Online Appendix

When does product liability risk chill innovation? Evidence from medical implants

Alberto Galasso and Hong Luo

Appendix A: DuPont's revised supply policy

Below, we present the January 15, 1993 letter that DuPont sent to its customers describing the change in its supply policy regarding implant manufacturers. The source of this letter is the May 20, 1994 hearing before the Subcommittee on Regulation and Government Information of the Committee on Governmental Affairs of the US Senate.

Dear (Customer's Name):

This communication affects only those customers who use DuPont materials in implantable medical devices.

Recently DuPont has determined that unpredictable and excessive costs of doing business with manufacturers of implantable medical devices no longer justifies unrestricted sale of standard raw materials to such manufacturers at customary prices. Our new Policy and Caution Statement regarding these sales are attached. Under DuPont's new Policy there is a very strong presumption against sales to customers making permanent implants.

Therefore, as of January 15, 1993, DuPont will begin to phase out sale of materials to customers using our materials in medical articles intended for permanent implantation in the human body or in permanent contact with internal body fluids or tissues. We intend to complete this phase out as soon as possible, but no later than January 31, 1994.

To allow our customers time to locate alternate suppliers of materials, or alternate materials, during this phase out period we will honor our existing customer/supplier relationships. Also, effective immediately Du Pont will restrict sales of materials to companies who use those materials in medical articles intended for brief or temporary implantation in the human body or in contact with internal body fluids or tissues. DuPont will not supply the material to customers making temporary implants, unless the material comes directly from DuPont under a contract which expressly acknowledges the contemplated use and contains specific business risk management requirements.

Permission to refer to material Master Files will be withdrawn, and given only to direct customers who are purchasing material from DuPont under contract. We intend to complete transition to this type of supplier/customer relationship as soon as possible, but no later than January 31, 1994.

Unless expressly agreed by contract, do not make reference to the Du Pont name or any DuPont trademark in association with any implantable medical device. Do not use a DuPont trademark as the descriptive name of an implantable medical device. A copy of DuPont's Policy and Caution are attached. We sincerely regret any inconvenience this may cause you. If you have any questions, please contact me at (xxx-xxx-xxxx).

Sincerely.

Appendix B: Back-of-the-envelope welfare calculation

This Appendix explains in greater detail the welfare calculation conducted in Section 7.3. The calculation follows four steps.

In step 1, we obtain the total surplus that would have been generated from having one new device. This number is the product of the total number of procedures involving each of the four device types used in the analysis—which are obtained from the 1992 annual summary of the National Hospital Discharge Survey—and the increase in total surplus per procedure when physicians have access to a new medical device, estimated by Grennan and Swanson (2017). Note that the increase in total surplus is the sum of the increase in consumer surplus (physician, patient, and hospital combined) and producer gross profit (price minus marginal cost). For example, for hip replacement, the total estimated increase in surplus is \$7,233 + \$932 = \$8,165 per procedure. The number of procedures in 1992 for hip replacement (ICD-9 code 81.51 in Table 22) was 127K. Thus, the increase in total surplus is \$1.03B per year for hip replacement. This number for knee replacements, pacemakers, and cardiac catheterization is, respectively, \$3.9B, \$2.6B, and \$4.2B.

In step 2, we derive the reduction in the total number of devices per year based on our estimates. Our preferred model (column 3 of Table 6) implies an average reduction of 0.14 FDA device applications per year for implant product codes relative to non-implant codes. Multiplying this average effect by the number of product codes involving medical implants (107 codes), we obtain an estimated reduction of 15.96 implant devices per year.

In step 3, we obtain the drop in the number of new devices associated with the four specific implant types. Assuming that the drop in applications is distributed across categories in proportion to the level of applications before the increase in liability risk (that is, between 1985-1989), the yearly reductions in the number of applications are, respectively, 4.2, 0.1, 0.4, and 3.4 for hip implants, knee implants, pacemakers, and catheters.

In step 4, multiplying the above numbers of yearly reductions in applications by the increase in total surplus per new device per year yields the estimated reduction in total surplus due to the increase in liability risk. The welfare loss for these four device types, in total, is \$20.3B. Grennan and Swanson (2017) show that for these four device categories, a typical product is in the consideration set of 56 percent to 91 percent of hospitals. Taking these penetration rates into account, the decline in the total surplus for these four implant categories combined is \$11.9B per year.

Note that Grennan and Swanson (2017) provide estimates of the splits of the total surplus between consumers surplus and producer gross profit for each device category. Repeating the above four steps using each of the two components in Step 1 would provide us with an estimate of the loss in consumer surplus as \$10.6B per-year and the loss in producer gross profits as \$1.2B per-year.[25]

If we use the lowest penetration rate documented by Grennan and Swanson (2017) across all Class-III devices for all four categories, which is 20 percent, the decline in total surplus is \$4.1B.

[25]For reference, one industry estimate suggests that the total sales of implant devices was \$43B in 2011 ("Understanding the market for implantable medical devices," by Keith Lind, AARP Insights, August, 1-15, 2017). Assuming that the share of revenues corresponds to the share of FDA application counts and that the average gross margin is 60 percent, an estimate of \$1.2B loss in producer profit for these four product categories would suggest that the increased liability risk resulted in about 5.3 percent of revenue loss.

