Received: 22 February 2022 | Revised: 25 April 2023 | Accepted: 29 April 2023

DOI: 10.1002/smj.3511

RESEARCH ARTICLE

STRATEGIC MANAGEMENT JOURNAL WILEY

Who gains and who loses from more information in technology markets? Evidence from the Sunshine Act

Huiyan Zhang[1,2] | **Lee Branstetter**[1,3] | **Raffaele Conti**[4] | **Samir Mamadehussene**[5]

[1]Heinz College, Carnegie Mellon University, Pittsburgh, Pennsylvania, USA

[2]Catolica Lisbon School of Business and Economics, Palma de Cima, Lisbon, Portugal

[3]National Bureau of Economic Research, Cambridge, Massachusetts, USA

[4]ESSEC Business School, Cergy-Pontoise Cedex, France

[5]Naveen Jindal School of Management, University of Texas at Dallas, Richardson, Texas, USA

Correspondence
Huiyan Zhang, Heinz College, Carnegie Mellon University, Pittsburgh, PA 15213 USA.
Email: huiyanz@andrew.cmu.edu

Abstract

Research Summary: We consider the context of a technology market where participants (in particular, sellers) differ in reputation, and sellers observed participating in the transactions might suffer a reputation loss. Our theoretical model predicts that low-reputation idea sellers, thanks to the improvement in information disclosure, are more likely to be involved in technology transactions; at the same time, high-reputation idea sellers, to protect their reputations, might prefer avoiding any transactions. This shift in seller composition might affect the quantity and quality of collaborations. To test our theory, we assess the effect of the Physician Payment Sunshine Act on physician-firm collaborations. Overall, our findings indicate that while information disclosure might benefit some market participants, it can have unintended negative consequences for others.

Managerial Summary: In technology markets, more information about market participants generally leads to better outcomes. However, in contexts where sellers suffer a reputation loss if their transactions become known, higher-reputation sellers may leave the market,

affecting the quality of ideas being traded and impacting buyers. On the other hand, lower-reputation sellers may benefit from increased visibility and share their ideas more frequently. Our research examined these effects in the context of the Physician Payment Sunshine Act, which made physician collaborations with medical device companies visible. The results suggest that the effects of information disclosure are not uniform and that some market participants may benefit while others may suffer losses.

KEYWORDS

information environment, innovation rate, markets for technology, medical device industry, Sunshine Act

1 | INTRODUCTION

Both scholars and practitioners increasingly recognize the importance of markets for technology, where knowledge is traded directly rather than embodied in physical goods (Arora et al., 2001; Arora & Gambardella, 2010b; Conti et al., 2014; Fosfuri, 2006; Fosfuri & Giarratana, 2010; Gans & Stern, 2003). For upstream inventors, these markets provide the possibility of monetizing their ideas, without having to acquire the full set of capabilities needed for commercialization (Teece, 1986). For incumbent producers, these markets allow them to identify new innovations emerging outside of their organizational boundaries and exploit them via their existing downstream marketing and production capabilities (Chatterji & Fabrizio, 2016; Leone & Reichstein, 2012). The benefits of specialization and division of labor across upstream inventors and downstream producers, and the ensuing gains from trade, are widely seen as beneficial, from both a private and a societal perspective (Arora et al., 2001; Arora & Fosfuri, 2003).

Several scholars have outlined how uncertainty and lack of information could represent key obstacles to the smooth functioning of markets for technology (Agrawal et al., 2015; Ceccagnoli et al., 2014; Fosfuri & Giarratana, 2010; Gans et al., 2008; Luo, 2014). Previous research points out the existence of situations where there are relevant information asymmetries between sellers and buyers about the value of ideas—whose real quality might be better known by inventors than by potential buyers (Aghion & Tirole, 1994; Akerlof, 1970; Anton & Yao, 2002; Gallini & Wright, 1990; Pisano, 2006; Wuyts & Dutta, 2008)—or in which neither buyers nor sellers know exactly whether a certain idea can be successfully commercialized (Agrawal et al., 2015; Arora & Gambardella, 2010a). Nearly all of this prior work suggests that more information—especially more information about external collaborators and ideas—will be good for any agent transacting in the market and for overall social welfare as more and higher-quality innovations will be eventually commercialized (Agrawal et al., 2015; Arora et al., 2001; Hegde & Luo, 2018).

However, previous research has generally neglected the consideration that participants in the markets for technologies—and sellers in particular—differ in terms of their reputation, or the extent to which they are renowned experts in a certain technological field. High-reputation

sellers might be averse to disclosing their identity when technology market transactions are seen as "repugnant" (Gans & Stern, 2010; Roth, 2007). This might occur in contexts such as academia (Gans & Stern, 2010) or the open-source software community (Lerner & Tirole, 2005), where the free exchange of knowledge and ideas is generally the norm, and monetary exchanges of ideas are instead seen with suspicion. Or it might occur in the context of research collaboration between medical device firms and physicians, which might raise concerns about the personal integrity of physicians involved in the collaborations, as well as about the objectivity of their research and the safety of human subjects (Cohen, 2001; DeAngelis, 2000). Therefore, if information disclosure about knowledge transactions—such as the identity of the idea sellers and the price—is required, some potential idea sellers, especially the most highly reputed ones, might decide to abandon technology markets in order to avoid suffering any reputation loss (Haleblian et al., 2017; Zavyalova et al., 2016). Hence, more information might be detrimental for well-reputed idea sellers, who tend to abandon the market, and, as a result, also for some potential buyers who lose the possibility of acquiring ideas from high-reputation sellers.

Overall, in contexts where sellers differ in reputation, an improvement in the information environment of technology markets has a more nuanced effect than what past research has generally assumed. To capture those nuances, we develop a simple theoretical model in which firms need to set up a collaboration project with an external inventor in order to develop a new idea. Firms do not know which inventors are a good match for a given project and must rely on noisy signals of external inventor quality. There exist two types of inventors: some "well-reputed" inventors (type-R) are experts in a certain technological area. As a result, assessing their fit with a project is relatively easy. The remaining "no-reputation" inventors (type-N) are not yet publicly known, and they incur some participation costs (e.g., attending conferences) if they want to be considered for possible collaborations. A policy mandating disclosure of information about external inventors affects future collaborations via two channels: (i) a publicity channel, by revealing a wider pool of type-N inventors who might fit the project; and (ii) a reputation channel, which tends to push type-R inventors out of the market. Hence, type-N inventors should start collaborating more with firms, whereas type-R inventors should collaborate less. The overall effect on collaboration quantity and quality is ambiguous. More information allows firms to pick among a wider pool of type-N inventors—which, ceteris paribus, increases the quantity and (under mild assumptions) also the average quality of collaboration. At the same time, type-R inventors tend to leave the market—which, ceteris paribus, lowers the quantity and average quality of collaboration. So, the ultimate impact of information disclosure on a firm innovative performance is theoretically ambiguous and depends on which of these two opposing forces predominates in practice.

To test the hypotheses generated by our theoretical framework, we focus on the American medical device industry, which is an ideal setting for several reasons. First, there are frequent collaborations between medical device firms and external inventors (usually physicians) to develop new technologies (Chatterji & Fabrizio, 2014, 2016). Second, the American medical device innovation industry is heavily regulated (Ball et al., 2018; Stern, 2017), and the US federal government mandated detailed information disclosures regarding physician-firm research collaborations that plausibly informed buyers about the identity and quality of technology sellers. As part of the Affordable Care Act (ACA), which passed in 2010 and was fully implemented in 2014, the US government required extensive disclosure of payments to collaborating physicians made by pharmaceutical or medical device companies. This part of the ACA is also known as the Sunshine Act. It imposed information disclosure requirements on all firm-physician research transactions, such that even the less-reputed physicians who have

collaborated with a firm become widely known. Consistent with our theory, the Act was met with resistance from some physicians, who were concerned about potential reputation losses following the disclosure of their relationships with pharmaceutical and medical device companies (Lichter, 2015; Sullivan, 2018a, 2018b). Third, medical device companies are extensive users of the patent system, and patents provide us with a "paper trail" that documents firm-physician research collaborations. Using patent data, it is possible to track the quantity and quality of collaborations, both before and after the implementation of the Sunshine Act.[1]

We construct a dataset considering the innovative outputs of 275 publicly traded medical device companies that were granted USPTO patents between 2005 and 2018, some of which were the result of collaborations with physicians. Physicians with a strong reputation due to their academic publications are designated as type-R inventors, while the remaining physicians are designated as type-N inventors. This allows us to use a difference-in-differences design to compare the effect of the Act on the two groups of physicians. Our findings show that while the Sunshine Act increased the number of collaborations by type-N inventors, it reduced the number of collaborations by type-R inventors, indicating there are winners and losers. On the side of medical device firms, changes in the composition of the pool of inventors collaborating with these companies resulted in an overall increase in the quantity of collaborations. However, the quality of these collaborations remained fairly stable on average but may have decreased or increased for the least or most reputable firms. Therefore, it appears that there are winners and losers on both the buyer and seller sides of the market.

The rest of the paper proceeds as follows. Section 2 provides a review of the literature and develops our conceptual framework. Section 3 describes the empirical setting. Section 4 reports the construction of the sample and the identification strategy. Section 5 provides the main empirical results and the results of a series of robustness checks to rule out alternative mechanisms and, more broadly, corroborate the validity of our findings. Section 6 discusses the results and implications.

2 | THEORETICAL DEVELOPMENT

2.1 | Previous literature: Markets for technology and the repugnance problem

Strategy scholars have increasingly acknowledged the importance of well-functioning markets for technologies (Arora et al., 2004; Arora & Gambardella, 2010a; Fosfuri, 2006; Gans et al., 2000; Gans & Stern, 2003; Teece, 1986), which foster incentives for specializing and reaping benefits through trading (Arora & Ceccagnoli, 2006; Galasso et al., 2013; Lamoreaux & Sokoloff, 2001).

Well-functioning technology markets create strategic opportunities for both upstream inventors, who can sell their ideas, and downstream buyers, who can acquire external ideas. Without technology markets, organizations or individuals generating a new idea can only profit by selling products that embody that idea. This means that actors who do not possess downstream

[1]Of course, not all collaborations result in patents, but the most valuable ones are likely to generate that outcome. US patent law requires that parties making significant contributions to a new invention be named as inventors. If an external inventor's name were deliberately withheld from a patent application, this would violate the law and could subject the patent holder to serious penalties.

assets to commercialize an idea may not be able to monetize their ideas, given the costs associated with developing or acquiring the necessary downstream assets. In contrast, with well-functioning markets where knowledge can be easily exchanged, upstream inventors can readily sell their ideas to downstream buyers, allowing them to monetize their knowledge without incurring any costs associated with producing or marketing final products (Arora et al., 2004; Conti et al., 2014; Padula et al., 2015). Moreover, large incumbent firms equipped with downstream production and commercialization assets can seek out new ideas beyond their organizational boundaries, which can improve their innovative and economic performance (Cohen & Levinthal, 1990; Rosenkopf & Almeida, 2003). Specifically, licensing-in can broaden incumbent firms' exploration space (Laursen et al., 2010), leading to quicker invention generation by licensees and a more immediate stream of revenues (Leone & Reichstein, 2012). The advantages of markets for inventions are particularly evident for firms that conduct broad and in-depth searches (Laursen & Salter, 2006), although the positive effects of this type of search on performance may decrease beyond a certain point, suggesting that further search can become unproductive. Overall, technology markets allow incumbent firms to readily implement an open-innovation strategy (Cassiman & Valentini, 2016), exploring new ideas from other incumbents, new entrants, product users, or suppliers.

