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

Abstract

Several scholars have emphasized how uncertainty and a lack of information impede the functioning of markets for technology. One might intuit that an improvement in the information environment in technology markets will particularly benefit those firms that frequently rely on external collaborations and ideas. Instead, our theoretical model predicts that the opposite: when firms differ in their private information about external collaborators and ideas, an improvement in the information environment reduces the competitive advantage of firms which collaborate extensively external inventors: these firms will experience a relative decline in both the quantity and quality of ideas developed in collaboration with external inventors—especially with those collaborators not yet publicly known for the quality of their previous work—with respect to the firms that collaborated less extensively. To test our theory, we construct a unique panel dataset on 276 publicly traded companies in the medical device industry, which is a sector where physicians often collaborate with firms to generate and market new inventions. Then we assess the effect on innovation of an exogenous increase in information induced by the Physician Payment Sunshine Act, enacted as part of the Affordable Care Act. Results are largely consistent with our theoretical predictions.

Keywords: markets for technology; information environment; medical device industry; innovation rate; 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 and Gambardella 2010, Arora, Fosfuri and Gambardella 2001, Fosfuri and Giarratana 2010, Gans and Stern 2003). For upstream inventors, these markets provide the inventors with the possibility to monetize their ideas, without having to acquire the full set of capabilities needed for commercialization (Teece, 1986). For incumbent producers, these markets allow incumbents to quickly identify new innovations emerging outside of their organizational boundaries and exploit them via their existing downstream marketing and production capabilities (Chatterji and Fabrizio, 2016). 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, Fosfuri and Gambardella 2001, Arora and 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, Cockburn and Zhang 2015, Ceccagnoli, Higgins and Palermo 2014, Fosfuri and Giarratana 2010, Gans, Hsu and Stern 2008, Luo 2014). In particular, they point 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 (Anton and Yao 2002, Aghion and Tirole 1994, Gallini and Wright 1990). In these circumstances, markets for technologies might be afflicted by a "lemons" problem (Akerlof, 1978), which might discourage potential buyers from participating in those markets and thus reduce the volume of technology transactions (Wuyts and Dutta 2008, Pisano 2006). This chain of logic leads to the commonly held view that more information – especially more information about the quality of external collaborators and ideas – will be good for any agent transacting in the market (Agrawal, Cockburn and Zhang 2015, Hegde and Luo 2018). In particular, downstream buyer companies might find it easier to assess valuable collaborators and ideas (Arora, Fosfuri and Gambardella 2001).

However, previous research has generally neglected the consideration that buyers in technology markets might differ in the extent of their private information about the quality of sellers and their ideas. This private information might allow some of these buyers to participate in knowledge transactions even when technology markets are informationally opaque. So, when the information environment improves for all buyers, these formerly privileged firms might lose any competitive advantage they once had due to their superior information concerning the pool of external collaborators and ideas. This could imply that, in contrast to what past research has generally assumed, an improvement in the information environment of technology markets is not unequivocally good for all buyer firms. Rather, among these companies, there are winners and losers from broad disclosure of information.

To flesh out the mechanism at the core of our paper, we develop a simple theoretical model in which firms might decide to set up a collaboration project with an external inventor. 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 firms: some firms (type H) often collaborate with external inventors and therefore possess private information and more precise signals about the pool of external inventors and ideas; the remaining firms (type L) rely on external collaborations much less frequently and therefore have less precise signals. Hence, the former type of company has an information advantage when selecting external inventors, and this advantage naturally supports *more frequent* and *higher-value* collaborations, especially when choosing from the set of "no-reputation" inventors, that is, inventors not yet publicly known for the quality of their previous work. Yet, when the information environment improves for all firms, this initial information advantage fades. Type H firms will experience a decline in both the quantity and quality of collaborations with external inventors, relative to type L firms, and this will be especially true for collaborations with no-reputation inventors.

To verify the hypotheses generated by our model, 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 and Fabrizio 2016). Second, the America medical device innovation industry is heavily regulated (Stern 2017, Ball, Macher and Stern 2018), and the U.S. federal government mandated detailed information disclosures about these collaborations that plausibly informed buyers about the quality of technology sellers. As part of the Affordable Care Act (ACA), which passed in 2010 and was fully implemented in 2014, the U.S. 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 imposes information disclosure requirements on all firm-physician research transactions, including the amount paid to physicians for the collaboration (which plausibly reflects the quality of the collaborator) and a brief description of the collaboration. 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]

[1] Of course, not all collaborations result in patents, but the most valuable ones are likely to generate that outcome. U.S. patent law requires that parties making significant contributions to a new invention be named as inventors. If

We construct a unique panel dataset measuring the innovative inputs and outputs of 276 publicly traded medical companies, which received USPTO patent grants between 2005 and 2018. Firms that were frequently reliant on collaboration with physicians before the Sunshine Act will be designated type H firms, whereas the remaining firms will be designated type L firms. This allows us to deploy a difference-in-differences design, comparing the effect of the Act on firms that intensively relied on unaffiliated physicians before the Act versus firms that did not. Consistent with our theoretical predictions, we find that the increase in information generated by the Sunshine Act significantly reduced both the quantity and quality of inventions done in collaboration with external physicians by firms that used to rely on external inventors for their research projects. Furthermore, this negative effect is more salient for inventions created with no-reputation inventors for whom publicly available data provided little to no insight into their potential quality.

The rest of the paper proceeds as follows. Section 2 develops the theoretical model and derives its main predictions. Section 3 describes the empirical setting, the construction of the sample, and the identification strategy. Section 4 reports the main empirical results. Section 5 provides 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. Conceptual Framework

In this section, we provide a theoretical framework to understand how public information regarding external inventors impacts the innovation landscape.

2.1 Setup

Consider a firm that comes up with an idea for a project, and it requires external expertise in order to execute it. The firm can hire an external inventor to help develop the project. There are two types of external inventors: a fraction μ of inventors have already built a reputation from previous successful projects (type R) whereas the remaining share $(1-\mu)$ of no-reputation inventors are not yet known for the quality of their previous work (type N).[2]

The value that the project generates for the firm depends on the match between the inventor and the project. For simplicity, it is assumed that the project is worth one to the firm if it is developed with an inventor who is a good match for the project, and the project is worthless to the firm otherwise. External

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.

[2] For example, inventors of type R may have a large number of 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.

inventors who collaborate with firms must spend time and effort transferring their ideas to firms to help them develop a product. This effort cost is denoted by ω.[3] The surplus accruing to an external inventor who collaborates with a firm is the difference between the payment that he or she receives from the firm and the cost of effort. For each project, a measure ρ_R of inventors of type R and a measure ρ_N of inventors of type N are a good match, where $\rho_R > \rho_N$. Firms do not know exactly which individual external inventors are a good match for a given project, and must rely on signals regarding the quality of these external inventors.

There are two types of firms, that differ in the amount of information they have regarding external inventors: some firms (type H) are well informed regarding the pool of inventors (for example, these firms may have collaborated frequently with inventors in the past, which gives them privileged access to information regarding their abilities); the remaining firms (type L) have little information regarding inventors' abilities (possibly because they rarely collaborate with them). We denote by λ_H (λ_L) the amount of information regarding external inventors held by firms of type H (L), where $\lambda_H > \lambda_L$.[4]

A firm with information λ receives a private signal regarding the match between the project and a (random) inventor with probability λ. The signal that the firm may receive regarding an inventor can take only two values: g (a signal that the inventor is a good match) or *b* (a signal that the inventor is not a good match). We assume that, regardless of the information held by the firm, the probability of receiving signal g from an inventor of type R is ρ_R and the probability of receiving signal g from an inventor of type N is ρ_N. This assumption states that the signals are, on average, correct. The precision of the signal, however, depends on the information that the firm holds. In particular, a good signal is accurate with probability $\phi(\lambda)$, where $\phi(.)$ is strictly increasing. That is, the probability that an inventor is a good match with the project, conditional on receiving signal g from such inventor, is $\phi(\lambda)$.

We analyze two scenarios. First, we consider the case in which there is no public disclosure of information regarding external inventors, and firms make their decisions using only their private signals. Afterward, we consider the case in which public information regarding external inventors is available. We

[3] For simplicity, we assume that both types of external inventors have the same effort cost. It may be reasonable, however, that inventors of type R have a higher opportunity cost of time. In Appendix C, we argue that our results are robust to this alternative assumption.

[4] For some readers, the greater prevalence of collaboration among type H firms may raise the possibility that these firms have more effective R&D divisions conducting more R&D projects. Thus, part of the reason type H firms have better information on collaborators is because they are simply better at R&D than type L firms. While our theoretical model does not explicitly consider this possibility, we will present empirical results that are difficult to attribute solely to a level difference in research capability across these two groups of firms.

then compare the two scenarios to understand the impact of public information regarding external inventors on the innovation landscape.

2.2 Absence of Public Information

First, let us consider the case in which the firm has received signal g from an inventor. We assume that $\phi(\lambda_L) > \rho_R$, so that an inventor with signal g is, on average, a better match with the project than a random inventor of type R. We also assume that the information held even by firms of type L is extensive enough that hiring an inventor from whom the firm received a positive signal is worthwhile, i.e. $\phi(\lambda_L) > \omega$. Notice that, if this assumption did not hold, then the information held by firms of type L would be worthless. When a firm receives signal g from an inventor, there are expected gains from collaboration. Thus, the firm and the inventor collaborate, and they split those gains using some bargaining process. Because we are interested in how public information influences the quantity and quality of collaborations, and not on how the surplus is split between firms and inventors, we refrain from modeling the bargaining process. However, our results are robust to any standard bargaining process. In particular, our results hold under the generalized Nash bargaining solution, which is commonly used in the literature (e.g. Gans, Hsu and Stern 2008).

Next, let us consider the case in which the firm did not receive a signal (or received signal b). In this case, the firm can choose to hire an inventor even though it has no private information regarding his or her fit with the project. We assume that the probability that a random inventor of type N is a good match with a project is small enough that it is never worth hiring, i.e. $\rho_N < \omega$. This is a realistic assumption, as the pool of inventors with no reputation is typically very large. Under this assumption, a firm never hires an inventor with no reputation in the absence of some information regarding his or her match with the project.

The firm may, however, direct an offer to an inventor with a well-developed reputation. We assume that there are gains from collaboration from hiring a "reputable" inventor even in the absence of private information, i.e. $\rho_R > \omega$. We believe this to be the most interesting case. However, our main results are robust to the alternative assumption ($\rho_R \leq \omega$) that firms only hire inventors in the case that they have private information regarding their match with the project. When the firm receives no signal g from an inventor, it looks for an inventor of type R. The firm can be matched with an inventor of type R with probability α, in which case the firm and the inventor split the gains from collaboration using some bargaining process. Figure 1 depicts the timeline and the optimal strategy for the firm.

