Tort Reform and Innovation[1]

Alberto Galasso
University of Toronto and NBER

Hong Luo
Harvard Business School

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Abstract

Current academic and policy debates focus on the impact of tort reforms on physicians' behavior and medical costs. This paper examines whether these reforms also affect incentives to develop new technologies. We find that, on average, laws that limit the liability exposure of healthcare providers are associated with a significant reduction in medical device patenting. Tort reforms have the strongest impact in medical fields in which the probability of facing a malpractice claim is the largest, and do not seem to affect the propensity to develop technologies of the highest and lowest quality. Our results underscore the importance of considering dynamic effects in economic analysis of tort laws.

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JEL Codes: O3, K4, I1

1 Introduction

Economists have long recognized the crucial role played by innovation for economic growth. A key feature of research and development (R&D) investments is their public-good nature, which generates under-investment in innovation relative to the socially optimal level (Arrow, 1962; Bloom et al., 2013). How to avoid such under-investment and how to provide greater innovation incentives are central questions in the macroeconomic and public policy literatures.

To increase R&D incentives, governments typically implement a variety of policies - such as patents and subsidies - directly targeted at innovation investments. To assess and quantify the effects of these policies is a key focus of the innovation literature. Only recently, economists have recognized that policies which are not directly targeted at innovation investments may also have large impacts on R&D incentives and the direction of technological progress (Finkelstein, 2004). Documenting and quantifying these indirect and dynamic effects is crucial not only to understand the determinants of innovation activities, but also to evaluate the costs and benefits of policy reforms. The objective of this paper is to examine the innovation investment response to a prominently debated public policy: tort reform.

Torts are actions which injure someone and which are recognized by law as grounds for a lawsuit. The role of the tort system is to deter people from injuring others. An important class of torts related to professional negligence is medical malpractice. A danger prominently voiced in public debates is that large settlements arising from medical malpractice litigation lead doctors to practice "defensive medicine," i.e. to perform excessive tests and procedures because of concerns about malpractice liability. Policy debates typically contrast the high costs of defensive medicine procedures with their low expected benefits to patients. A number of studies have investigated the relationship between tort system and treatment intensity or medical expenditures, and they provide evidence for the practice of defensive medicine (inter alia see Kessler and McClellan, 1996; and Avraham and Schanzenbach, 2015).

In addition to their effects on procedure use and malpractice claims, tort reforms may also impact R&D investments and technological change. In particular, a number of law scholars have warned about a possible "chilling effect" of the current tort system on innovation; that is, high damages and the court's reliance on custom may reduce physicians' willingness to adopt new, but riskier technologies even if they are potentially superior to customary treatments (e.g. Parchomovsky and Stein, 2008; Greenberg, 2009; and Priest, 2011). Despite these claims, the empirical literature on the relationship between liability risk and innovation is scarce. We aim

to address this gap by studying the impact of tort reforms on innovation in the medical device sector, a technology field closely linked to malpractice litigation.

To illustrate the channels through which tort reforms may affect innovation incentives, we begin our analysis with a simple theoretical model. In our framework, physicians adopt medical technologies considering both their expected benefits to patients and their "riskiness," i.e. the likelihood that adoption leads to malpractice liability. A tort reform, such as the introduction of caps on malpractice damages, will affect physicians' adoption decisions. Consistently with the idea of a chilling effect, our model predicts that a reduction in the cost associated with malpractice litigation will *increase* the propensity of physicians to use riskier technologies with high patient benefits. However, our analysis also shows an additional effect of tort reforms, i.e. they *reduce* the propensity of physicians to avoid suits by "defensively adopting" low-risk technologies when their benefits to patients are limited. These shifts in technology adoption affect up-stream R&D investments, and the overall impact on the development of new devices depends on the relative strengths of the two effects.

While our theoretical framework shows that tort reforms have an ambiguous effect on innovation, it also provides two additional testable predictions. The first is that tort reforms are likely to reduce innovation incentives in technology fields characterized by high risk of malpractice claims. This is because in these fields physicians have stronger incentives to use technologies that reduce the risk of malpractice disputes, even if their benefits to patients are marginal. Second, when we compare technologies of different qualities, the effect of tort reform is non-monotonic with a more pronounced drop in research incentives for technologies of intermediate quality, and less significant impact on technologies of highest and lowest qualities. Intuitively, low quality technologies will not be adopted by physicians independently of the malpractice liability regime. Conversely, if the value of a new technology is sufficiently large, adoption is likely to occur independently of the liability regime. For intermediate quality levels, our model shows a U-shaped effect of tort reforms on innovation investments, which is driven by a combination of the mitigation of defensive-adoption motives and chilling effect, as well as changes in the profits that the innovator can extract from the new technology.

To test these predictions, we combine standard measures of innovation, based on US patent data, with data on state tort reforms from the American Tort Reform Association for the period 1985-2005. We use the inventor address information provided by the United States Patent and Trademark Office (USPTO), and the application year of a patent to link patents

with U.S. state-years. We also exploit the USPTO 3-digit technology classification to identify medical instrument patents. The class of tort reform central to our empirical analysis is the introduction of caps on non-economic damages, which involve damages other than monetary losses (e.g. pain and suffering). These damages typically comprise a substantial fraction of total awards and represent the main focus of tort reform advocates.

Our main result shows that patenting in medical instruments is reduced by roughly 14 percent in the presence of caps on non-economic damages. This negative effect suggests that the demand for new technologies that high liabilities generate through defensive-adoption exceeds their negative chilling effect on medical device innovation. This finding is robust to a wide variety of alternative specifications and controls. In particular, the synthetic control method by Abadie et al. (2010) provides clear graphical evidence that medical instrument patenting responds to tort reforms and mostly after five years. Results are similar if we exclude from the sample states for which caps on non-economic damages affect only medical malpractice rather than general torts. Moreover, we show that our findings are not driven by the largest states, or by the largest medical device producers. Finally, we run a placebo test which indicates no effect of tort reforms in the sample of non-medical, measuring and testing instruments.

Following Moretti and Wilson (2014), we test whether the policy change in one state also affects medical device patenting in nearby states. We find very limited evidence of an effect on states that are geographically close, and no evidence of spillovers on states that are geographically distant or states that are economically close as measured by migratory flows. We show that such local nature of the policy impact is related to a key feature of the medical device industry, which is the involvement of practicing physicians. Indeed, a sizable fraction of the negative impact of tort reforms appears to be driven by the patenting activity of physician innovators located in the state.

We extend these baseline results in several directions to confirm the predictions of our theoretical model. First, we show that the effect of tort reforms is much more pronounced for patenting related to specialities with high frequency of malpractice litigation (such as surgery and orthopedics). Conversely, caps on damages have a small and statistically insignificant effect on patenting in medical fields with few malpractice suits (such as dental and optics). Second, exploiting patent citations as a proxy for technological value, we document a non-monotonic U-shaped relationship between the effect of tort reforms and innovation quality, as predicted by our theoretical model. Caps on damages have no statistically significant effect for innovation

at the lowest and highest quality quintiles. The effect is negative, statistically significant and of large magnitudes at intermediate quality levels.

Taken together, our findings indicate that tort reforms can have an impact on the level and direction of innovation and that an effective assessment of these policies should consider both their static impact on patients and their dynamic effects on medical technologies. While on average caps on damages appear to reduce the propensity to innovate, our analysis shows that this effect is highly heterogeneous and depends on characteristics of the devices and the medical fields.

The paper is organized as follows. Section 2 summarizes the related literature. In Section 3 we present a simple model which links tort reforms with innovation incentives. Section 4 describes the data and the econometric specification. Section 5 presents the baseline estimates of the average effect of tort reforms on medical device patenting. In Section 6 we show that the impact of tort reform is heterogeneous, and depends on the characteristics of the field and the innovation. We conclude with a brief summary of the findings.

2 Related literature

Our paper is related to studies that investigate the determinants and the direction of innovation, in line with the induced-innovation and the directed technical change literatures. In the context of pharmaceuticals, a number of papers have investigated the impact of variations in potential market size, exploiting shifts in population demographics (Acemoglu and Linn, 2004), the introduction of Medicare Part D (Blume-Kohout and Sood, 2013), and variation in effective patent life (Budish et al., 2015). More specifically, our paper is related to studies on the effects on innovation of public policies focusing on achieving some social goal other than innovation. In the health sector, Finkelstein (2004) exploits three different policy changes designed to increase the usage of preexisting vaccines and finds that these policies are associated with a 2.5-fold increase in clinical trials for new vaccines. Acemoglu et al (2006) find that the introduction of Medicare is not associated with an increase in drug consumption among the elderly; and consistent with this, they find no evidence of an increase in the approval of new drugs targeting diseases that affect the elderly. In the energy and environment sector, Jaffe and Palmer (1997) conclude that environmental compliance standards increased R&D spending at the firm level.