However, the market institutions that govern how knowledge and ideas are exchanged in technology markets are often characterized by relevant frictions that make open-innovation strategies difficult, and so negatively impact both the potential buyers' participation in technology markets and the potential sellers' incentives to collaborate or exchange their knowledge (Arora et al., 2004). Such frictions are typically related to the lack of relevant information about the quality of idea sellers and/or of their ideas. For instance, prior work has pointed out the existence of relevant information asymmetries between sellers and buyers about the value of ideas—whose real quality might be better known by inventors than by potential buyers—such that markets for technologies might be afflicted by a "lemons" problem, which reduces the volume of technology transactions (Aghion & Tirole, 1994; Akerlof, 1970; Anton & Yao, 2002; Gallini & Wright, 1990; Pisano, 2006; Wuyts & Dutta, 2008). Other prior research points to contexts in which neither buyers nor sellers know exactly whether a certain idea can be successfully commercialized (Agrawal et al., 2015; Arora & Gambardella, 2010a). Relatedly, Gans et al. (2008) illustrate how also the lack of information about whether an idea will eventually be patented can pose obstacles to the functioning of technology markets.

The natural conclusion of all of this prior work is that more information—especially more information about external collaborators and ideas—will be good for any agent transacting in the market and for overall social welfare, as more and higher-quality innovations will be eventually commercialized (Agrawal et al., 2015; Arora et al., 2001; Hegde & Luo, 2018). In this paper, we challenge this commonly-held view and propose that frictions affecting the functioning of technology markets might sometimes arise because there is *too much* information.

We build on the intuition that even markets for technologies might be characterized by a repugnance problem (Gans & Stern, 2010). In general, in repugnant markets, "there may be willing suppliers and demanders of certain transactions", yet "aversion to those transactions by others may constrain or even prevent the transactions" (Roth, 2007, p. 40). In technology markets, receiving remuneration for selling an idea might be viewed with suspicion and concern, and sellers might face a social penalty, stemming from their peers or other relevant audiences, in terms of reputation loss. For instance, in academia, the free exchange of knowledge and ideas is generally the norm. So, any research collaboration with for-profit companies might be viewed with suspicion by academic researchers' institutions and colleagues (Gans & Stern, 2010). This

"repugnance" issue also exists within the open-source software community. Developers, and, in particular, the leaders who initiate projects could face substantive social penalties should they decide to sell their technology to private companies rather than keep it open (Lerner & Tirole, 2005). In the context of research collaboration between medical device firms and physicians, which is the focus of this paper, some collaborating physicians can face "repugnance" problems. When physicians receive funds from a firm for their research collaboration, it can call into question not only their personal integrity but also the objectivity of their research and the safety of human subjects. All of these issues can put the reputation of collaborating physicians at stake (Cohen, 2001; DeAngelis, 2000).

In the next section, we consider the case where participants in markets for technologies—and sellers in particular—differ in terms of their reputation or the extent to which they are renowned experts in a certain scientific or technological field. We argue that, in this context, mandated information disclosure about knowledge transactions—such as the identity of the idea sellers and the prices of transactions—will exert a dual effect. First, those idea sellers who have produced valuable knowledge and have developed a good reputation (Haleblian et al., 2017; Zavyalova et al., 2016)—might decide to abandon technology markets in order to avoid suffering any reputation loss. We call this the *reputation* effect. At the same time, mandated information disclosure just increases the pool of the less reputed inventors that firms are aware of and consider for potential collaborations. We call this the *publicity* effect. We will show how these two effects will have nuanced implications for upstream inventors and downstream buyers.

2.2 | Conceptual framework

In this section, we provide a theoretical framework to understand how a policy mandating the disclosure of information regarding external inventors would impact the innovation landscape. A formal mathematical model, where we detail all the assumptions we make and derive our main predictions, is reported in online Appendix S1.

2.3 | Mandated information disclosure in technology markets: Publicity effect and reputation effect

We consider the case of an economy consisting of firms that require external expertise in order to execute project ideas. There are two types of external inventors that firms can hire: inventors of type-R have already built a reputation and are renowned experts in a certain scientific or technological field; inventors of type-N are instead not generally known.[2] Because firms are generally aware of type-R inventors, they can choose to make them an offer to collaborate. By contrast, if a type-N inventor wants to work with a firm, he must exert a participation cost in order to make firms aware of him. For example, a physician who wishes to collaborate with a medical device firm may go to conferences and engage in networking to signal that he is willing to collaborate.

[2]For example, inventors of type-R may have citations to their previous patented projects, in contrast to inventors of type-N. As information about patents and their citations is readily available, the inventor's type is assumed to be publicly known.

Projects developed by type-R inventors are, on average, of higher quality than projects developed by type-N inventors. Moreover, because type-N inventors are not generally known, there is uncertainty regarding the quality that each type-N inventor is able to generate when working on a given project. Each firm has access to only a small subset of type-N inventors. Although the firm does not know the quality of those inventors, it observes a signal regarding which of those inventors has a better fit with the project. For example, the firm may inspect the inventors' CVs and get a sense of which inventor has worked on projects that are similar to the project that the firm wants to execute.

Against this background, a policy mandating the disclosure of information regarding external inventors will produce a dual effect. First, a "*publicity*" effect, which makes firms aware of *all* type-N inventors who have previously collaborated with any firm. The implication of this effect is twofold. First, since the firm has a wider range of type-N inventors to choose from, the expected quality of a project developed by the type-N inventor that has the best-fit increases. Whereas without disclosure the firm was selecting the type-N with a better fit out of the small subset of inventors that the firm had access to, with disclosure the firm can choose the type-N with a better fit out of all type-N inventors listed in the public database. Second, after working with a firm and being listed on the public database, type-N inventors no longer need to incur participation costs in the following periods if they want to collaborate with a firm. Once a type-N inventor is in the database, firms become aware of him and may send him offers to collaborate in future periods. However, the disclosure of information leads to a reputation loss that increases inventors' reservation values—we call this the "*reputation*" effect. Naturally, this reputation loss will be higher for type-R than type-N inventors.

2.4 | Effect on idea sellers

Each of these channels (publicity and reputation) will influence the quantity of projects developed by inventors of type-R and type-N. First, the publicity channel will affect the incentives for type-N inventors to collaborate. Notably, this will occur right after the announcement of the disclosure policy (i.e., even before information is actually made public). Indeed, in absence of the disclosure policy, a type-N inventor who wishes to collaborate with a firm must exert a participation cost (such as going to conferences) so that some firms are aware of him and eventually he may collaborate with one of these firms. However, after the collaboration is over, he is back to his initial position as an unknown type-N inventor. By contrast, when the disclosure policy is announced, there is an additional benefit to a type-N inventor from collaborating: after collaborating with a firm, the type-N inventor appears in a public database and may receive more offers to collaborate in future periods. Hence, information disclosure raises the value that type-N inventors derive from incurring the participation cost, which leads to an increase in supply of type-N inventors—and this occurs immediately after the announcement of the information disclosure policy, even before information regarding external inventors is actually made public. After the information is disclosed, firms are able to choose the inventor with the best fit from a larger set of inventors, which raises the value that a firm derives from collaborations with type-N inventors. This leads firms to substitute away from type-R inventors towards the less expensive type-N inventors.

At the same time, the reputation channel reduces the supply of type-R inventors after the announcement of the disclosure policy (and even before the information is disclosed). This leads to an increase in the equilibrium price to hire type-R inventors. As type-R inventors

become more expensive, the reputation channel also leads firms to substitute away from type-R inventors towards type-N inventors.

Because both channels have the same effect, the impact of information disclosure on the quantity of projects developed by type-R and type-N inventors is unambiguous: *The quantity of projects developed by type-R (type-N) inventors starts decreasing (increasing) when the information disclosure policy is announced, and it decreases (increases) even more after the policy is implemented*.

Whereas both channels have the same effect on the quantity of projects developed by type-R versus type-N inventors, it is possible to disentangle the reputation and publicity channels by considering the collaborations with reputable partners, on one side, and new partners, on the other side.

First, if firms differ in their "reputability," the extent of the reputation loss that a type-R inventor suffers will depend on whether the inventor is collaborating with a reputable versus disreputable firm. For example, suppose firm A has experienced some relevant reputation loss in the past (e.g., it was forced to recall products from the market, because they were dangerous or ineffective) whereas firm B has not. Based on the reputation channel, the backlash that a type-R inventor suffers when collaborating with the former will be higher when it collaborates with firm A than when it collaborates with firm B. Therefore, we expect that *the disclosure policy will lead to a larger decrease in collaborations of type-R inventors with the least reputable firms*.

Second, firms might differ in their prior collaborations, such that the same company might be, for some inventors, a familiar partner, while for other inventors it would be a completely new partner. Based on the publicity channel, we might expect that, following the mandated information disclosure, type-N inventors increase their chances of collaborating with new firms. Indeed, collaboration between an inventor and a firm starts when either a firm that already knows the inventor approaches him or when an inventor incurs the participation cost (e.g., going to conferences) and finds a firm that wants to collaborate. As we have previously discussed, the announcement of the information disclosure policy increases the value that type-N inventors derive from incurring the participation cost. Thus, *after the policy is announced, more type-N inventors will publicize their availability and competence among new industry partners with whom they have not collaborated before*, which ultimately leads to more first-time collaborations by type-N inventors.

2.5 | Effect on idea buyers

Given the effect on sellers, it is worth considering the implications of mandated information disclosure on buyers—and, in particular, on their ability to initiate collaborations and the resulting quality of projects. Let us first consider the effect of mandated information disclosure on the total quantity of completed projects. After the disclosure policy is announced, and even before information is disclosed, type-R inventors become less willing to collaborate with firms (via the reputation channel), whereas type-N inventors become more willing to participate (through the publicity channel). Therefore, the impact of information disclosure on the total quantity of projects executed is ambiguous. In other words, *after the announcement of the information disclosure policy, the total project quantity increases if the extent of the reputation loss is not too large, and it decreases otherwise*.

The quality of completed projects will also be impacted by the disclosure of information, through both the publicity and the reputation channels. On the one hand, the reputation

channel pushes some of the high-quality inventors out of the market, which reduces the average quality of collaborations. On the other hand, the publicity channel allows firms to direct offers to those type-N inventors who have a better fit with the projects they want to execute. The total impact of the disclosure of information on the average quality of completed projects is ambiguous, and it depends on the strengths of these two countervailing forces. Hence, *after the actual informal disclosure*, *the average quality of completed projects may increase* (*if the publicity effect is stronger*) *or decrease* (*if the reputation effect is stronger*).

3 | EMPIRICAL SETTING

To evaluate the implications of mandated information disclosure on technology markets, we focus on the response of physician-firm collaboration in the American medical device industry to the enactment of the Sunshine Act, which was a significant part of the broader ACA of 2010. The Sunshine Act requires all pharmaceutical and medical device manufacturers to disclose any financial payment above $10 to licensed physicians and teaching hospitals. Whereas the Sunshine Act was initially passed in 2010, it was fully implemented only in 2014, after a period of debate and uncertainty about the procedures companies should enact for disclosing their collaborations with physicians.

Physician-firm (financial) connections have traditionally raised many concerns for both the public and policymakers. Close physician-firm connections might bias physicians' decisions regarding the use of particular medical devices (a decision that should be based exclusively on an objective assessment of the merit of the device and its fit to patients' conditions). Furthermore, the close connection between physicians and incumbent medical device companies might limit potential competition from new market entrants. The resulting lack of competition could, in turn, increase medical expenditure, which is already quite high in the United States.