Let $Q_N^A(\lambda)$ and $Q_R^A(\lambda)$ denote, respectively, the equilibrium quantity of collaborations developed by a firm that holds information λ with inventors of type N and R, in the setting where public information is absent. Moreover, let $Q^A(\lambda) \equiv Q_N^A(\lambda) + Q_R^A(\lambda)$ denote the total quantity of collaborations undertaken by a firm with information λ. Let $\bar{\rho} \equiv \mu\rho_R + (1-\mu)\rho_N$. It follows that

$$Q_N^A(\lambda) = \lambda(1-\mu)\rho_N$$

$$Q_R^A(\lambda) = \lambda\mu\rho_R + \alpha(1-\lambda\bar{\rho}).$$

Firms of type H collaborate more frequently with type N inventors than firms of type L. Moreover, we assume that $\alpha < \frac{\mu\rho_R}{\bar{\rho}}$, so that $Q_R^A(\lambda_H) > Q_R^A(\lambda_L)$, i.e., firms of type H also collaborate more frequently with type R inventors.

Finally, let $V^A(\lambda)$ denote the average value of a collaboration developed by a firm with information λ, in a setting where public information is absent.

$$V^A(\lambda) = \frac{\lambda\bar{\rho}\phi(\lambda) + \alpha(1-\lambda\bar{\rho})\rho_R}{Q^A(\lambda)}.$$

2.3 Presence of Public Information

In this setting, a firm with private information λ will face one of three events: i) with probability λ, it receives a private signal regarding the match between the project and a (random) inventor - the precision of a good private signal is $\phi(\lambda)$; ii) with probability λ_P, it receives a public signal regarding the match between the project and a (random) inventor - the precision of a good public signal is $\phi(\lambda_P)$; iii) with probability $1-\lambda-\lambda_P$ it receives no signal.[5]

When a firm receives signal g from an inventor, be it a private or public signal, there are gains from collaboration. Thus, the firm and the inventor collaborate, and they split those gains using some bargaining process. If, however, the firm does not receive signal g from an inventor, it looks for an inventor of type R. The firm can be matched with an inventor of type R with probability α, in which case the firm and the inventor split the gains from collaboration using some bargaining process. Figure 2 depicts the timeline and the optimal strategy for the firm.

Let $Q_N^P(\lambda)$ and $Q_R^P(\lambda)$ denote, respectively, the equilibrium quantity of collaborations developed by a firm that holds information λ with inventors of type N and R, in the setting where public information is present. Moreover, let $Q^P(\lambda) \equiv Q_N^P(\lambda) + Q_R^P(\lambda)$ denote the total quantity of collaborations developed by a firm with information λ. It follows that

[5] Naturally, we assume that hiring an inventor for whom the firm received a good public signal is worthwhile, i.e. $\phi(\lambda_P) > \omega$.

$$Q_N^P(\lambda) = (\lambda + \lambda_P)(1 - \mu)\rho_N$$

$$Q_R^P(\lambda) = (\lambda + \lambda_P)\mu\rho_R + \alpha[1 - (\lambda + \lambda_P)\bar{\rho}].$$

Finally, let $V^P(\lambda)$ denote the average value of a collaboration developed by a firm with information λ, in a setting where public information is present.

$$V^P(\lambda) = \frac{\lambda\bar{\rho}\phi(\lambda) + \lambda_P\bar{\rho}\phi(\lambda_P) + \alpha[1 - (\lambda + \lambda_P)\bar{\rho}]\rho_R}{Q^P(\lambda)}.$$

2.4 The Impact of Public Information on the Number and Value of Collaborations realized by type H vs type L firms

We now analyze how the availability of public information impacts the innovation landscape. We start by analyzing how public information influences the asymmetry regarding the number of collaborations. Let $\Delta Q^A \equiv \frac{Q^A(\lambda_H)}{Q^A(\lambda_L)}$ denote a measure of the asymmetry in the number of collaborations performed by the two types of firms in the absence of public information and let $\Delta Q^P \equiv \frac{Q^P(\lambda_H)}{Q^P(\lambda_L)}$ be defined analogously for the setting where public information is present.

Lemma 1: $\Delta Q^P < \Delta Q^A$.[6]

Firms develop a collaboration whenever they receive a good signal regarding the match between an inventor and the project. In absence of public information, there is a large degree of asymmetry in receiving signals, because firms of type H have more private information than firms of type L. Such asymmetry is reduced when public information is present. Indeed, public information is equally available for both firms. Therefore, whereas firms of type H are more likely to receive a private signal than firms of type L, both types of firms are equally likely to receive a public signal. This insight is summarized in the following hypothesis.

Hypothesis 1: The availability of public information reduces the asymmetry in the number of collaborations developed by firms of type H vs. firms of type L.

Let $\Delta Q_R^A \equiv \frac{Q_R^A(\lambda_H)}{Q_R^A(\lambda_L)}$ and $\Delta Q_R^P \equiv \frac{Q_R^P(\lambda_H)}{Q_R^P(\lambda_L)}$ denote a measure of the asymmetry in collaborations with inventors of type R. Let $\Delta Q_N^A \equiv \frac{Q_N^A(\lambda_H)}{Q_N^A(\lambda_L)}$ and $\Delta Q_N^P \equiv \frac{Q_N^P(\lambda_H)}{Q_N^P(\lambda_L)}$ be defined analogously for type N inventors.

[6] Proofs of all lemmas are reported in Appendix B.

Lemma 2: $\frac{\Delta Q_N^P}{\Delta Q_N^A} < \frac{\Delta Q_R^P}{\Delta Q_R^A} < 1$.

Whereas firms collaborate with type N inventors only when they receive a positive signal regarding their match with a project, they sometimes collaborate with type R inventors even in absence of any signal. The availability of public information attenuates the heterogeneity of firms regarding the information about potential collaborators. Therefore, although the relative decrease in collaborations developed by firms of type H vs firms of type L holds both for collaborations developed with type N and type R inventors, such decline is more pronounced for collaborations developed with type N inventors. This insight leads to the following hypothesis.

Hypothesis 2: After public information becomes available, the asymmetry in the number of collaborations developed by firms of type H vs firms of type L will be reduced both for collaborations with type N and type R inventors. However, the decline will be more pronounced for collaborations with type N inventors.

We now analyze how the availability of public information impacts the asymmetry in the quality of the collaborations developed by the two types of firms. Let $\Delta V^A \equiv \frac{V^A(\lambda_H)}{V^A(\lambda_L)}$ and $\Delta V^P \equiv \frac{V^P(\lambda_H)}{V^P(\lambda_L)}$ denote a measure of the asymmetry in the value of collaborations performed by the two types of firms.

Lemma 3: $\Delta V^P < \Delta V^A$.

Firms of type H have more private information, which is reflected in the higher precision of their signals. In particular, the expected value of a collaboration developed by a firm when it has a private signal from an inventor is larger for firms of type H, $\phi(\lambda_H)$, than for firms of type L, $\phi(\lambda_L)$. Therefore, in the absence of public information, there is a large asymmetry in the value generated from collaborations performed by these two types of firms. The availability of public information reduces such asymmetry because public signals are equally accurate for both types of firms.

Hypothesis 3: The availability of public information reduces the asymmetry in the value of collaborations developed by firms of type H vs firms of type L.

Summing up, we find that the availability of public information influences the asymmetry in outcomes for type H vs type L firms. When public information is not available, type H firms have a large comparative advantage on the information about external inventors, as they receive better and more frequent private signals. Because public information is equally accessible to all firms, the comparative advantage enjoyed by type H firms is reduced when public information is present. As a result, type H firms will experience a relative decline in both the quantity and the quality of their collaborations, when compared with type L firms. This decline is particularly salient for those collaborations performed with type N inventors, as firms only collaborate with those inventors when they receive a signal that they are a good match with the project.

3. Data and Methodology

In order to test our hypotheses, we need an empirical setting in which publicly available information about the pool of external inventors increases. Then, we could observe how such an improvement in the information environment affects: (a) the number of collaborations, in general; (b) the number of collaborations with no-reputation, type N external inventors vs. with high-reputation, type R external inventors; c) the value of collaborations. In particular, we are interested in assessing the differential effect across two groups of companies: type H firms—or firms that, before the improvement in the information environment, had private information about external inventors and used to collaborate frequently with them—and type L firms—or firms less informed about the pool of external inventors and less used to collaborate with them. The American medical device industry provides such a setting. The Physician Payment Sunshine Act, enacted in 2010 and fully implemented in 2014, mandated extensive public disclosure about the financial collaborations between medical device companies and external physicians, not working as paid employees of medical device firms. In this section, we introduce the Physician Payment Sunshine Act and describe in detail the data used in our empirical analyses. We also explain how we leverage the Sunshine Act to identify the effect of information transparency on collaborative innovation in the medical device sector.

3.1 The Physician Payment Sunshine Act

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 US. Because of these issues, the US government has scrutinized the financial relationships between medical device manufacturers and physicians for several years. In 2005, five leading orthopedic companies[7] were investigated by the Department of Justice for improper payments to

[7] Biomet, DePuy Orthopaedics unit of Johnson and Johnson, Smith and Nephew, Stryker Orthopaedics, Zimmer. The five companies account for 93% of the American hip and knee implant market by the time of the investigation.

physicians. Furthermore, several US states[8] established information disclosure requirements for pharmaceutical and medical device companies before the federal government did so nationwide (Guo, Sriram and Manchanda 2019).

The Physician Payment Sunshine Act was enacted as an effort by the U.S. federal government to regulate physician-firm financial connections. This Act – which was a significant part of the broader Affordable Care Act of 2010 – requires all pharmaceutical and medical device manufacturers to disclose any financial payment above $10 to licensed physicians and teaching hospitals. The initial purpose of this policy was to curb increasing medical expenditure by eliminating improper payments from firms to physicians. Payments subject to reporting are comprehensive, including "general payments" on 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 collaborations 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 data set 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 product, information on collaborating physicians and firms, and payment purpose. Failure to report can trigger fines ranging from $1,000 to $10,000 per unreported payment with an annual maximum of $150,000. For *deliberate* failure to report, the fine increases to $10,000 to $100,000 per payment with a maximum penalty of $1 million.

The Sunshine Act mandated a clear improvement in the information environment for physician-firm collaboration, for several reasons. 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 key financial details related to physicians' compensation typically remained private, often even legally protected by a non-disclosure agreement. Payment information might be quite crucial for assessing the quality of a physician, and the Sunshine Act made any financial information about collaborations between firms and external physicians completely public. 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

[8] State government legislation were enacted in Minnesota in 1993; in Vermont in 2001; District of Columbia, 2003; Maine, 2004; West Virginia, 2004; Massachusetts, 2008.

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. Finally, the Sunshine Act undermined any non-disclosure agreement between physicians and companies, since some of the information protected by those agreements was now required to be disclosed by federal law. So, the Sunshine Act likely induced companies to rely less on confidentiality agreements, as this contractual tool for protecting knowledge disclosure lost some of its efficacy[9].

Overall, there is strong reason to believe that, thanks to the Sunshine Act, firms generally were better able to assess the 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 Deloitte (2012) just before the Sunshine Act was fully implemented, surveyed firms planned to utilize the disclosed data to identify high-quality physicians as well as promising technological areas. Therefore, the Sunshine Act appears to offer the kind of information shock we modeled in the theory section.