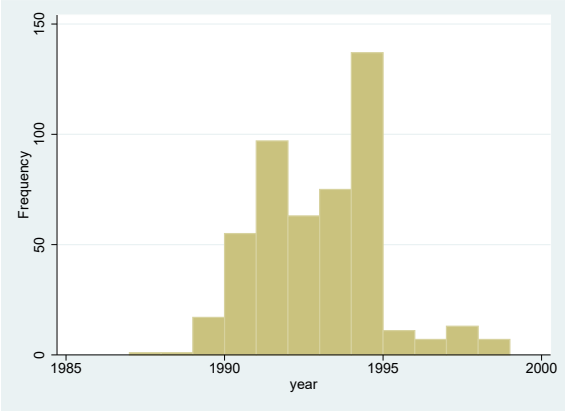
Appendix C: Additional empirical analysis

C.1. Timing of the shock

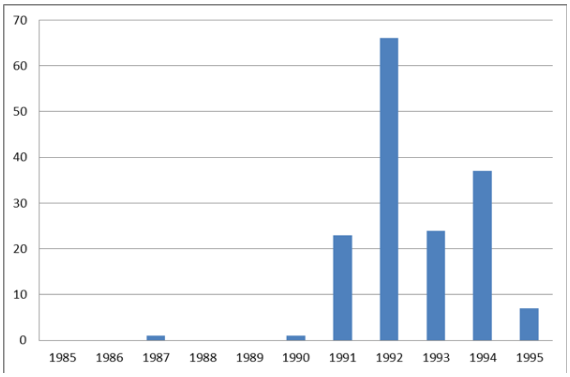
Figure A1 provides additional evidence for the choice of our treatment timing—that is, years including and after 1990. Panel (a) plots the timing of TMJ lawsuits involving DuPont as one of the defendants, collected from Bloomberg Law.[26] The figure shows a sharp increase in the number of lawsuits DuPont faced starting from 1990, the year Vitek filed for bankruptcy. Panel (b) plots the timing of news articles referring to DuPont's implant litigation, retrieved through keyword searches in the Factiva (Dow Jones) database. This figure shows that the media coverage of implant-related litigation events involving DuPont increased substantially in 1991 and persisted throughout the following years.

Figure A1: TMJ Lawsuits involving DuPont and medical implants media mentions

(a) TMJ lawsuits with DuPont among the defendants



(b) Media mentions of medical implants



Note: Source: (a) Bloomberg Law; (b) Factiva (Dow Jones), search keywords are 'implant,' 'DuPont,' 'jaw,' and 'breast.'

C.2. Robustness of the baseline results

Recall that in the baseline analysis, we define a patent subclass as an implant subclass if at least 80 percent of the patents belonging to this class are implant patents. The first two columns of Table A1 show that our baseline result is robust to different thresholds of defining implant subclasses.

For about five percent of the subclasses in our sample, we observe no patenting during the entire sample period of 1985-95. In column 3 of Table A1, we show that our result is robust to dropping these subclasses. In column 4, following Moser and Voena (2012), we show that our results are robust in an unbalanced panel that includes only subclasses-years for which we observe at least one patent in year t or in the years before

[26] We searched the database using two keywords in the full text: DuPont (and other variations of the company's name) and Vitek. We included lawsuits in the following categories: personal injury/health care/pharmaceutical personal injury/product liability; personal injury/product liability; personal property/product liability; and contract/product liability. The initial search returned about 650 cases, which is consistent with the number in Schmucki (1999). Removing "spin-off" cases that originated from a different case left us with 485 unique lawsuits. In 44% of these lawsuits, DuPont was named as one of the defendants, while Vitek was not (because Vitek had filed for bankruptcy). In the remaining 56%, both DuPont and Vitek were named among the defendants.

Table A1: Robustness of baseline results

Dependent variable	Patents (1)	Patents (2)	Patents (3)	Patents (4)	Patents (5)
Implant x After 1990	-0.428***	-0.568***	-0.556***	-0.606***	-0.550***
	(0.092)	(0.116)	(0.096)	(0.100)	(0.093)
Year effects	YES	YES	YES	YES	YES
Subclass effects	YES	YES	YES	YES	YES
Drop observations	NO	NO	Subclasses with no patents	Subclasses with no patents & years before first patent	Pacemakers & heart valves
Implant subclass thresholds	0.5	0.9	0.8	0.8	0.8
Observations	29733	29733	27830	26819	28809

Note: OLS regressions. Patents = the number of patent applications in a subclass-year. In column 1, implant = 1 if the fraction of implant patents in the subclass exceeds 0.5; in column 2, implant = 1 if the fraction of implant patents in the subclass exceeds 0.9; and in columns 3-5, implant = 1 if the fraction of implant patents in the subclass exceeds 0.8 (as is in the baseline analysis). Column 3 drops subclasses with no patenting during our sample period. Column 4 exploits an unbalanced panel in which a subclass enters the sample in the first year of positive patenting. Column 5 drops subclasses involving pacemakers and heart valves. Robust standard errors clustered at the subclass level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

t. This approach, which excludes subclasses with no patenting before year t, gives an estimate very similar to that in column 2. In column 5 of Table A1, we reestimate our baseline, dropping two prominent patent subclasses: pacemakers and heart valves. These subclasses include complex technologies that experienced very large growth in the 1990s and were associated with the greatest number of adverse events. Our estimates show that our results are robust in this subsample.