Because of these issues, even before the enactment of the Sunshine Act, the US government had scrutinized the financial relationships between medical device manufacturers and physicians for several years. In 2005, five leading orthopedic companies[3] were investigated by the Department of Justice for improper payments to physicians. Furthermore, several US states[4] established information disclosure requirements for pharmaceutical and medical device companies before the federal government did so nationwide (Guo et al., 2019; Staman & Yeh, 2009). However, the Sunshine Act constitutes the first federal attempt to eliminate improper payments

[3]The firms were Biomet, DePuy Orthopedics unit of Johnson and Johnson, Smith and Nephew, Stryker Orthopedics, and Zimmer. The five companies accounted for 93% of the American hip and knee implant market at the time of the investigation.

[4]State legislation were enacted in Minnesota in 1993; in Vermont in 2001; District of Columbia, 2003; Maine, 2004; West Virginia, 2004; Massachusetts, 2008. It is worth noting that most of these laws imposed publicity rules only on pharmaceutical manufacturers or wholesale drug distributors—that is, medical device companies were not explicitly targeted. Upon closer examination of these laws, it appears that only Massachusetts explicitly includes medical device firms among the companies required to disclose their collaborations with physicians registered within the state and mandates the disclosure of full information about these collaborations. However, it is unclear whether also research collaborations should be disclosed. Furthermore, the fine for not compliance was quite limited ("no more than 5000 euros), especially if compared to the penalties introduced by the Sunshine Act (up to 1.15 million dollars). Hence, the deterring effect of this regulation is likely to be limited. In any case, we replicated our analysis to compare whether there is a differential effect of the Sunshine Act on physicians in Massachusetts versus those in other states. As expected, we found that the effect is significantly smaller for physicians in Massachusetts compared to those in other states (results available upon request).

from firms to physicians. Payments subject to reporting are comprehensive, including "general payments" for consulting, gifts, trips and entertainment, meals, education materials, grants, and charity; current or prospective ownership or investment interest, royalties, and licenses; and research payments for different types of research activities, including any research collaboration between firms and physicians.

The disclosed payment data are collected by the Center for Medicare and Medicaid Services (CMS). After inspecting and compiling the raw data, the CMS publishes a fully accessible dataset for each fiscal year. The first batch, including data from the second half of 2013, was completed and made public in 2014. The disclosed dataset is constructed at the individual payment level. Each payment entry includes the amount of money, targeted medical product, information on collaborating physicians and firms, and payment purpose. Failure to report can trigger fines ranging from $1000 to $10,000 per unreported payment with an annual maximum of $150,000. For *deliberate* failure to report, the fine increases from $10,000 to $100,000 per payment with a maximum penalty of $1 million.

Anecdotal evidence suggests that the improvement in the information environment determined by the Sunshine Act raised reputation concerns among physicians (Sullivan, 2018a). Indeed, physicians generally "regarded the Physician Payment Sunshine Act as a personal and professional threat to privacy and reputation" (Chimonas et al., 2017, p. 9), whereas "critics of disclosure suggest that these laws stigmatize physicians who maintain collaborative relationships with industry" (Chen et al., 2019, p. 441).[5] Sullivan (2018c) documents two cases of physicians who disclosed that they are taking measures to avoid appearing on the database. Nogah Haramati, MD and professor of clinical radiology at Albert Einstein College of Medicine requires manufacturers "to provide a written guarantee that he receives no value and won't appear in the database for any activity or conference call he participates in. If the manufacturer can't provide a guarantee, he pulls out". Robert Hitchcock MD, argues that "most physicians [...] will seriously rethink any collaboration they might have with drug companies". Moreover, he claims that "as a practicing physician, I really don't want my name on a list for having been to this CME [Continuing Medical Education conference] and gotten this amount of money from Pfizer and this amount from Schering-Plough. I know that I personally will no longer be attending CME that is sponsored like that."

Several aspects regarding the implementation of the Sunshine Act amplify the reluctance of physicians to collaborate with industry. On one side, the Sunshine Act required the disclosure of corporate expenses related to the dissemination of research results (Ratain, 2014). According to Mark Ratain, MD, a professor of medicine at the University of Chicago, "some investigators will choose not to participate in a publication effort that will be associated with a report of an imputed payment to CMS". He also argues that "some physicians may be reluctant to even engage in company-supported clinical trials because of potential stigmatization by CMS reports in the context of abstracts and publications."

On the other side, Morain et al. (2014) notice that the disclosure requirements may convey a distorted image of certain physician-industry relationships. In particular, "physicians conducting research involving donated drugs will have the monetary value of those drugs listed as 'research payments' within public databases". They provide an example under which an investigator enrolling just 10 patients would be reported as receiving $840,000 from a manufacturer

[5]It is also interesting to notice that even physicians in other countries, when confronted with the possibility of disclosing the payment from collaborations with industry, exhibit similar reputation concerns to their US counterparts, as they "report fears about losing their reputation due to disclosures" (Stoll et al., 2022, p. 1).

for the drugs used in the treatment, even though "donated drugs are intended for use by patients and do not provide direct monetary value to physician-investigators." Morain et al. (2014) conclude that "confusion over reporting for donated study drugs may have a chilling effect on physicians' willingness to participate in research, should physicians choose to avoid the appearance of financial relationships that raise the potential for misinterpretation."

Notably, reputation concerns are possibly particularly salient for physicians who are highly reputed such as for instance, physicians who, due to their achievements, are key opinion leaders. Indeed, Lichter (2015) warned that "industry advisors are suggesting that, as a result of the Sunshine Act, key opinion leaders will back away from industry to protect their reputations." This is echoed by Sullivan (2018b), noting that "the Sunshine Act may have a chilling effect on continued partnerships between firms and physicians at medical schools that have produced a great deal of discoveries and innovative therapies.

At the same time, the Sunshine Act clearly had the publicity effect we described in our theory. First, although some data on physician-firm collaboration could have been obtained, even before the Act, from sources such as published patent documents, this information—which still takes energy, time, and resources to collect—was likely to be incomplete since some projects—especially if not leading to any patentable inventions—are likely to remain secret and protected by nondisclosure agreements. Second, sometimes collaborations take time before producing patentable inventions, such that a long time might pass between the start of the collaboration and the disclosure of any publicly accessible information about it. The Sunshine Act made information about collaborations between firms and physicians immediately available (even when there was no patent related to that collaboration). Hence, all firms could assess, at any point in time, the pool of inventors potentially available and competent to work in a given research area. Overall, there is strong reason to believe that, thanks to the Sunshine Act, firms generally were better able to assess a larger pool of external inventors. This view is strongly reinforced by the opinions of firm managers. According to a survey of medical device firms conducted by Hodgson & Whitelaw (2012) just before the Sunshine Act was fully implemented,[6] surveyed firms planned to utilize the disclosed data to identify potential collaborators among physicians as well as promising technological areas.

4 | DATA AND METHODOLOGY

In order to track the collaborations between co-inventor physicians and firms in the medical device industry, and to assess their quality, we focus on publicly traded medical device companies operating in the United States and collect their innovation and financial data from 2005—5 years before the approval of the Sunshine Act, and about 10 years before its implementation—through 2018. Using the Compustat Global database, we first select publicly traded companies that have R&D expenditure data for at least two continuous years. We include multinational firms that manufacture or sell medical devices in the American market, even though they are not based in the United States.[7] There are several reasons why we only

[6]This information is reported on page 22 of the report:
https://images.forbes.com/forbesinsights/StudyPDFs/deloitte_ppsa_report.pdf

[7]Given the size of the U.S. market and the quality of U.S.-based biomedical researchers, many medical device firms based outside the U.S. conduct at least some of their R&D activity within the U.S. Some of this R&D can involve collaboration with external physicians.

focus on publicly traded companies. First, although some non-listed firms (especially small start-ups) have made nontrivial contributions to medical device innovation, publicly-traded firms still dominate the market in terms of employment and assets. Gravelle and Lowry (2016) show that 82% of assets are owned by 1% of firms in this industry. Second, by selecting publicly traded firms, we can easily collect data on a range of firm-level variables. In particular, we can easily gather firm financial data such as annual R&D expenditure, revenues, number of employees, and market value from the Compustat dataset. All data have been adjusted for inflation using the GDP deflator for the country in which the firm was based. We use market exchange rates to convert financial data reported by multinationals in a foreign currency into US dollars.

We measure collaborations between firms and physicians related to medical device technologies using patent data, collected from the Patent Examination Research Dataset (PatEx). The PatEx dataset contains all published patent applications filed at USPTO, along with their initial US patent classes. This allows us to select all patents filed to USPTO that belong to USPTO-identified medical device patent classes.[8] We focus on all patent applications to USPTO, instead of patents granted by the USPTO, for two reasons. First of all, using patent applications is more appropriate than patent grants for the purposes of measuring physician-firm collaborations, since some collaborations may have produced patent applications that were not granted. Second, the use of patent applications helps mitigate the truncation problem which would have potentially biased our estimates for the several years at the end of our observation window. Given that the average pendency lag (time between patent application and grant) exceeds 30 months, patents applied for in 2018 might not be granted until 2021 and therefore will not be included in our sample if we use patent grants. The omission of patent applications awaiting grant decisions will lead to an underestimate of patent counts in the final years, which is avoided by using patent applications.

To match the publicly traded companies with patent assignees, we first use the crosswalk file provided by Bessen (2009), which links assignee identification from the NBER patent data set with the gvkey number, the unique firm identifier from Compustat. This crosswalk file reflects ownership changes via mergers, acquisitions, or spin-offs. However, Bessen's list is not updated to 2018, the end year of our observation. For the rest of the unidentified medical device patents, we collect information on assignees from USPTO PatentView data and manually match them with a list of firm names which is obtained by standardizing the Compustat firm names and adding ownership changes using LexisNexis Corporate Affiliations. This yields 49,288 medical device patent applications filed by 275 publicly traded firms to USPTO from 2005 to 2018.

We match the inventors named in patents with a comprehensive physician list provided by the National Plan and Provider Enumeration System (NPPES) dataset in order to identify patents co-invented by firms and independent healthcare professionals. The NPPES data, available after 2004, provide full names, practice locations, medical specialties, and license number(s) for any physician with a National Provider Identifier, a unique identification number for licensed physicians in the United States. Compared with other databases used to identify physicians, the NPPES data covers more types of licensed healthcare providers, such as dentists and nurse practitioners, who are also important users of medical devices (DesRoches et al., 2015). Based on the method used by Chatterji and Fabrizio (2016), we identify physician-inventors by matching, sequentially, on first and last names, middle names if applicable, and locations (combined statistical area, or CBSA, and county). Patents issued by firms in our sample that include at least

[8] https://www.uspto.gov/web/offices/ac/ido/oeip/taf/meddev.htm.

one independent healthcare provider as a co-inventor constitute our proxy for measuring collaborations between firms and physicians. For assessing the value of a collaboration, we use the number of forward citations received by a patented co-invention, received within 3 years after the patent grant. We measure citations received during this short interval in order to account for the fact that more recently generated patents will receive fewer citations than older ones, complicating the measurement of invention quality since the implementation of the Sunshine Act.

In the context of our study, we are particularly focused on the component of a physician's reputation that serves as a signal of her value as a potential co-inventor and, at the same time, is related to the social evaluation relevant peers have of the focal physicians. Academic publications in medical journals constitute an appropriate reputation measure. On one side, companies might use them to identify experts for possible collaborations. On the other side, a physician who has invested decades of effort in accumulating a portfolio of scientific publications in top-rated journals has much to lose if her readers or academic peers begin to suspect that her conclusions are influenced by her corporate sponsors, that results in unfavorable to corporate sponsors are being quietly buried, or that the data provided by corporate collaborators is incomplete or biased. Physicians with no or few academic publications have less to lose from these questions or concerns.