Our paper contributes to the literature on the relationship between legal liabilities and

medical practice.[1] Most studies in this literature exploit the variations provided by state tort reforms. Kessler and McClellan (1996) examine Medicare beneficiaries treated for serious heart diseases and find that tort reforms lead to reductions of 5-9 percent in medical expenditures without substantial effects on mortality or medical complications. Similarly, Avraham and Schanzenbach (2015) find that the probability of heart patients receiving a major intervention drops by five percent after a state implements non-economic damage caps. These results provide evidence for the practice of defensive medicine when liability risks are high. Other papers provide more nuanced evidence on the influence of liability risks on physician behaviors. Currie and MacLeod (2008) find that caps on non-economic damages increase while the joint and several liability rule decreases the use of cesarean sections. Shurtz (2014) shows that the effects of tort reforms may depend on physicians' financial incentives. Frakes (2013) shows that states' utilization rates of various treatments and diagnostic procedures changed substantially following the adoption of a rule requiring physicians to follow national, as opposed to local, malpractice standards of care. The only empirical study that we are aware of linking liability and innovation is Viscusi and Moore (1993) who show that, on average, liability costs increase firms' R&D intensity. The paper differs from ours in a number of dimensions. Theoretically, they study the direct effect of product liability on firm's R&D investment whereas, in our model, changes in liability risks affect innovation indirectly as they first influence physicians' demand for new technologies. Empirically, they study the impacts of cost of product-liability insurance using a cross-industry dataset covering large firms in the period 1984-1987. We focus on the effects of state tort reforms on medical device patenting for all firms in the period 1985-2005.

The paper relates to the literature on innovation and technology diffusion in the medical device industry. Clemens (2013) finds that the introduction of Medicare and Medicaid had a positive effect on U.S.-based medical equipment patenting. Chatterji and Fabrizio (2014) study the role of users in medical device innovation. Grennan and Town (2015) examine the impact of regulatory testing requirements for medical devices on innovation diffusion. Stern (2015) shows that medical device innovation incentives are shaped by the regulatory approval process. Nistor and Tucker (2015) show that FDA's decision to allow for third-party certification of

[1] Another stream of studies examines the effects of tort reforms on malpractice claims such as the frequency and severity (e.g. Danzon, 1984; and Avraham, 2007) and malpractice insurance-related outcomes such as insurers' reported losses, mean payments, and insurance premiums (e.g., Barker,1992; and Viscusi and Born, 1995). For an overview of the malpractice system and the effects of tort reforms, see the survey by Kessler (2011).

medical devices led to more adverse medical events.

Finally, our work is related to the literature on the determinants of state and regional innovation. For example, Agrawal and Cockburn (2003) report evidence in support of the anchor tenant hypothesis that large, local, R&D-intensive firms have a positive impact on regional innovation. Marx et al. (2009) show that regional non-compete regulations affect inventor mobility and knowledge spillovers. Galasso et al. (2013) show that state-level taxes strongly impact knowledge diffusion through the decision to trade patent rights. Vakili and Zhang (2015) show that liberalization policies are associated with an increase in the level of state innovation.

3 Theoretical model

In this section, we develop a simple theoretical model to explore the effects of tort reforms on innovation incentives. In our framework, innovations are characterized by multidimensional heterogeneity, as in Weyl and Tirole (2012). Policy reforms affect technological progress through their impact on downstream technology adoption, which, in turn, shapes upstream R&D investments as in Aghion et al (2015).

3.1 Basic framework

We consider a medical field with a representative (consumer) physician. We assume that the physician's utility from adopting a medical technology includes the patient's expected benefits as well as the expected cost of medical malpractice liability as in Schurtz (2014). A medical technology, i, is thus characterized by two parameters: $b_i \in [0,1]$ and $r_i \in [0,1]$, where b_i is the expected benefit to the patient, and r_i is the technology-specific malpractice liability risk (e.g. the probability of a bad patient outcome). The expected liability cost is H, which captures the probability that a bad patient outcome would result in a malpractice claim (or even a suit), and the costs the physician expects to face if involved in such a dispute. The literature on medical malpractice points out that even when physicians are insured against claims for monetary damages, they still suffer from malpractice disputes due to additional costs such as time loss, stress, and damages to the physician's reputation.[2] We model a tort reform as a decrease in H, which may operate through two channels: (i) a reduction in the frequency of

[2] As discussed in Currie and MacLeod (2008), payments made on behalf of a physician to settle malpractice claims are registered in the National Practitioners' Data Bank (NPDB) which is often accessed by hospitals, health care professionals and lawyers.

malpractice claims given bad patient outcomes;[3] and (ii) a reduction in the expected costs associated with malpractice disputes.

The physician's utility, when she adopts technology i is

$$U_i = b_i - r_i H. \tag{1}$$

For a simple micro-foundation of our setting, consider an environment in which each innovation i is characterized by a distribution of potential patient outcomes $y \sim G_i$, with mean μ_i and support $[0,1]$. If a dispute between the patient and the physician arises when the realized outcome is below a certain threshold $\underline{y}$, the utility of the physician is $U_i = \mu_i - G_i(\underline{y})H$, which is equivalent to equation (1) once we set $\mu_i = b_i$ and $r_i = G_i(\underline{y})$.

There is an innovator with an idea for a new patentable technology, which we denote as N. The medical field is characterized by a dominant standard technology O, which is freely available to physicians. We model the idea generation process following Scotchmer (1999), and assume that b_N and r_N are independent draws from the uniform distribution over the interval $[0,1]$. We assume that b_O and r_O are exogenously given, and that $U_O > 0$ and $U_O < 1 - H$. These assumptions rule out extreme outcomes and ensure that there are no regions in which the old technology is dominated or dominant for all values of r_N.

An idea can be developed into a new technology through an R&D process. Successful development takes place with probability $p(x) = x$ if the innovator incurs a research cost $C(x) = x^2/2$. As in Aghion et al (2015), we refer to x as the "innovation intensity" which captures the likelihood of successfully developing a new technology.

The timing of the game is as follows. The innovator draws the idea, observes b_N and r_N and decides whether and how much to invest in R&D to develop the new technology. If the new technology is developed, the innovator makes a take-it-or-leave-it offer to the physician who decides whether to adopt N or O. If N is not developed, the physician adopts O.

For an illustrative example of how liability risks influence the physician's choice between alternative technologies, consider the case of heart-attack patients. Avraham and Schanzenbach (2015) show that the probability of receiving a major intervention in the form of either an angioplasty or bypass, instead of drug management and monitoring, declines by 1.25–2 percentage points after non-economic damage caps are enacted. This provides evidence that damage

[3]For example, Avraham (2007) finds that caps on noneconomic damages enacted in a state significantly decrease the number of cases per 1,000 doctors by 10-15 percent.

limitations can reduce treatment intensity. Furthermore, they also find evidence of substitution between major interventions. Angioplasty declines by roughly 2 percentage points after caps are imposed, while by-pass, which is more invasive and remunerative than angioplasty, rises by 0.5-0.6 percentage points.

More broadly, we can also interpret the two technologies as complements. When bundled together, the new technology help the physician improve the patient outcome and/or better manage the risk. In other words, U_N is the utility of the bundle combining the old and the new technologies, and the innovator is rewarded with the extra-utility generated to the physician when the new technology is included in the bundle. Such examples include a surgical device allowing for an easy delivery of the fetus during a cesarean section when fetal head is deeply wedged in the female pelvic cavity, an apparatus and method that position a patient for rapid and effective endotracheal intubation, and a device delivering bioactive materials that help wound recovery after surgeries.

3.2 Tort reforms and innovation incentives

If technology N is developed, the innovator makes a take-it-or-leave-it offer to the physician for a transfer, t. The physician decides whether to accept the offer which yields a payoff of $U_N - t$ or to adopt the old technology which yields U_O. This implies that the payoff of the innovator will be either $U_N - U_O$ or zero, depending on whether the new technology offers lower utility to the physician than the old technology.[4]

The new technology will be adopted by the physician if $U_N \geq U_O$ which occurs when b_N is above the following threshold:

$$b_N^* = b_O - H(r_O - r_N). \tag{2}$$

Figure 1 illustrates the parameter region in which the new technology is adopted and the shift associated with tort reforms (i.e. a decrease in H). For a fixed level of liability, H, physicians trade-off technology quality with the risk of malpractice litigation. Riskier technologies ($r_N > r_O$) are adopted as long as their quality ($b_N - b_O$) is large enough. Conversely, safer technologies are adopted only if their quality is not too low. A decrease in H rotates clockwise the line identifying the adoption threshold. There is an increase in the adoption of high quality but riskier technologies, which is consistent with the "chilling effect" of high damages suggested

[4] Our results are robust to replacing the take-it-or-leave it offer with a Nash bargaining protocol in which the surplus is split between the innovator and the physician.

by Parchomovsky and Stein (2008). At the same time, there is a reduction in the adoption of low quality and safer technologies. This can be interpreted as a "defensive-adoption effect" of high damages that triggers the usage of low-risk technologies even if their benefits to patients are limited. There is, however, no effect on the adoption of technologies of high quality and low risk or technologies with low quality and high risk.

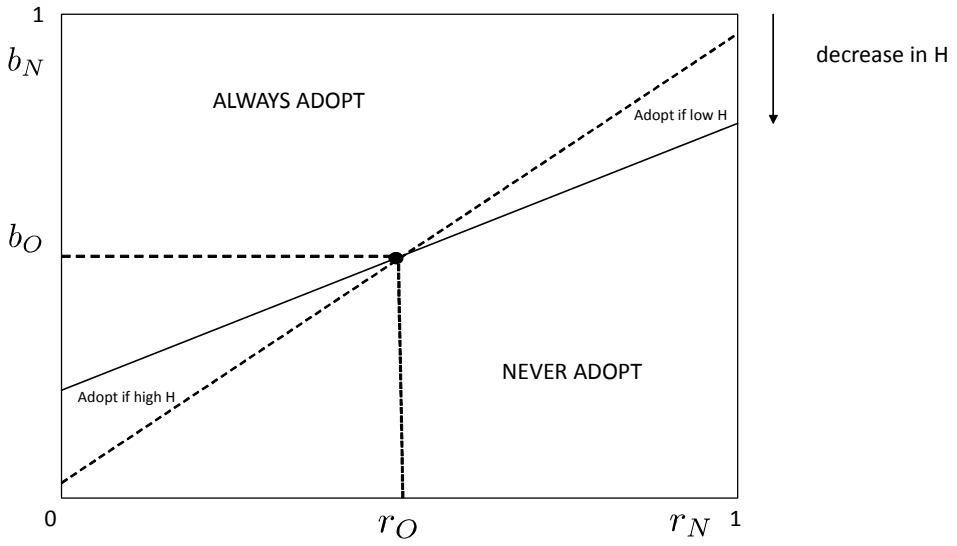

Figure 1: Tort reform (reduction in H) and technology adoption

An important implication of Figure 1 is that the overall effect of a tort reform on technology adoption is ambiguous, and depends on the relative strengths of the chilling and defensive-adoption effects. The following proposition shows that a decrease in H results in an overall decrease in the adoption of new technologies if the old technology is sufficiently risky.