3.2 Data and summary statistics

We focus on publicly traded medical device companies operating in the US and collect their innovation and financial data from 2005—five years before the approval of the Sunshine Act, and about ten years before its implementation—to 2018. Using the Compustat Global database, we first select publicly traded medical device companies that have R&D expenditure data for at least two continuous years and own medical device patents granted by United States Patent and Trademark Office (USPTO). We include multinational firms that manufacture or sell medical devices in the American market, even though they are not based in the U.S.[10] There are several reasons why we only focus on publicly traded companies. First, although some non-listed firms (especially small start-ups) have made non-trivial 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 percent of assets are owned by one percent of firms in this industry. Second, by selecting publicly traded firms, we can easily collect 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

[9] This argument, which has been validated by an IP lawyer, suggests that the effect of the Sunshine Act might have been immediate, even preceding the establishment of a public registry documenting all transactions between companies and physicians.

[10] 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.

market exchange rates to convert financial data reported by multinationals in a foreign currency into U.S. dollars.

We measure collaborations between firms and physicians related to medical device technologies using patent data, collected from USPTO Patentview. After obtaining all patents granted by USPTO to our sample firms, we identified medical device patents. Before 2015, identifying those patents is trivial, as the USPTO provides a list of technological classes related to medical device technologies, based on the US Patent Classification System (USPC). Unfortunately, usage of the USPC ceased in 2015, in favor of the Cooperative Classification System (CPC). To identify patents related to medical device technologies granted after 2015, we use a machine-learning algorithm based on the matching between USPC and CPC codes, patent titles and abstracts. This yields 50,141 granted medical device patents.[11]

We matched the inventors named in patents with a comprehensive physician list provided by the National Plan and Provider Enumeration System (NPPES) dataset, to identify patents co-invented by firms and independent health care 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 US. Compared with other databases used to identify physicians, the NPPES data covers more types of licensed health care providers, such as dentists and nurse practitioners, who are also important users of medical devices (DesRoches 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 and county). Patents granted to firms in our sample that include at least one independent health care 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 5 years after the patent grant.

Overall, we obtain an unbalanced panel of 276 firms, with data from 2005 to 2018. Table 1 shows the summary statistics of our major dependent variables. For our sampled firms, patented co-inventions only comprise a small portion of the overall patent portfolio, around 8 percent at the firm-year level (panel A) and 5 percent at the patent level (Panel B). However, the average firm value of patents made with physicians, measured by the average number of forward citations, is 13.5 percent higher than that of in-house patents (firm-year level Panel A). This implies that physicians’ research input, though limited in the quantity, might be important for the more valuable and innovative patents generated by our sample firms.

[11] The code used for this machine learning algorithm and other details are available upon request.

To test our predictions, we define "type H" firms as those that filed at least one co-patent with physicians *each year* during the pre-shock period (2005 to 2013). Any other firms in the sample are defined as "type L". This definition intends to distinguish the group of firms that, before the Sunshine Act, were well informed about external physicians and so used to frequently collaborate which them, from the other companies, which rarely collaborated with physicians. Table 2 shows the pre-shock average of key financial variables and innovation output measures of these two groups of firms. Type H firms are bigger than type L firms, as the former, compared to the latter, and not only yield higher volumes of innovations (either patents or new products) but also have more employees, earn higher revenues and spend more money in R&D activities. In the main analysis, we address these disparities between the two groups of firms by controlling for revenues and R&D expenditures, as well as for firm fixed effects. Furthermore, in robustness checks, we: (a) match on major pre-shock covariates, to reduce the imbalance among the two groups; and (b) use different and less restrictive definitions of type H firms (e.g., firms that filed at least one patent with physicians in *most years* during the pre-shock period), which should make the difference with type L firms less salient.

To test the hypotheses suggested by our model, we also need to measure a physician's reputation, in order to distinguish between "type R" or well-reputed physicians, and "type N" or no-reputation physicians. In the context of our study, we are particularly focused on that component of a physician's reputation that pertains to her value as a potential co-inventor. Prior to the disclosure mandated by the Sunshine Act, at a time when collaborating physicians were often bound by non-disclosure agreements to avoid saying much publicly about their prior collaborations with firms, what broadly available data might firms look to in order to gauge a physician's reputation as a co-inventor? While general measures of professional prominence (i.e., professional awards, affiliation with leading hospitals, etc.) might be useful measures of some dimensions of physician quality, they are not necessarily highly correlated with the usefulness of a particular physician as a co-inventor on a particular medical device. The public nature of patenting data probably made it a critical resource for firms seeking this kind of knowledge prior to the Sunshine Act. The quality of (co)patented inventions can be hard to measure, but extensive research documents that more valuable patents are more likely to be cited by subsequently granted patents. Therefore, in any given year, we measure physicians' reputation as the number of forward citations received by all their patents, within a 5-year window *before* that year. These data constitute a noisy signal. Accordingly, we categorize a subset of our physicians into two disjoint groups : "top reputation" physicians whose cumulative citations place in them in the top 10 percent in terms of coinventing physicians[12]; and “zero reputation” physicians, or physicians who have not received any citations within the 5-year window before the focal year. The former group represents the upper tail of type R physicians, whereas the latter group constitutes the lower tail of type N physicians.

--Insert Tables 1 and 2 here--

3.3 Identification strategy

In essence, our identification approach is a simple difference-in-differences regression, comparing firms that frequently collaborated with physicians before the Sunshine Act, or type H firms, with the rest, or type L firms, before and after the enactment of the Sunshine Act. This approach allows us to disentangle the effect of a better information environment—which exerts a heterogeneous effect on firms, based on whether or not they used to collaborate with physicians even when the information environment was opaque—from any common time trend effect, which would equally affect all companies in the industry. More specifically, we estimate through ordinary least squares (OLS) the effect of the Sunshine Act using the following equation:

$$Y_{it} = \rho_0 + \delta_i + \gamma_t + \beta(TypeHFirm_i * PostSunshine_t) + \alpha X_{it-1} + \varepsilon_{it} \qquad (1)$$

Where i and t denote individual firm and year, respectively. $PostSunshine_t$ is a dummy variable equal to 1 for any year after the information about firm-physician collaboration went public (2014 and later), consistent with the requirements of the Sunshine Act. To control for time-invariant unobservable firm effects and macro demand factors similarly impacting the whole industry, we include firm fixed-effects δ_i and year fixed-effects γ_t[13]. ρ_0 is the constant. We include as controls the logarithm of annual revenues and R&D expenditures from the previous year into the vector X_{it-1}, as additional control variables. Following Bertrand and Mullainathan (2004), in order to avoid underestimating the standard errors due to serial correlation—and therefore overestimate the statistical significance of our results—we cluster standard errors at the firm level, which is the level of the treatment.

Our hypothesis 1 predicts that the public information made available by the Sunshine Act will reduce firm-physician collaborations for type H firms relative to type L firms. This arises because Type H firms lose the information advantage they previously held over Type L firms. Now, thanks to extensive

[12] As a robustness check, we also used top 25 percent reputation physicians to define type R physicians. Results hold valid when using this different measure (tables available upon request).
[13] A standard difference-in-differences specification would be $Y_{it} = \rho_0 + \tau TypeHFirm_i + \varphi PostSunshine_t + \beta(TypeHFirm_i * PostSunshine_t) + \alpha X_{it-1} + \varepsilon_{it}$. Here the firm fixed effects term (δ_i) absorbs the second term, estimation for τ, thus is omitted. Estimation for φ, the post Sunshine Act period, is broken down and absorbed by year fixed effects γ_t, which captures the time trends more precisely.

public disclosure of information related to physician quality, Type L firms are better positioned to seek out the services of qualified physician collaborators. The distribution of physician-firm collaborations could thus shift away from Type H firms and toward Type L firms. To test this hypothesis, we consider as our dependent variable Y_{it} in (1) the logarithm of (one plus) the number of patents invented in collaboration with a physician. We expect β (the coefficient representing the differential effect of the Sunshine Act for type H vs. type L firms) to be negative and statistically significant. This would imply that, as predicted, the availability of public information reduces the asymmetry in the number of collaborations developed by firms of type H vs. firms of type L.

Our hypothesis 2 predicts type H firms, relative to type L firms, will especially reduce their collaborations with type N physicians, after the Sunshine Act. This effect arises because the previous information advantage held by Type H firms is likely to be especially strong when the publicly available information on a physicians quality as a collaborator (which could be inferred from patent data) is limited or missing. When public information about physician quality is widely disclosed, type L firms are just as able to identify high-quality collaborators with little prior experience in the data record as are type H firms. To test this, we estimate (1) considering as the dependent variable the logarithm of (one plus) the number of patents invented in collaboration with type N physicians. We then compare this to results obtained when we replace the dependent variable with the lobgarithm of (one plus) the number of patents invented in collaboration with type R physicians. In this case, our hypothesis will be corroborated if β is more negative for collaborations with type N physicians, rather than for collaborations with type R physicians. This would imply that any relative reduction in the number of collaborations by firms of type H vs firms of type L, is mainly driven by collaborations with type N physicians.

Our final hypothesis 3 predicts that the value of firm-physician collaborations will decline for type H firms compared with type L firms after the Sunshine Act. This is an additional logical consequence of the loss of type H firms' information advantage after public disclosure. To test this hypothesis, we measure the value of collaboration by the average count of forward citations received by a firm's (co-invented) patents within a 5-year window after patent grant. When we test hypothesis 3, the coefficient of major interest is β. We expect this coefficient to be significantly negative.

4. Results

4.1 Main results

We start by evaluating the three major predictions derived in section 2. Specifically, we examine how the quantity and quality of collaborations pursued by type H firms changed after 2013, when the Sunshine Act was implemented, relative to type L firms.

Once information on physician inventors' quality becomes widely available, thanks to the Sunshine Act, type H firms lose their information advantage over type L firms. Based on Hypothesis 1, we expect that type H firms should experience a relative decline in the number of collaborations compared to type L firms, such that the asymmetry in the number of collaborations between the two groups of firms should decrease. As shown in Table 3, the Sunshine Act exerts a negative effect on the quantity of physician co-invented inventions patented by type H firms, compared with type L firms. The decline is equal to about 37 percent (column 4), which is statistically significant at the one percent level.[14] Interestingly, the number of in-house patents does not appear to change – there is no statistically significant impact on this alternative category of patents. This confirms that our estimates are not capturing the effect of a generic negative innovation shock affecting type H firms.

Figure 3 depicts how the difference in physician co-patents and in-house patents between the two groups of firms evolves. Before the Sunshine Act, there is a difference in the levels of co-patent across the two groups, but no difference in the *trend* of physician co-patents between type H and type L firms over time. However, after 2013, when the information environment started improving following the implementation of the Sunshine Act, collaborative patents by type H firms start to fall relative to the other firms; the negative coefficients become larger over time, implying a persistent decline trend after the shock. Overall, these results are consistent with Hypothesis 1: after the information environment is improved, type H firms—which used to collaborate extensively with physicians when the information environment was more opaque—experience a greater decline in the number of collaborations with physicians, compared to type L firms.

--Insert Table 3 and Figure 3 here--

Hypothesis 2 of our theoretical model predicts that the relative decline in the number of collaborations experienced by type H firms should be more salient for collaborations with type N, no-reputation physicians—or physicians who do not have a long history of successful patenting—than for collaborations with type R, high-reputation physicians. As table 4 shows, empirical results support this prediction. After the implementation of the Sunshine Act, collaborative patents with type N ("zero reputation") physicians decline by about 49 percent, which is significantly different from zero. In contrast, collaborations with type R physicians, or physicians in the top 10 percent based on their past patent productivity, decrease by only 26 percent. Notably, the difference in the decrease in the number of collaborations with type N and type R physicians is not only economically but also statistically significant (p value=0.03).