In any given year, we measure physicians' reputations based on the cumulative number of publications (weighted by the impact factors of the journal in which the article was published) from 1990 until that year. There might be a relationship between collaborations with industry (affected by the Sunshine Act) and publications, as several studies are financed by private firms. Hence, to alleviate any endogeneity concern, after 2010 (including) our measure of reputation is time-invariant. We categorize physicians into two disjoint groups: "type-R physicians" are those with at least one publication, whereas "type-N physicians" are those who do not have any publications.[9] Publication data are retrieved from PubMed, which is a publicly available database maintained by the US National Library of Medicine, containing over 14 million articles from almost 5000 journals published in the United States and more than 70 other countries from 1950 to the present. We gathered these data using PubHarvester, an open-source software tool (Azoulay et al., 2017).

To assess the effect of the Sunshine Act on sellers and buyers, we use two datasets. The first dataset is a balanced panel of 3712 physicians with data on their basic demography and co-patenting from 2005 to 2018. We use this dataset for testing the prediction states that the effect of an improvement in the information environment on the number of collaborations undertaken by type-R versus type-N physicians. Panel A of Table 1 shows the summary statistics of our major dependent variables. The second dataset comprises 3050 observations at the firm-patent type (co-invented vs. in-house)-year level. We utilize this dataset to assess the connection between advancements in the information environment and alterations in the overall quantity and quality of research collaboration output. As panel B of Table 1 shows, although co-invented patents with physicians are a minority of all medical device patents filed by sample firms, the average 3-year forward citations received by these co-invented patents are higher than that the citations of in-house patents. This implies that physicians' research input, though limited in the quantity, might be important for the most valuable and innovative patents generated by the sample firms.

[9]Overall, 10,616 physician-year observations are classified as referring to type-R inventors, and 41,352 classified as referring to type-N inventors.

TABLE 1 Summary statistics.

	#Observations	Mean	Std. dev.	Min	Max
Panel A physician-year level					
Physician co-invented patents	51,968	0.20	0.71	0	35
Co-invented patents by type-R physicians	10,616	0.14	0.55	0	15
Co-invented patents by type-N physicians	41,352	0.21	0.75	0	35
Physician experience	51,968	6.40	7.92	0	45
Co-invented patents with disreputable firms	51,968	0.16	0.65	0	35
Co-invented patents with reputable firms	51,968	0.04	0.30	0	12
Panel B firm-patent-type-year level					
Physician co-invented patents	3050	1.47	5.30	0	81
In-house medical device patents	3050	17.05	58.09	0	627
3-year forward citations of physician-co-invented patents	754	3.44	10.46	0	141
3-year forward citations of in-house medical device patents	1829	3.40	8.11	0	94

Note: Observation units are physician-year and firm-patent-type for panels A and B, respectively. Physician experience is the number of years from the first year when the focal physician filed a patent to the focal year *t*.

5 | RESULTS

5.1 | Effect on idea sellers

Based on our conceptual framework, we expect that the public information made available by the Sunshine Act will reduce collaborative projects by "type-R" or highly reputed physicians, while increasing collaborative projects by "type-N" or no-reputation physicians. To provide some preliminary evidence of the hypothesized effects, we start from a nonparametric graphical analysis and univariate difference-in-differences analysis. In Figure 1 we depict the evolution in the number of collaborations for type-R and type-N physicians. Before the enactment of the Sunshine Act, both the levels and the trend in terms of the number of co-patents look similar across the two groups of physicians, even if type-R physicians seem to reduce the number of collaborations about 2 years before the Sunshine Act was actually enacted. This might be due to some sort of anticipation effect, related to the timing of the Sunshine Act discussion and enactment. This Act was first proposed in 2007 by two US senators Charles Grassley, a Republican Senator from Iowa, and Herb Kohl, a democratic senator from Wisconsin. The act was "so named because it aims to shine a much-needed ray of sunlight on a situation that contributes to the exorbitant cost of health care," according to cosponsor Senator Charles Schumer" (Campbell, 2007). Although an anticipation effect cannot be completely ruled out, our findings support our theory that it is primarily after the passage of the Sunshine Act in 2010 that type-R physicians begin to withdraw from collaborations. This behavior may be attributed to their desire to avoid damaging their reputation if their identity and compensation are disclosed in the federal database. At the same time, type-N physicians start getting involved in more collaborations.

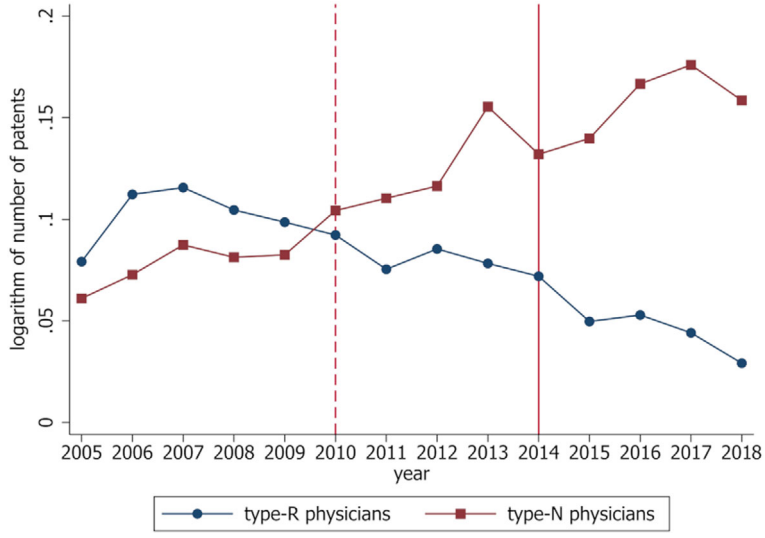

FIGURE 1 Effect of the Sunshine Act on the number of co-invented patents made by type-R and type-N physicians. *Y*-axis shows the logarithm of annual average of co-invented patents made with the two types of physicians. *X*-axis shows the year. Before 2010, physician reputation is measured as the number of publications (weighted by the journal impact factors) the physician authored from 1990 to year $t-1$ (therefore changing annually); after 2010, physician reputation is measured by the total number of weighted publications authored by the focal physician from 1990 to 2009 (therefore time invariant). The baseline is year 2009.

This trend accelerates after 2014, when information about former collaborations became publicly available.

Table 2 shows the average number of collaborations undertaken by type-R and type-N physicians, before and after the Sunshine Act. Given that the Sunshine Act was implemented in two steps (enacted in 2010, and fully implemented in 2014), we consider two different "post" periods: after 2010, and after 2014. Regardless of which post period we consider, we observe that, consistent with our model, the number of collaborations between type-N physicians and firms increases, whereas the number of collaborations between type-R physicians and firms decreases.

The previous findings are promising and provide preliminary support for our theory. However, they need to be corroborated with multivariate regression analyses.

Thus, we estimate (via both a Poisson and an OLS log-linear model[10]) the following equation, where the dependent variable is the number of co-patents realized by a physician:

$$Y_{it} = \tau \text{TypeRphysician}_{it} + \beta(\text{TypeRphysician}_{it} * \text{Post}_t) + \varphi \text{Post}_t + cX_{it} + \varepsilon_{it}, \quad (1)$$

where i and t denote individual physician and year, respectively. As we said before, given that the Sunshine Act was implemented a few years after its enactment, as Post_t we consider two different dummy variables: (a) a dummy variable equal to 1 for any year after the enactment of the Sunshine Act (2010 and later); (b) a dummy variable equal to 1 for any year after

[10]All our results are retrieved when using an inverse hyperbolic sine transformation of our dependent variable (table available upon request).

TABLE 2 Univariate difference-in-differences analysis on the number of co-patents.

	Co-invented patents by type-R physicians	Co-invented patents by type-N physicians	Difference	*p*-value for the difference
Before and after 2010				
Before 2010	0.174	0.137	0.037	.004
After 2010	0.109	0.248	−0.139	.000
After 2010 versus Before 2010			−0.176	.000
	Co-invented patents by type-R physicians	**Co-invented patents by type-N physicians**	**Difference**	***p*-value**
Before and after 2014				
Before 2014	0.166	0.173	−0.007	.594
After 2014	0.078	0.278	−0.199	.000
After 2014 versus Before 2014			−0.192	.000

Note: * the difference is type-R physicians minus type-N physicians. Standard errors are clustered at the physician level.

the information about firm-physician collaborations went public (2014 and later). X_{it} is a vector of control variables, including physician fixed effects and the logarithm of physician's inventing experience, measured by the number of years since the focal physician filed patents for the first time. Following Abadie et al. (2017), we cluster the standard errors at the physician level, since based on our theory, the effect of the treatment might change according to the characteristics of the physician.

The coefficient of interest is β, and we expect it to be significantly negative. This would imply that, relative to type-N physicians, type-R physicians will start collaborating less after the enactment of the Sunshine Act. However, based on our theory, we also expect: (a) φ, to be positive, as type-N physicians will start collaborating more than they did in the period preceding the Sunshine Act; and (b) $(\beta+\varphi)$ to be negative, as type-R physicians will collaborate less than before. Also, we expect β to be immediately negative after 2010 (when the Sunshine Act was approved but not yet implemented, but physicians were already reacting to the possible future implementation), and to become even more negative after 2014 (when the Sunshine Act was implemented and information was actually disclosed).

Table 3 shows the results of the estimation of (1). In particular, column 1 shows that the collaborative patents by type-R physicians declined after the Sunshine Act was enacted in 2010, by around 79% (p-value = .000),[11] relative to type-N physicians. When we disentangle the effect of the Sunshine Act in the preimplementation versus postimplementation phase, we find that, immediately after the approval and before the implementation, the number of collaborations done by type-R physicians relative to type-N physicians decreases by 67% (p-value = .000), and

[11]This number and the following interpretive numbers are calculated using $e^{\beta}-1$, where β is the coefficient of interaction term of physician reputation dummy and post-shock dummy. For example, in this case, β equals -1.581 according to column 1 of Table 3, and $e^{-1.581}-1=-0.79$. Because the interaction term can only take 0 or 1 as the value, this implies that when the interaction term changes from 0 to 1, which is the effect of the Act on type-R physicians after 2010 relative to type-N physicians, the number of co-invented patents made by type-R physicians decreases by 79% relative to type-N physicians.

TABLE 3 Effect of the Sunshine Act on the number of co-invented patents by type-R versus type-N physicians.