Proposition 1 *When the old technology is sufficiently risky (i.e. $r_O > 1/2$), a decrease in H generates an overall decrease in the propensity to adopt new technologies.*

Proof. See Appendix. ■

This result highlights an interesting source of heterogeneity in the overall effect of tort reforms. A tort reform has two distinct effects. First, by mitigating the defensive-adoption effect of high damages, tort reforms screens out technologies which produce limited benefits to the patients but were adopted because of their lower risk profile. Second, by mitigating the chilling effect of high damages, tort reforms encourage the adoption of riskier technologies

that provide higher patient benefits. When the old technology is sufficiently risky, in the absence of tort reforms, the incentive to avoid malpractice claims by defensively adopting safer technologies dominates the chilling effect. As a result, a tort reform would result in an overall decrease in the propensity of adopting new technologies.

So far our analysis has focused on the effect of tort reform on technology adoption. The overall impact of a tort reform on innovation combines its impact on adoption with the effects on the incentives to invest in R&D. When $U_N \geq U_O$, the profits from a successful innovation are $U_N - U_O$, and the innovator will invest in R&D, x, to the point where the marginal cost of R&D equals its marginal benefits. The characterization of the optimal R&D intensity shows that the overall effect of a tort reform on innovation incentives is ambiguous and non-monotonic with respect to the expected benefit of the technology.

Proposition 2 *The impact of a decrease in H on innovation intensity is non-monotonic in b_N, and it is most negative when $b_N = b_O$. The overall effect (integrated over the distribution of b_N) is negative when the old technology is sufficiently risky ($r_O > 1/2$) and ambiguous otherwise (i.e. when $r_O \leq 1/2$).*

Proof. See Appendix. ■

Figure 2 provides a graphical representation of this finding, which is useful to develop the economic intuition for the above result. When b_N is close to zero, tort reforms have no effect on innovation investments. This is because these technologies are of low quality and physicians do not adopt them independently of the malpractice liability regime. When b_N is sufficiently large but still less than b_O, the reform has an unambiguously negative effect on innovation intensity, which gets larger as b_N approaches b_O. In the absence of tort reforms, these technologies are defensively adopted because they are safer than the old technology. Tort reforms reduce their profitability (i.e. a decrease in H reduces the physician's utility from these technologies relative to the old technology) and, thus, have negative impacts on innovation incentives. For lower values of b_N, the number of technologies with a safety premium large enough to be preferred to the old technology is smaller. As b_N increases toward b_O, the fraction of technologies that are defensively adopted increases, and this magnifies the effect of the tort reforms.

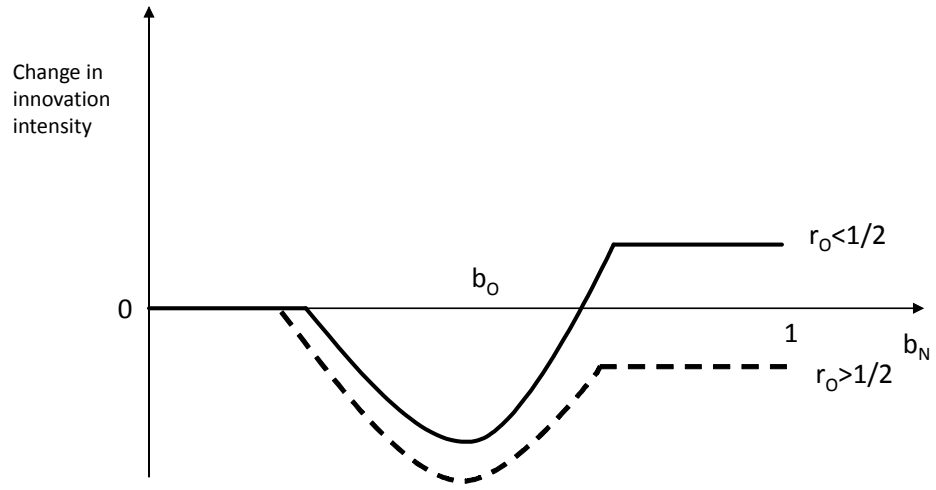

Figure 2: Tort reform (reduction in H) and innovation investment

For levels of b_N which exceed b_O, doctors adopt technologies which can be safer or riskier than the old technology. A reduction in H decreases the profits of technologies with $r_N < r_O$ and increases the profits for those with $r_N > r_O$. The total impact on innovation incentives is given by the combination of these two effects. As b_N increases, the fraction of riskier technologies adopted increases and the magnitude of the positive effect gets larger. This reduces the negative effect of the tort reform on innovation and may even lead to a positive impact on aggregate research incentives. For b_N large enough, technologies are adopted independently of the liability regime. In this case, the fraction of technologies which benefits and those that do not benefit from the tort reform remains constant.

As illustrated in Figure 2, if $r_O > 1/2$, the net effect of a reduction in H on innovation intensity is negative for all values of b_N. Thus, the overall effect of tort reforms on innovation incentives (integrated over the distribution of b_N) is negative. When $r_O < 1/2$, for sufficiently high values of b_N, tort reforms increase the profitability for the majority of the technologies, and innovation incentives go up. As a result, the overall effect of tort reforms after integrating over the distribution of b_N is ambiguous.

To summarize, our simple model shows that tort reforms have an ambiguous effect on innovation. Moreover, it generates the following testable predictions that we can take to the data:

1. The impact is likely to be negative in technology fields characterized by high risk of malpractice litigation.

2. The negative effect of tort reform on innovation is likely to be more pronounced for technologies of intermediate quality, and less significant for low and high quality innovation.

3.3 Discussion of the main modeling assumptions

The model builds on a number of assumptions that are worthy of additional discussion. First, in describing the idea generation process we assume that parameters are drawn from uniform distributions. Uniform distribution is a common assumption when modeling ideas given the abstract nature of the creative process (Scotchmer, 1999). An important feature of our model is that, even though ideas are uniformly drawn, the distribution of ideas developed into technologies is not restricted to be uniform. The innovator chooses endogenously how much to invest in development and she invests more when ideas are more profitable.

Second, our framework assumes that b and r are independently distributed. A priori, there is no reason to impose correlation between b and r in the idea space. Under the interpretation of b and r as features of a distribution of patient outcomes, correlation between b and r requires restricting the shapes of the outcome distributions across ideas. For developed ideas, correlation between b and r arises endogenously in our model and depends on H.[5]

Finally, for simplicity - and differently from Schurtz (2014) - our model does not include physicians' financial incentives. Therefore, the parameter b should be interpreted as a combination of the utility that the physician attaches to patients' benefits and the financial incentives associated with the adoption of the medical technology. These financial incentives typically depend on the insurance plans of patients, and in our empirical analysis we will show that our estimates do not change when we control for the extent of public and private insurance coverage of a state.

4 Data and methods

We begin with a U.S. state-year panel dataset measuring tort reforms during the period 1985-2005. The main source of data on tort reforms is the American Tort Reform Association (ATRA), which lists information on reforms implemented since 1986. We complement these

[5] If we extend the model imposing a negative correlation between b and r, we would expect a lower impact of a tort reform on innovation incentives. This is because negative correlation renders more likely ideas with high benefit and low risk (which are developed independently of the malpractice regime) and ideas with high risk and low benefits (which are not developed even in the presence of caps on damages). Conversely, we would expect positive correlation between b and r to amplify the impact of tort reforms.

data with additional information collected by Currie and MacLeod (2008) on the pre-1986 status quo and on laws overlooked by ATRA because they were overturned.

We merge this panel with the United States Patent and Trademark Office (USPTO) patent dataset to measure patenting activity across U.S. states during our sample period. We use the address information of the first inventor and the application year of a patent to aggregate patents to the state-year level. Each patent is classified by the USPTO using 3-digit technology classes, and we exploit such detailed classification system to identify medical instrument patents.[6] We also obtain data on the gross product, the population and the number of physicians in a state.[7]

USPTO patents offer a unique source of data for large-scale studies on innovation. Nonetheless, certain qualifications should be kept in mind. First, not all inventions are patented, but the innovation literature has shown that technologies with greater impact on social welfare and economic growth are more likely to be patented (Pakes and Griliches, 1980). Second, innovation is a process for which it is impossible to measure the origin. Relative to alternative measures such as an FDA-approved device and the location information of its manufacturer, the application date of a patent and the location of the inventors are probably the best available measures to capture the timing and location of the origin of the invention.