In Table A2, we confirm our findings using a number of alternative econometric models. Column 1 shows that the results are robust to using the logarithm of the number of patents in the subclass as the dependent variable. This specification mitigates concerns related to the skewed nature of the distribution of patenting. Column 2 shows that our results are also robust to using the count of patents weighted by the citations received from other patents as the dependent variable. As we discuss in greater detail in Section 5.4 on heterogeneous effects, citations are a common measure of patent value in the economics of innovation literature (Pakes and Griliches, 1980). Finally, we confirm our results with two Poisson models. Column 3 uses the fixed-effects Poisson estimator of Hausman et al. (1984), which isolates the within-subclass variation in patenting and drops subclasses in which there is no patenting for our entire sample period. Column 4 uses the Poisson 'mean scaling' estimator of Blundell et al. (1999). To implement this method, we calculate the mean of the dependent variable in the 1972-1982 pre-sample data and use it directly in the estimation to control for the initial condition. In both models, we find a large negative decline in implant patenting after 1990.

The USPTO subclass system follows a hierarchical nested structure in which subclasses are grouped into

Table A2: Alternative econometric models

Dependent variable	log(patents+1)	Citations	Patents	Patents
Model	OLS	OLS	Poisson	Poisson mean scaling estimator
	(1)	(2)	(3)	(4)
Implant x After 1990	-0.073***	-34.107***	-0.147*	-0.309***
	(0.012)	(10.631)	(0.077)	(0.054)
Year effects	YES	YES	YES	YES
Subclass effects	YES	YES	YES	NO
Observations	29733	29733	27830	29733

Note: Patents = the number of patent applications in a subclass-year. Implant = 1 if the fraction of implant patents in a subclass exceeds 0.8. Column 1 includes a dummy for subclasses-years with no patenting. Column 4 includes the log of pre-sample patenting as control. Robust standard errors clustered at the subclass level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

subclasses at higher indent levels. Our main analysis uses the most disaggregated level of classification and takes each subclass as a unique group without explicitly considering the hierarchical structure. The benefit of this approach is that it avoids imposing an arbitrary level of aggregation, given that indent levels across technical fields are not necessarily consistent (for example, indent level 2 in Prosthesis may not have the same level of technological detail as indent level 2 in Surgery). A potential downside is that subclasses cut the data quite thin, and many subclass-year observations have zero patents.

Table A3: Aggregation of patent subclasses

Dependent variable	Patents	Patents	Patents
Aggregated subclasses	1871	1184	462
	(1)	(2)	(3)
Implant x After 1990	-0.600***	-1.189***	-3.049**
	(0.182)	(0.392)	(1.279)
Year effects	YES	YES	YES
Subclass effects	YES	YES	YES
Observations	20581	13024	5082
Mean dep. Variable	2.269	3.585	9.189

Note: Patents = the number of patent applications in an (aggregated) subclass-year. Implant =1 if the fraction of implant patents in an aggregated subclass exceeds 0.8. Robust standard errors clustered at the subclass level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table A3, we show that our baseline analysis is robust to using more-aggregate technology classifications. Specifically, building on the USPTO hierarchical structure, we rerun our analysis using 1,871 subclasses (aggregating associated 'children' subclasses, if applicable, up to indent level 3), 1,184 subclasses (up to indent level 2), and 462 subclasses (up to indent level 1). These aggregations increase the average

patenting activity per (aggregated) subclass and reduce the number of cases in which patenting is zero. In all aggregation levels, we find a strong negative decline in implant relative to non-implant technologies.

To further clarify how the estimated effect may vary by subclass size, Table A4 reports DID regressions that use subclasses for which the pre-treatment patenting level belongs to three different terciles of the distribution. Column 4 uses subclasses in the 25th-75th percentile range. The results show that the effect is small and statistically insignificant for subclasses in the first tercile of pre-treatment patenting (one patent or fewer in 1985-89), but it becomes significant for the upper two terciles of the distribution (2-5 patents and six patents or more). The last column shows that the effect remains significant when we drop the bottom and top quartiles of the distribution. Overall, the results show that the treatment effect is driven by relatively active patenting subclasses. Though it is largest in the most active classes, the treatment effect is not localized to these technologies. The effect is also present in the middle of the distribution.

Table A4: Effects by patent class size

Dependent variable	Patents	Patents	Patents	Patents
Sample	Below 33rd perc.	33rd-66th perc.	Above 66th perc.	25th-75th perc.
	(1)	(2)	(3)	(4)
Implant × After 1990	-0.003	-0.258***	-1.341***	-0.262***
	(0.081)	(0.086)	(0.433)	(0.070)
Year effects	YES	YES	YES	YES
Subclass effects	YES	YES	YES	YES
Observations	10032	10802	8899	17578

Note: Patents = the number of patent applications in a subclass-year. Implant =1 if the fraction of implant patents in a subclass exceeds 0.8. The first three columns include subclasses for which the pre-shock patenting level falls in the three terciles of the distribution, respectively. Column 4 includes subclasses for which the pre-shock patenting level falls in the middle two quartiles. Robust standard errors clustered at the subclass level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.3. Substitution toward non-implant patents

To examine the extent to which the effect of liability risk spills over to the control group, we exclude patenting by assignees active in both the implant and non-implant subclasses in the paper (column 4 in Table 2). In the following, we conduct a separate exercise to isolate the potential spillover effect. In particular, we contrast patenting in implant patent subclasses with an alternative control group—patenting in subclasses that include only pharmaceutical drug innovations and not medical device innovations.[27] The technological distance between implant and drug classes mitigates the concern that liability risk may spill over from the treated to the control subclasses. At the same time, this alternative control group is likely to respond to macro-shocks affecting the entire health sector.