[14] This number corresponds to $1 - e^{-0.473}$.

The dynamic patterns of collaboration with physicians of different reputational quality are depicted in Figure 4. Before the Sunshine Act, type H firms were the ones increasing their collaborative patents with type N physicians, whereas type H and type L firms did not differ in the extent to which they relied on collaborations with well-reputed physicians for generating new patents. After the implementation of the Sunshine Act, type H firms decrease their collaborations relative to type L firms in general, but the relative decline is more substantial for collaborations with no-reputation physicians, as predicted by hypothesis 2.

--Insert Table 4 and Figure 4 here--

Finally, hypothesis 3 of our model predicts that, compared to type L firms, type H firms will also experience a relative decrease in the *value* of collaborations with physicians. To verify whether this is the case, we assess the effect of the Sunshine Act on the average quality of co-invented patents. The results are presented in table 5. The value of all inventions patented by type H firms, as measured by forward citations, significantly decline relative to type L firms after the Sunshine Act. However, this effect is mainly due to the decline of the average value of physician co-patents, around 71 percent. The coincident relative decline in measured quality of in-house patents made by type H firms, in comparison to those made by type L firms, suggests the possible existence of spillover effects between external and internal R&D. However, the decrease in the relative value of in-house patents is much smaller than the measured decline in the relative value of co-patents, which were plausibly directly affected by the regulatory change.

The heterogeneous effect of the Sunshine Act on the value of inventions patented by type H vs. type L firms is also visually evident in Figure 5. The average quality of collaborative patents made by type H firms was growing compared to the quality of collaborative patents made by type L firms before the Act. After the Sunshine Act is enacted, though, the average quality of co-patents made by type H firms, relative to type L firms, starts decreasing and keeps falling. Overall, this set of results is consistent with our Hypothesis 3: after more information on physicians becomes publicly available, any information advantage initially owned by type H firms vis-à-vis type L firms diminishes. So, the latter group of firms becomes better able to identify and engage especially valuable inventors, such that the relative value of their collaborations increases, at the expense of the former group of firms.

--Insert Table 5 and Figure 5 here--

4.2 Additional results

In this section, we perform additional analyses, testing other predictions potentially consistent with our theoretical model. First of all, it is plausible that firms collaborate with external physicians mainly for exploring novel technologies, which are outside their internal competencies. If so, the decline in collaborations experienced by type H firms, compared to type L firms, should mainly result in a decline of novel vs. incremental innovations. To test whether this is the case, we collected data on new products introduced by all firms in our sample. Any medical device that is manufactured or sold in the US must be approved by the Food and Drug Administration (FDA). The FDA categorizes medical device products into three types based on the levels of safety for usage by human patients. Devices in classes I and II can be marketed after submitting a premarket notification, commonly known as a 510(k) notification, in which manufacturers demonstrate the device is "substantially equivalent" to a previously approved product, known formally as a "predicate device." The similarity to current devices is the key feature allowing a 510(k) application to be approved without a substantial review of the product's safety and efficacy. So, 510(k) applications are usually viewed as describing relatively incremental innovations with relatively low risks (Chatterji and Fabrizio 2014, Smith and Shah 2013). By contrast, devices assigned to class III must go through the premarket approval (PMA) process for which a predicate device is not available, such that manufacturers are required to submit concrete evidence (clinical data) to prove the safety and efficacy of the new device. PMA devices are usually considered to be more substantive (even sometimes radical) innovations, with correspondingly higher risk.[15]

Using data on the new products introduced by the firms in our sample, we assess how the Sunshine Act affected the number of 510(k) products, which represent incremental innovations, vis-a-vis the number of PMA products, which constitute more novel innovations. Table 6 shows the results. Consistent with our expectations, after the regulatory change, for type H firms compared to type L firms, only the relative decline in PMA product introductions is statistically significant.

Additional implications of our theoretical model concern physicians. As is the case with collaborating firms, not all physicians will benefit equally from the improvement in the information environment. Type N, no-reputation physicians will be the ones benefiting more. The reasoning goes as follows (for a formal proof, see Appendix C). When a firm receives a good signal regarding an inventor, it forms a collaboration, regardless of whether the inventor is of type N or type R. If the firm receives no good signal from an inventor, it looks exclusively for an inventor of type R. In absence of public information, the firm ends up frequently with no good signal from an inventor, in which case it looks for an inventor with reputation. Public information makes it less likely that the firm ends up with no positive signals about an inventor and, therefore, it reduces the probability that the firm goes looking exclusively for an inventor of type R. In other words, when public information is available, firms' decisions regarding who to collaborate will rely more on signals regarding the match between inventors and projects and rely

[15]We manually match counts of approved 510(k) and PMA products in the FDA dataset with our sample firms. All supplement PMA filings are excluded, following the prior literature.

less on the reputation of inventors. Hence, the availability of public information increases the share of collaborations performed by inventors with no reputation.

The former reasoning implies that, after the Sunshine Act improved the information environment, type L firms start approaching no-reputation inventors, potentially competing with type H firms for their collaborative innovation services. This greater attention and competition could improve match quality for the no-reputation inventors. Consistent with this line of reasoning, Table 7 shows that type N, no-reputation physicians, significantly increase both the quantity and quality of their collaborations (columns 2 and 4). In contrast, type R, high-reputation physicians experience significant declines in both the quantity and quality of collaborations (columns 1 and 3), as also depicted in Figure 6.

--Insert Table 6, Table 7 and Figure 6 here--

5. Robustness checks

Our main results confirm the theoretical predictions that: information transparency concerning collaborators tends to narrow the gap in both the quantity and quality of collaborations among firms that, before the regulatory change, used to intensively collaborate and firms that did not. Furthermore, firms that used to collaborate frequently experience a relative decline that is especially concentrated in collaborations with low-reputation physicians. In this section, we provide additional evidence to determine to what extent a causal interpretation of these findings could be warranted. To do so, we: (a) attempt to control for pre-existing differences between type H and type L firms that could affect our results; (b) rule out alternative mechanisms driving our findings.

5.1 Reducing imbalance between type H and type L firms

Summary statistics suggest that the two groups of firms we examine in our difference-in-differences regressions are quite different in terms of observable features. Type H firms, compared with type L firms, are relatively larger firms with more R&D input, higher revenues, and more innovation output. As we noted, the two groups of firms do not exhibit different pre-shock trends in major outcomes (Figure 3), or, if they do (as in Figure 4), the different trends, if present, run in the direction opposite to that which could lead to spurious empirical inference (such that our estimates would be conservative). This should alleviate concerns that differences in trends between the two groups are driving our findings. However, to address any remaining concerns, we perform additional analyses.

Matching. First, to reduce the imbalance between type H and L firms, we match the two groups of firms on observable features using propensity score matching. Specifically, we match based on average R&D expenditure, revenues, market value, number of employees, and the total number of patents before 2013 (inclusive of patents in that year). After matching, the two groups of companies are much more similar to each other (cf. Appendix Table A1). Using the propensity score matching coefficients as regression weights does not substantially affect our findings, as shown in table 9. Specifically, the relative decline in the number of physician co-patents, after matching, is very similar to that estimated in our baseline regression (cf. Table 3), while the relative decline in quality of co-patents is of smaller magnitude (cf. Table 5), though still statistically significant. Overall, this evidence corroborates our major findings.

--Insert Table 8 here--

Alternative definitions of type H and type L firms. Our results might be sensitive to how we define type H and type L firms. To partly alleviate this concern, we use a less restrictive definition of type H firms: companies co-inventing with physicians in at least 5 of the years falling within the pre-shock period. This definition allows us to assess the effect of the Sunshine Act on groups that are more balanced and similar. Table 9 shows the results on major outcome variables under the same specifications using these new definitions. The estimated effects are quite similar to those estimated in prior specifications (see Table 3), suggesting our main results are robust to alternative definitions of type H and type L firms.

--Insert Table 9 here--

Excluding technological areas where type L and type H firms differ most. One might think that type H and type L firms might be significantly different in the distributions of their patents across technological areas. If so, a technological shock affecting those technological areas where type H or type L firms were differentially active might drive our findings. To rule out this possibility, we first examine the percentage distributions of patents in each technological section for type H firms and type L firms (Appendix Table A2). As Panel A shows, the two groups of firms mainly differ in the technological sections "F," "G," and "H," which are major categories in the patent classification system upon which the CPC is based. After excluding these potentially confounding areas, as shown in Panel B, the percentage distribution of patents in each section becomes much more balanced across the two groups of firms. With the restricted sample, we run the regressions on major outcomes and results stay substantially the same (Appendix Table A3).

Dropping observations related to investigated firms. Finally, as Chatterji and Fabrizio (2016) note, five firms – Biomet, Johnson & Johnson, Smith & Nephew, Stryker Orthopedics, and Zimmer – were investigated in 2005 by the US government because of their suspicious connections with healthcare providers, including physicians. After the investigation, these firms experienced a sharp decline in their innovation performance. As all these firms are included in the group of type H firms, this could potentially confound our findings. To make sure our results are not affected by these "outliers", we exclude them from our sample. As reported in Table A4 of the Appendix, our major results still hold.

5.2 Ruling out alternative explanations

Our results might in principle be driven by other mechanisms related to the Sunshine Act (such as an increase in the costs of complying with the new regulation), or by other unrelated shocks occurring during the time period considered in our study. In this section, we therefore show the results of additional analyses, to rule out possible alternative explanations.

Increase in costs. One could argue that our findings might be driven by the costs imposed by the Sunshine Act on the medical device companies, via stricter government scrutiny and additional resources needed to comply with the regulation. This increase in costs might have disrupted physician-firm connections and even hampered firm innovation. Indeed, Chatterji and Fabrizio (2014) find that those orthopedic medical device firms that were investigated by the government because of their suspicious connections with physicians experience a quite significant decline in their innovative performance, compared to a similar sample of companies not under investigation. However, we do not think this mechanism (even if present) can account for our findings. First, there is no reason to think that the cost of collaborations increased differently for type H and type L firms. Therefore, it seems unlikely that an increase in regulatory costs alone cannot explain the differential effects of the Sunshine Act across these two groups of firms. Furthermore, it seems unlikely that any increase in regulatory costs can explain the sharp differences we observe in terms of the measured impact on collaboration with type R vs. type N physicians. Thus, we believe that a mere increase in regulatory costs—even if it were driven by the Sunshine Act—does not provide a compelling alternative explanation of our findings.

The American Invents Act (AIA). Another threat to the internal validity of our difference-in-differences design comes from other policy changes implemented around the same time as the Sunshine Act (2014) which could potentially affect type H and type L firms differently, confounding our results. One candidate could be the Leahy-Smith America Invents Act (AIA), which was enacted in 2011 and finally took effect in 2013—such that it is essentially simultaneous to the Sunshine Act. By establishing the Patent Trial and Appeal Board (PTAB), the AIA provides a cost-efficient way to invalidate a granted patent, which is an alternative to traditional litigation in court (Spivey, Munson and Wurth 2014). With such a low-cost "invalidation weapon," small firms—which used to be easily "barred" from entering areas fenced by big firms' patents—can defend themselves more effectively when facing litigation risks initiated by big companies' with large patent portfolios. As the "entry deterring power" of patents declines, large companies might apply for fewer patents. As noted in the summary statistics section, type H firms are usually bigger firms in terms of the number of patents, R&D expenditure, and revenues compared with type L firms. Therefore, the significant decline in patenting experienced by type H firms might result from the AIA.