It is unlikely that the tort law changes that we exploit in the paper are driven by, or systematically correlated with, trends in medical device innovation for the following reasons. First, most of the law changes in the ATRA sample are modifications of the general tort statutes and are not aimed directly at medical malpractice. As described in Currie and MacLeod (2008), there is little evidence that tort laws were passed in response to specific developments in the health sector, and most laws apply to all torts. Priest (1987) argues that an important driver of early tort reforms was a doctrinal change in the interpretation of tort law leading some courts to increase substantially injury compensations. Moreover, a number of more recent tort reforms were influenced by large media publicity of the Liebeck v. McDonald's Restaurants 1992 case, in which a woman was awarded more than 2 million when she accidentally spilled hot coffee in her lap. Finally, it is important to notice that our data also include instances in which laws were turned-off by state courts because of constitutionality issues. As we show

[6] Specifically, we follow a list provided by the USPTO indicating patent classes related to medical devices: http://www.uspto.gov/web/offices/ac/ido/oeip/taf/meddev.htm.

[7] These data are obtained from the US Census and the BEA. Information on the number of physicians is not reported in the US Census Statistical Series for the years 89, 91 and 93 and are imputed by interpolation.

later, analysis focusing on these reforms alone provides results that are consistent with our baseline results.[8]

Our paper focuses on the demand channel of liability risks (that is, changes in malpractice liability risks affect physicians' demand for new technologies) instead of the direct effect of product liability risk on manufacturers for the following reasons. First, different from many other sectors, medical devices are subject to national regulation. Specifically, manufacturers of medical devices reviewed by the Food and Drug Administration (FDA) are subject to the Medical Device Amendments to the Federal Food and Drug and Cosmetic Act passed in 1976 that preempts state tort claims (Bivans, 1995). This implies that changes in state tort laws exploited in the paper are likely to affect manufacturers through their impact on downstream users rather than through product liability costs. Second, the product-liability risk channel seems too narrow to capture the phenomenon in our context (defensive medicine, in particular). For example, technologies that are demanded for defensive reasons (e.g., diagnostic and monitoring technologies, devices that aid smooth delivery of babies during cesarean sections, or a small diameter steerable guidewire for use in procedures in narrow arteries) are unlikely to be targets of liability claims, rendering the product-liability channel irrelevant.

The class of tort reforms central to our empirical analysis is the introduction of caps on non-economic damages, which involve damages other than monetary losses (e.g. pain and sufferings). As discussed in Avraham et al (2012), these damages comprise a substantial fraction of total awards and have often been the main focus of tort reform advocates. Consistent with the literature, we capture tort reforms using a dummy variable, Damage Caps, which equals to one if caps on non-economic damages are in place. An indicator variable is preferable in our setting to the actual level of caps for two reasons. First, for some of the reforms, it is difficult to identify a precise dollar amount (i.e. they do not impose a cap of a fixed dollar amount and use a multiplier of the economic damages). Second, and more importantly, with fixed-effects models, changes in the presence of a cap within a state provide more meaningful identification variations than cross-state variations in the level of caps. While caps on non-economic damages are a common state-level tort reform, we also control for other (less common) tort reforms such as caps on punitive damages or changes in the joint-and-several liability rules.

[8] Moreover, Deng and Zanjani (2015) do not find evidence of an influence of private interest groups - such as doctors or insurance industry professionals - on tort reform adoption. Similarly, Avraham and Schanzenbach (2015) exploit a detailed dataset of patients experiencing heart attacks and show that passages of tort reforms do not appear correlated with pre-existing trends in treatment intensity.

During our sample period, 25 states experience changes in caps on non-economic damages. Of these states, 16 switch from no caps to a cap, whereas the remaining 9 states experience multiple shifts (e.g. caps were instituted and then turned-off, and in some cases they are turned-on again). About half of the reforms take place in the late 80s. The states in which caps on damages are not implemented for the entire sample period are not statistically different from states in which caps are present in some years in term of medical device patenting, population and gross state product in 1985.

Table 1 provides summary statistics. Caps on non-economic damages are present in about 34 percent of the state-year observations of our sample. On average, inventors in a state apply for roughly 1,700 patents (eventually granted), and about 100 of these patents are classified by the USPTO in one of the medical device technology classes.

4.1 Econometric specification

Our main econometric model focuses on the relationship between measures of innovative activity Y_{jt} in state j and period t and the indicator for the presence of caps on non-economic damages in state j and period t. Our baseline specification is:

$$\log Y_{jt} = \beta \text{Damage Caps}_{jt} + \lambda' X_{jt} + \theta_t + \mu_j + \varepsilon_{jt},$$

where X_{jt} is a vector of control variables, and μ_j and θ_t are, respectively, the state and year fixed effects. The coefficient β captures the effect of tort reforms on patenting in the state: for example, $\beta < 0$ means that innovators located in a state reduce their patent applications when damage caps are in place. We cluster the standard errors at the state level.

Our identification comes primarily from changes in damage caps over time within a state. The controls X_{jt} and state effects μ_j, therefore, play an important role in our analysis. As discussed previously, there is little evidence that tort reforms used in our analysis are driven by, or systematically correlated with, trends in medical device innovation. Nonetheless, we perform several robustness checks designed to placate remaining endogeneity concerns and to isolate confounding factors. For example, we construct better controls to each of the states affected by a tort reform using the synthetic control method developed by Abadie et al. (2010). We also exclude large states and large device companies to confirm that the results are not driven by states that may have implemented pro-innovation policies or by large companies that are particularly innovative during the sample period.

5 Baseline empirical results

In this section, we report the overall effects of the presence of non-economic damage caps on patent applications in the medical device fields. In the next section, we explore the heterogeneity in the data to further test the predictions of our model. The regressions in Table 2 show a strong negative correlation between medical device patenting by innovators located in the state and the presence of caps on non-economic damages. All the specifications include year and state effects. These results are consistent with the idea that, in the absence of tort reforms, the defensive-adoption effect of high damages dominates the chilling effect, on average.

Column 1 presents the estimates of an OLS regression with the number of medical patents as the dependent variable. The coefficient implies an average reduction of roughly 30 patents in years in which damage caps are present. Column 2 shows that the results are similar with an OLS regression with log of patents as the dependent variable. Exponentiation of the coefficient implies that in periods when caps on damages are in place, innovation is reduced by roughly 14 percent. Evaluated at the median level of patenting for state-years without damage caps (i.e. 28 patents), this effect is equivalent to a reduction of roughly 4 medical device patents per year.[9]

In column 3 we show that results are not affected if we introduce a variety of controls: lagged total patenting, population and the number of physicians in the state. Column 4 controls for other changes in tort law: cap on punitive damages, modifications of the collateral-source rule, and modifications of the joint-and-several liability rule. The coefficients on these dummies are all statistically insignificant and small in magnitude, confirming the predominance of non-economic damages. Finally, column 5 shows that results are robust to excluding from the sample states for which caps on non-economic damages pertained only to medical malpractice rather than to torts more generally. This helps addressing the concern that the effects are driven by legislation passed in response to specific incidents of malpractice.[10]

We perform a variety of robustness tests to confirm of our main finding. First, there is the concern that our regressions ignore the count nature of our dependent variable. To address this issue, we show that our results are robust to estimating the effect of caps on damages using

[9] The difference between the average effect presented in column 1 and the effect evaluated at the median is due to the skeweness in the distribution of patenting across state-years. In Section 5.2, we report the estimated effects separately for each treated state.

[10] These states are identified by Currie and Macleod (2008) as Montana, Nevada and Alaska.

a Poisson regression model with fixed effects (column 1 in Appendix Table A1).

A second series of extensions demonstrates that our main results are robust to including extra covariates. First, Table A1 shows that results are similar when allowing for dynamics and use a multiplicative feedback model that controls for the logarithm of lagged patenting in medical instruments. In Table A1 we also extend our baseline model including additional controls for gross state products (GSP), the percentage of population in the state with medical insurance coverage, and the percentage of population with private medical insurance. These variables are proxies for the demand of new medical technologies in the state, and their inclusion reduces the concern that tort reforms are correlated with other unobservable demand shocks affecting innovation. The coefficient on tort reform is stable and the coefficients on the insurance variables are small and statistically insignificant.[11] In unreported regressions we also confirm that our results are robust to including a control, constructed by Frakes (2013), for the adoption of rules requiring physicians to follow national, as opposed to local, standards.[12]

We also examined whether our results are robust to: (i) excluding the five states with the largest number of medical device patents in 1984 and (ii) dropping the ten largest patentees over our sample period. The regressions reported in Table A1 indicate that the estimated effect is not driven by the largest states or the largest firms. These findings mitigate a number of concerns over confounding factors (e.g. that large patenting firms happen to be located in control states or that large control states happen to have implemented pro-innovation policies).

Finally, in the last column of Table A1, we present a placebo test which estimates our baseline model using the sample of non-medical measuring and testing instruments (USPTO class 073). The estimated coefficient is statistically insignificant and small in magnitude suggesting that tort reforms have not affected patenting in this technological field. This finding help addressing the concern that the impact of cap-on-damages on medical device patenting may reflect omitted variables (e.g. pro-innovation policies), or pre-trends in patenting correlated with tort reforms.

We turn next to two extensions that are of independent interest.

[11] The insurance variables are obtained from the US census, which only reports data for the period 1987-2005. We extrapolate the time series to construct the data for the two missing years.

[12] The coefficient on tort reform is stable, whereas the dummy on national standardization is negative, small and insignificant. A priori, it is not clear how standardization of physician practice may impact innovation incentives, because it may combine a positive demand effect for devices used in national standard procedures, and a negative impact for devices employed in local procedures which deviates from the standard.

