THE IMPACT OF MEDICAL ERRORS ON PHYSICIAN BEHAVIOR: EVIDENCE FROM MALPRACTICE LITIGATION*

Ity Shurtz†

Abstract

How do medical errors affect physician behavior? Despite the importance of this question empirical evidence about it remains limited. This paper studies the impact of obstetricians' medical errors that resulted in malpractice litigation on their subsequent choice of whether to perform a C-section, a common procedure that is thought to be sensitive to physician incentives. The main result is that C-section rates jumped discontinuously by 4% after a medical error, establishing an association between medical errors and treatment patterns. C-section rates continued to increase afterwards, bringing the cumulative increase 2.5 years after a medical error to 8%.

Keywords: Physician treatment styles, Peer effects
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†Ity Shurtz, Department of Economics, The Hebrew University, Jerusalem 91905, Israel. Phone: 972-2-5883240. Fax: 972-2-5816071. Email: ity.shurtz@mail.huji.ac.il.

I INTRODUCTION

Medical errors, their causes, and their impact on physician behavior have become central issues in the political debate and the scientific discourse in the past decade. Until recently, there was very little evidence on the issue of medical errors, their scope, and their consequences (Wu, 2000). However, the scientific and policy making communities are increasingly aware that medical errors, often resulting in severe patient outcomes and even death, are very common (Kohn et al., 2000).

An important question in understanding the consequences of medical errors and reducing their incidence is whether a relation exists between medical errors and physician behavior. Conventional wisdom in the medical community has it that physicians' medical errors affect treatment patterns. Self reported data support this view: in surveys, physicians consistently report that they change their treatment patterns after making a medical error (Wu et al., 1991, Wu et al., 1993, Fischer et al., 2006). Nevertheless, perhaps because physicians are concerned about the implications of disclosing errors (Gallagher et al., 2003) and despite the growing interest in the issue, observational evidence is scarce and the mechanisms underlying this association are poorly understood.

This study examines the impact of physicians' medical error on their subsequent behavior. It focuses on an important subgroup of medical errors, those that result in malpractice lawsuits.[1] This subgroup offers a unique opportunity to rigorously examine the impact of a medical error on physician behavior. Using data from Florida, one may directly observe the exact timing of physicians' medical errors that resulted in litigation and match it with data on their treatment patterns over time. Together, these data create a very appropriate setting for the assessment of the research question.

While this subgroup of medical errors provides a rare opportunity to examine the impact of a medical error on physicians' treatment patterns, one should keep in mind that the interaction between medical-malpractice law and physicians' personal exposure to litigation may also be associated with physicians' treatment patterns. It is often argued that fear of lawsuits affects treatment patterns and may encourage high-cost, low-benefit medical treatment ("defensive medicine") (Studdert et al., 2005, Kessler and McClellan, 1997, Reyes, 2010). Therefore, this study examines the impact of physicians' medical errors on their subsequent behavior and its underlying mechanisms, while bearing in mind the role of malpractice lawsuits.

The physicians whom I investigated were obstetricians, who are regarded as par-

[1] I use the terms lawsuit and medical malpractice claim interchangeably in reference to malpractice cases reported by a physician to her insurer.

ticularly sensitive to malpractice concerns (Reyes, 2010). I studied their responses by examining their decision to perform C-sections, a common procedure that is thought to be sensitive to obstetrician incentives (Currie and MacLeod, 2008). The analysis draws on inpatient data from Florida, matched with data on the physicians' malpractice claim history.

I use the timing of an *adverse event*, which I define as a procedure that ultimately led to a lawsuit, to demarcate a pre-medical-error period and measure the impact of a medical error that resulted in a lawsuit on subsequent medical treatment. First I use a simple "before and after" analysis to examine the physicians' discontinuous response immediately after an adverse event. Then I use an event study approach to study the effect of an adverse event on medical treatment over time, estimating physicians' response by controlling for physician and time fixed effects as well as other covariates. To complement the analysis, I estimate the "very long-run" effect of an adverse event, up to four and a half years after the event, using a matching method that pairs each affected physician with an individually-tailored control group.

The main findings of the empirical analysis are as follows. First, an adverse event is followed by a discontinuous increase of about 1 percentage point in C-section rates. Second, two to two and a half years after the adverse event the cumulative increase in C-section rates adds up to roughly 2.2 percentage points. Given that the base C-section rates before the adverse event are roughly 25%, these results reflect an increase of 4% and 8% in C-section rates, respectively. Using the matching approach, I find that the effect of the adverse event and the lawsuit persists for at least four and a half years after the adverse event. Additionally, I find no evidence of a hospital-wide change in treatment patterns in response to an adverse event. Finally, the response is concentrated among claims which are ultimately successful and hence are more likely to be associated with a medical error, implying that the response is not occasioned by an emotional or institutional reaction to the bad outcome that led to the lawsuit.