To rule out this mechanism, we run the same regression on non-medical-device patents assigned to our sampled firms. Specifically, we look at the effect of the Sunshine Act patents granted to firms in our sample but in technological areas unrelated to pharmaceutical or medical device products. These patents could be affected by the AIA, but not by the Sunshine Act. Hence, the comparison with medical device patents, affected both the AIA and the Sunshine Act, would allow us to isolate the effect of the Sunshine Act. Table 10 shows that, following the Sunshine Act, type H firms experience a relative decline in non-pharmaceutical & non-medical-device patents, but the decrease is quite limited and not statistically significant (column 4). This suggests that the effect we observe in medical device patents is largely due to the Sunshine Act, rather than to the AIA or any other contemporaneous regulatory change affecting patenting activity in general.

--Insert Table 10 here—

State-level regulatory changes. Finally, as noted above, six states had similar disclosure regulations before the Sunshine Act. If these state-level regulations led to an improvement in the information before the Sunshine Act, our estimates might be lower than the real effect of the shock. If instead, the improvement in the information environment occurred around at the time of the Sunshine Act, the estimated effect might be greater than the actual ones. To control for the confounding effect of similar state-level regulations, we exclude patents filed by physician inventors from the six states: as Table A5 of the Appendix shows, results on physician co-patents still hold.

6. Discussion

In the growing literature on markets for technology, the dominant view is that lack of information impedes the functioning of the market, limit transaction volume, and lower social welfare (Agrawal, Cockburn and Zhang 2015, Gans, Hsu and Stern 2008, Luo 2014). Some previous research has even assumed that these markets might be afflicted by a relevant “lemons problem” (e.g., Pisano 2006, Anton and Yao 2002, Aghion and Tirole 1994, Gallini and Wright 1990). Hence, the reasoning goes, any institution enhancing the information available to potential buyers when choosing external R&D collaborators and projects will be beneficial for all companies intending to buy ideas or collaborations for developing ideas (Arora, Fosfuri and Gambardella 2001, Hegde and Luo, 2018).

In our work, we show that this is not the case. When firms buying the services of external inventors possess heterogeneous private information about the pool of external inventors, then more public information will be detrimental for those firms that possess better private information. The competitive advantage enjoyed by these firms erodes as more public information is disclosed.

Our work also contributes to a related stream of literature focusing on the downsides 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 (Verrecchia 1983, Dye 1985, Darrough and Stoughton 1990, Graham, Harvey and Rajgopal 2005). Our work identifies a new theoretical mechanism 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 firms that initially possess better private information about the pool of external inventors and ideas.

Like any study, this paper also has its limitations. First, 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 health care providers, and this sector was also affected by the Sunshine Act – future work will investigate the degree to which the Act had a similar impact in this adjacent market for technology. Another limitation is that to avoid severe truncation bias, we focus on patented inventions that are granted by the end of 2018. Whereas this might be a problem, we do think the truncation affects the type H and type L firms in a relatively equal way; therefore, comparing these two types of firms helps to control the truncation to a certain extent.

Despite these limitations, our work may have important managerial implications. 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, Fosfuri and Gambardella 2001, Arora and Gambardella 2010). In this respect, conventional wisdom suggests that policies for expanding technology markets should focus on improving the information environment, especially for buyers who might decide not to participate in those markets in the first place, given the risk of purchasing "lemons." One could expect all firms should support these policies. 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, as well as the relative average quality of transactions, for those firms that, before the improvement in the information environment, were relying more extensively on collaborations. More information may not be better for everyone.

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Table 1 Summary statistics

	min	median	mean	max	st.dev.	Obs.
Panel A Firm-year level outcomes						
Patents	0	1	13.04	682	52.31	3864
Physician co-patents	0	0	0.63	55	2.87	3864
In-house patents	0	1	12.41	627	49.98	3864
Average forward citations to patents	0	0	3.25	176.08	11.14	3864
Average forward citations to co-patents	0	0	1.06	252	7.40	3864
Average forward citations to in-house patents	0	0	3.22	222	11.56	3864
Co-patents with type R physicians	0	0	0.14	38	1.11	3864
Co-patents with type N physicians	0	0	0.31	46	1.90	3864
Panel B Patent level outcomes						
Physician co-patents	0	0	0.05	1	0.21	50141
Forward citations to the patent	0	1	11.45	743	45.32	50141
Forward citations to physician co-patents	0	2	8.36	552	28.07	2385
Forward citations to in-house patents	0	1	11.60	743	46.01	47756
Panel C Physician-year level outcomes						
Co-patents by top 10% physicians	0	0	0.33	12	0.98	1766
Co-patents by zero reputation physicians	0	0	0.17	14	0.55	7196

Table 2 Summary statistics on pre-shock average of major variables by "type H" and "type L" firms

	min	median	mean	max	st.dev.	Obs.
Panel A "Type H" firms						
Patents	4.9	61.9	148.1	531.1	184.5	16
Physician co-patents	1.3	6.4	9.3	35.0	8.8	16
In-house patents	0.7	55.4	138.8	496.4	176.9	16
Employees	0.1	9.3	24.0	119.9	32.6	16
R&D expenditure	5.2	390.5	1135.8	8130.9	2067.2	16
Revenues	18.2	4491.3	10171.1	64797.6	16512.8	16
Market values	116.2	18940	604,700,000	9,674,000,000	2,419,000,000	16
Panel B "Type L" firms						
Patents	0.0	1.1	7.7	223.9	21.8	260
Physician co-patents	0.0	0.0	0.2	3.7	0.5	260
In-house patents	0.0	1.1	7.5	222.0	21.6	260
Employees	0.002	0.4	8.8	407.0	38.1	231
R&D expenditure	0.002	7.8	200.0	8499.3	946.7	255
Revenues	0.1	79.3	2751.0	163407.9	13931.5	258
Market values	3.1	6232.4	2,181,000,000	156,800,000,000	13,480,000,000	250

Note: the unit for employees is thousand people. Units for R&D expenditure, revenues and market values are thousand dollars.

Table 3 The effect of the Sunshine Act on the number of patents made by type H vs. type L firms

	(1) Patents	(2) Patents	(3) Physician co-patents	(4) Physician co-patents	(5) In-house patents	(6) In-house patents
TypeHFirm *PostSunshine	-0.294*	-0.290*	-0.473***	-0.473***	-0.289	-0.283
	(0.172)	(0.171)	(0.160)	(0.160)	(0.176)	(0.175)
Controls	no	yes	no	yes	no	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	3,064	3,064	3,064	3,064	3,064	3,064
R-squared	0.196	0.198	0.070	0.071	0.190	0.193
Number of groups	272	272	272	272	272	272

Note: The dependent variable is the log of one plus the number of patents, in columns 1 and 2; the log of one plus the number of patents in collaboration with a physician, in columns 3 and 4; and the log of one plus the number of in-house patens, in columns 5 and 6. “TypeHFirm” is a dummy indicating firms that filed at least one co-patent with a physician in each year during the pre-shock period. “PostSunshine” is a dummy indicating the time after 2014 (including). Control variables include log annual revenues and log annual R&D expenditures from the previous year. Firm fixed effects and year fixed effects are included. OLS estimation. Robust standard errors are clustered at the firm level, shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 4 The effect of the Sunshine Act on the number of co-patents made by type H vs. type L firms with physicians of heterogeneous reputation

	(1) Co-patents with type R physicians	(2) Co-patents with type R physicians	(3) Co-patents with type N physicians	(4) Co-patents with type N physicians
TypeHFirm *PostSunshine	-0.297**	-0.299**	-0.674***	-0.674***
	(0.149)	(0.150)	(0.157)	(0.156)
Controls	no	yes	no	yes
Firm fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	3,064	3,064	3,064	3,064
R-squared	0.038	0.038	0.106	0.107
Number of groups	272	272	272	272

Note: The dependent variables is the log of one plus the number of patents made by firms with type R physicians (or physicians in the top 10 percent in terms of cumulative forward citations in the past 5 years), in columns 1 and 2, and with type N physicians (or physicians with zero forward citations in the past 5 years), in columns 3 and 4. “TypeHFirm” is a dummy indicating firms with at least one physician co-patent in each year during pre-shock period. “PostSunshine” is a dummy indicating the time after 2014 (including). Control variables include log annual revenues and log annual R&D expenditures from the previous year. Firm fixed effects and year fixed effects are included. OLS estimation. Robust standard errors are clustered at the firm level, shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 5 The effect of the Sunshine Act on the average value of patents for type H vs. type L firms

	(1) Average citations to patents	(2) Average citations to patents	(3) Average citations to physician co-patents	(4) Average citations to physician co-patents	(5) Average citations to in-house patents	(6) Average citations to in-house patents
TypeHFirm *PostSunshine	-0.729***	-0.719***	-1.253***	-1.254***	-0.700***	-0.689***
	(0.172)	(0.182)	(0.167)	(0.169)	(0.180)	(0.190)
Controls	no	yes	no	yes	no	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	3,064	3,064	3,064	3,064	3,064	3,064
R-squared	0.283	0.288	0.142	0.143	0.269	0.274
Number of groups	272	272	272	272	272	272

Note: The dependent variable is log number of one plus the average number of forward citations (within 5 years after the patent is granted) per patent. “TypeHFirm” is a dummy indicating firms which filed at least one physician co-patent in each year during pre-shock period. “PostSunshine” is a dummy indicating the time after 2014 (including). Control variables include log annual revenues and log annual R&D expenditures from the previous year. Firm fixed effects and year fixed effects are included. OLS estimation . Robust standard errors are clustered at the firm level, shown in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6 The effect of the Sunshine Act on new products for type H vs. type L firms

	(1) 510(k)	(2) 510(k)	(3) 510(k)	(4) PMA	(5) PMA	(6) PMA
TypeHFirm *PostSunshine	-0.178	-0.180	0.112	-0.115**	-0.116**	-0.108*
	(0.211)	(0.209)	(0.330)	(0.0459)	(0.0458)	(0.0552)
Controls	no	yes	yes	no	yes	yes
PPS weighted	no	no	yes	no	no	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	3,064	3,064	510	3,064	3,064	510
R-squared	0.058	0.061	0.212	0.025	0.025	0.083
Number of groups	272	272	41	272	272	41

Note: The dependent variable is the log of one plus the number of 510(k) products, in columns 1 to 3, and of PMA products, in columns 4 to 6. “TypeHFirm” is a dummy indicating firms with at least one physician co-patent in each year during the pre-shock period. “PostSunshine” is a dummy indicating the time after 2014 (including). Control variables include log annual revenues and log annual R&D expenditures from the previous year. Firm fixed effects and year fixed effects are included. OLS estimation. Robust standard errors are clustered at the firm level, shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 7 The effect of the Sunshine Act on the number and value of co-patents made by type R vs. type N physicians