5.1 Spatial spillovers of tort reforms

Our analysis has assumed that the impact of tort reforms on innovation is localized, i.e. it affects only innovators in states with policy changes. This section discusses this assumption and shows that, empirically, it largely holds in our context.

There are a number of possible channels through which a cap on damages imposed by one state can impact innovation incentives in other states. For example, if caps on damages in one state substantially reduce the demand for certain technologies in the state, they may decrease R&D investments toward these technologies by local innovators as well as by innovators located in other states. This would lead us to under-estimate the impact of tort reform on innovation. More complex spillover effects may also arise through competitive interaction between medical device firms in treated states and those in control states.

To explore this possibility, we investigate directly whether there is evidence of geographical spillovers across states. In column 1 of Table 3, we extend our baseline model by adding a dummy for damage caps implemented in bordering states. A tort reform in a bordering state does not have a significant impact on innovation incentives of the focal state, with an estimated coefficient being negative but statistically insignificant. In column 2, we introduce a weighted average of the tort reforms in other states, in which weights are constructed from the state-to-state migration flows data in the 2005 American Community Survey of the US Census Bureau. The larger the population flow from state j to state i, the greater is the weight of a reform in state j for state i. The coefficient on this variable is also small and statistically insignificant, suggesting that spillover effects are not widespread.

Column 3 of Table 3 introduces a flexible specification that allows for non-linear effects of distance. Specifically, we employ five dummy variables for reforms within 500Kms, 500-750Kms, 750-1,000Kms, 1,000-1,250Kms and 1,250-1,500Kms from the focal state. The distance is constructed from the latitude and longitude coordinates of states' population centroids provided by the Census Bureau. The only coefficient statistically significant (at the 0.1 level) and with magnitude substantially larger than the others is the one for reforms within 500Km. In all regressions, the coefficient of the direct effect of a tort reform within the focal state is stable and similar in magnitude to the baseline regression. Overall, the data suggest that geographical spillover effects appear to be small and concentrated within 500Kms from the focal state.

Various features of the medical device industry may explain this local effect. More specifically, the medical device innovation process is characterized by substantial involvement

of practicing physicians. Chatterji et al (2008) find that roughly 20 percent of medical device patents list a licensed physician among their inventors. This occurs because physicians often develop new technologies and either patent them directly or collaborate with manufacturing firms to protect and commercialize the technologies (Chatterji and Fabrizio, 2014). This widespread user-innovation paradigm suggests that the local nature of the effect of tort reforms on innovation may be explained by changes in patenting by local physicians who are directly affected by the policy change.

To examine more directly the importance of this channel, we exploit data from Chatterji et al (2008) and identify the patents in our sample listing a licensed physician as inventor for the period 1990-1996. We find that 19.1 percent of the 1990-96 medical device patents in our sample are classified as invented by doctors or with the participation of doctors, a figure very similar to the one in Chatterji et al. (2008). In column 1 of Table 4, we show that our main finding is robust to focusing on the 1990-96 sub-period. In columns 2 and 3, we contrast the effect of tort reforms for patents involving practicing physicians and other patents. The negative impact of tort reforms appears statistically significant only for patents involving physicians, with a coefficient twice as large as the one for the other patents. This result supports the idea that a sizable fraction of the tort reform effect is driven by local physician innovators who are directly affected by tort law in a state.[13]

On top of doctors' involvement in patenting, the local effect of tort reforms can also be explained by an informational advantage of local innovators. Medical device innovators geographically located closer to physicians affected by tort reforms may be better suited at understanding and addressing their technological needs.

5.2 Synthetic control method

Our analysis so far has focused on the average effect (across treated states and over time). In this section, we use the synthetic control method (Abadie et al., 2010) to obtain a clear graphical representation of the effect of adopting the damage cap for some of the key treated states. This allows us to see which states drive the average results and the timing and magnitude of the effect for each state.

Specifically, for each of the 16 states that transitioned from no cap to adopting a cap, we

[13] In our theoretical model, physicians act as users of medical devices, not as inventors. Our theoretical results generalize to the case in which physicians are also innovators, as long as they can appropriate in part or fully the rents from commercialization. For Table 4, we only control for state and year effects because of the smaller size of this sample.

construct a synthetic control using the 23 states that do not have a cap throughout our sample period (donor states). The predictor variables used to construct the synthetic controls are the number of medical patents, the total number of patents, population, GSP, and physicians per population. The weights on the donor states are reported in Table A2 for selected treated states.[14]

The treated states vary substantially in their inventive activities. For example, the total number of medical patents applied for between 1974 and 1986 ranges from 3 to 416. We report, in Figure 3, the results for the top six treated states (according to their pre-1987 patent stock).[15] Before adopting the cap, the number of medical patents in the treated state is similar to the corresponding synthetic control state, while patenting decreases relatively after the tort reform. The treatment effect, defined as $(N_{\text{treated,after}} - N_{\text{treated,before}}) - (N_{\text{control,after}} - N_{\text{control,before}})$ where N is the yearly average, ranges from -82.2 to -11.4 patents per year for these six states. The mean and the median are, respectively, -36.9 and -30.3. Visual inspection shows that, when tort reforms make a difference, the magnitude increases over time and starts to become meaningful after five or six years. The treatment effects for the other ten smaller states that switched from no cap to a cap (not reported graphically) range from -7.38 to 4.9 patents per year, with the mean and median being both -1.5. We confirm robustness of these results to excluding large patenting states, top ten assignees, or states that are less than 500Kms from the control.

We use the placebo tests suggested by Abadie et al (2010) for inference. For each treated state, we iteratively apply the synthetic control method to every state in the donor pool. Specifically, we re-assign the adoption of the cap to each of the 23 donor states and shift the treated state to the donor pool. This iterative procedure provides a distribution of estimated treatment effects for states in which no intervention took place. The results for the top-six treated states, presented in Figure A1, show that the estimated effect for the true treated state is among the most negative in this distribution.

Exploiting this methodology, we also examine two large states, Texas and Ohio, which

[14] Because the method requires a relatively long pre-treatment period, we extend the sample back to 1977. We obtain the weights on the donor states by minimizing the distance between the average values of the predictor variables in the pre-treatment period for a treated state and those for its synthetic control, subject to: (i) all weights must be non-negative, and (ii) they sum to one.

[15] The top six treated states are Colorado, Maryland, Michigan, Missouri, Utah and Wisconsin. There is a discrete drop in the pre-1987 patent stock between the sixth and the seventh states: the number is 221 for the former and 89 for the latter.

switched their damage caps off during the sample period. The estimated treatment effects of switching off the cap are positive, and equal to 48.3 and 61.9, respectively, for Texas and Ohio. These results are consistent with our theoretical model, confirming that the negative effect of the presence of a cap on patenting activities is unlikely to be caused by the general trend of increasing inventive activities in the control state.[16]

6 Heterogeneous effects

In this section, we examine the heterogeneity in the impact of tort reforms in line of the two predictions of the theoretical model developed in Section 3: (1) by the extent of malpractice risk of a particular medical field, and (2) by the quality of an invention.

6.1 Malpractice risk and innovation incentives

The model predicts that the impact of tort reforms is more likely to be negative in technology fields characterized by frequent malpractice risk (i.e. high r_O). Intuitively, in these fields, it is more likely that physicians adopt new technologies mostly for defensive reasons. Thus, if caps on damages are implemented, the incentives to use these technologies decline, and this reduces innovation incentives.

Jena et al. (2011) study US malpractice data from 1991 through 2005. They show that the proportion of physicians facing litigation risk varies substantially across medical specialities. The likelihood of facing a malpractice claim is the largest in surgery (especially in neurosurgery and thoracic-cardiovascular surgery) and orthopedics where the annual probability of facing a claim is about 20 percent. Conversely, malpractice claims are not frequent in specialities such as psychiatry, optics or dentistry where the annual probability of a claim is below 3 percent. Building on these findings, we exploit the detailed USPTO patent classification system and identify medical instrument patents related to four technology fields: surgical, orthopedics, optics, and dental.[17]

Table 5 provides the estimates for the effect of tort reforms on patenting in each of these four fields. As predicted by our model, there is a large negative effect for medical instrument patenting related to specialities in which the frequency of malpractice claims is high (surgery

[16] Both Texas and Ohio switched on the cap later again in 2004, and we do not use 2004 and years after that in our analysis. Ohio also had a brief one-year switch-on in 1999, which we ignore in the analysis.

[17] We use the following 3-digit classes: 128 and 600-607 for surgical; 433 for dental, 351 and 356 for optics and various sub-classes from class 623 for orthopedics.

and orthopedics). Conversely, the effect is small and statistically insignificant for devices associated to specialities with fewer malpractice claims (dental and optics). While we cannot reject that the effects on surgery and orthopedic devices have the same magnitude ($p = 0.97$), we can strongly reject that the effect for surgery is equal to the effect for optics ($p < 0.01$) or to the effect for dental ($p < 0.01$).

6.2 Tort reform and innovation quality

Another prediction of our model is a non-monotonic relationship between tort reforms and innovation quality (Figure 2). Tort reforms have a strong negative effect on technologies of intermediate quality, but their impact is less significant for innovations of very low or very high value. Intuitively, low quality technologies will not be adopted by physicians independently of the malpractice liability regime. Conversely, if the value of a new technology is sufficiently large, adoption is likely to occur independently of the liability regime. For intermediate quality levels, the U-shaped effect is driven by a combination of the mitigation of defensive-adoption motives and chilling effects, as well as by changes in the profits that the innovator can extract from the new technology.