Column 1 of Table A5 estimates equation (1) in the paper, using this alternative control group. To

[27] Specifically, we exploit USPTO patent classes 424 and 514, both titled "Drug, bio-affecting and body treating compositions." The number of firms operating in both the treated and control fields is smaller than in our main sample (only one percent of the assignees).

address the concern that trends in patenting in drug subclasses may differ from those in implant subclasses, in column 2, we match each implant subclass with one of the drug subclasses, minimizing differences in patenting before 1990. Specifically, for each implant subclass, *c*, we identify the nearest neighbor drug subclass with the smallest distance from class c in terms of patenting in each year from 1985 to 1989. The estimates in columns 1 and 2 are similar to our baseline results. This finding, based on an alternative control group in which contamination concerns are less severe, provides additional support for the idea that the substitution effect is not the primary driver of our main result.

Table A5: Drug patenting as an alternative control group

Dependent variable	Patents	Patents	Patents
	(1)	(2)	(3)
Implant x After 1990	-0.815***	-0.501***	
	(0.109)	(0.135)	
Non-implant x After 1990			0.031
			(0.125)
Year effects	YES	YES	YES
Subclass effects	YES	YES	YES
Observations	21626	5302	29733
Sample	implant and drug subclasses	implant and matched drug subclasses	non-implant and matched drug subclasses

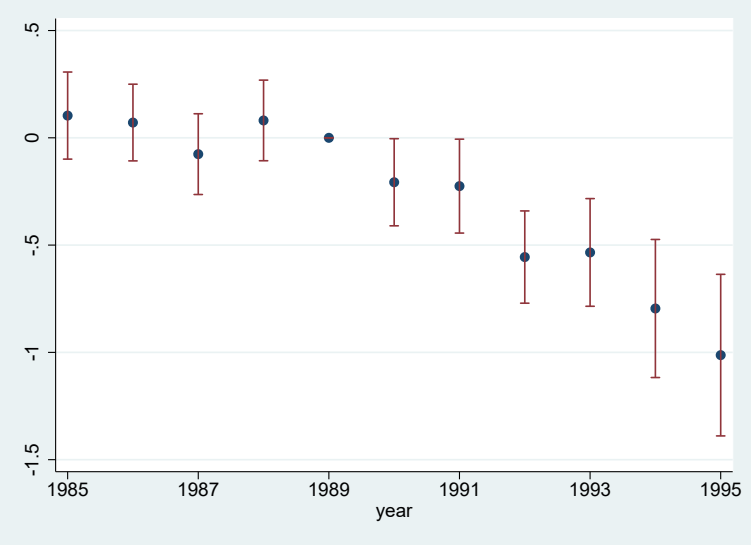
Note: Patents = the number of patent applications in a subclass-year. Implant = 1 if at least 80 percent of all the patents in a subclass are implant patents. Non-implant = 1 if less than 80 percent of all the patents in a medical device subclass are implant patents. Drug subclasses are based on USPTO patent classes 424 and 514, both titled "Drug, bio-affecting and body treating compositions." Robust standard errors clustered at the subclass level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The last column of Table A5 compares the two control groups—non-implant medical device subclasses and the (matched) drug subclasses used in column 2. The difference-in-differences coefficient of this placebo analysis is small and statistically insignificant. This result suggests that non-implant devices grew similarly to other areas of the medical sector, which is consistent with the idea that the estimated effect in our baseline regression is driven by a slowdown in implant technologies.

C.4. Time-specific effects

Table A6 examines the timing of the effects for four separate subsamples, divided by patent value—patents with citations (after excluding subclass and application year fixed effects) above versus below the median—and by firm size (the six largest firms versus applicants outside the top six, including smaller firms, non-profit organizations, and individual inventors). Please see the definitions of patent citations and firm size in Section 5.4 "Heterogeneous effects." In these DID regressions, we define three treatment windows: 1990-1991; 1992-1993; and 1994-1995. The results show that for both below-median and above-median citation patents, top-6 firms experience greater delays than smaller firms, non-profit organizations, and individual

Figure A2: Estimated annual treatment effects



Note: The regression is analogous to equation (2) in the paper, in which the year dummies are interacted with the fraction of implant patents in a subclass. The figure plots the coefficients (and 95% confidence intervals) of the interaction terms.

inventors. Within assignees of similar sizes, the effect is more immediate for less-important patents (those with below-median citations) than for more-important patents.