When interpreting the results as reflective of a change in practice patterns, one must be concerned about the possibility that the adverse event led to a change in patient composition. I address this concern by testing for observed differences in the number of births, the risk level of the pool of mothers, mothers' mean age, and the share of mothers insured by a private carrier before and after the adverse event. I find no evidence of a change in the number of births or the characteristics of mothers following an adverse event, thereby alleviating these concerns.

This study is related to earlier work that used similar data to study the association between healthcare and personal experience with malpractice litigation. Grant and McInnes (2004) related the change in Florida obstetricians' propensity to perform C-

sections between 1992 and 1995 to their malpractice experience in 1993 and 1994. They found that claims that ultimately resulted in large indemnity payments were associated with an increase in C-section rates and conversely, claims that ultimately resulted in small indemnity payments were associated with a decrease in C-section rates, with a small effect overall on C-section rates. Gimm (2010), using inpatient data from 1992-2000, aggregated in physician-year cells, did not find statistically significant evidence of a change in physicians' patterns of practice in response to malpractice claims. Dranove and Watanabe (2010) studied the response of physicians to news about malpractice litigation by carefully examining whether physicians changed their C-section rates after first being contacted about a lawsuit. Their results imply small and short-lived increases in C-section rates after a physician is contacted about a malpractice claim. Dranove et al. (forthcoming) extend this literature further and study the demand side response to litigation by examining the change in patient volume and composition around the time of filing of a lawsuit, the time when the alleged medical malpractice case officinally becomes public information. They find that starting in the second year after the time of filing of a lawsuit high-quality physicians see fewer PPO patients but this decline is offset by an increase in the number of HMO and Medicaid patients. On the other hand, low-quality physicians see a decline in the overall number of patients they treat.

The findings that follow expand on the foregoing literature in several ways. First, my main and most robust finding is that C-section rates show a discontinuous increase after a medical error that results in a lawsuit. This result establishes, for the first time to my knowledge, the existence of a statistically significant and economically important relation between a physician's medical error and her medical treatment patterns. While this result in itself does not explain the mechanisms that underly this association, it strongly suggests that further examination of this association is important for understanding the consequences of medical errors and the extent to which physicians correct themselves after making them.

Second, this study shows a substantial and persistent impact of medical errors that result in lawsuits on medical treatment. This finding is of interest for the discourse on the interaction between medical-malpractice law and a physician's exposure to malpractice litigation. Put together with the results of Dranove and Watanabe (2010) and Dranove et al. (forthcoming), the results in this study imply that physicians' response to malpractice litigation (the so-called "supply side" response) takes place immediately after the adverse event and it is persistent. Afterwards, a year after the filing of a lawsuit, a demand side response occurs, affecting patient volume and the mix of patient characteristics.

Finally, this study shows one special case in which a physician's medical errors directly affect her choice of medical treatment, a finding consistent with conventional wisdom but poorly documented in the literature.

The rest of the paper is organized as follows. Section II reports the data, Section III offers evidence about physicians' response to an adverse event, Section IV presents evidence on peer effects, and Section V concludes.

II THE DATA

I use the universe of all births recorded in the Florida Hospital Inpatient Discharge Database (the "inpatient data") in 1992-2008. Births are linked to physicians and physicians who performed fewer than 25 deliveries throughout the entire period are excluded from the analysis. This leaves about three million births performed by 2,307 physicians, comprising 99.8% of all births. I merged the inpatient data with the Practitioner Profile Data File (the "profile data") which contains information about physicians' education history. Next, I matched the Medical Professional Liability Files (the "closed claims data") for 1979-2008 to the data, using both medical license numbers and physicians' names. The claims data contain a history of closed medical malpractice claims, payments made if any, severity of injury, and dates of the injury, and the reportage and closing of malpractice claims. I then create an *adverse event panel*: a five-year balanced panel, comprised of physicians who appear in the data ten quarters before and after the adverse event. I limit the number of adverse events per physician in the analysis to one by considering only the first adverse event covered by the inpatient-data period for each physician. It is important to note that while I analyze a five year balanced panel, the physicians who appear in the adverse event panel are responsible for roughly 40% of all the births in Florida during the sample period.