We test this prediction exploiting information on the citations received by each patent. Patent citations identify prior knowledge upon which a patent builds. USPTO patent examiners are responsible for insuring that all appropriate prior art has been cited, and this delimits the scope of property rights granted to the patentee. Because of this important legal function, the economics of innovation literature has often employed the number of citations received by a patent as an indirect measure of patent value (Pakes and Griliches, 1980). Since citation counts are inherently truncated and levels may differ across technology areas, we filter citations by removing grant-year and 3-digit technology class effects. We then identify the (filtered) citation quintile in which each patent belongs.

Consistent with the prediction of our model, the estimates show a non-monotonic relation between damage caps and patenting across patents of different quintiles (Table 6). The effect is not statistically significant for innovations in the lowest quintile of innovation quality. The effect becomes negative and significant in the second quintile, and the magnitude of the negative effect is larger as innovation quality increases (with the largest being in the fourth quintile). The effect, again, becomes small and insignificant for innovations in the top quality quintile.

We perform a variety of tests to confirm robustness of this finding. First, we re-estimate the relationship between damage caps and patenting disaggregating at the finer level of citation

deciles. The (unreported) estimates are in line with those from the quintile analysis and show a U-shaped relationship between tort reform and innovation. There is a statically significant negative impact only for patents from the 4th to the 9th deciles, with the largest effects on the 7th decile of the distribution. Second, we confirm that the pattern is robust to using alternative measures of patent quality. In Appendix Table A3, we construct quintile bins exploiting residuals obtained from regressing citations against year effects, technology effects and the number of claims. This alternative measure - which captures normalized citations per patent claim – yields results very similar to those obtained in Table 6.[18]

Notice that our theoretical model illustrates a non-monotonic relationship between tort reform and b_N, which is the expected benefit to the patient from the new technology. In performing this comparative statics, we let r_N (the expected risk level of the new technology) vary endogenously for each level of b_N. To empirically disentangle b_N from r_N is very challenging with our data, and citations are a measure of quality available for a variety of different medical technologies. While it is likely that the lowest quintile of the citation distribution captures innovations with very low b_N and that patents in the top quintile capture technologies with very large b_N, intermediate quintiles may contain technologies with mixed levels of b_N and r_N. Despite the presence of such measurement error, the estimates are consistent with the predictions of the model, suggesting that citations may be a reasonable proxy for b_N.

In U.S., medical devices are subject to the Food and Drug Administration (FDA) regulatory process. One of the regulatory pathways within the FDA to bring a device to market is the Pre-market Approval (PMA) process which requires detailed product information and evidence of safety from clinical trials (Stern, 2015). The FDA requests PMAs for "high-risk" devices that are used to support or sustain human life, and the expenditure required to complete PMAs is substantial (75 million per device according to survey evidence in Makower et al., 2010). This high cost combined with the "high-risk" nature of the medical devices involved in PMAs suggests that data on PMAs may provide a reasonable window on technologies with high b_N and r_N. Our theoretical framework suggests that innovation incentives for these devices will not be strongly affected by tort reforms. The model predicts an ambiguous effect for these technologies, with a magnitude (positive or negative) lower than the one for devices with lower b_N.

[18] We also obtain similar results: (i) filtering citations removing only the grant year effects, (ii) measuring quality with the number of patent claims filtered by 3-digit technology effects.

Exploiting the data released by the FDA for PMA requests as a measure of innovation, we run a variety of (unreported) regressions estimating the impact of tort reforms. Coefficients are small and statistically insignificant across the various specifications. While this insignificant effect is in line with our theory, two key qualifications should be kept in mind. First, FDA applicants are often manufacturers who are not necessarily the innovators. Second, there is evidence of strategic delays in the introduction of medical devices in the U.S. market relative to the European markets (Grennan and Town, 2015). Both of these issues may generate substantial measurement errors for innovative activities and geographic locations and, hence, bias the coefficients toward zero.

7 Conclusions

This paper investigates how tort reforms affect the development of new medical device technologies, exploiting state tort reforms and patent data for the period 1985-2005. We develop a theoretical model in which tort reforms increase the propensity of physicians to adopt riskier technologies by mitigating the "chilling effect" of high damages emphasized by legal scholars. At the same time, we show that tort reforms also reduce the propensity of physicians to defensively adopt low-risk technologies in order to avoid malpractice liability, even when their benefits to patients are limited. These shifts in technology adoption affect up-stream R&D investments, and the overall impact on the development of new devices depends on the relative strengths of the two effects.

Our empirical analysis shows that the introduction of caps on non-economic damages is associated with an average decline in patenting for medical instrument technologies. This suggests that, on average, the demand for new technologies generated by high liabilities exceeds the negative chilling effect that damages have on medical device innovation. Consistent with the model's predictions, we find that tort reforms have a greater negative effect in specialities with high frequency of malpractice claims (and, hence, stronger defensive-adoption effects when damages are high). Moreover, we find that the effect is the most negative for patenting at intermediate quality levels, while it is insignificant for patenting at the top and the bottom of the quality distribution. For the most valuable medical technologies, the insignificant effect of tort reforms indicates that, empirically, the positive effect of caps on damages on medical innovation counter-balance their negative effect.

More broadly, our paper provides empirical evidence that tort reforms can affect the

rate of technological change, indicating that these policies have dynamic effects on innovation incentives that go beyond their short term impact on patients and health costs. As stressed by Finkelstein (2004), recognizing and estimating these dynamic effects is crucial to evaluate the costs and benefits of tort reforms.

There are several useful directions for further research. Our paper infers the differential effects of tort reforms on different types of technologies without directly categorizing the technologies. With patent textual analysis, it may be possible to measure more precisely the impact of tort reforms across finer classes of medical devices. Second, our paper does not evaluate the welfare effect of tort reforms on innovations. This would require a more structural analysis of the value of safer technologies versus riskier but potentially more effective technologies to physicians and to patients, as well as the spillover effects of these technologies to other sectors of the economy.

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Appendix

Proof of Proposition 1

The area in the (b_N, r_N) space in which technology is adopted is equal to

$$\begin{aligned} AD &= \int_0^1 (1 - b_O + H(r_O - x))dx \\ &= 1 - b_O + H(r_O - \frac{1}{2}) \end{aligned}$$

with derivative $\frac{dAD}{dH} = r_O - \frac{1}{2}$ which is positive if $r_O > 1/2$.

Proof of Proposition 2

The optimal innovation intensity for an innovator with idea (b_N, r_N) solves

$$\max_x x\left(b_N - b_O - H(r_N - r_O)\right) - \frac{x^2}{2}$$

which is equal to $x^* = U_N - U_O$. Consider an innovator with an idea with expected benefit b_N. She will invest in R&D as long as

$$b_N - b_O - H(r_N - r_O) \geq 0$$

or

$$r_N \leq \frac{b_N - b_O}{H} + r_O \equiv \overline{r}.$$

The innovation intensity for firms at b_N is

$$\int_0^{\overline{r}} b_N - b_O - H(x - r_O)dx = \frac{H\overline{r}^2}{2}. \tag{3}$$

Considering the corner solutions when $\overline{r}$ is outside the unit interval in (3), we obtain the expected innovation intensity for a fixed level of b_N:

$$i(b_N, H) = \begin{cases} 0 & \text{if } b_N < b_0 - Hr_0 \\ \frac{H}{2} \quad \frac{b_N - b_O}{H} + r_O^2 & \text{if } b_0 - Hr_0 < b_N < H + b_0 - Hr_0 \\ b_N - b_O + H(r_O - \frac{1}{2}) & \text{if } b_N \geq H + b_0 - Hr_0. \end{cases} \tag{4}$$

We exploit formula (4) to study the impact of tort reforms on innovation as well as the heterogeneity in the impact across technologies with different levels of expected benefits. To compute the total expected innovation investment we integrate $i(b_N, H)$ for each value of b_N. The total effect comprises 3 parts. The first part is

$$\int_0^{b_O - Hr_0} 0 db_N = 0.$$

The second part is

$$\int_{b_O - Hr_O}^{H + b_O - Hr_O} \frac{H}{2} \quad \frac{b_N - b_O}{H} + r_O^2 \quad db_N = \frac{1}{6}H^2$$

The third part of the innovation intensity is

$$\begin{aligned} & \int_{H + b_O - Hr_O}^{1} \left(b_N - b_O + H(r_O - \frac{1}{2}) \right) db_N \\ = \quad & \frac{1}{2}H^2 r_O^2 - \frac{1}{2}H^2 r_O - Hb_O r_O + \frac{1}{2}Hb_O + Hr_O - \frac{1}{2}H + \frac{1}{2}b_O^2 - b_O + \frac{1}{2}. \end{aligned}$$

Which implies that the expected innovation intensity as function of (b_O, r_O) is equal to

$$I(H, b_O, r_O) = \frac{1}{2}H^2 r_O^2 - \frac{1}{2}H^2 r_O + \frac{1}{6}H^2 - Hb_O r_O + \frac{1}{2}Hb_O + Hr_O - \frac{1}{2}H + \frac{1}{2}b_O^2 - b_O + \frac{1}{2}$$

The following derivative captures the impact of a tort reform:

$$\frac{\partial I}{\partial H} = \frac{1}{3}H + \frac{1}{2}b_O + r_O - Hr_O - b_O r_O + Hr_O^2 - \frac{1}{2}.$$