C.5. Patents by foreign firms and triple-differences regressions

Figure A3 plots the time-specific treatment effects (equation 2) using only patents by US assignees as the dependent variable. The results appear to be sharper than those in Figure 2, which uses all patents. The estimated differences between implant and non-implant subclasses before the liability regime shift are all very small. They are not only statistically indistinguishable from the default year of 1989, but also indistinguishable from each other. The decline in implant patenting started in 1990 but became statistically significant only in 1991. The magnitude of the decline increased steadily until the end of the sample period.

Figure A4 presents the triple-interaction coefficients in a year-specific version of the regression presented in column 4 of Table 3. This figure illustrates a pattern that is qualitatively consistent with that in Figures 2 and A3, suggesting that the liability shock had a substantially lower impact on foreign firms that commercialize in the US. The estimated differential effects on implant patenting experienced by US firms were slightly smaller and more delayed after controlling for the patenting trends by foreign assignees.

C.6. FDA and patent approval delays

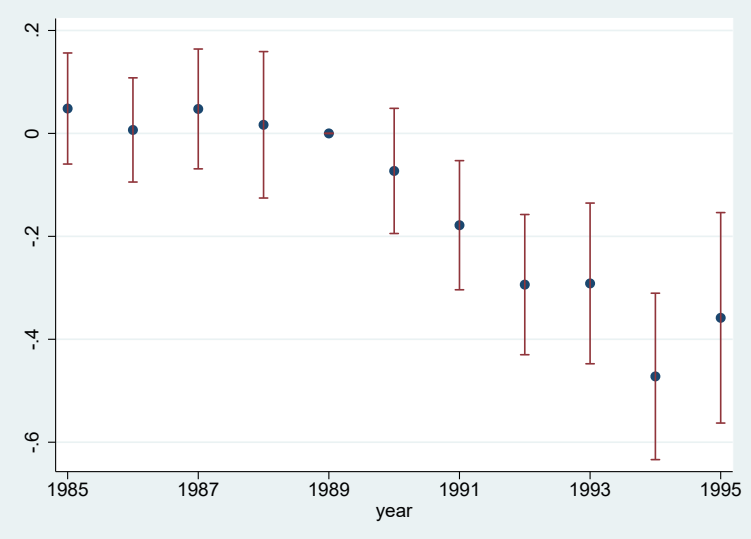
The first two columns in Table A7 present FDA application-level regressions, in which the dependent variables are the number of months between the application date and the decision date and its logarithm. The regressions use applications that underlie the sample used in column 4 of Table 4; that is, control and treatment product codes are matched on the pre-trend, and two outlier product codes are excluded. The estimates

Table A6: Timing-specific effects by firm size and patent value

Sample	Below-median citations		Above-median citations	
	Exclude top 6 firms	Top 6 firms	Exclude top 6 firms	Top 6 firms
Dependent variable	Patents	Patents	Patents	Patents
	(1)	(2)	(3)	(4)
Implant X (1990-1991)	-0.176***	-0.011	-0.032	-0.012
	(0.043)	(0.007)	(0.053)	(0.008)
Implant X (1992-1993)	-0.341***	-0.028**	-0.131**	-0.026**
	(0.058)	(0.011)	(0.051)	(0.012)
Implant X (1994-1995)	-0.566***	-0.027***	-0.227**	-0.023
	(0.071)	(0.008)	(0.098)	(0.014)
Year effects	YES	YES	YES	YES
Subclass effects	YES	YES	YES	YES
N	29733	29733	29733	29733
Sample mean	0.747	0.039	0.739	0.046

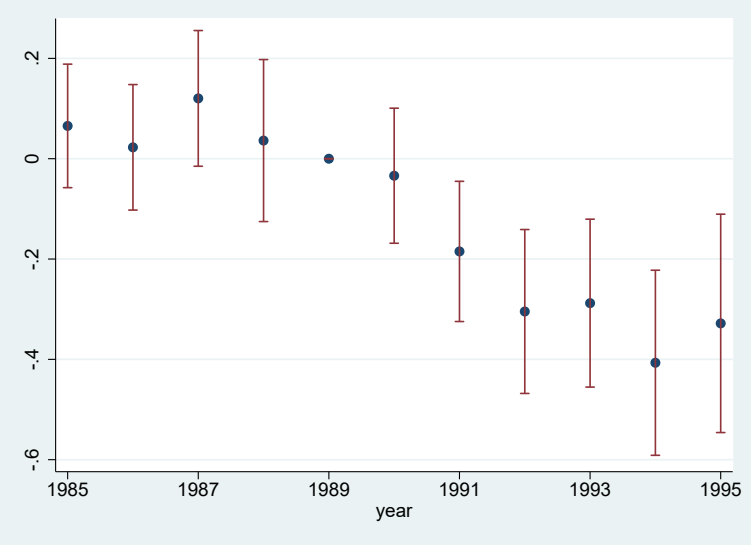
Note: Patents = the number of patent applications in a subclass-year. Implant = 1 if at least 80 percent of all the patents in a subclass are implant patents. Robust standard errors clustered at the subclass level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A3: Year-specific DID coefficients using US patents



Note: This regression corresponds to equation (2) in the paper, using only patents by US assignees and controlling for subclass and year fixed effects. The figures plot the coefficients (and 95% confidence intervals) of the interaction terms between year dummies and the implant class dummy, which equals one if at least 80 percent of all the patents in the subclass are implant patents.