	(1) Physician co-patents	(2) Physician co-patents	(3) Average citations to co-patents	(4) Average citations to co-patents
TypeRphysician *PostSunshine	-0.0578***		-0.234***	
	(0.0178)		(0.0371)	
TypeNphysician *PostSunshine		0.0964***		0.141***
		(0.0078)		(0.0101)
Physician fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	17,790	17,790	17,790	17,790
R-squared	0.030	0.036	0.045	0.043
Number of groups	1,186	1,186	1,186	1,186

Note: The analysis is at the physician level. "PostSunshine" indicates the time after 2014 (including). "TypeRphysicians" are physicians in the top 10 percent in terms of cumulative forward citations in the past 5 years; "TypeNphysicians" are physicians with zero forward citations in the past 5 years. Physician fixed effects and year fixed effects are included. OLS estimation. Robust standard errors are clustered at the physician level, shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8 The effect of the Sunshine Act on the number and value of patents made by type H vs. type L firms – propensity score matching

Panel A number and value of patenting

	(1) Patents	(2) Average citations to patents	(3) Physician co-patents	(4) Average citations to physician co-patents	(5) in-house patents	(6) Average citations to in-house patents
TypeHFirm *PostSunshine	-0.120	0.124	-0.459***	-0.535**	-0.108	0.186
	(0.229)	(0.237)	(0.159)	(0.223)	(0.235)	(0.241)
Controls	yes	yes	yes	yes	yes	yes
PPS weighted	yes	yes	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	510	510	510	510	510	510
R-squared	0.610	0.783	0.298	0.387	0.603	0.727
Number of groups	41	41	41	41	41	41

Panel B co-patents with physicians

	(7) Co-patents with type R physicians	(8) Co-patents with type L physicians
TypeHFirm *PostSunshine	-0.161	-0.611***
	(0.164)	(0.171)
Controls	yes	yes
PPS weighted	yes	yes
Firm fixed effects	yes	yes
Year fixed effects	yes	yes
Observations	510	510
R-squared	0.111	0.231
Number of groups	41	41

Note: "TypeHFirm" is a dummy indicating firms with at least one physician co-patent in each year during pre-shock period. "PostSunshine" is a dummy indicating the time after 2014 (including). Type R physicians are physicians in the top 10 percent in terms of cumulative forward citations in the past 5 years; type N physicians are physicians with zero forward citations in the past 5 years. Control variables include log annual revenues and log annual R&D expenditures from the previous year. Firm fixed effects and year fixed effects are included. OLS estimations. Robust standard errors are clustered at the firm level, shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 9 The effect of the Sunshine Act on the number and value of patents – alternative definitions of type H and type L firms

Panel A number of patents						
	(1) Patents	(2) Patents	(3) Physician co-patents	(4) Physician co-patents	(5) In-house patents	(6) In-house patents
TypeHFirm *PostSunshine	-0.281*	-0.278*	-0.327***	-0.328***	-0.255*	-0.251*
	(0.144)	(0.143)	(0.0767)	(0.0769)	(0.146)	(0.146)
Controls	no	yes	no	yes	no	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	3,064	3,064	3,064	3,064	3,064	3,064
R-squared	0.199	0.201	0.075	0.076	0.193	0.196
Number of groups	272	272	272	272	272	272
Panel B value of patents						
	(7) Average citations to patents	(8) Average citations to patents	(9) Average citations to physician co-patents	(10) Average citations to physician co-patents	(11) Average citations to in-house patents	(12) Average citations to in-house patents
TypeHFirm *PostSunshine	-0.692***	-0.677***	-1.012***	-1.014***	-0.685***	-0.669***
	(0.0976)	(0.0989)	(0.0868)	(0.0869)	(0.101)	(0.102)
Controls	no	yes	no	yes	no	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	3,064	3,064	3,064	3,064	3,064	3,064
R-squared	0.296	0.301	0.184	0.185	0.283	0.287
Number of groups	272	272	272	272	272	272
Panel C co-patents with physicians						
	(13) Co-patents with type R physicians	(14) Co-patents with type R physicians	(15) Co-patents with type N physicians	(16) Co-patents with type N physicians		
TypeHFirm *PostSunshine	-0.147**	-0.149**	-0.374***	-0.374***		
	(0.0648)	(0.0654)	(0.0771)	(0.077)		
Controls	no	yes	no	yes		
Firm fixed effects	yes	yes	yes	yes		
Year fixed effects	yes	yes	yes	yes		
Observations	3,064	3,064	3,064	3,064		
R-squared	0.025	0.026	0.085	0.086		
Number of groups	272	272	272	272		

Note: "TypeHFirm" is a dummy indicating firms with at least one physician co-patent for five or more years during pre-shock period. "PostSunshine" is a dummy indicating the time after 2014 (including). Type R physicians are physicians in the top 10 percent in terms of cumulative forward citations in the past 5 years; type N physicians are physicians with zero forward citations in the past 5 years. Control variables include log annual revenues and log annual R&D expenditures from the previous year. Firm fixed effects and year fixed effects are included. OLS estimations. Robust standard errors are clustered at the firm level, shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 10 The effect of the Sunshine Act on the medical device patents and non-medical device patents by sampled firms

	(1) Medical device patents	(2) Medical device patents	(3) Other patents	(4) Other patents
TypeHFirm *PostSunshine	-0.294*	-0.290*	-0.190	-0.189
	(0.172)	(0.171)	(0.220)	(0.215)
Controls	no	yes	no	yes
Firm fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	3,064	3,064	3,064	3,064
R-squared	0.196	0.198	0.092	0.100
Number of groups	272	272	272	272

Note: The dependent variable is the log of one plus the number of medical device patents, in columns 1 and 2, and of patents that are neither medical device nor pharmaceutical patents, in columns 3 and 4. "TypeHFirm" is a dummy indicating firms with at least one physician co-patent in each year during pre-shock period. "PostSunshine" is a dummy indicating the time after 2014 (including). Control variables include log annual revenues and log annual R&D expenditures from the previous year. Firm fixed effects and year fixed effects are included. OLS estimation. Robust standard errors are clustered at the firm level, shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Figure 1 Firms' decision timeline in the absence of public information

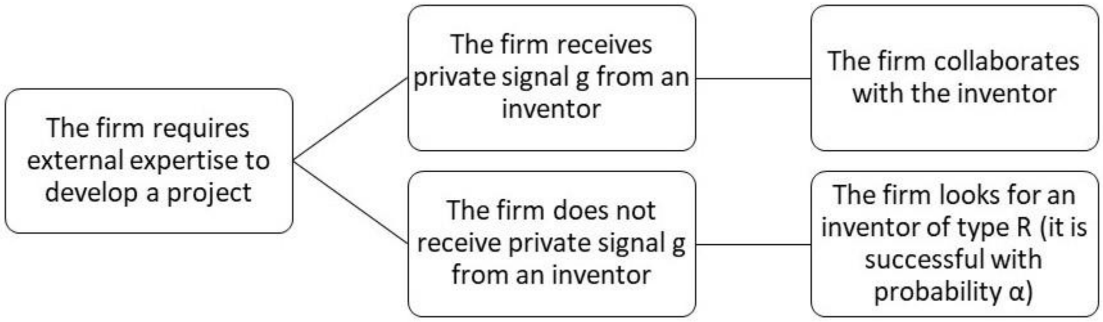


Figure 2 Firms' decision timeline in the presence of public information

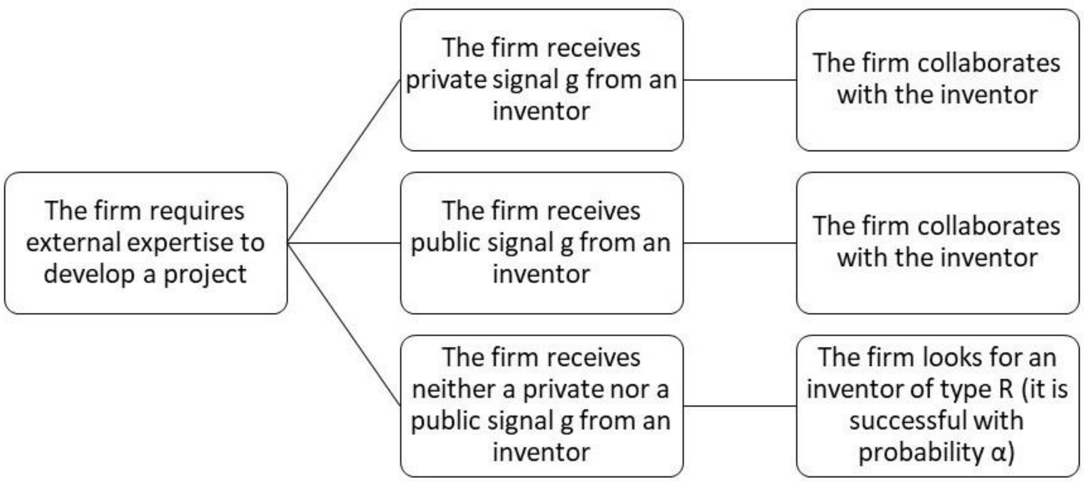
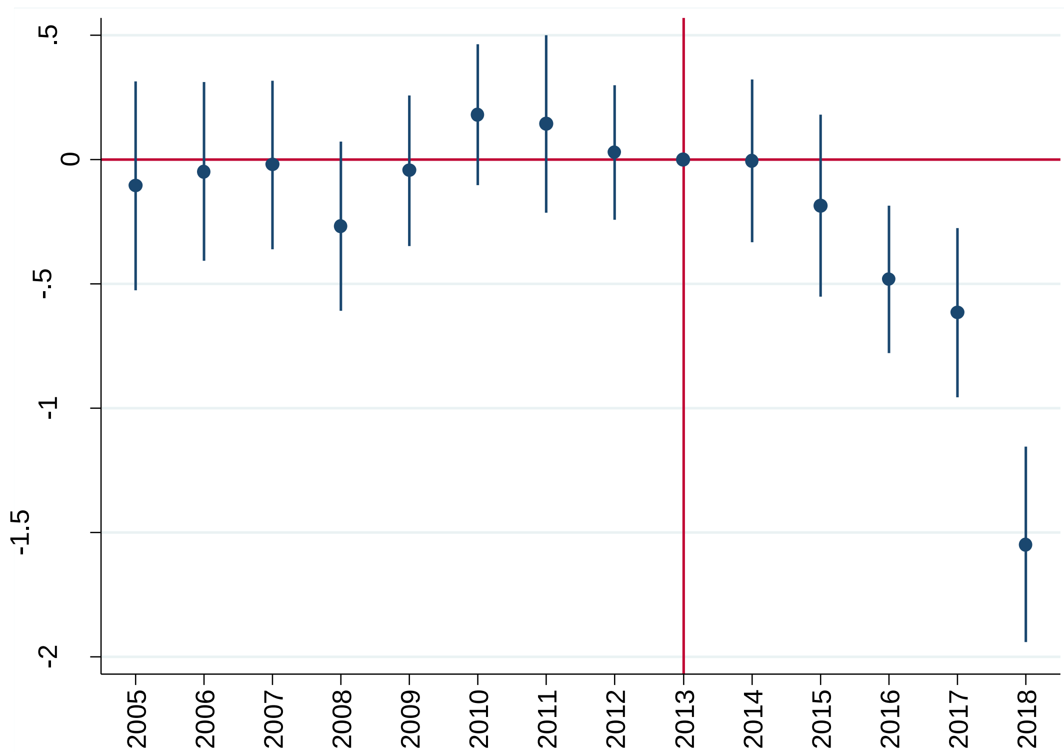
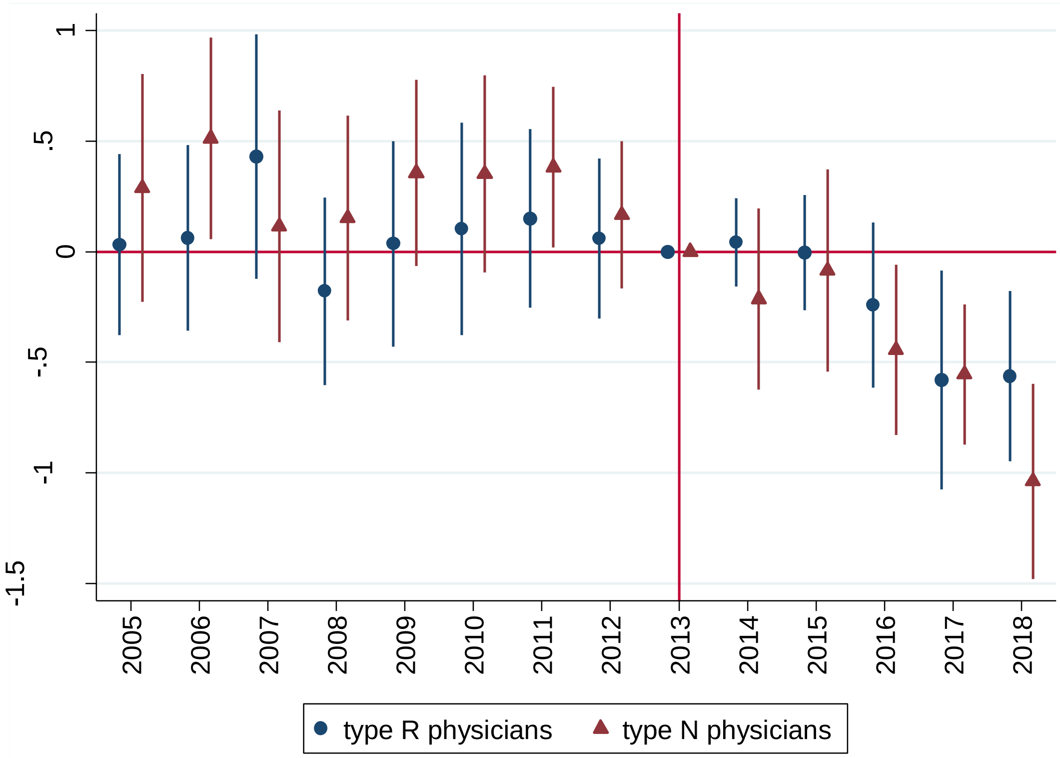