	Physician co-patents			Physician co-patents (log)		
Dependent variable	**(1) Poisson**	**(2) Poisson**	**(3) Poisson**	**(4) OLS**	**(5) OLS**	**(6) OLS**
Type-R physician*post2010	−1.674		−1.205	−0.186		−0.147
	(0.098)		(0.117)	(0.008)		(0.009)
	.000		*.000*	*.000*		*.000*
Type-R physician*post2014		−1.559	−0.932		−0.145	−0.071
		(0.113)	(0.141)		(0.008)	(0.009)
		.000	*.000*		*.000*	*.000*
post2010	0.641		0.595	0.070		0.062
	(0.061)		(0.062)	(0.004)		(0.004)
	.000		*.000*	*.000*		*.000*
post2014		0.480	0.341		0.065	0.048
		(0.066)	(0.061)		(0.005)	(0.005)
		.000	*.000*		*.000*	*.000*
Type-R physician	−1.008	−1.394	−0.985	−0.043	−0.084	−0.040
	(0.202)	(0.193)	(0.196)	(0.006)	(0.005)	(0.006)
	.000	*.000*	*.000*	*.000*	*.000*	*.000*
Physician experience	0.060	0.032	−0.100	−0.002	−0.008	−0.021
	(0.049)	(0.050)	(0.061)	(0.004)	(0.004)	(0.004)
	.220	*.526*	*.101*	*.646*	*.050*	*.000*
Constant	−1.331	−1.044	−1.187	0.098	0.125	0.112
	(0.076)	(0.072)	(0.078)	(0.005)	(0.005)	(0.005)
	.000	*.000*	*.000*	*.000*	*.000*	*.000*
Physician fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,968	51,968	51,968	51,968	51,968	51,968
R-squared				0.167	0.163	0.169
Log-likelihood	−24,364	−24,486	−24,270			
Number of physicians	3712	3712	3712	3712	3712	3712

Note: Columns 1–3 are Poisson pseudo-likelihood fixed effects models, and columns 4–6 are log-linear fixed effects models. Before 2010, physician reputation is measured by the number of publications (weighted by the journal impact factors) the physician authored from 1990 to year $t-1$ (therefore changing annually); after 2010 (including), physician reputation is measured by the total number of weighted publications authored by the focal physician from 1990 to 2009 (therefore time-invariant). *Type-R physicians* are physicians whose physician reputation measure is positive at year *t*. *Type-N physicians*, physicians are physicians whose reputation measure is zero at year *t*. *Post2010* and *post2014* are dummy variables taking value of one of the year is, respectively, after 2010 or 2014. *Physician experience* is the number of years from the year the physician filed the first patent to year *t*. Robust standard errors, clustered by a physician, are shown in parentheses; *p*-value in italics.

after the information was made public, in 2014, the co-invented patents by type-R physicians decline even further, by around 61% (p-value = .000) (column 3). Estimations with the same specifications using log-linear models (columns 4–6) yield similar results.

To get a more comprehensive understanding of the effect of the Sunshine Act over time, we assess the dynamics of the effect by substituting the $Post_t$ dummy with a series of year dummies. Figure 2 shows how, before the implementation of the Sunshine Act, type-R and type-N physicians were collaborating at the same rate. However, immediately after the implementation of the Act, the number of collaborations starts diverging significantly.

We conduct several robustness checks to ensure the validity of our major findings. First, the estimated effect of the Sunshine Act on co-invented patents made by type-R physicians relative to type-N physicians could be sensitive to the zero-publication threshold used for defining high-reputation (type-R) physicians versus low-reputation (type-N) physicians. So, to further ensure the robustness of our results, we create a continuous measure of reputation, which is the number of publications authored by the physician.[12] The results, shown in Table 4, indicate that the interaction term of the post-Sunshine Act dummy and the continuous measure for physicians' reputations is negative. This suggests that physicians who, based on their past publications, had stronger reputations are less likely to collaborate with firms and create fewer co-invented patents following the Sunshine Act. A more detailed look at the estimation results shows that a 1% increase extra publication received by a physician in the pre-shock period is associated with a 0.26% reduction in co-patenting activity after 2010 (p-value = .000). Second, we show that our findings are robust when using a time-varying measure of reputation, which takes into account the cumulative number of publications of an inventor up to a given year, including those after 2010 (cf., Table A1 and Figure A1).

Finally, one could argue that, despite being useful indicators, publications might be only loosely correlated with the usefulness of a particular physician as a co-inventor on a particular medical device. In this respect, patenting data—which are publicly available and were observable by potential buyers even before the Sunshine Act—may provide a more reliable signal. Therefore, we use a patent-based measure of reputation. More in detail, in any given year, we measure physicians' reputations as the number of forward citations received by all their patents, in the previous 5-year window (when the Sunshine Act is enacted). As the number of citations might (also) depend on the possibility to collaborate with medical device firms, the Sunshine Act might affect our measure of physicians' reputations. Hence, to alleviate any endogeneity concern, for any year after 2010, our measure of reputation is fixed and is based on the number of citations received between 2005 and 2010. Table A2 and Figure A2 show the results. It is evident that before 2010, the year when the Sunshine Act was approved, the two groups of physicians do not differ significantly in terms of the number of co-patents they made with medical device firms. However, after 2010, the type-R physicians started to experience a continuous decrease in the quantity of co-patents compared with type-N physicians.

[12]Similar to the main results in Table 3, the continuous reputation measure is calculated in two steps: for any year before 2010, we count the logarithm of one plus the total number of publications authored by the physician during the five-year window before year t; after 2010 (including), we count the logarithm of one plus the total number of publications authored by the physician from 1990 to 2009.

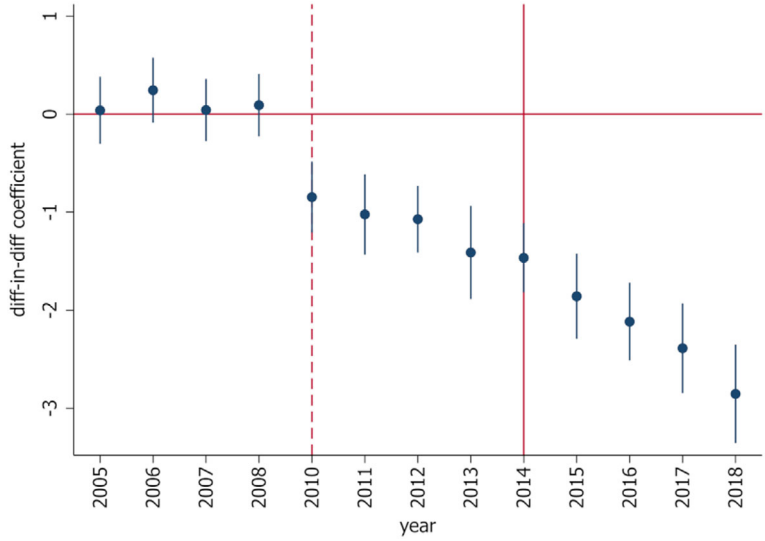

FIGURE 2 Effect of the Sunshine Act on the number of co-invented patents made by type-R versus type-N physicians. The figure plots the coefficients of interaction terms of a series of year dummies with a dummy indicating type-R physicians. The dependent variable is the number of co-patents made by physicians and firms. Poisson fixed effects models are used. *Y*-axis shows the DID point estimations with vertical bars showing the 95% confidence intervals for each point estimate. *X*-axis shows the year. Before 2010, physician reputation is measured by the number of publications (weighted by the journal impact factors) the physician authored from 1990 to year $t - 1$ (therefore changing annually); after 2010, physician reputation is measured by the total number of weighted publications authored by the focal physician from 1990 to 2009 (therefore time-invariant). The baseline is year 2009.

5.2 | Evidence of the reputation and publicity mechanisms

The decrease in the number of collaborations between type-R versus Type-N physicians might be due to both the reputation and the publicity mechanism. Hence, it is important to provide evidence that the two effects are *both* operating and driving our findings.

5.2.1 | Reputation mechanism

If the reputation mechanism is operating, the decrease in collaborations of type-R physicians (vis-à-vis type-N physicians) following the Sunshine Act should be especially salient when those collaborations involve firms with dubious reputation. Indeed, especially highly reputed physicians might be concerned about being perceived (by their peers or other audiences) as associated with disreputable industry partners. So, they will avoid any collaboration with those partners if information on collaborations is publicly disclosed. In the context of our work, we define a firm as "disreputable" if its products have been recalled from the market because considered to be in violation of the laws administered by the FDA—data on product recalls are gathered from the FDA website. Specifically, we measure firm "reputability" using the number of products recalled by the focal firm from 2005 to 2009 and we define disreputable firms as

TABLE 4 Effect of the Sunshine Act on the number of co-invented patents by physicians (a continuous measure of reputation).

	Physician co-patents			Physician co-patents (log)		
Dependent variable	**(1) Poisson**	**(2) Poisson**	**(3) Poisson**	**(4) OLS**	**(5) OLS**	**(6) OLS**
Physician reputation*post2010	−0.344		−0.239	−0.039		−0.031
	(0.027)		(0.030)	(0.002)		(0.002)
	.000		*.000*	*.000*		*.000*
Physician reputation*post2014		−0.338	−0.216		−0.031	−0.015
		(0.029)	(0.034)		(0.002)	(0.002)
		.000	*.000*		*.000*	*.000*
post2010	0.570		0.528	0.066		0.058
	(0.058)		(0.060)	(0.004)		(0.004)
	.000		*.000*	*.000*		*.000*
post2014		0.443	0.328		0.061	0.046
		(0.065)	(0.061)		(0.005)	(0.005)
		.000	*.000*		*.000*	*.000*
Physician reputation	−0.345	−0.440	−0.336	−0.012	−0.020	−0.011
	(0.048)	(0.052)	(0.046)	(0.001)	(0.001)	(0.001)
	.000	*.000*	*.000*	*.000*	*.000*	*.000*
Physician experience	0.066	0.042	−0.088	−0.002	−0.007	−0.021
	(0.048)	(0.050)	(0.061)	(0.004)	(0.004)	(0.004)
	.171	*.399*	*.146*	*.561*	*.059*	*.000*
Constant	−1.254	−0.995	−1.119	0.100	0.125	0.114
	(0.073)	(0.072)	(0.076)	(0.005)	(0.005)	(0.005)
	.000	*.000*	*.000*	*.000*	*.000*	*.000*
Physician fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,968	51,968	51,968	51,968	51,968	51,968
R-squared				0.165	0.162	0.167
Log-likelihood	−24,408	−24,491	−24,321			
Number of physicians	3712	3712	3712	3712	3712	3712

Note: Columns 1–3 are Poisson pseudo-likelihood fixed effects models, and columns 4–6 are log-linear fixed effects models. Physician-fixed effects are included. We measure *physician reputation* as the following: before 2010, we calculate the measure for each year t by using the number of publications (weighted by the journal impact factors) authored by the focal physician from 1990 to year $t-1$; after 2010 (including), we use the number of weighted publications authored by the focal by the focal physician from 1990 to 2009, which is time-invariant. To address the skewness of this measure, we take logarithm of the raw measure. *Post2010* and *post2014* are dummy variables taking value of one of the year is, respectively, after 2010 or 2014. *Physician experience* is a continuous variable measured by the number of years from the first year the focal physician filed a patent to the year t. Robust standard errors, clustered by a physician, are shown in parentheses; p-value in italics.

those with positive number of recalls. We assess the effect of the Sunshine Act on the collaborations of type-R (vs. type-N) physicians with disreputable firms, on one side, and reputable firms, on the other side. We prefer a log-linear model over a Poisson model because the latter discards

TABLE 5 Effect of the Sunshine Act on the number of co-invented patents by type-R versus type-N physicians, with disreputable versus reputable firms.