Figure A4: Year-specific triple-interaction coefficients in a triple-differences regression



Note: Year-specific version of the triple-differences regression in column 4 of Table 3, controlling for subclass and year fixed effects, a complete set of year-specific double-interaction terms, and a dummy variable indicating US patentees. The figures plot the year-specific triple-differences coefficients (and 95% confidence intervals).

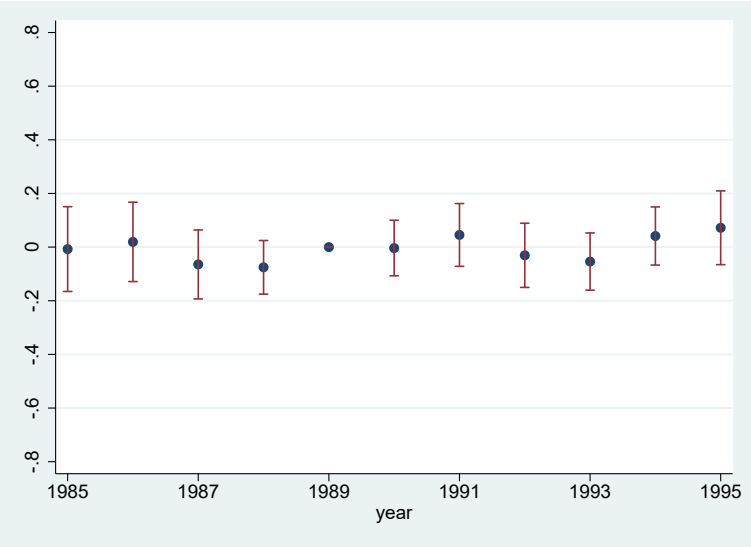
show that the amount of time required to obtain the FDA approval is not significantly longer for implant devices than for non-implant devices. If anything, the coefficient in column 2 suggests that implant devices, on average, experience a (marginally) shorter approval delay after 1990.

Table A7: Approval timing

	FDA applications		Patent applications	
	log(Time)	Time	log(Time)	Time
	(1)	(2)	(3)	(4)
Implant X After 1990	-0.292	-7.574*	-0.038*	-1.487**
	(0.382)	(4.464)	(0.020)	(0.711)
Adverse events reports	0.021	0.546		
	(0.086)	(0.615)		
Patent subclass/FDA product code FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	374	374	46491	46491

Note: For the first two columns, time = number of months between the application date and the decision date of an FDA application, implant = 1 if the FDA identifies the product code as an implant, and adverse events reports = the number of product code-associated reports on deaths, injuries, and malfunctions in a given year. For the second two columns, time = the number of months between the application date and the grant date of a patent, and implant = 1 if at least 80 percent of all the patents in a subclass are implant patents. Robust standard errors clustered at the subclass level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A5: Estimated annual treatment effects using patents published by the UK patent office



Note: This regression uses medical device patents published by the UK patent office and applied for between 1985 and 1995. The regression corresponds to equation (2) in the paper, controlling for subclass and year fixed effects. The figure plots the coefficients (and 95% confidence intervals) of the interaction terms between year dummies and the implant class dummy. We use the classification system used in Europe during our sample period and define class A61 ("Medical or Veterinary Science, Hygiene") as medical device patents. We use a less demanding textual algorithm than we use for US patents—that is, searching only for keywords of 'implant, graft, prosthesis, or prosthetic' without combining that with the device name keywords—to identify implant patents because our data for UK, Germany and France contain fewer textual variables. Similar to our baseline analysis, the cutoff threshold for defining an implant class is chosen so that the treated implant subclasses contain roughly the top tenth percentile of the distribution of the fraction of implant patents.

In the second two columns of Table A7, we replicate the above analysis for patent grant delays (from the application date to the grant date) at the USPTO. We use the patents underlying our baseline sample and define implant subclasses as those with a fraction of implant patents above the 80-percent threshold, as we do in the baseline analysis. The regressions control for year and patent subclass fixed effects. The results also do not show any differential increase in grant delays for implant subclasses relative to non-implant subclasses. These results on FDA approval time and patent grant delays help mitigate the concern that our main results in the paper are driven by heavier regulatory burdens for implant technologies.

C.7. Heterogeneous effects

Panel A of Table A8 estimates our baseline regression across five groups of patentees. For each assignee in our sample, we construct a patent portfolio equal to the number of medical device patents between 1985 and 1995. Because of the skewness in the distribution of patent portfolios, we allocate patentees into three groups: 'small patentees' (assignees with one to four total patents) cover 50.5% of the patents; 'medium patentees' (assignees with five to 40 total patents) cover 24.2% of the patents; and 'large patentees' (assignees with more than 40 patents) cover the remaining 25.2% of the patents. In addition, we further examine the effect on patenting by the largest assignees, creating two additional groups: the 'Top 16 assignees' group covers roughly 10% of the patents, and 'Top six assignees' group covers roughly 5% of the patents.

The coefficients are negative and statistically significant across all groups.

