investment becomes important. Note that the agent employed by firm $i$ prefers to continue the investment at the intermediate date $\tau_t = 0.5$ if

$$\theta_i w_m + (1 - \theta_i) w \geq w_A.$$

The firm prefers continuation if

$$\theta_i\left(\frac{x_m}{1-\delta} - w_m\right) + (1 - \theta_i)(\mathrm{E}x - w) \geq L + \mathrm{E}x - w_A. \tag{A.2}$$

In what follows, let

$$PV^{pat} = \left(1 - q^e_{\theta_G}\right)\left(L + \frac{v^{pat}}{1-\delta}\right) + q^e_{\theta_G}\left(\theta_G \frac{x_m}{1-\delta} + (1-\theta_G)\frac{v^{pat}}{1-\delta}\right) \tag{A.3}$$

$$PV^{ts} = \left(1 - q^e_{\theta_M} - q^e_{\theta_G}\right)\left(L + x_{DD} + \frac{\delta v^{pat}}{1-\delta}\right) \tag{A.4}$$

$$+ \sum_{\theta_i \in \{\theta_M, \theta_G\}} q^e_{\theta_i}\left(\theta_i \frac{x_m}{1-\delta} + (1-\theta_i)\left(x_{DD} + \frac{\delta v^{pat}}{1-\delta}\right)\right)$$

denote the present values of investing depending on whether firm $i$ chooses to patent, in which case it continues the investment only in state $\theta_G$, or not to patent, in which case it continues the investment in both states $\theta_M$ and $\theta_G$.

**Disclosure regime (patenting) and cooperation**. Suppose for now that the continuation decision lies with the firm and that it continues the investment if and only if it is ex post efficient to do so (i.e., $\theta_i = \theta_G$). After deriving the contract that maximizes the firm's expected payoff, we verify that this allocation of control rights will, indeed, lead to ex post efficient continuation.

The agent's incentive constraint is

$$\Delta_{\theta_G}(\theta_G w_m + (1-\theta_G)w - w_A) \geq c.$$

From this constraint, it is immediately apparent that setting $w_A = 0$ relaxes the agent's incentive constraint while increasing the firm's expected payoff.

Using that $w_A = 0$, it must hold that $\theta_G w_m + (1-\theta_G)\, w \geq \frac{c}{\Delta_{\theta_G}}$. Maximizing the firm's expected payoff further requires this expression to be satisfied with equality. Using this, we obtain that the firm's expected payoff is

$$\begin{aligned}\Pi^{pat} &= PV^{pat} - q^e_{\theta_G}(\theta_G w_m + (1-\theta_G)w) \\ &= PV^{pat} - q^e_{\theta_G}\frac{c}{\Delta_{\theta_G}}.\end{aligned}$$

We now verify that the firm makes the ex post efficient continuation decision at the intermediate date $\tau_t = 0.5$. Observe that if the signal is $\theta_M$, then for $\frac{x_m}{1-\delta} \in (X', X'')$, condition (A.2) would not be satisfied for any $w_m, w \geq 0$. If the signal is $\theta_G$, then condition (A.2) reduces to $\theta_G\left(\frac{x_m}{1-\delta} - \mathrm{E}x\right) - L \geq \frac{c}{\Delta_{\theta_G}}$, which is implied by the assumption that exerting effort increases the project's value from an ex ante perspective.

**No disclosure regime (trade secrecy) and non-cooperation**. If the firm chooses trade secrecy, it continues the investment if $\theta_i \in \{\theta_M, \theta_G\}$, possibly after renegotiations. In what follows, we first solve for the contract maximizing the firm's expected payoff for this continuation rule when there are no renegotiations. Subsequently, we consider renegotiations.

From the incentive constraint, we obtain that

$$\sum_{\theta_i \in \{\theta_M, \theta_G\}} \Delta_{\theta_i}(\theta_i w_m + (1-\theta_i)w - w_A) \geq c. \tag{A.5}$$

From this constraint, it is again immediately apparent that setting $w_A = 0$ maximizes the firm's expected payoff while relaxing the incentive constraint. Furthermore, satisfying this constraint with equality by lowering $w$ or $w_m$ is optimal, as it increases the firm's payoff.