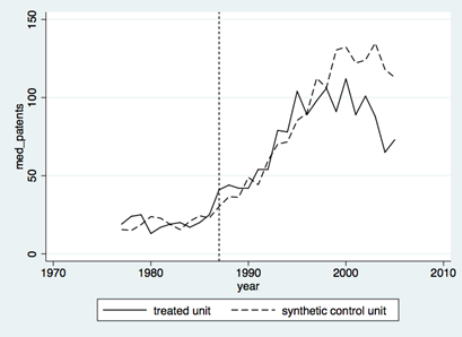
When $r_O = 0.5$ we have that $\partial I / \partial H = H/12 > 0$. Moreover $\dfrac{\partial^2 I}{\partial H \partial r_O} = 1 - H - b_O + 2Hr_O$ which is increasing in r_O for every value of b_O if $r_O \geq 1/2$. We now look at the effect across various levels of b_N. When $b_N < b_O - Hr_O$, we have that $\dfrac{\partial i}{\partial H} = 0$ and $\dfrac{\partial^2 i}{\partial H \partial b_N} = 0$. When $b_O - Hr_O \leq b_N \leq H + b_O - Hr_O$ we have that

$$\frac{\partial i}{\partial H} = \frac{r_O^2}{2} - \frac{(b_N - b_O)^2}{2H^2} \geq 0.$$

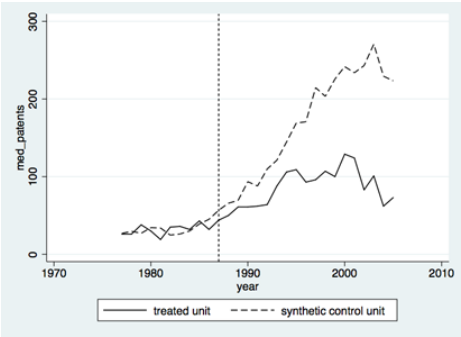
The positive inequality follows because $b_O - Hr_O < b_N$ implies $b_O - b_N < Hr_O$ which in turn implies $(b_N - b_O)^2 < (Hr_O)^2$. Moreover $\dfrac{\partial^2 i}{\partial b_N \partial H} = -\dfrac{b_N - b_O}{H^2}$ which is increasing when $b_N - b_O < 0$ and decreasing when $b_N - b_O > 0$. Thus the derivative is maximized at $b_N = b_O$. Finally, when $b_N \geq H + b_O - Hr_O$, we have that $\dfrac{\partial i}{\partial H} = (r_O - \frac{1}{2})$ and $\dfrac{\partial^2 i}{\partial H \partial b_N} = 0$. Notice that the maximum value that $\dfrac{\partial i}{\partial H}$ can take is $\dfrac{r_O^2}{2}$ because $\dfrac{r_O^2}{2} > r_O - \frac{1}{2}$ for any $r_O \leq 1$.

Figure 3. Medical patenting in treated states and synthetic controls

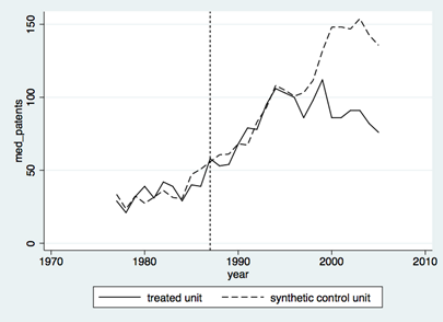
CO



MD



MI



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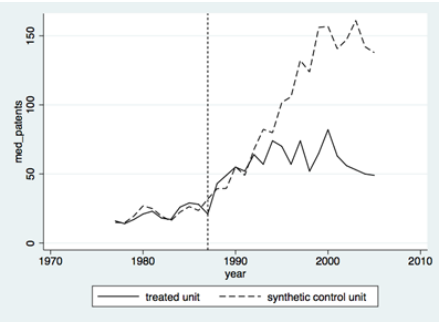

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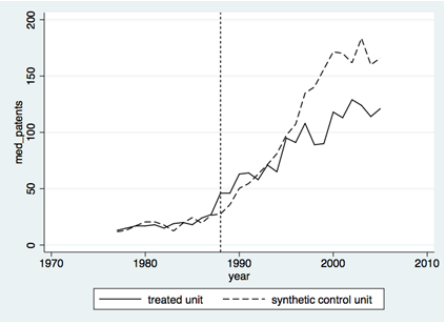

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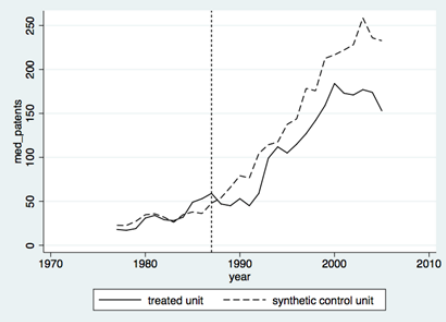


NOTES: This figure plots the number of medical patents by the application year for a treated state and its synthetic control. These six states had the largest pre-1987 medical-patent stock among the 16 states that switched from having no cap to imposing a cap on non-economic damages between 1977 and 2005. The control is generated using the same 23 states that did not impose a cap throughout the sample period. Vertical lines separate the pre- and post-cap periods.

Table 1. Summary statistics

	Obs.	Mean	Std. Dev.	Min	Max
Total Patents	1071	1697.8	3110.4	21	28383
Medical Device Patents	1071	98.8	210.4	0	2070
Damage Caps	1071	0.3	0.5	0	1
Year	1071	1995	6.1	1985	2005
Population (1,000)	1071	5189.2	5753.1	453.5	35827.9
Physicians per 1,000 population	1071	2.3	0.9	1.2	7.9

NOTES: Unit of observation is U.S. state-year. Total Patents is the total number of patents applied for (and eventually granted) in a year in the state. Medical Device Patents are applications classified by the USPTO in one of the medical device patent classes. Damage Caps is equal to one if the state has a cap on non-economic damages. Data on population and physicians are from US Census and Bureau of Economic Analysis (BEA).

Table 2 . Damage caps and medical device patenting

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Med Pats$_t$	log(Med Pats$_t$)	log(Med Pats$_t$)	log(Med Pats$_t$)	log(Med Pats$_t$)
Damage Caps$_t$	-29.708**	-0.150**	-0.159***	-0.152***	-0.162**
	(12.52)	(0.06)	(0.06)	(0.06)	(0.07)
log(Population)			1.134***	1.400***	1.094**
			(0.44)	(0.43)	(0.42)
Physicians per 1,000 population			0.130	0.119	0.112
			(0.16)	(0.162)	(0.17)
log(Total Patents$_{t-1}$)			0.045	0.030	0.083
			(0.13)	(0.13)	(0.14)
Punitive Damage Cap				-0.084	
				(0.07)	
Collateral-source rule				0.053	
				(0.09)	
Joint and Separate Liability				-0.030	
				(0.07)	
Year Effects	YES	YES	YES	YES	YES
State Effects	YES	YES	YES	YES	YES
Drop states with malpractice-focused reform					YES
Observations	1071	1071	1071	1071	1008

NOTES: OLS estimation. * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Med Pats = number of patent applications in medical device fields in the state. Damage Caps =1 if a cap on non-economic damages is present in the state. Total Patents = total patent applications in the state. Other reform dummies are indicator variables for cap on punitive damages, modifications of the collateral-source rule and modifications of the joint-and-several liability rule. Robust standard errors clustered at the state level. In columns 2-5 we add 1 to Med Pats and include a dummy which equals one for state-years without patenting.

Table 3. Geographic spillover of tort reforms

	(1)	(2)	(3)
Dependent Variable	log(Med Pats$_t$)	log(Med Pats$_t$)	log(Med Pats$_t$)
Damage Caps$_t$	-0.149***	-0.161***	-0.147***
	(0.06)	(0.06)	(0.05)
Cap in border state	-0.086		
	(0.06)		
Population-flow		0.068	
weighted Caps		(0.26)	
Cap within 500 Km			-0.119*
			(0.07)
Cap in 500 to 750 Km			0.093
			(0.07)
Cap in 750 to 1000 Km			-0.001
			(0.06)
Cap in 1000 to 1250 Km			-0.003
			(0.09)
Cap in 1250 to 1500 Km			0.093
			(0.06)
Control variables	YES	YES	YES
Year Effects	YES	YES	YES
State Effects	YES	YES	YES
Observations	1071	1071	1071

NOTES: OLS estimation. * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Med Pats = number of patent applications in medical device fields in the state. Damage Caps =1 if a cap on non-economic damages is present in the state. We add 1 to Med Pats and include a dummy which equals one for state-years without patenting. Cap in border state = 1 if caps present in border state. Population-flow weighted Caps = weighted average of caps in other states using population flows. Other dummies =1 if cap present within geographical distance. Control variables include log(Population), Physicians per 1,000 population, and lagged log(TotalPatents).

Table 4 . Damage caps and physicians' patents

	(1)	(2)	(3)
Dependent Variable	log(Med Pats$_t$)	log(Med Pats$_t$) by physicians	log(Med Pats$_t$) by other inventors
Damage Caps$_t$	-0.268*	-0.426***	-0.210
	(0.13)	(0.15)	(0.13)
Year Effects	YES	YES	YES
State Effects	YES	YES	YES
Observations	357	357	357

NOTES: OLS estimation. * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Med Pats = number of patent applications in medical device fields in the state. Damage Caps =1 if a cap on non-economic damages is present in the state. Robust standard errors clustered at the state level. Data on medical patenting by physicians is from Chatterji et al (2008).