Table A8: Heterogeneous effects

(a) Firm size

Dependent variable	Patents	Patents	Patents	Patents	Patents
Firm size	Small	Medium	Large	Top 16	Top 6
Percent of patents	50%	25%	25%	10%	5%
	(1)	(2)	(3)	(4)	(5)
Implant × After 1990	-0.153***	-0.110***	-0.154***	-0.046***	-0.014**
	(0.042)	(0.023)	(0.027)	(0.010)	(0.006)
Year effects	YES	YES	YES	YES	YES
Subclass effects	YES	YES	YES	YES	YES
Sample mean	0.793	0.381	0.396	0.167	0.085
Observations	29733	29733	29733	29733	29733

(b) Citation quintiles

Dependent variable	Patents	Patents	Patents	Patents	Patents
Quintile	Q1 (lowest)	Q2	Q3	Q4	Q5 (highest)
	(1)	(2)	(3)	(4)	(5)
Implant × After 1990	-0.081***	-0.098***	-0.046**	-0.032	-0.079***
	(0.022)	(0.015)	(0.021)	(0.022)	(0.026)
Year effects	YES	YES	YES	YES	YES
Subclass effects	YES	YES	YES	YES	YES
Sample mean	0.314	0.314	0.314	0.314	0.314
Observations	29733	29733	29733	29733	29733

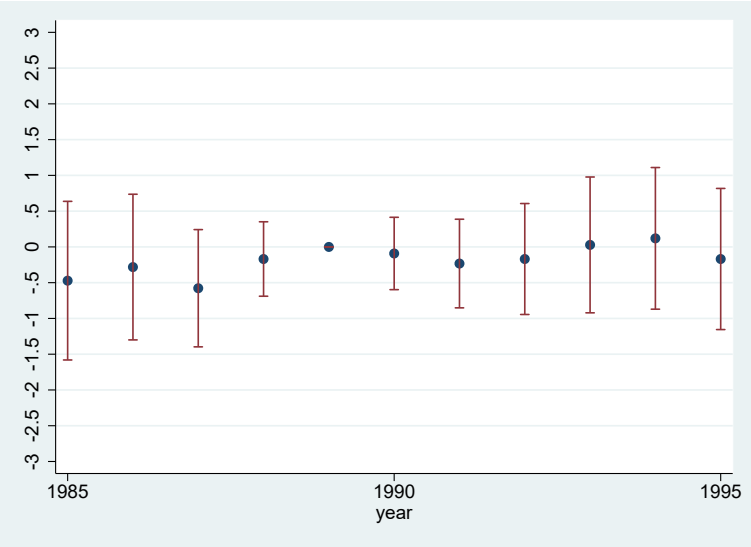
Note: OLS regressions. Patents = the number of patent applications in a subclass-year. Implant = 1 if the fraction of implant patents in the subclass exceeds 0.8; and = 0, otherwise. In (a), small patentees if portfolio has fewer than five patents; medium if portfolio has five to 40; and large if portfolio size is above 40. Top 16 includes the largest 16 assignees in the sample, and Top 6 includes the six largest assignees. In (b), each column includes only patents of a specific citation quartile (filtered by application year and technology class). Robust standard errors clustered at the subclass level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel B of Table A8 presents results across patents of different quality. To unbundle the heterogeneous effects of the increase in liability risk across different quality levels, we exploit information on the citations received by each patent. The economics of innovation literature has often employed the number of citations that a patent receives as an indirect measure of patent value (Pakes and Griliches, 1980). Since citation counts are inherently truncated, and levels differ across technology areas, we filter citations by removing application-year and (two-digit) technology class effects. We then identify the (filtered) citation quintile to which each patent belongs. The coefficients are also negative and statistically significant across all five quality quintiles, even though the magnitude of the effect appears to be the smallest for the intermediate-quality range.

C.8. Impacts on upstream patenting

Figure A6 plots the DID coefficients estimated from a regression similar to equation (2) in the paper but uses patents related to resin and organic compounds in 1985-1995. The sample used in this regression includes all affected-polymer subclasses (i.e., the treatment group) and control subclasses (i.e., the fraction of affected-polymer patents is less than 80 percent) that are matched to minimize the difference in the pre-trend (1985-1989) from the treated group. The results show that upstream polymer patenting is not affected by the liability shock.

Figure A6: Estimated year effects on upstream innovation

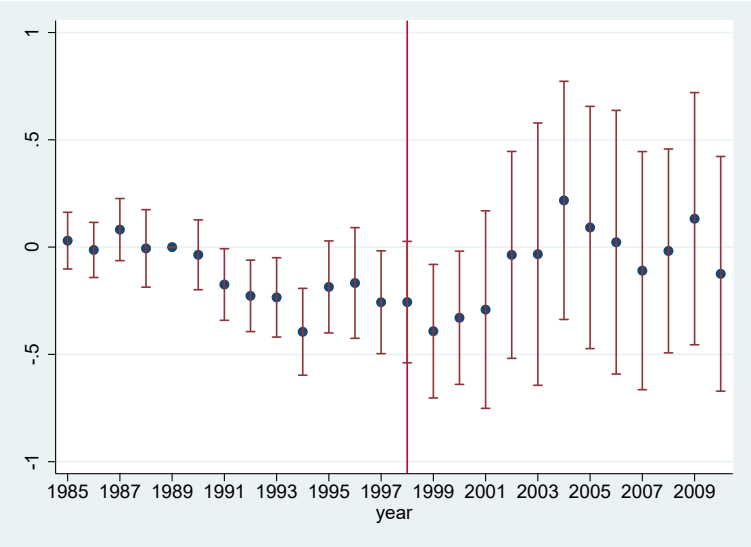


Note: The regression is similar to equation (2) in the paper, using patents related to resin and organic compounds in 1985-1995 and controlling for subclass and year fixed effects. The figure plots the coefficients (and 95% confidence intervals) of the interaction terms between year dummies and the affected-polymer class dummy, which equals one if at least 80 percent of all the patents in the subclass are affected-polymer patents.