To find the contract maximizing the firm's expected payoff, define the Lagrangian

$$\Lambda = PV^{ts} - \sum_{\theta_i \in \{\theta_M, \theta_G\}} \left(q^0_{\theta_i} + \Delta_{\theta_i}\right)(\theta_i w_m + (1-\theta_i) w) \tag{A.6}$$

$$+\mu \left( \sum_{\theta_i \in \{\theta_M, \theta_G\}} \Delta_{\theta_i} (\theta_i w_m + (1-\theta_i) w) - c \right) + \zeta w + \xi w_m,$$

where $\mu$, $\zeta$, $\xi$ are the weakly positive Kuhn–Tucker multipliers. Note that it cannot be that $w = w_m = 0$, as then (A.5) is not satisfied. Thus, either $\mu, \zeta > 0$ or $\mu, \xi > 0$. As the incentive constraint (A.5) is satisfied with equality, we can replace $\sum_{\theta_i \in \{\theta_M, \theta_G\}} \Delta_{\theta_i} (\theta_i w_m + (1-\theta_i) w)$ in the first line of (A.6) with $c$. Applying Kuhn–Tucker's theorem and taking the first-order conditions, we have

$$\frac{\partial \Lambda}{\partial w_m} = - \sum_{\theta_i \in \{\theta_M, \theta_G\}} q^0_{\theta_i} \theta_i + \mu \sum_{\theta_i \in \{\theta_M, \theta_G\}} \Delta_{\theta_i} \theta_i + \xi = 0 \tag{A.7}$$

$$\frac{\partial \Lambda}{\partial w} = - \sum_{\theta_i \in \{\theta_M, \theta_G\}} q^0_{\theta_i} (1-\theta_i) + \mu \sum_{\theta_i \in \{\theta_M, \theta_G\}} \Delta_{\theta_i} (1-\theta_i) + \zeta = 0. \tag{A.8}$$

Suppose now that $w_m > 0$. Then, $\xi = 0$, and from (A.7), we have that $\mu = \frac{\sum_{\theta_i \in \{\theta_M, \theta_G\}} q^e_{\theta_i} \theta_i}{\sum_{\theta_i \in \{\theta_M, \theta_G\}} \Delta_{\theta_i} \theta_i}$. Plugging into (A.8), we obtain

$$\left(q^0_{\theta_G} \Delta_{\theta_M} - q^0_{\theta_M} \Delta_{\theta_G}\right) \frac{\theta_G - \theta_M}{\theta_G \Delta_{\theta_G} + \theta_M \Delta_{\theta_M}} + \zeta.$$

Hence, if $q^0_{\theta_G} \Delta_{\theta_M} \leq q^0_{\theta_M} \Delta_{\theta_G}$, we must have that $\zeta > 0$. That is, $w = 0$ and $w_m = \frac{c}{\sum_{\theta_i \in \{\theta_M, \theta_G\}} \Delta_{\theta_i} \theta_i}$. The firm's expected payoff with this contract is

$$\Pi^{ts} = PV^{ts} - \frac{\sum_{\theta_i \in \{\theta_M, \theta_G\}} q^e_{\theta_i} \theta_i}{\sum_{\theta_i \in \{\theta_M, \theta_G\}} \Delta_{\theta_i} \theta_i} c. \tag{A.9}$$

However, if $q^0_{\theta_G} \Delta_{\theta_M} > q^0_{\theta_M} \Delta_{\theta_G}$, the above contract gives a contradiction to (A.8). In this case, we can set $\zeta = 0$, derive $\mu = \frac{\sum_{\theta_i \in \{\theta_M, \theta_G\}} q^0_{\theta_i} (1-\theta_i)}{\sum_{\theta_i \in \{\theta_M, \theta_G\}} \Delta_{\theta_i} (1-\theta_i)}$ from (A.8), and verify that (A.7) implies then $\xi > 0$. Hence, $w_m = 0$ and $w = \frac{c}{\sum_{\theta_i \in \{\theta_M, \theta_G\}} \Delta_{\theta_i} (1-\theta_i)}$. The firm's expected payoff with this contract is

$$\Pi^{ts} = PV^{ts} - \frac{\sum_{\theta_i \in \{\theta_M, \theta_G\}} q^e_{\theta_i} (1-\theta_i)}{\sum_{\theta_i \in \{\theta_M, \theta_G\}} \Delta_{\theta_i} (1-\theta_i)} c. \tag{A.10}$$

**Renegotiations**. We have already shown that there are no renegotiations in the patenting regime if the continuation control right is with the firm. We, now, consider whether renegotiations are needed if the firm chooses trade secrecy.