	Physician co-patents with disreputable firms (log)			Physician co-patents with reputable firms (log)		
Dependent variable	**(1) OLS**	**(2) OLS**	**(3) OLS**	**(4) OLS**	**(5) OLS**	**(6) OLS**
Type-R physician*post2010	−0.146		−0.114	−0.042		−0.034
	(0.008)		(0.008)	(0.004)		(0.004)
	.000		*.000*	*.000*		*.000*
Type-R physician*post2014		−0.114	−0.056		−0.032	−0.015
		(0.008)	(0.008)		(0.004)	(0.004)
		.000	*.000*		*.000*	*.000*
post2010	0.056		0.050	0.014		0.012
	(0.004)		(0.004)	(0.002)		(0.002)
	.000		*.000*	*.000*		*.000*
post2014		0.051	0.037		0.014	0.010
		(0.005)	(0.005)		(0.002)	(0.002)
		.000	*.000*		*.000*	*.000*
Type-R physician	−0.032	−0.065	−0.030	−0.011	−0.019	−0.010
	(0.006)	(0.005)	(0.006)	(0.003)	(0.003)	(0.003)
	.000	*.000*	*.000*	*.001*	*.000*	*.002*
Physician experience	−0.002	−0.006	−0.017	0.001	−0.001	−0.004
	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
	.496	*.081*	*.000*	*.706*	*.439*	*.078*
Constant	0.077	0.099	0.088	0.021	0.027	0.024
	(0.004)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)
	.000	*.000*	*.000*	*.000*	*.000*	*.000*
Physician fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,968	51,968	51,968	51,968	51,968	51,968
R-squared	0.181	0.178	0.183	0.235	0.234	0.235
Number of physicians	3712	3712	3712	3712	3712	3712

Note: Columns 1–3 use the logarithm of physician co-patents with disreputable firms plus one as the dependent variable; columns 4–6 use the logarithm of physician co-patents with reputable firms plus one as the dependent variable. Physician-fixed effects are included. Disreputable firms are those firms that have recalled medical device products from 2005 to 2009. *Post2010* and *post2014* are dummy variables taking value of one of the year is, respectively, after 2010 or 2014. Physician experience is a continuous variable measured by the number of years from the first year the focal physician filed a patent to the year *t*. Robust standard errors, clustered by a physician, are shown in parentheses; *p*-value in italics.

several observations when physician-fixed effects are included. Table 5 shows that, as expected, the decrease in collaborations is particularly substantial for collaborations with disreputable firms (p-value = .000). As demonstrated in Table A3, the Poisson model yields substantially similar results. Figure 3 confirms that the gap in collaborations between type-R and type-N physicians determined by the Sunshine Act is especially relevant for collaborations with

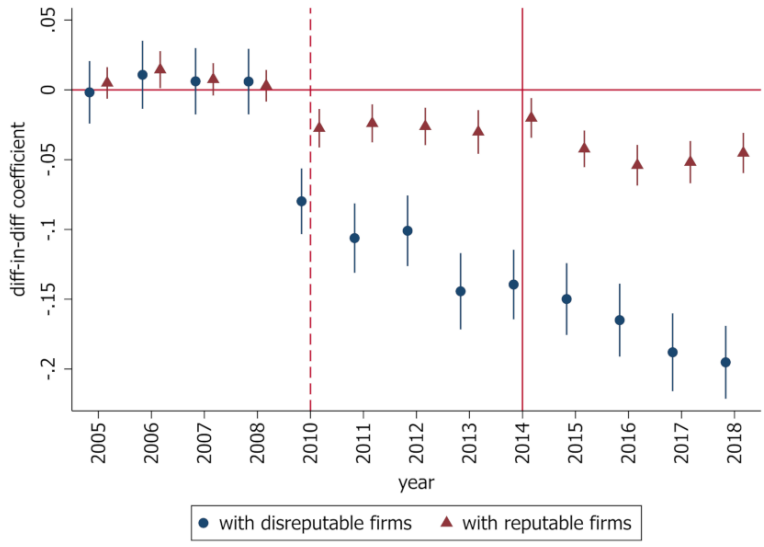

FIGURE 3 Effect of the Sunshine Act on the number of co-invented patents by type-R versus type-N physicians, with reputable and disreputable partners. The figure plots the coefficients of interaction terms of a series of year dummies with a dummy variable indicating whether the physician is a type-R physician. The dependent variable is the number of co-patents made by physicians with reputation-disreputable firms (blue circles) and with reputation-reputable firms (red triangles). OLS fixed effects models are used. *Y*-axis shows the DID point estimations with vertical bars showing the 95% confidence intervals for each point estimate. *X*-axis shows the year. The baseline is year 2009.

disreputable industry partners and suggests this gap starts materializing immediately after the Sunshine Act is enacted.[13]

Regarding the reputation mechanism, it is reasonable to assume that inventors' reputation may have a price, meaning that type-R inventors may be willing to trade their reputation for monetary compensation. Thus, in the context of our paper, type-R physicians, even after the implementation of the Sunshine Act, may still consider collaborating with medical device firms in exchange for higher financial returns. To determine whether this is the case, we analyzed how the propensity to collaborate changes according to partner profitability in Table A4. Our findings suggest that the decline in collaborations of type-R physicians is less (more) salient when those collaborations involve more (less) profitable industry partners—define as those companies whose profitability per product line is above (below) the median.

5.2.2 | Publicity mechanism

A straightforward implication of the publicity effect is that type-N physicians should start collaborating with firms they have not collaborated with before. Indeed, based on our theoretical model, the incentive for type-N physicians to incur the participation cost (to enter the pool of potential collaborators) increases immediately after the Sunshine Act was passed. Thus, we

[13]This result also holds if we consider as "disreputable" firms in the top 25% of the product recall distribution, or in the top 25% of the *ratio* between product recalls and product lines (results available upon request).

TABLE 6 Effect of the Sunshine Act on the likelihood for physicians to work with a new firm, type-R versus type-N physicians.

	Work with new firms					
Dependent variable	**(1) Logit**	**(2) Logit**	**(3) Logit**	**(4) LPM**	**(5) LPM**	**(6) LPM**
Type-R physician*post2010	−2.509		−1.902	−0.185		−0.143
	(0.098)		(0.151)	(0.006)		(0.007)
	.000		*.000*	*.000*		*.000*
Type-R physician*post2014		−2.495	−1.335		−0.145	−0.073
		(0.141)	(0.189)		(0.005)	(0.006)
		.000	*.000*		*.000*	*.000*
post2010	0.958		0.884	0.080		0.066
	(0.052)		(0.051)	(0.004)		(0.004)
	.000		*.000*	*.000*		*.000*
post2014		1.333	1.103		0.117	0.100
		(0.061)	(0.060)		(0.005)	(0.005)
		.000	*.000*		*.000*	*.000*
Type-R physician	−1.424	−1.879	−1.361	−0.063	−0.102	−0.056
	(0.164)	(0.134)	(0.144)	(0.005)	(0.004)	(0.005)
	.000	*.000*	*.000*	*.000*	*.000*	*.000*
Physician experience	−0.459	−0.787	−0.990	−0.040	−0.069	−0.084
	(0.047)	(0.046)	(0.044)	(0.003)	(0.003)	(0.004)
	.000	*.000*	*.000*	*.000*	*.000*	*.000*
Constant				0.126	0.174	0.160
				(0.004)	(0.004)	(0.004)
				.000	*.000*	*.000*
Physician fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,968	51,968	51,968	51,968	51,968	51,968
Log-likelihood	−10,785	−10,691	−10,502			
R-squared				0.044	0.048	0.055
Number of physicians	3712	3712	3712	3712	3712	3712

Note: Columns 1–3 are logit fixed effects model, and columns 4–6 are linear probability model (LPM). The dependent variable is a dummy variable that takes one of the focal physician works with a new firm in year *t*. Before 2010, physician reputation is measured by the number of publications (weighted by the journal impact factors) the physician authored from 1990 to year $t-1$(therefore changing annually); after 2010 (including), physician reputation is measured by the total number of weighted publications authored by the focal physician from 1990 to 2009 (therefore time-invariant). *Type-R physicians* are physicians whose physician reputation measure is positive at year *t*. *Type-N physicians*, physicians are physicians whose reputation measure is zero at year *t*. *Post2010* and *post2014* are dummy variables taking value of one of the year is, respectively, after 2010 or 2014. *Physician experience* is the number of years from the year the physician filed the first patent to year *t*. Robust standard errors clustered by a physician, shown in parentheses; *p*-value in italics.

expect that since 2010 type-N physicians (vs. type-R physicians) should experience a higher probability of collaboration with a partner they have not collaborated with before. Table 6 and Figure 4 confirm this prediction. It turns out the Sunshine Act increases the probability of

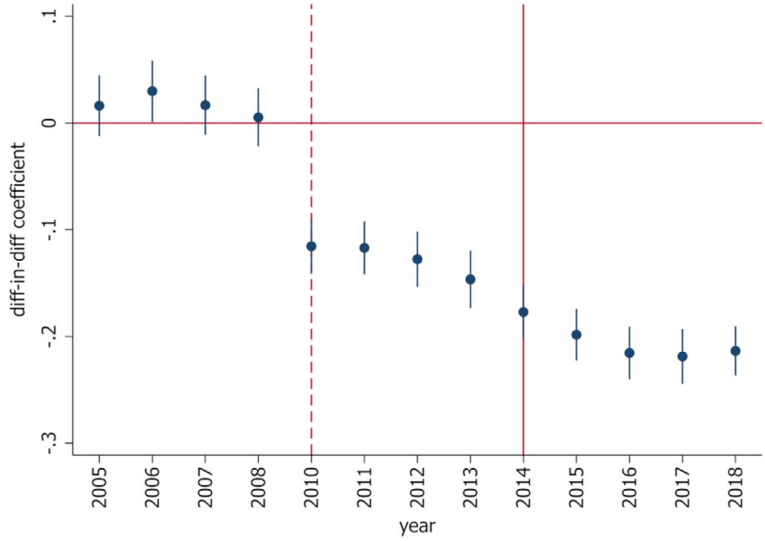

FIGURE 4 Effect of the Sunshine Act on collaborations with new firms by type-R versus type-N physicians. The figure plots the coefficients of interaction terms of a series of year dummies with a dummy variable indicating whether the physician is a type-R physician. The dependent variable is a dummy variable that takes one of the focal physician works with a new firm in year *t*. A linear fixed effects model is used. *Y*-axis shows the DID point estimations with vertical bars showing the 95% confidence intervals for each point estimate. *X*-axis shows the year. The baseline is year 2009.

collaborating with a new firm for type-N but not for type-R physician—as the magnitude of the positive coefficient for *post2010* (*post2014*) is lower than the negative coefficient of the interaction between *post2010* (*post2014*) with the dummy identifying type-R inventors.

5.3 | Effect on idea buyers

Apart from comparing type-R physicians with type-N physicians, we examine the effect of the Sunshine Act on the innovative performance of buyers, in terms of both quantity and quality of their patented inventions sourced by physicians. When describing our conceptual framework, we stated that the effect of more information on the overall quantity of co-developed innovations is in principle ambiguous. Indeed, it depends on whether the decline in projects developed by type-R inventors (which, as we have shown tend to leave the market immediately after the Sunshine Act approval in 2010) outweighs the increase in projects developed by type-N inventors. Therefore, the empirical assessment of the net impact of the Sunshine Act on the number of collaborations is quite relevant.

Using the in-house patents of sample firms as the reference group (to get rid of any trend affecting medical device innovations in general), we estimate the change in the number of co-patents relative to the in-house patents after the Sunshine Act by employing the following specification:

$$Y_{ijt} = \alpha_j + \beta\left(\text{CoPatent}_{ij} * \text{Post}_t\right) + \varphi \text{Post}_t + cX_{jt} + \varepsilon_{ijt}. \quad (2)$$

TABLE 7 Effect of the Sunshine Act on the number of physician co-invented patents versus in-house medical-device patents.