C.9. Policy remedy: the 1998 Biomaterials Access Assurance Act

Figure A7 plots the year-specific DID coefficients estimated from a regression that uses patents by US assignees, analogous to that for Figure A3 but extended to 2010. The graph shows that the negative effect of our liability shock is sustained after 1995 and remains similar in magnitude until the end of the 90s. The effect starts to become increasingly less negative in 2000 and turns small and positive in 2002. The coefficients afterwards are statistically similar to the baseline year, 1989 (the year before our liability shock). The difference-in-differences coefficients of later years are more noisily estimated. However, comparing the coefficients for the years with the most negative impact and the years after 2002 shows mostly statistically significant differences.

Figure A7: Estimated annual effects, extended to 2010



Note: The baseline year is 1989. The figures plot the coefficients (and 95% confidence intervals) of the interaction terms between year dummies and the implant class dummy, which equals one if at least 80 percent of all the patents in the subclass are implant patents.

C.10. Additional evidence for assessing alternative mechanisms

The primary mechanism we propose in the paper is due to input supply restrictions. The litigations primarily targeted polymer (including silicone) suppliers. In the following, we provide an analysis that intended to determine whether the impact is more negative for implant innovations that are polymer-based than for those that are not.

We exploit the 1995 congressional hearing documents that include a list of devices that rely on polymers. The list includes about 100 major product categories of implanted devices, ranging from sutures, to batteries, to cardiac material, to various types of orthopedic implants, to catheters, and to pacemakers. Matching this list to patent subclasses or FDA device codes is not a simple exercise. Some of these device names are easy to identify; however, some capture components or basic building materials (e.g., "molded component" or "cardiac material") that may be present in many devices and, thus, hard for us to match to patent applications or FDA codes. Other times, the device names in the congressional documents may be very general and refer to a broad set of products. For example, the list includes "neuro stimulator," which could refer to all types of stimulators in neurology.

We begin with the patent data by using textual information to identify patents in implant subclasses that appear to be polymer-based. Specifically, we classify a patent as a 'polymer-based implant' if the title, the abstract, or the first claim of the document contains these device names listed in the congressional hearing document. Then, we use this information to distinguish implant subclasses that rely heavily on polymers from those that do not. We label a subclass as a 'polymer-based implant subclass' if the fraction of polymer-based patents is greater than 80 percent, which leads 63% of implant subclasses to be defined as polymer-

based, and 37% as not polymer-based (consistent with the widespread use of polymers). The first column of Table A9 compares the polymer-based implant subclasses to non-polymer-based implant subclasses. The result shows that polymer-based implant subclasses, according our definition, are (marginally) significantly more negatively affected than non-polymer-based implant subclasses.

Table A9: Polymer-based implants versus non-polymer based implants

	Patents	FDA applications
	(1)	(2)
Polymer implant x After 1990	-0.394**	-0.082*
	(0.167)	(0.045)
Patent subclass/FDA product code FE	Yes	Yes
Year FE	Yes	Yes
N	2651	1232

Note: Patents = the number of patent applications in a subclass-year. FDA applications = number of FDA applications in a product code-year. In column 1, polymer implant = 1 if at least 80 percent of all the patents in an implant subclass are defined as polymer-based; and in column 2, polymer implant is defined based on manual matching. Robust standard errors clustered at the subclass level (in parentheses). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We conduct a similar exercise for FDA device applications. To the best extent we can, we manually match the device names in the list provided to the congressional hearing with FDA device names. Our approach classifies about 70 percent of the implant product codes as using polymer. Similar to column 1, column 2 of Table A9 compares polymer-based implants to non-polymer-based implants using the FDA data. The coefficient also shows that polymer-based implant devices are (marginally) more negatively affected. Overall, the empirical evidence presented above is consistent with the idea that the relative decline in innovation is greater for medical implants that rely more substantially on polymers.

As we explain above, the classification is subject to substantial measurement error because detailed information indicating which devices or patents do not rely on polymers is not readily available. In addition, as we discuss in Section 2, input disruptions were not exclusively restricted to polymeric materials. Paul Citron (1994), a vice president at Medtronic at the time, stated that "while the impact has been greatest for implanted polymeric and elastomeric materials, it has not been restricted to them. The adverse experience with product liability has caused suppliers of essentially all components used in implants to assess their willingness to supply. For example, certain well-established manufacturers of integrated circuits have refused to supply their chips for implanted devices." Because of these issues, we do not want to over-rely on this specific heterogeneous effect but, rather, on the collective set of results discussed in Section 7.2 as evidence for our proposed mechanism.