Consider the case in which $q^0_{\theta_G}\Delta_{\theta_M} \leq q^0_{\theta_M}\Delta_{\theta_G}$, in which case $w_m = \frac{c}{\sum_{\theta_i\in\{\theta_M,\theta_G\}}\Delta_{\theta_i}\theta_i}$ and $w = 0$. Giving the continuation control right to the agent ensures that she always continues the investment if $\theta_i \in \{\theta_M, \theta_G\}$ because she does not obtain anything in case of abandonment. Moreover, she also finds it weakly optimal to abandon investment if $\theta_i = 0$, as then her payoff is zero regardless of whether the investment is continued. Thus, if $q^0_{\theta_G}\Delta_{\theta_M} \leq q^0_{\theta_M}\Delta_{\theta_G}$, there are no renegotiations, and the firm's expected payoff when choosing trade secrecy is given by (A.9).

Next, consider the case in which $q^0_{\theta_G}\Delta_{\theta_M} > q^0_{\theta_M}\Delta_{\theta_G}$ in which case maximizing the firm's expected payoff would require that $w_m = 0$ and $w = \frac{c}{\sum_{\theta_i\in\{\theta_M,\theta_G\}}\Delta_{\theta_i}(1-\theta_i)}$. First, consider the case in which the continuation control right is with the agent. The agent's incentive is to continue continue the project if $w_A < \theta_i w_m + (1-\theta_i)\, w$. Thus, if the firm offers the contract we derived in the previous step (where $w_A = 0$), the firm and the agent will have to renegotiate if $\theta_i = 0$. As the firm has all bargaining power in renegotiations, the agent's expected payoff from renegotiating is equal to her outside option, $w^r_A = w$. Hence, from the effort constraint,

$$\sum_{\theta_i\in\{\theta_M,\theta_G\}} \Delta_{\theta_i}(\theta_i w_m + (1-\theta_i)\, w - w) \geq c,$$

we obtain that it is optimal to set $w = 0$, leading to the same contract as when $q^0_{\theta_G}\Delta_{\theta_M} \leq q^0_{\theta_M}\Delta_{\theta_G}$. The firm's expected payoff is, thus, again given by (A.9).

Second, suppose that the continuation control right is with the firm. The firm always abandons the project if the state is $\theta_i = 0$. The problematic case is when the state is $\theta_M$. If the firm has the correct incentives to continue investment with the contract derived in the previous step, the firm's expected payoff is given by (A.10). If, instead, the firm does not have incentives to continue the investment if $\theta_i = \theta_M$, the firm and the agent will renegotiate. As in such negotiations, the agent obtains her outside option of $w_A$, the agent's incentive constraint reduces to

$$\Delta_{\theta_G}(\theta_G w_m + (1-\theta_G)\, w - w_A) \geq c,$$

leading to the same expected payment to the agent of $q^e_{\theta_G}\frac{c}{\Delta_{\theta_G}}$ as under patenting and cooperation. Comparing this expected payment to that under agent control, which is given by $\frac{\sum_{\theta_i\in\{\theta_M,\theta_G\}} q^e_{\theta_i}\theta_i}{\sum_{\theta_i\in\{\theta_M,\theta_G\}}\Delta_{\theta_i}\theta_i}c$, we obtain that the latter is strictly smaller because we are in the case of $q^0_{\theta_G}\Delta_{\theta_M} > q^0_{\theta_M}\Delta_{\theta_G}$. Thus, whenever the firm anticipates renegotiations, it will optimally choose agent control, and the firm's expected payoff will be given by (A.9).