Table 5. Damage caps and litigation risk

	(1)	(2)	(3)	(4)
Dependent Variable	log(Med Pats$_t$) in surgery	log(Med Pats$_t$) in orthopedics	log(Med Pats$_t$) in optics	log(Med Pats$_t$) in dentistry
Damage Caps$_t$	-0.190***	-0.192**	-0.013	0.058
	(0.05)	(0.08)	(0.04)	(0.06)
Control variables	YES	YES	YES	YES
Year Effects	YES	YES	YES	YES
State Effects	YES	YES	YES	YES
Observations	1071	1071	1071	1071

NOTES: OLS estimation. * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Med Pats = number of patent applications in medical device fields in the state. Damage Caps =1 if a cap on non-economic damages is present in the state. Robust standard errors clustered at the state level. We add 1 to Med Pats to include state-years with no patenting. Regressions controls for lagged total patenting, log(Population), Physicians per 1,000 population, and a dummy which equals one for state-year without patenting.

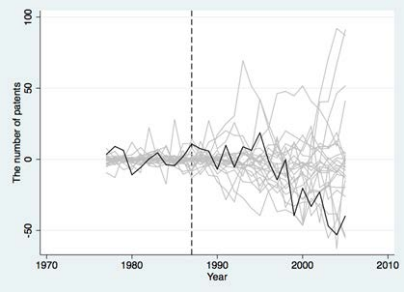
Table 6. Damage caps and patent quality

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	log(Med Pats$_t$) in 1st citation quintile	log(Med Pats$_t$) in 2nd citation quintile	log(Med Pats$_t$) in 3rd citation quintile	log(Med Pats$_t$) in 4th citation quintile	log(Med Pats$_t$) in 5th citation quintile
Damage Caps$_t$	0.312	-0.399**	-0.603***	-0.810***	-0.177
	(0.21)	(0.16)	(0.18)	(0.16)	(0.14)
Control variables	YES	YES	YES	YES	YES
Year Effects	YES	YES	YES	YES	YES
State Effects	YES	YES	YES	YES	YES
Observations	1071	1071	1071	1071	1071

NOTES: OLS estimation. * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Med Pats = number of patent applications in medical device fields in the state. Damage Caps =1 if a cap on non-economic damages is present in the state. Citations quintiles constructed from citations filtered by grant-year and technology-class effects. Robust standard errors clustered at the state level. We add 1 to Med Pats to include state-years with no patenting. Regressions controls for lagged total patenting, log(Population), Physicians per 1,000 population, and a dummy which equals one for state-years without patenting.

Figure A1. Effect of damage caps in treated and placebo states

CO



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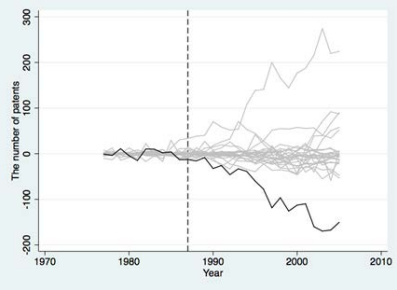

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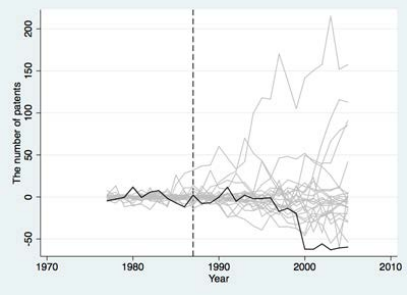

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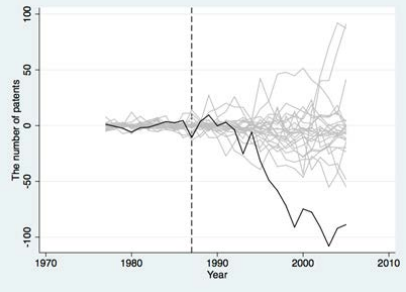

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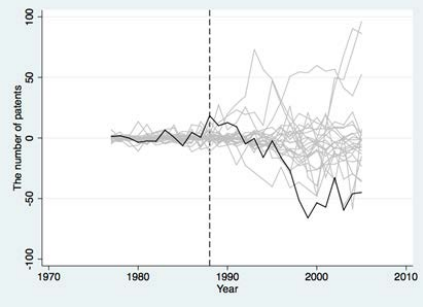

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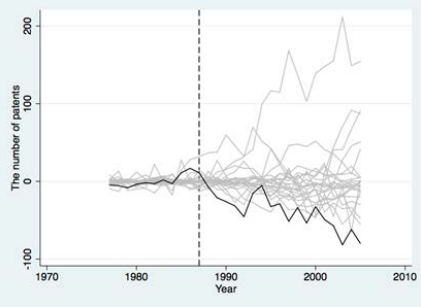

NOTES: For each of the six largest states switching from no caps on non-economic damages to a cap, we apply the same synthetic control method to each of the same 23 donor states (i.e., those states that do not impose a cap throughout the sample period). During each iteration, this particular treated group is allocated to the donor pool. We follow Abadie et al. (2010) and exclude the placebo states for which the pre-intervention MSPE is more than twice as large as that of the treated state.

Table A1. Robustness of baseline specification

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Med Pats$_t$	log(Med Pats$_t$)	log(Med Pats$_t$)	log(Med Pats$_t$)	log(Med Pats$_t$) dropping largest assignees	log(Mesurement Pats$_t$)
Estimation Method	Poisson	OLS	OLS	OLS	OLS	OLS
Sample	full	full	full	drop largest states	full	full
Damage Caps$_t$	-0.097**	-0.132***	-0.186**	-0.154***	-0.163***	-0.027
	(0.04)	(0.05)	(0.09)	(0.06)	(0.06)	(0.06)
log(MedPats$_{t-1}$)		0.231***				
		(0.06)				
Percentage of population with insurance coverage			-0.008			
			(0.01)			
Percentage of population with private insurance			-0.002			
			(0.01)			
log(GSP)			0.255			
			(0.312)			
Control variables	YES	YES	YES	YES	YES	YES
Year Effects	YES	YES	YES	YES	YES	YES
State Effects	YES	YES	YES	YES	YES	YES
Observations	1071	1071	1071	966	1071	1071

NOTES: OLS estimation. * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Med Pats = number of patent applications in medical device fields in State. Damage Caps =1 if a cap on non-economic damages is present in the state. GSP= Gross State product. Robust standard errors clustered at the state level. We include a dummy which equals one for state-years with zero patenting. In column 4 we drop states with largest patenting in medical devices in 1984 (CA, DE, NY, NJ and FL). In column 5 we drop the 10 largest patentees in medical instruments over our sample period. In Column 6, we conduct a placebo test using the measuring and testing (patent class 73). Columns 2-6 also control for lagged total patenting, log(Population), and Physicians per 1,000 population.

Table A2. Weights of donor states used to contruct the synthetic controls

Donor States	CO	MD	MI	MO	UT	WI
AZ	0.021	0	0	0.008	0	0.009
AR	0.019	0	0	0.003	0.408	0.01
CT	0.016	0	0	0.008	0	0.007
DE	0.007	0	0	0.003	0	0.003
DC	0.097	0.164	0	0.018	0	0.003
GA	0.466	0.445	0	0.666	0	0.28
IN	0.018	0	0	0.008	0	0.277
IA	0.01	0	0	0	0	0.016
KY	0.004	0	0	0.001	0	0.015
ME	0.006	0	0	0.004	0	0.007
MA	0.019	0.298	0	0.016	0	0.006
MN	0.071	0.093	0	0.081	0.229	0.202
NE	0.02	0	0	0.004	0	0.009
NJ	0.014	0	0	0.008	0	0.011
NY	0.014	0	0	0.009	0	0.022
NC	0.008	0	0.513	0.001	0	0.035
PA	0.013	0	0.487	0.007	0	0.014
RI	0.015	0	0	0.005	0	0.006
SC	0.013	0	0	0.003	0	0.012
TN	0.006	0	0	0.121	0	0.015
VT	0.013	0	0	0.004	0.284	0.005
VA	0.023	0	0	0.018	0	0.02
WY	0.105	0	0	0.004	0.079	0.016

NOTES: This table reports the weights of the 23 donor states used to construct the synthetic controls for the largest six states that changed from without a non-economic damage cap to having one. See Figure 3 for the estimates of the synthetic control method.

Table A3. Damage caps and patent quality - Robustness to extra-filtering

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	log(Med Pats$_t$) in 1st citation quintile	log(Med Pats$_t$) in 2nd citation quintile	log(Med Pats$_t$) in 3rd citation quintile	log(Med Pats$_t$) in 4th citation quintile	log(Med Pats$_t$) in 5th citation quintile
Damage Caps$_t$	0.234	-0.404**	-0.678***	-0.733***	-0.193
	(0.18)	(0.19)	(0.18)	(0.17)	(0.13)
Control variables	YES	YES	YES	YES	YES
Year Effects	YES	YES	YES	YES	YES
State Effects	YES	YES	YES	YES	YES
Observations	1071	1071	1071	1071	1071

NOTES: OLS estimation. * significant at 10 percent, ** significant at 5 percent and *** significant at 1 percent. Med Pats = number of patent applications in medical device fields in the state. Damage Caps =1 if a cap on non-economic damages is present in the state. Citations quintiles constructed from citations filtered by grant-year effects, technology-class effects and number of claims. Robust standard errors clustered at the state level. We add 1 to Med Pats to include state-years with no patenting. Regressions also control for lagged total patenting, log(Population), and Physicians per 1,000 population.