	Number of patents			Number of patents (log)		
Dependent variable	**(1) Poisson**	**(2) Poisson**	**(3) Poisson**	**(4) OLS**	**(5) OLS**	**(6) OLS**
Physician co-patent*post2010	0.410		0.238	0.204		0.074
	(0.109)		(0.100)	(0.039)		(0.033)
	.000		*.017*	*0.000*		*.026*
Physician co-patent*post2014		0.490	0.376		0.292	0.253
		(0.102)	(0.095)		(0.042)	(0.038)
		.000	*.000*		*.000*	*.000*
post2010	−0.109		0.086	−0.104		0.029
	(0.086)		(0.064)	(0.036)		(0.032)
	.205		*.176*	*.004*		*.354*
post2014		−0.407	−0.446		−0.266	−0.277
		(0.082)	(0.062)		(0.037)	(0.034)
		.000	*.000*		*.000*	*.000*
Physician co-patent	−2.722	−2.598	−2.722	−1.116	−1.081	−1.116
	(0.146)	(0.121)	(0.146)	(0.071)	(0.066)	(0.071)
	.000	*.000*	*.000*	*.000*	*.000*	*.000*
Log(revenues) ($t-1$)	0.006	0.020	0.010	0.005	0.012	0.008
	(0.019)	(0.019)	(0.020)	(0.007)	(0.008)	(0.008)
	.766	*.290*	*.601*	*.486*	*.116*	*.283*
Log(R&D) ($t-1$)	0.099	0.152	0.139	0.026	0.034	0.030
	(0.067)	(0.086)	(0.075)	(0.014)	(0.016)	(0.015)
	.144	*.077*	*.063*	*.065*	*.030*	*.040*
Constant	3.912	3.512	3.637	1.330	1.297	1.309
	(0.407)	(0.482)	(0.433)	(0.055)	(0.056)	(0.057)
	.000	*.000*	*.000*	*.000*	*.000*	*.000*
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6050	6050	6050	6100	6100	6100
#Firms	266	266	266	271	271	271
Log-likelihood				0.750	0.753	0.754
R-squared	−14,283	−13,582	−13,512			

Note: Columns 1–3 are Poisson pseudo-likelihood fixed effects models; columns 4–6 are log-linear fixed effects models. Physician co-patents is a dummy variable equal to 1 if the patent is a medical device patent co-invented with physicians. The reference group is in-house medical device patents, not co-invented with physicians. The analysis unit is patent-type-firm-year. *Post2010* and *post2014* are dummy variables taking value of one of the year is, respectively, after 2010 or 2014. Firm fixed effects are included. When using the Poisson model, a few observations are dropped. Robust standard errors, clustered by firm, are shown in parentheses; *p*-value in italics.

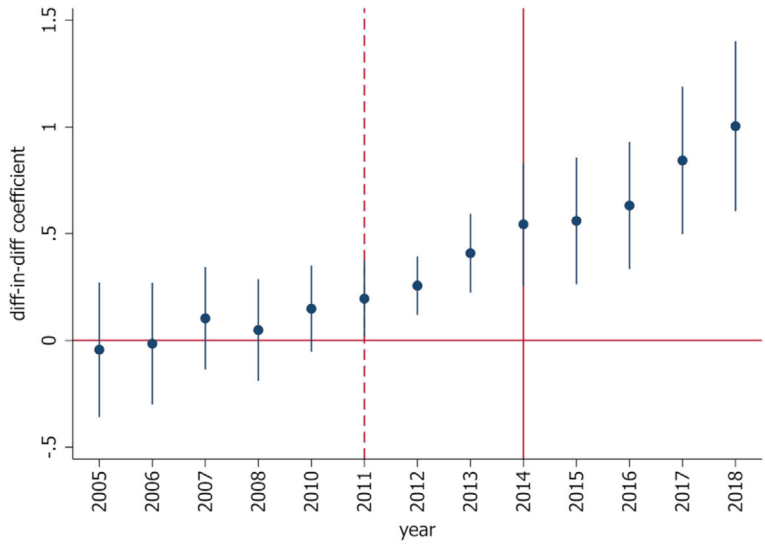

FIGURE 5 Effect of the Sunshine Act on the number of co-patents versus in-house patents made by medical device firms. The figure plots the coefficients of interaction terms of a series of year dummies with a dummy indicating physician co-invented patents. The dependent variable is the number of patents. Poisson fixed effects models are used. *Y*-axis shows the diff-in-diff point estimations with vertical bars showing the 95% confidence intervals for each estimation. *X*-axis shows the year. The baseline is year 2009.

The analysis is performed at patent-type-firm-year level, thus i denotes the patent type (physician co-invented patents or in-house patents), j denotes firm j and year t is denoted by t. Each observation is patent type i, firm j, and year t. Specifically, for each firm j at year t, there are two observations: observation of physician co-invented patents made by firm j at year t and observation of in-house patents made by firm j at year t. Y_{ijt} is the number of patents of patent type i, firm j at year t. α_j is firm fixed effects; CoPatent_{ij} is a dummy taking 1 if the focal observation's patent type is a physician co-invented patent; Post_t is a dummy variable taking 1 for years after 2010 (or 2014). X_{jt} are a series of time-variant control variables at the firm level, including the log of revenues and the log of R&D expenditures from the previous year.

Results are shown in Table 7. It is evident that the number of co-invented patents made by sample firms increases relatively to the number of in-house patents after the Sunshine Act. Columns 1 and 2 show that co-invented patent counts increase by 51% compared to in-house patents, after 2010. Column 3 decomposes this effect, by including the interaction of "Co-Patent" with the "Post 2010" and "Post 2014" dummies. It shows that the co-patents increase by 27% between 2010 and 2014 (p-value = .017) and by an additional 46% (p-value = .000) after 2014. Columns 4–6 further corroborate the robustness of these results by using log-linear models.

To get a more detailed picture of the effect of the Sunshine Act over time, we check the dynamic of the effect by substituting the Post_t dummy with a series of year dummies. Figure 5 plots the coefficients of the interaction terms of year dummies with the indicator for physician co-invented patents, CoPatent_{ij}. Each dot shows the change in physician co-invented patents relative to in-house patents with the bars showing the 95% confidence intervals. Before 2010, the coefficients are negative but relatively stable over time, indicating a parallel evolutionary pattern of these two groups. After 2010, the physician co-invented patents start increasing, even if not dramatically, suggesting that the increase in supply of type-N physicians due to the

TABLE 8 Effect of the Sunshine Act on the quality of physician co-invented patents versus in-house medical-device patents.

	Average forward citation per patent (log)		
Dependent variable	**(1) OLS**	**(2) OLS**	**(3) OLS**
Physician co-patent*post2010	−0.062		−0.026
	(0.086)		(0.077)
	.471		*.740*
Physician co-patent *post2014		0.013	0.015
		(0.095)	(0.095)
		.894	*.873*
post2010	−0.321		−0.115
	(0.091)		(0.086)
	.001		*.185*
post2014		−0.607	−0.557
		(0.057)	(0.062)
		.000	*.000*
Physician co-patent	−0.322	−0.338	−0.317
	(0.104)	(0.081)	(0.104)
	.002	*.000*	*.003*
Log(revenues) ($t-1$)	−0.073	−0.083	−0.071
	(0.038)	(0.035)	(0.035)
	.056	*.020*	*.043*
Log(R&D) ($t-1$)	−0.194	−0.147	−0.129
	(0.100)	(0.063)	(0.055)
	.055	*.019*	*.019*
Constant	3.432	3.184	3.033
	(0.667)	(0.453)	(0.434)
	.000	*.000*	*.000*
Firm fixed effects	Yes	Yes	Yes
Weighted	Yes	Yes	Yes
Observations	2583	2583	2583
#Firms	234	234	234
R-squared	0.749	0.799	0.802

Note: Models are OLS and are weighted by the number of patents filed by firm *j* in patent type *i* (in-house patents or physician co-patents) in year *t*. *Physician co-patent* is a dummy variable equal to 1 if the patent is a medical device patent co-invented with physicians. The reference group is in-house medical device patents, not co-invented with physicians. The analysis unit is patent-type-firm-year. Forward citations are counted as the total citations received by the focal patent within 3 years after patent grant. Average forward citations are the mean citations per patent received by each firm at year *t*. *Post2010* and *post2014* are dummy variables taking value of one of the year is, respectively, after 2010 or 2014. Firm fixed effects are included. Compared to Table 7, we have a smaller number of observations as we drop observations related to firm that have zero patents in a given year. Robust standard errors, clustered by firms, are shown in parentheses; *p*-value in italics.

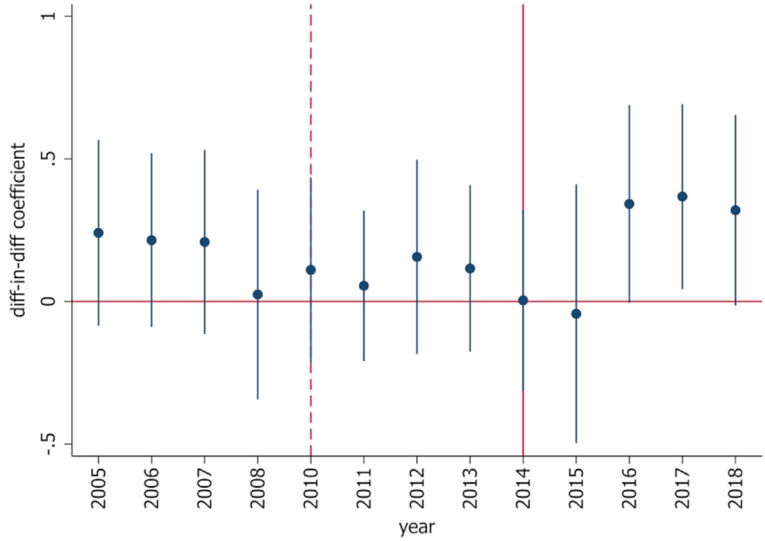

FIGURE 6 Effect of the Sunshine Act on the quality of co-patents versus in-house patents made by medical device firms. The figure plots the coefficients of interaction terms of a series of year dummies with a dummy indicating physician co-invented patents. The dependent variable is the logarithm of a number of average forward citations per patent by the focal firm. OLS fixed effects models are used. The models is weighted using the number of patents of the focal patent type filed by firm *j* in year *t*. *Y*-axis shows the DID point estimations with vertical bars showing the 95% confidence intervals for each estimation. *X*-axis shows the year. The baseline is year 2009.

publicity channel was stronger than the decrease in supply of type-R physicians due to the reputation channel. This trend intensifies after 2014 when information becomes available.

Similar to the effect of the Sunshine Act on the quantity of collaborations, the effect of the Sunshine Act on the average quality of collaborations is also theoretically ambiguous. Our conceptual model predicts that the quality of collaborative projects might decrease or increase, depending on whether the reputation channel will dominate the publicity channel. To assess the effect on the quality of collaborations, we, therefore, focus on the number of citations received by any co-invented patent, using in-house medical device patents filed by our sample firms as the "control" group, and we estimate the effect of the Sunshine Act on the forward citations received by co-invented patents relative to the in-house medical device patents. This allows us to control for any trend affecting all patents invented by sample firms.

To evaluate the effect of the Sunshine Act on the quality of collaborations (vs. in-house R&D projects) we estimate Equation (2) with OLS, but replace the dependent variable with the logarithm of (one plus) the average number of forward citations received per patent within 3 years since patent filing, by patent type *i*, firm *j* filed in year *t*. To make sure that our findings are representative of the effect of the Sunshine Act at the medical-device industry level (where larger firms coexist with smaller ones), we weight the sample using the number of patent applications made by firm *j* in year *t* for each type of patent. In this way, we give more importance to those firms that are more innovative and possibly more active in the markets for technologies. Table 8, column 3, shows the results. It turns out that, as soon as type-R physicians start leaving the market but information is still not disclosed (i.e., between 2010 and 2014) the quality of co-invention patents versus in-house inventions declines, even if the statistical significance is weak

($\beta = -.026$, p-value = .74). After the Sunshine Act is fully implemented (that is, after 2014) the quality of inventions seems to improve, even if, again, the statistical significance is too low to draw any definite conclusion ($\beta = .15$, p-value = .873). However, it is worth noting that when using a Poisson model, the post-2014 quality increase is not present (cf., Table A5). Overall, it seems that, when it comes to collaboration quality, the reputation effect and the publicity effect possibly counterbalance each other.

TABLE 9 Effect of the Sunshine Act on the quality of physician co-invented patents versus in-house medical-device patents, for reputable versus disreputable firms.