**Comparing the firm's expected payoffs under patenting and trade secrecy**. Comparing the firm's maximum expected payoff under patenting and trade secrecy, we obtain

$$\Pi^{pat} - \Pi^{ts} = \begin{cases} PV^{pat} - PV^{ts} - \frac{\theta_M}{\Delta_{\theta_G}} \frac{q^0_{\theta_G}\Delta_{\theta_M} - q^0_{\theta_M}\Delta_{\theta_G}}{\theta_G \Delta_{\theta_G} + \theta_M \Delta_{\theta_M}} c & \text{if } \Pi^{ts} \text{ is given by (A.9)} \\ PV^{pat} - PV^{ts} - \frac{(1-\theta_M)}{\Delta_{\theta_G}} \frac{q^0_{\theta_G}\Delta_{\theta_M} - q^0_{\theta_M}\Delta_{\theta_G}}{\theta_G \Delta_{\theta_G} + \theta_M \Delta_{\theta_M}} c & \text{if } \Pi^{ts} \text{ is given by (A.10)} \end{cases}. \quad \text{(A.11)}$$

Observe that if $q^0_{\theta_G}\Delta_{\theta_M} \leq q^0_{\theta_M}\Delta_{\theta_G}$, patenting leads to a higher expected payoff for the firm. However, if $q^0_{\theta_G}\Delta_{\theta_M} > q^0_{\theta_M}\Delta_{\theta_G}$, the agency costs under trade secrecy are lower, which could make trade secrecy preferable. To find when trade secrecy dominates in this case, we use that from expressions (A.3)–(A.4)

$$PV^{pat} - PV^{ts} = \left(1 - \theta_G q^e_{\theta_G}\right)\left(v^{pat} - x_{DD}\right) - q^e_{\theta_M}\theta_M \left(\frac{x_m}{1-\delta} - \frac{L}{\theta_M} - x_{DD} - \frac{\delta v^{pat}}{1-\delta}\right).$$

Plugging this difference into expression (A.11) and differentiating with respect to $\Delta_{\theta_M}$, we obtain that $\frac{\partial(\Pi^{pat}-\Pi^{ts})}{\partial \Delta_{\theta_M}} < 0$ (to see this, recall that we are in the case of $\frac{x_m}{1-\delta} \geq \frac{L}{\theta_M} + x_{DD} + \frac{\delta v^{pat}}{1-\delta}$). Hence, in terms of comparative statics, we obtain that trade secrecy becomes more attractive as $\Delta_{\theta_M}$ increases. In particular, there is a threshold $\Delta^*_{\theta_M}$ (where $\Delta^*_{\theta_M} > \frac{q^0_{\theta_M}\Delta_{\theta_G}}{q^0_{\theta_G}}$), implicitly defined by $\Pi^{pat} = \Pi^{ts}$, for which it holds that trade secrecy is better if $\Delta_{\theta_M} > \Delta^*_{\theta_M}$. If the parameter values are such that $\Delta^*_{\theta_M} > 1 - q^0_{\theta_M} - q^e_{\theta_G}$, there is no feasible $\Delta_{\theta_M}$ for which $\Pi^{pat} \leq \Pi^{ts}$, and patenting and cooperation are always optimal. □

## APPENDIX B: VALIDATING COOPERATION AND TRADE SECRECY INDEXES

### B.1 VALIDATION OF COOPERATION INDEX

In 2013, the Antitrust Division of the Department of Justice (DOJ) undertook a significant restructuring by closing four of its seven regional offices located in Atlanta, Cleveland, Dallas, and Philadelphia. These offices' primary responsibility was the oversight of local markets and the enforcement of criminal antitrust operations. Subsequent to the closures, some of the regional responsibilities were transferred to the remaining offices in Chicago, New York, and San Francisco, with a considerable portion being centralized in Washington, DC (specifically, to the Washington Criminal I and II divisions). This reorganization, necessitated by budgetary constraints, has been criticized by analysts and local policy makers for diminishing the DOJ's ability to monitor and prosecute regional antitrust violations, leading to a strategic pivot toward prioritizing large-scale, national cases. The closures impacted 23 states and territories, which include Alabama, Arkansas, Delaware, Florida, Georgia, Kentucky, Louisiana, Maryland, Michigan, Mississippi, New Jersey, New Mexico, North Carolina, Ohio, Oklahoma, Pennsylvania, South Carolina, Tennessee, Texas, Virginia, and West Virginia. Following the closures, there was, indeed, a sharp drop in the number of case filings in the affected jurisdictions. For a more detailed discussion of the closures and evidence that the closures were unrelated to firm-level characteristics within the affected jurisdictions, see Ha, Ma, and Zaldokas [2024].