Figure 3 The effect of the Sunshine Act on the number of co-patents with physicians made by type H vs. type L firms



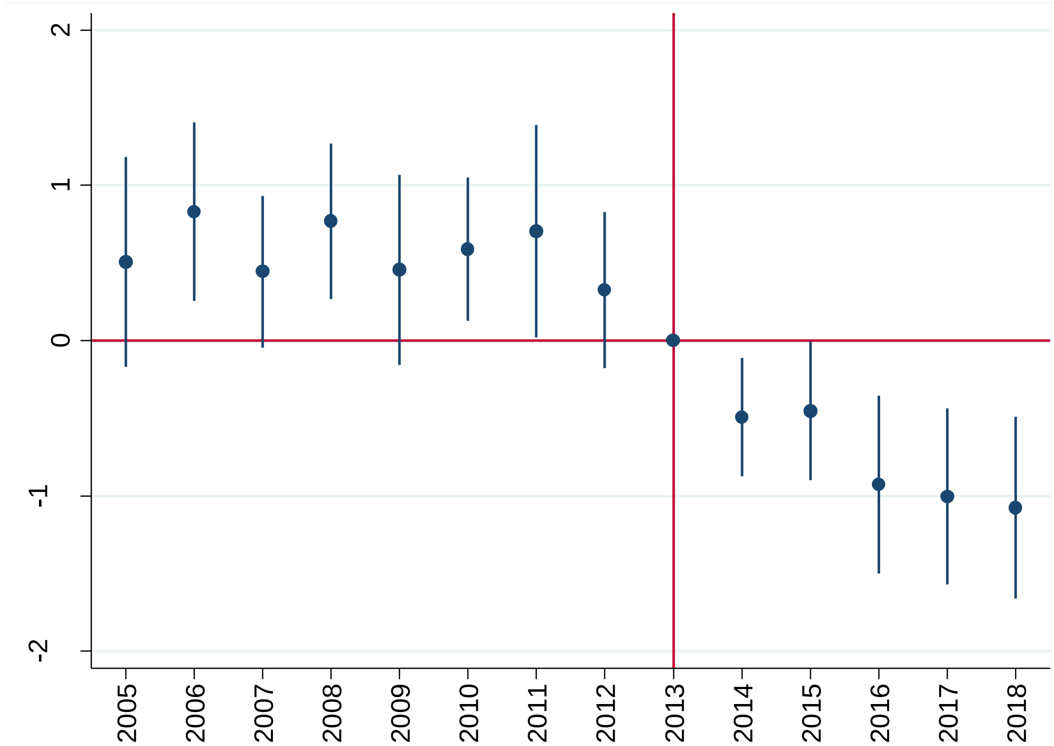
Note: The dependent variable is the log of one plus the number of co-patents. Difference-in-differences coefficients are estimated for type H firms relative to type L firms. Type H firms are firms with at least one physician co-patent in each year during pre-shock period, while type L firms are the rest firms in the sample. Control variables include log annual revenues and log annual R&D expenditures from the previous year. Firm fixed effects and year fixed effects are included. OLS estimation. Robust standard errors are used, clustered at the firm level.

Figure 4 The effect of the Sunshine Act on the quantity of co-patents made by type H vs. type L firms, with type R vs. type N physicians



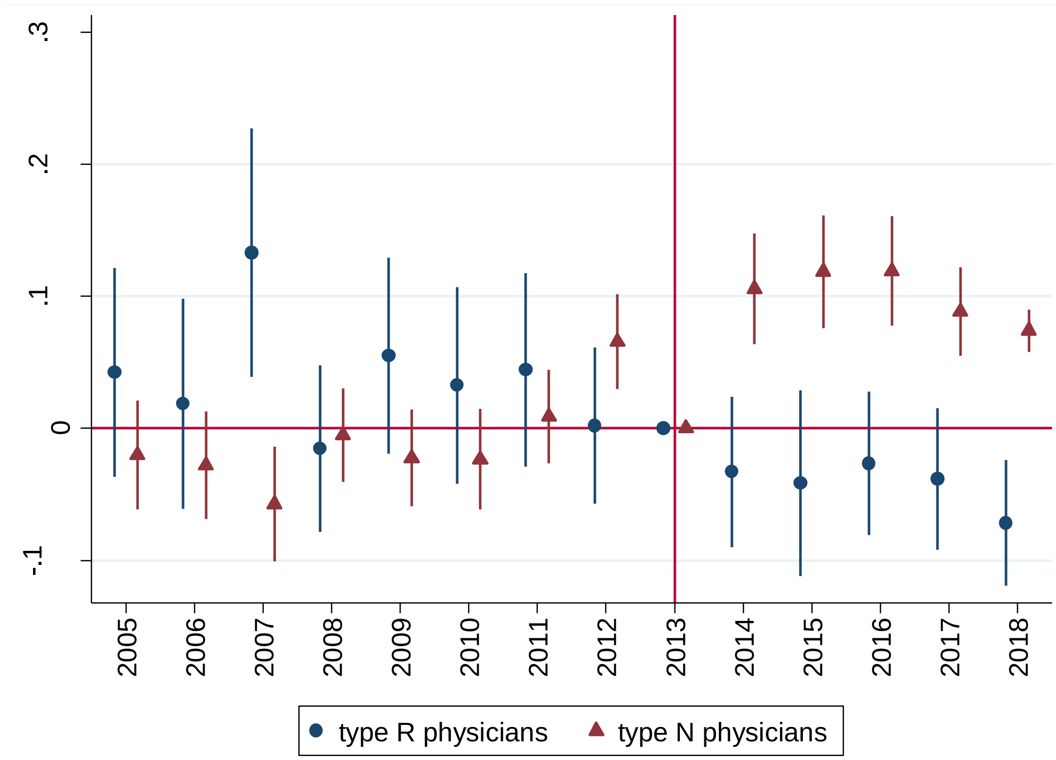
Note: Dependent variables is the log of one plus the number of patents made by firms with type R physicians (or physicians in the top 10 percent in terms of cumulative forward citations in the past 5 years), marked by blue circles, vs. type N physicians (or physicians with zero forward citations in the past 5 years), marked by red triangles. Difference-in-differences coefficients are estimated for type H firms relative to type L firms. Firm fixed effects and year fixed effects are included. Control variables are log of revenues and R&D expenditures from the previous year. OLS estimation. Robust standard errors are used, clustered at the firm level.

Figure 5 The effect of the Sunshine Act on the value of co-patents made by type H vs. type L firms



Note: The dependent variable is the log of one plus the firm average number of forward citations per patent. Difference-in-differences coefficients are estimated for type H firms relative to type L firms. Type H firms are firms with at least one physician co-patent in each year during pre-shock period, while type L firms are the rest of firms in the sample. Control variables include log annual revenues and log annual R&D expenditures from the previous year. Firm and year fixed effects are included. OLS estimations. Robust standard errors are clustered at the firm level.

Figure 6 The effect of the Sunshine Act on the quantity of co-patents made by type N vs. type R physicians



Note: The analysis is at the physician level. Dependent variables is log of one plus the number of co-patents. Type R physicians are physicians in the top 10 percent in terms of cumulative forward citations in the past 5 years, marked by blue circles; type N physicians are physicians with zero forward citations in the past 5 years, marked by red triangles. Physician fixed effects and year fixed effects are included. OLS estimations. Robust standard errors are clustered at the physician level.

Appendix A

Table A1 Summary statistics of “type H” and “type L” firms before and after propensity score matching

		Mean		%reduction	t-test
Variable		**Treated**	**Control**	**|bias|**	**p>|t|**
Log(patents)	Unmatched	4.229	1.276	78.800	0.000
	Matched	4.229	3.603		0.123
Log(employees)	Unmatched	2.429	0.950	47.400	0.000
	Matched	2.429	1.652		0.103
Log(R&D expenditures)	Unmatched	5.632	2.827	64.100	0.000
	Matched	5.632	4.625		0.100
Log(revenues)	Unmatched	7.943	4.878	64.200	0.000
	Matched	7.943	6.846		0.125
Log(market values)	Unmatched	10.018	11.360	60.800	0.456
	Matched	10.018	9.492		0.725

Table A2 Percentage of patents from CPC sections by two groups of firms

	"type L" firms	"type H" firms	Total
Panel A before excluding confounding areas			
A	80.51	93.87	87.73
B	1.25	1.05	1.14
C	0.93	0.85	0.89
D	0.05	0.05	0.05
E	0.01	0.01	0.01
F	0.51	0.19	0.34
G	14.88	2.82	8.36
H	1.86	1.16	1.48
Panel B after excluding confounding areas			
A	97.29	97.95	97.67
B	1.51	1.1	1.27
C	1.13	0.88	0.99
D	0.06	0.05	0.06
E	0.01	0.01	0.01

Note: figures in each cell are the percentage of patents in each CPC sections over the full patent portfolio of firms with at least one co-patent in each year from 2005 to 2013 (column 2), of firms without such co-patents (column 1), all firms (column3). After excluding "F" "G" "H", the percentages of each remaining CPC section become more balanced.