	Disreputable firms			**Reputable firms**		
	Average forward citation per patent (log)			**Average forward citation per patent (log)**		
Dependent variable	**(1) OLS**	**(2) OLS**	**(3) OLS**	**(4) OLS**	**(5) OLS**	**(6) OLS**
Physician co-patent*post2010	−0.126		−0.076	0.158		0.168
	(0.099)		(0.088)	(0.072)		(0.100)
	.209		*.391*	*.031*		*.095*
Physician co-patent *post2014		−0.016	0.009		0.103	0.023
		(0.112)	(0.112)		(0.131)	(0.158)
		.884	*.938*		*.433*	*.884*
post2010	−0.304		−0.089	−0.432		−0.277
	(0.104)		(0.100)	(0.065)		(0.065)
	.005		*.374*	*.000*		*.000*
post2014		−0.604	−0.563		−0.601	−0.506
		(0.066)	(0.073)		(0.085)	(0.095)
		.000	*.000*		*.000*	*.000*
Physician co-patent	−0.297	−0.343	−0.294	−0.393	−0.301	−0.394
	(0.129)	(0.096)	(0.128)	(0.120)	(0.123)	(0.123)
	.024	*.001*	*.024*	*.001*	*.015*	*.002*
Log(revenues) ($t - 1$)	−0.041	−0.055	−0.044	−0.124	−0.135	−0.116
	(0.028)	(0.027)	(0.024)	(0.015)	(0.017)	(0.021)
	.156	*.044*	*.069*	*.000*	*.000*	*.000*
Log(R&D) ($t - 1$)	−0.168	−0.133	−0.119	−0.293	−0.221	−0.171
	(0.115)	(0.071)	(0.063)	(0.140)	(0.100)	(0.099)
	.148	*.064*	*.065*	*.038*	*.029*	*.084*
Constant	3.124	2.986	2.839	3.462	3.119	2.924
	(0.757)	(0.472)	(0.438)	(0.621)	(0.477)	(0.505)
	.000	*.000*	*.000*	*.000*	*.000*	*.000*
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Weighted	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1370	1370	1370	1213	1213	1213

TABLE 9 (Continued)

	Disreputable firms			Reputable firms		
	Average forward citation per patent (log)			Average forward citation per patent (log)		
Dependent variable	**(1) OLS**	**(2) OLS**	**(3) OLS**	**(4) OLS**	**(5) OLS**	**(6) OLS**
#Firms	77	77	77	157	157	157
R-squared	0.768	0.819	0.821	0.564	0.609	0.628

Note: Models are OLS and are weighted using the number of patents of the focal patent type filed by firm *j* in year *t*. The dependent variables are the logarithm of the average forward citations received by patents filed by disreputable firms (columns 1–3) and by reputable firms (columns 4–6). Disreputable firms are those firms that have recalled medical device products from 2005 to 2009. Physician co-patent is a dummy variable equal to 1 if the patent is a medical device patent co-invented with physicians. The reference group is in-house medical device patents, not co-invented with physicians. The analysis unit is patent-type-firm-year. Forward citations are counted as the total citations received by the focal patent within 3 years after patent grant. Average forward citations are the mean citations per patent received by each firm at year *t*. *Post2010* and *post2014* are dummy variables taking value of one of the year is, respectively, after 2010 and 2014. Firm fixed effects are added. Robust standard errors, clustered by firm, are shown in parentheses; *p*-value in italics.

Figure 6 shows graphically the annual trend in the average quality of co-inventions versus in-house inventions. As we did in Figures 2, 3, we substitute the post-period dummy in Table 8 with a series of year dummies. Consistent with the results shown in Table 8, the dynamic diff-in-diff estimators in Figure 6 indicate that, overall, the Sunshine Act has not exerted any dramatic impact in the quality of physician co-patents (vs. in-house patents). Yet, a more careful look at the dynamics suggests that the Sunshine Act might have somehow hampered the quality of physician-firm collaborative innovations, in the very short run, between 2010 and 2014 (possibly due to "reputation channel"). However, after the Sunshine Act implementation in 2014, the quality of physician-firm collaboration might have even improved (thanks to the "publicity channel"). These findings complement the previous ones in indicating that both channels are operating, with opposite effects on the quality of collaborations.

The previous results indicate that both the reputation and publicity mechanisms may be at work, and they offset each other when it comes to the quality of inventions. Therefore, we did not observe any significant variation in quality. However, this null finding may conceal that the Sunshine Act has a heterogeneous effect on firms based on their "reputability." To investigate this further, we split our sample into "reputable" and "disreputable" companies and replicated the previous table. As shown in Table 9, we found that "reputable" companies, which faced fewer difficulties in collaborating with type-R physicians under the Sunshine Act, and had more opportunities to identify good-fit type-N physicians, experienced an increase in the value of their collaborative inventions. Conversely, "disreputable" firms suffered more from the implementation of the Sunshine Act, in terms of the quality of their collaborations, possibly because they faced more difficulties in collaborating with type-R physicians. Overall, our results suggest that the effects of information disclosure on the buyer side of technology markets may not be as uniform as previously assumed, similar to the seller side. Specifically, our findings indicate that following the implementation of the Sunshine Act, reputable firms tend to have better quality collaborations with physicians compared to disreputable firms.

6 | DISCUSSION

In the growing literature on markets for technology, the dominant view is that a lack of information impedes the functioning of the market, limits transaction volumes, and lowers social welfare (Agrawal et al., 2015; Gans et al., 2008; Luo, 2014). Some previous research has assumed that these markets might be afflicted by a relevant information asymmetry problem (Aghion & Tirole, 1994; Anton & Yao, 2002; Gallini & Wright, 1990; Pisano, 2006), or, even worse, by a symmetric absence of information (Arora et al., 2004; Agrawal et al., 2015) that lowers transactions volumes, impedes market efficiency, and constrains social welfare. In the contexts examined by this prior research, almost any institutional change or policy shift that enhances the information available when choosing external R&D collaborators and projects will be beneficial for all parties transacting in technology markets, and for society overall (Arora et al., 2001; Hegde & Luo, 2018).

In our work, we show that this is not always the case. When a "repugnance" problem is present, inventors—especially highly-reputed ones—do not want information about their identity and remuneration to be disclosed. Hence, whereas the effect of more information is generally beneficial for no-reputation or low-reputation inventors, whose ideas and collaborations are more likely to be picked by companies when more information is available, it is detrimental for those inventors who do not want to suffer reputation loss. Some high-reputation inventors will therefore leave the market when more information disclosure is required. These are the "losers," whereas the "winners" are the less reputed inventors that increase their chances of collaborating and selling their ideas. Notably, for buyers, the effect of more information is quite nuanced. They might initially suffer a loss when high-reputation idea sellers leave the market, but eventually, thanks to more information available, they might recover by selecting the best less-reputed sellers. Indeed, our findings indicate that the Sunshine Act has impacted the markets for technologies via both a negative reputation channel and a positive publicity channel. Overall, our findings depict a quite nuanced picture of what happens when the information environment of technology markets improves, in contexts characterized by a repugnance problem.

Our work also contributes to a related stream of literature focusing on the downside of greater information in innovation markets. Several recent papers have argued (and found) that information transparency might discourage corporate innovation since the leakage of private information to rivals disadvantages the firm from which information leaks (Darrough & Stoughton, 1990; Dye, 1985; Graham et al., 2005; Verrecchia, 1983). Our work identifies a new theoretical mechanism—the "reputation-loss" channel—through which more information might reduce the value of technology market transactions. However, the effect we identify is more nuanced as it only negatively affects those high-reputation inventors that have already proved their ability to produce successful technologies.

To the best of our knowledge, our work is the first paper to evaluate the influence of the Sunshine Act on the quantity and quality of collaborative research between medical device firms and physicians. Our findings strongly suggest that the implementation of the act prompted several capable physicians to reduce their collaboration or exit the market altogether. This supports the concerns expressed by Sullivan (2018a, 2018b), Lichter (2015), and Chatterji and Fabrizio (2016), who had feared that new regulations would impede collaboration and innovation. Nonetheless, our analysis indicates that increased transparency facilitates collaboration with less-established physicians initially. Our empirical evidence suggests that this effect may offset the decline in participation by more established physicians, at least in terms of

collaboration quantity. However, the evidence regarding collaboration quality is mixed, and it appears to largely depend on the reputability of buyers. Specifically, our data indicate that reputable firms are better able to enhance the quality of their collaborations with inventors. Overall, our findings suggest that there may be winners and losers on both the buyer and seller sides of the market.

Like any study, this paper also has its limitations. Our work focuses on a single industry; the extent to which this mechanism operates in other sectors remains a topic for future research. However, the medical device sector has a significant direct impact on human welfare through its impact on human health. Like the medical device industry, the biopharmaceutical sector also features an extensive amount of collaboration between firms, academic experts, and healthcare providers, and this sector was also affected by the Sunshine Act—future work will investigate the degree to which the Sunshine Act had a similar impact in this adjacent market for technology.

Despite these limitations, our work may have important managerial and policy implications. First, our findings allow us to address concerns raised by researchers, physicians, and firms that compliance with the Sunshine Act would raise the costs of physician-firm collaboration, reduce the quantity (and, potentially, the quality) of those collaborations, and wind up harming social welfare rather than abetting it. In examining the impact of government scrutiny on orthopedic device firms' research collaborations, an episode that helped build support for the Sunshine Act, Chatterji and Fabrizio (2016) found disquieting evidence of a sharp drop in research collaborations—suggesting a significantly negative effect on innovation and new product introductions. This earlier research considered some of the collaboration-inhibiting effects of disclosure that we incorporate into our model, but not the collaboration-promoting effects. Our paper shows that the net impact of the Sunshine Act on the firm-physician research collaborations is possibly more nuanced than what prior work would suggest.

Second, our findings are helpful for assessing whether and what buyers and sellers have to lose or gain from more information in technology markets. The existence and growth of markets for technologies might be quite valuable for firms and the economy at large, via the benefits deriving from specialization and the division of innovative labor (Arora et al., 2001; Arora & Gambardella, 2010b). In this respect, conventional wisdom suggests that policies for expanding technology markets should focus on improving the information environment. However, our work suggests a much more complicated relationship between information on (co)inventor quality and innovative outcomes. In our context, more public information appears to have significantly reduced relative transaction volume for highly reputed inventors, at the advantage of less reputed inventors. It is possible that, in the long run, as with Gresham's law, the former (potentially lower quality) physicians could drive the latter out of the market. More information may not be better for everyone.

ACKNOWLEDGMENTS

We thank the Editor, Brian Silverman, and two anonymous reviewers for their precious help and guidance. We also thank participants at the Strategic Management Society annual conference (Toronto, 2021), AOM annual conferences (2021, 2022), Wharton Technology and Innovation Conference 2021, and seminar at the HKUST for comments on earlier drafts. Raffaele Conti acknowledges financial support from CY Initiative. Huiyan Zhang acknowledges the generous financial support from Fundação para a Ciência e a Tecnologia (SFRH/BD/127987/2016, COVID/BD/151593/2021) and Nagin Fellowship of the year 2022.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Huiyan Zhang https://orcid.org/0000-0003-3406-4021
Lee Branstetter https://orcid.org/0000-0001-7835-0527
Raffaele Conti https://orcid.org/0000-0002-5314-1451
Samir Mamadehussene https://orcid.org/0000-0002-9275-8622

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Zhang, H., Branstetter, L., Conti, R., & Mamadehussene, S. (2023). Who gains and who loses from more information in technology markets? Evidence from the Sunshine Act. *Strategic Management Journal*, 1–36. https://doi.org/10.1002/smj.3511