Following Ha, Ma, and Zaldokas [2024], we posit that geographical distance serves as an indirect measure of the likelihood and efficacy of antitrust oversight. This premise is supported by literature suggesting that closer geographical proximity between regulators and firms lowers the barriers to monitoring and reduces information asymmetry, thereby facilitating more effective oversight (Kedia and Rajgopal [2011], Gopalan, Kalda, and Manela [2021]). Particularly in the context of antitrust enforcement, where leniency programs are a common tool for dismantling collusive arrangements, the propensity of local firms to divulge information may increase with closer proximity to regulatory offices. Consequently, companies operating within the affected jurisdictions faced a reduced likelihood of collusion detection with local competitors, thereby making such schemes more appealing to firms.

Based on this reasoning, we employ a difference-in-differences methodology, treating the change in geographical distance between a firm's headquarters and that of its regulator as a continuous variable indicative of a firm's exposure to the restructured antitrust enforcement landscape. Specifically, we estimate:

$$Cooperation\ index_{it} = \alpha + \beta_1 Treatment_{it} \times Post13 + \gamma X_{it} + \nu_i + \mu_t + \varepsilon_{it},$$

where $Treatment_{it}$ is the log of the difference in miles between the firm's headquarters and the DOJ's local office responsible for the oversight of firms in the same ZIP code before and after 2013; $Post13$ is an indicator variable equal to 1 for filing years including and following 2013. We consider an event window of four years around the closures and cluster standard errors at the state level. Approximately 14% of our sample firms are affected by these changes, with a mean of the log of the change in distance (conditional on this change being positive) of 4.56 and a standard deviation of 0.98.

Table B.1 shows the results. In line with our predictions, an increase in the distance between firms and the local DOJ office responsible for antitrust oversight has led to a significant increase in the cooperation index. In models (2) and (3) of table B.1, we split the sample of firms that are less and more similar to other firms.[25] Although all firms can benefit

[25] We use Hoberg and Phillips [2016] total similarity score, which measures how similar a firm's products and services are to those of other firms. We take the score from the year

**TABLE B.1**
*Validation of Cooperation Index*

| | Cooperation index | | | Ln(#cooperation) | | | Ln(#competition) | | |
|---|---|---|---|---|---|---|---|---|---|
| | All | Similarity | | All | Similarity | | All | Similarity | |
| | Firms | Low | High | Firms | Low | High | Firms | Low | High |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Treatment × post13 | 0.003*** | 0.000 | 0.009*** | 0.016* | 0.000 | 0.046*** | 0.004 | 0.003 | 0.004 |
| | (0.001) | (0.001) | (0.001) | (0.008) | (0.008) | (0.009) | (0.004) | (0.007) | (0.006) |
| SG&A/sales | 0.000 | 0.000 | 0.000 | 0.017*** | 0.024*** | 0.004 | 0.016*** | 0.024*** | 0.003 |
| | (0.001) | (0.001) | (0.002) | (0.004) | (0.008) | (0.007) | (0.003) | (0.006) | (0.009) |
| Ln(sales) | −0.003 | 0.000 | −0.005* | 0.096*** | 0.119*** | 0.084*** | 0.107*** | 0.117*** | 0.100*** |
| | (0.003) | (0.004) | (0.003) | (0.010) | (0.013) | (0.018) | (0.010) | (0.013) | (0.018) |
| Industry ln(sales) | 0.002 | 0.001 | 0.001 | −0.004 | 0.004 | −0.023 | −0.012** | 0.000 | −0.032* |
| | (0.002) | (0.003) | (0.004) | (0.011) | (0.014) | (0.025) | (0.006) | (0.008) | (0.017) |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 21,996 | 10,608 | 8426 | 22,033 | 10,630 | 8439 | 22,033 | 10,630 | 8439 |
| Adjusted $R^2$ | 0.746 | 0.736 | 0.765 | 0.778 | 0.748 | 0.795 | 0.756 | 0.72 | 0.753 |