Table A3 The effect of the Sunshine Act on the number and value of patents made by type H vs. type L firms – patents from CPC sections "F" "G" "H" are excluded

	(1) Patents	(2) Physician co-patents	(3) In-house patents	(4) Average citations to patents	(5) Average citations to physician co-patents	(6) Average citations to In-house patents
TypeHFirm *PostSunshine	-0.335*	-0.516***	-0.323*	-0.815***	-1.392***	-0.791***
	(0.187)	(0.180)	(0.191)	(0.128)	(0.134)	(0.138)
Controls	yes	yes	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	3,064	3,064	3,064	3,064	3,064	3,064
R-squares	0.189	0.077	0.184	0.280	0.161	0.265
Number of groups	272	272	272	272	272	272

Panel B Co-patents with physicians

	(7) Co-patents with type R physicians	(8) Co-patents with type N physicians
TypeHFirm *PostSunshine	-0.473***	-0.488***
	(0.160)	(0.176)
Controls	yes	yes
Firm fixed effects	yes	yes
Year fixed effects	yes	yes
Observations	3,064	3,064
R-squares	0.072	0.070
Number of groups	272	272

Note: Patents from CPC sections "F" "G" "H" are excluded. "TypeHFirm" is a dummy indicating firms with at least one physician co-patent for five or more years during pre-shock period. "PostSunshine" is a dummy indicating the time after 2014 (including). Type R physicians are physicians in the top 10 percent in terms of cumulative forward citations in the past 5 years; type N physicians are physicians with zero forward citations in the past 5 years. Control variables include log annual revenues and log annual R&D expenditures from the previous year. Firm fixed effects and year fixed effects are included. OLS estimations. Robust standard errors are clustered at the firm level, shown in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A4 The effect of the Sunshine Act on the number and value of patents made by type H vs. type L firms – five orthopedic companies under investigations are excluded

Panel A number and value of patents						
	(1) Patents	(2) Physician co-patents	(3) In-house patents	(4) Average citations to patents	(5) Average citations to physician co-patents	(6) Average citations to In-house patents
TypeHFirm *PostSunshine	-0.209	-0.446***	-0.192	-0.493**	-1.132***	-0.441*
	(0.145)	(0.129)	(0.158)	(0.215)	(0.232)	(0.225)
Controls	yes	yes	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
Observations	2,998	2,998	2,998	2,998	2,998	2,998
R-squares	0.188	0.054	0.184	0.272	0.103	0.257
Number of groups	267	267	267	267	267	267

Panel B Co-patents with physicians		
	(7) Co-patents with type R physicians	(8) Co-patents with type N physicians
TypeHFirm *PostSunshine	-0.383**	-0.539***
	(0.188)	(0.126)
Controls	yes	yes
Firm fixed effects	yes	yes
Year fixed effects	yes	yes
Observations	2,998	2,998
R-squares	0.048	0.063
Number of groups	267	267

Note: Biomet, Depuy (part of Johnson & Johnson), Zimmer, Stryker and Smith & Nephew are excluded from our sample. "TypeHFirm" is a dummy indicating firms with at least one physician co-patent for five or more years during pre-shock period. "PostSunshine" is a dummy indicating the time after 2014 (including). Type R physicians are physicians in the top 10 percent in terms of cumulative forward citations in the past 5 years; type N physicians are physicians with zero forward citations in the past 5 years. Control variables include log annual revenues and log annual R&D expenditures from the previous year. Firm fixed effects and year fixed effects are included. OLS estimations. Robust standard errors are clustered at the firm level, shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table A5 The effect of the Sunshine Act on the number and value of patents – co-patents invented by physicians from six states are excluded

	(1) Physician co-patents	(2) Average citations tophysician co-patents	(3) Co-patents by type R physicians	(4) Co-patents by type N physicians
TypeHFirm *PostSunshine	-0.518***	-1.289***	-0.465***	-0.474***
	(0.159)	(0.175)	(0.156)	(0.163)
Controls	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	3,064	3,064	3,064	3,064
R-squares	0.077	0.145	0.069	0.070
Number of groups	272	272	272	272

Note: Patents invented by physicians from Minnesota, Vermont, DC, Maine, West Virginia, and Massachusetts are excluded. "TypeHFirm" is a dummy indicating firms with at least one physician co-patent for five or more years during pre-shock period. "PostSunshine" is a dummy indicating the time after 2014 (including). Type R physicians are physicians in the top 10 percent in terms of cumulative forward citations in the past 5 years; type N physicians are physicians with zero forward citations in the past 5 years. Control variables include log annual revenues and log annual R&D expenditures from the previous year. Firm fixed effects and year fixed effects are included. OLS estimations. Robust standard errors are clustered at the firm level, shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Appendix B Proofs for lemmas

Proof of Lemma 1: After some algebra, it follows that $\Delta Q^A = \frac{\lambda_H \bar{\rho}(1-\alpha)+\alpha}{\lambda_L \bar{\rho}(1-\alpha)+\alpha}$ and $\Delta Q^P = \frac{\lambda_H \bar{\rho}(1-\alpha)+\alpha+\lambda_P \bar{\rho}(1-\alpha)}{\lambda_L \bar{\rho}(1-\alpha)+\alpha+\lambda_P \bar{\rho}(1-\alpha)}$. It is then straightforward that $\Delta Q^P < \Delta Q^A$.

Proof of Lemma 2: After some algebra, it follows that $\Delta Q_R^A = \frac{\lambda_H \mu \rho_R+\alpha(1-\lambda\bar{\rho})}{\lambda_L \mu \rho_R+\alpha(1-\lambda\bar{\rho})}$, $\Delta Q_R^P = \frac{\lambda_H \mu \rho_R+\alpha(1-\lambda\bar{\rho})+\lambda_P(\mu\rho_R-\alpha\bar{\rho})}{\lambda_L \mu \rho_R+\alpha(1-\lambda\bar{\rho})+\lambda_P(\mu\rho_R-\alpha\bar{\rho})}$, $\Delta Q_N^A = \frac{\lambda_H}{\lambda_L}$ and $\Delta Q_N^P = \frac{\lambda_H+\lambda_P}{\lambda_L+\lambda_P}$. It can be shown that $\frac{\Delta Q_R^P}{\Delta Q_R^A}$ is minimized at $\alpha = 0$. When $= 0$, $\frac{\Delta Q_R^P}{\Delta Q_R^A} = \frac{\Delta Q_N^P}{\Delta Q_N^A}$. Therefore, $\frac{\Delta Q_R^P}{\Delta Q_R^A} > \frac{\Delta Q_N^P}{\Delta Q_N^A}$ for $\alpha > 0$. It is also straightforward that $\Delta Q_R^A > \Delta Q_R^P$ under the assumption that $\alpha < \frac{\mu\rho_R}{\bar{\rho}}$.

Proof of Lemma 3: After some algebra it can be shown that $(\Delta V^A - \Delta V^P)$ is minimized at $\alpha = 1$. When $\alpha = 1$, $\Delta V^A = \frac{\lambda_H \bar{\rho}\phi(\lambda_H)+(1-\lambda_H\bar{\rho})\rho_R}{\lambda_L \bar{\rho}\phi(\lambda_L)+(1-\lambda_L\bar{\rho})\rho_R}$ and $\Delta V^P = \frac{\lambda_H \bar{\rho}\phi(\lambda_H)+(1-\lambda_H\bar{\rho})\rho_R+\lambda_P\bar{\rho}[\phi(\lambda_P)-\rho_R]}{\lambda_L \bar{\rho}\phi(\lambda_L)+(1-\lambda_L\bar{\rho})\rho_R+\lambda_P\bar{\rho}[\phi(\lambda_P)-\rho_R]}$. It follows that $(\Delta V^A - \Delta V^P) > 0$ when $\alpha = 1$ and, therefore, $(\Delta V^A - \Delta V^P) > 0$ for all α.

Appendix C

Robustness check: type R inventors have a higher opportunity cost of time than type N inventors

Let ω_R and ω_N denote, respectively, the effort cost of type R and type N inventors, where $\omega_R > \omega_N$. In the baseline model, we assumed that information held even by firms of type L is extensive enough that hiring an inventor from whom the firm received a positive signal is worthwhile, i.e. $\phi(\lambda_L) > \omega$. In this alternative setting (where inventors are heterogeneous in their effort cost), we instead require that $\phi(\lambda_L) > \omega_R$, i.e. hiring a type R inventor from whom the firm received a positive signal is worthwhile.

Moreover, in the baseline model we assumed that the probability that a random inventor of type N is a good match with a project is small enough that it is never worth hiring, i.e. $\rho_N < \omega$. Under this alternative setting, this assumption become $\rho_N < \omega_N$. Finally, we assumed that there are gains from collaboration from hiring a type R inventor even in absence of any information, i.e. $\rho_R > \omega$. In this alternative setting, this assumption becomes $\rho_R > \omega_R$.

The effect of public information on type N vs type R inventors

Let q_N^A and q_R^A denote, respectively, the number of collaborations performed by inventors of type N and R, in a setting where public information is absent. Let q_N^P and q_R^P be defined analogously for the setting in which public information is present. Then:

Lemma 4: $\frac{q_N^P}{q_R^P} > \frac{q_N^A}{q_R^A}$.

To prove Lemma 4, Let β denote the proportion of firms with information λ_H, and let $\bar{\lambda} \equiv \beta\lambda_H + (1-\beta)\lambda_L$. The quantity of collaborations performed by inventors of type N when public information is absent is $q_N^A = \beta Q_N^A(\lambda_H) + (1-\beta)Q_N^A(\lambda_L)$. The remaining quantities (q_R^A, q_N^P, q_R^P) can be obtained analogously. It follows that

$$q_N^A = \bar{\lambda}(1-\mu)\rho_N$$

$$q_R^A = \bar{\lambda}\mu\rho_R + \alpha\left(1 - \bar{\lambda}\bar{\rho}\right)$$

$$q_N^P = \left(\bar{\lambda} + \lambda_P\right)(1-\mu)\rho_N$$

$$q_R^P = \left(\bar{\lambda} + \lambda_P\right)\mu\rho_R + \alpha\left(1 - \left(\bar{\lambda} + \lambda_P\right)\bar{\rho}\right)$$

It then follows that $q_N^P q_R^A - q_N^A q_R^P = \alpha\lambda_P(1-\mu)\rho_N > 0$ which implies that $\frac{q_N^P}{q_R^P} > \frac{q_N^A}{q_R^A}$.