This table shows changes in the cooperation index, defined in (9), around the closures of four of the seven regional DOJ offices in 2013. *Treatment* is the log of the change in distance (in miles) between a firm and the DOJ offices responsible for the oversight of firms in its region. *Post*13 is a dummy variable equal to 1 for the years after 2013. *Similarity* is the Hoberg and Phillips [2016] total similarity score in 2013. The control variables are firm and median industry *Ln*(*sales*), which is the natural log of sales, adjusted to inflation (base year 2004), and *SG&A*/*sales*, which is sales, general, and administrative expenses over sales. These variables are winsorized at 1%. Robust standard errors clustered at the state level are in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

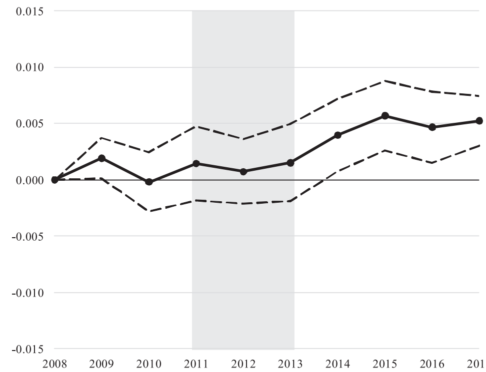



FIG. B.1.—Validation of cooperation index (closure of DOJ offices). This figure shows changes in the cooperation index in the years around the closure of four of the seven regional DOJ offices in 2013. The estimates $\beta_t$ and their 90% confidence intervals are from the difference-in-differences specification (13). The dependent variable is $Cooperation\ index$, defined in (9). The control variables are firm and median industry $Ln(sales)$, which is the natural log of sales, adjusted to inflation (base year 2004); $SG\&A/sales$, which is sales, general, and administrative expenses over sales. These variables are winsorized at 1%. Robust standard errors are clustered at the state level.

from more cooperation, the closure of local DOJ offices and the resulting laxer antitrust oversight should be particularly relevant for firms that are more similar to other firms, as they are more likely to become the focus of antitrust investigations. Indeed, the evidence shows that the effect is primarily due to such firms. In economic terms, a firm from the latter category affected by closures of DOJ offices has seen an average increase of $4.56 \times 0.009 = 0.041$ increase in its cooperation index, which corresponds to 21% of that variable's standard deviation. In models (4)–(9), we show that the increase in the cooperation index comes primarily from the more frequent mentioning of cooperation rather than the less frequent mentioning of competition in the firms' 10-K filings.

To support our assumption that the results are not driven by pre-existing trends, we further estimate regression (13), where $Y_{it}$ is replaced with $Cooperation\ index_{it}$. Figure B.1 in appendix B, shows that there is no difference between treatment and control firms in the years before 2013, followed by a sharp increase in cooperation in treated firms after 2013. The gray area corresponds to the time between the decision on the closure of the DOJ's regional offices and their actual closure in 2013.

2013 to avoid that the closure of the DOJ offices might have affected that score. The score is available for about 60% of the firms.

### B.2 VALIDATION OF TRADE SECRECY INDEX

To validate that our trade secrecy index (10) captures firms' reliance on trade secrecy, we follow Glaeser [2018] and test whether our index increases when U.S. states pass legislation that makes it easier for firms to protect trade secrets or protect themselves against the risk that former employees join competitors where they divulge proprietary information. The legislations we exploit are the staggered adoptions of the Uniform Trade Secrets Act (UTSA), the Inevitable Disclosure Doctrine (IDD), and staggered changes to the enforcement of noncompete agreements across U.S. states. In what follows, we discuss these legislations in turn.

**Uniform Trade Secrets Act**. The UTSA harmonized the legal landscape for trade secrecy protection across adopting states, enhancing the security of confidential business information. By standardizing the definition of trade secrets and the criteria for misappropriation, the UTSA facilitated a more predictable and uniform enforcement environment. Thus, this legal framework reduced the uncertainty and variability previously encountered in protecting trade secrets across state lines, giving firms more guidance on how to best protect their intellectual property through trade secrets.

Although the implementation of the UTSA is not uniform across states, and the UTSA did not eliminate all uncertainty, we do not attempt to quantify how the degree of legal protection provided by the UTSA differs across states, as this involves making many subjective choices. Instead, we follow Glaeser [2018] in taking a dummy variable taking the value of one for years after a state adopts the UTSA. For a more detailed description of the UTSA, we refer to Glaeser [2018]. We predict that firms in states adopting the UTSA are more likely to pursue trade secrets, because the UTSA in general increased the legal protection provided by trade secrets.

**Inevitable Disclosure Doctrine**. The Uniform Trade Secrets Act (UTSA) defines trade secrets and outlines conditions under which misappropriation occurs. It emphasizes the economic value derived from secrecy and the efforts made to maintain it. The Inevitable Disclosure Doctrine (IDD) extends this protection by addressing the potential for "threatened misappropriation" when employees move to similar positions in competing firms. This doctrine allows for legal action based on the mere threat of irreparable harm without proving actual misconduct, thus enhancing trade secret protection and addressing the mobility of employees across state lines, even in jurisdictions not adopting IDD. Specifically, the inevitable disclosure doctrine allows a court to prevent a former employee from working in a job that would inevitably lead them to rely on or divulge their former employer's trade secrets, even in the absence of a noncompete agreement. The doctrine's premise is that certain positions inherently require disclosure of confidential information, thus posing a risk to the former employer's proprietary interests. Furthermore, the IDD significantly boosts the enforceability of nondisclosure agreements and noncompete agreements, as the IDD does not entail any geographic restrictions (unlike noncompete agreements), and it allows courts to prohibit employment at a rival firm, as it has the potential for a future violation of a nondisclosure agreement.

The application of the IDD varies significantly across jurisdictions. To measure state court recognition of the Inevitable Disclosure Doctrine (IDD) over time, we follow Klasa et al. (2018) and track when a landmark case establishes case law, marking a shift in legal stance within a state. Specifically, we set an IDD indicator to zero before the case in question and to one from the year of the case onward unless a later decision explicitly overturns this recognition, reverting the indicator to zero. For states not evaluating or rejecting IDD, the indicator remains at zero throughout.

**Enforcement of Noncompete Agreements**. Furthermore, we expect that trade secrecy will be more prevalent in states with weaker enforcement of noncompete agreements. Such agreements are part of employment contracts that restrict the ability of employees to work for a rival firm within a certain period and within a certain geographical area after leaving. Marx (2011) finds that over 40% of engineers sign a noncompete agreement; the figure for senior executives is more than 70% (Garmaise, 2011), with noncompete agreements significantly limiting worker mobility (Marx, Strumsky, and Fleming 2009; Garmaise 2011). Though California famously considers such agreements void, they are legal and enforced to various degrees in most other states. The empirical strategy is to exploit the staggered *changes* in such noncompetition agreements over time and across states.

In particular, we expect that the weakening of noncompete agreements, which encourages worker mobility, makes it more important for firms to strengthen their trade secrecy protection. The reason is that filing for patents as an alternative protection of intellectual property is costly and takes, on average, two years until a patent is granted. Thus, relying more heavily on trade secrecy will be important at least in the short run. Moreover, not all information that firms would prefer to keep secret, such as customer lists or specific methods of doing things, can be patented. By contrast, strengthening a firm's trade secrecy policy can become effective immediately, and trade secrets can protect a wide range of information, including formulas, practices, processes, designs, instruments, patterns, or compilations of information.

The enforceability of noncompete agreements is proxied by an index used in Garmaise (2011), which ranges between 0 and 12. Higher values indicate higher enforceability. Crucially, several states change their practices regarding the enforcement of noncompete agreements in a staggered fashion, with some strengthening the enforcement, while others weakening it. Most of these changes resulted from court verdicts (and were not handed down by state Supreme Courts), and are plausibly exogenous to the use of trade secrets. Details on the political economy of the changes can be found in Ewens and Marx [2018], Marx [2018], and Kini, Williams, and Yin [2021]. In states in which the enforcement of noncompetition agreements changes, Garmaise's (2011) index is adjusted depending on the change in the answers to the 12 questions on which the index is based. To obtain

TABLE B.2
*Validation of Trade Secrecy Index*

| | Trade Secrecy Index (1) | Ln(#trade secrecy) (2) | Ln(#patenting) (3) |
|---|---|---|---|
| UTSA | 0.012** | 0.009 | 0.000 |
| | (0.005) | (0.017) | (0.030) |
| IDD | 0.010** | 0.049*** | 0.077*** |
| | (0.005) | (0.016) | (0.026) |
| Weak enforcement | 0.004* | 0.019*** | 0.012 |
| | (0.002) | (0.006) | (0.009) |
| Ln(sales) | 0.000 | 0.004* | 0.015*** |
| | (0.001) | (0.002) | (0.003) |
| Industry ln(sales) | 0.002 | 0.029*** | 0.054*** |
| | (0.002) | (0.006) | (0.010) |
| Tobin's Q | −0.002 | −0.001 | 0.004 |
| | (0.003) | (0.008) | (0.008) |
| Special items/assets | 0.000 | −0.003*** | −0.007*** |
| | 0.000 | (0.001) | (0.001) |
| Return on assets | −0.016*** | −0.095*** | −0.046 |
| | (0.006) | (0.030) | (0.045) |
| Ln(age) | −0.001 | −0.010** | −0.018** |
| | (0.001) | (0.004) | (0.007) |
| Firm FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 86,210 | 86,210 | 86,210 |
| Adjusted $R^2$ | 0.379 | 0.621 | 0.838 |

This table studies the determinants of the trade secrecy index, defined in (10). $Ln(\#trade\ secrecy)$ is the log of the number of times a firm mentions phrases related to trade secrecy in its 10-K filings. $Ln(\#patenting)$ is the log of the number of times a firm mentions phrases related to patenting in its 10-K filings. UTSA is an indicator variable taking the value of one after the state-level adoption of UTSA. IDD is an indicator variable equal to 1 in the years following the state-level adoption of the IDD. Weak enforcement is the negative of Garmaise's (2011) index of the enforcement of noncompetition agreements. Changes to that index come from Kini, Williams, and Yin [2021]. The control variables are $Ln(sales)$, which is the natural log of sales, adjusted to inflation (base year 2004). We further control for $Tobin's\ Q$, $Special\ items/assets$, the firm's return on assets, and the log of the firm's age, where age is defined as the number of years since the first time the firm appears is in Compustat. These variables are winsorized at 1%. Robust standard errors clustered at the state level are in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% levels, respectively.

an index of weaker enforcement ($Weak\ enforcement$), all index values are multiplied by minus one. Approximately 26% of the firms are in states in which there was a change in the enforceability of noncompete agreements.

**Results: Trade Secrecy Index and Legislative Changes**. Based on the above reasoning, we estimate the following model

$$Trade\ secrecy\ index_{it} = \alpha + \beta_1 UTSA_{s,t} + \beta_2 IDD_{s,t} + \beta_3 Weak\ enforcement_{s,t} + \gamma X_{it} + \nu_i + \mu_t + \varepsilon_{it},$$

where we include firm and year fixed effects. All standard errors are clustered at the state level. In line with Glaeser [2018], we include several control variables, including log of sales, Tobin's Q, Return on assets, and special items over total assets (in line with the literature on corporate transparency). The results are presented in table B.2.

The results are consistent with the prediction that changes in legislation that should make trade secrecy more attractive to firms lead to an increase in the trade secrecy index. Model (1) in table B.2 shows that all variables of interest—UTSA, IDD, and Weak Enforcement—are significant and have the predicted sign. In models (2)–(3), we show that the changes to the trade secrecy index come primarily from firms mentioning more frequently trade secrecy in their 10-K filings. Although these legislations may affect firms also in different ways that are unrelated to firms' propensity to use trade secrecy, the sign and significance of the statistical relationships are, in any case, supportive that our trade secrecy index should increase when economic reasoning suggests it should.

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