Figure I plots C-section rates in Florida for the years 1992-2008. The figure shows, consistent with the national trend (MacDorman et al., 2008), that C-section rates increased substantially from roughly 23% in 1996 to 38% in 2008. Table I provides summary statistics for two groups: the full sample and the adverse event panel. Mother characteristics in the full sample are very similar to those in the adverse event panel. Notably, the adverse event panel sample shows lower rates of mothers under Medicaid, lower rates of Afro-American and Hispanic mothers, and lower incidence of risk factors, suggesting that the mothers treated by physicians who are subject to lawsuits are of a higher socioeconomic status than the mothers in the full sample.

Figures IIa and IIb present the number of adverse events in Florida and in the

adverse event panel during the sample period, respectively. In the first several years of this period, the number of adverse events appear to be quite stable both in Florida and in the adverse event panel with about forty adverse events per year in the adverse event panel. The figures do not appear to show a trend in the number of adverse events, suggesting that there were no big changes in the legal environment during this period. In both figures, however, the number of adverse events declines toward the end of the period. This pattern reflects the fact that adverse events and lawsuits that were filed earlier are more likely to be resolved and therefore appear in the closed claim data. This "mechanical effect" may have led to the characteristics of adverse events observed in the data to vary by year, An issue that I address below.

Figure III presents the distribution of physicians' prior claims history, indicating that roughly 55% of the 459 physicians in the adverse event panel had no prior history of malpractice litigation at the time of the adverse event and approximately 90% of the physicians experienced no more than four claims.

Figure IV summarizes the distribution of nominal payments per claim in the adverse event panel, rounded to the closest multiple of $50,000. While roughly 31% of the claims in the adverse event panel are unsuccessful and result in zero payment (the first bar in Figure IV shows a 37% frequency because it includes claims that resulted in low payments), there are claims with payments of $1,000,000 or more. Interestingly, payments tend to "bunch" around $250,000 and $500,000, corresponding to standard per-claim ceilings of malpractice insurance, suggesting that the parties tend to reach a settlement based on the physicians' coverage.

III THE IMPACT OF AN ADVERSE EVENT ON MEDICAL TREATMENT

To analyze the impact of an adverse event on medical treatment, I normalize the timing of such an event to zero for all physicians and define other quarters relative to this base period. Figure V plots the average per-period C-section rates ten quarters before and ten quarters after an adverse event. To create a visual reference, I fit two quadratic regression models to the data separately, one before the adverse event and one after. Figure V shows a jump of about 1 percentage point immediately following the adverse event. Given that the base C-section rates are about 25%, this implies an increase of roughly 4% in C-section rates. Furthermore, the increase continues over time.

I estimate the discontinuous increase in C-section rates using the following OLS

regression:

$$(1) \quad C\text{-}section_{jit} = \alpha + \tau D + \beta_1 time + \beta_2 time^2 + \beta_3 time \cdot D + \beta_4 time^2 \cdot D + \varepsilon_{jit}$$

where $C\text{-}section_{jit}$ acquires the value of 1 if a mother j's baby is delivered by physician i at time t using a C-section, $time \in \{-10, ...-1, 0, ...9\}$ is the number of quarters that elapsed since the adverse event, and $D \in \{0, 1\}$ is a dummy variable that indicates post-event periods, so that $D = 1$ if $time \geq 0$, and $D = 0$ if $time < 0$. τ is the coefficient of interest in this specification because it captures the immediate effect of the adverse event on physician behavior.

Column (1) of Table II, displays the estimation results for Equation (1). The estimate supports the graphical evidence in Figure V, indicating a statistically significant increase of 1.1 percentage points in C-section rates after the adverse event. Columns (2) and (3) of Table II report the estimates of two additional specifications: basic controls, which add a set of mother characteristics,[2] and full controls, adding physician and year-quarter fixed effects to the basic controls. Both show a statistically significant increase in C-section rates of 0.9 and 0.76 percentage point respectively.

The discontinuous increase in C-section rates after an adverse event and the continued upturn in C-section rates over time establish the existence of an association between a physician's medical error and her subsequent treatment patterns. However, while the simple OLS regression convincingly establishes this association, one cannot estimate the increase in C-section rates after the adverse event over time separately from the secular time trend in C-section rates. To correct this drawback, I perform an event study analysis.

III.A The Event Study Approach

To apply the event study approach to the problem noted above, that is, to estimate the effect of an adverse event on medical treatment over time while accounting for the secular time trend in the outcome variable nonparametrically, I estimate the equation:

$$(2) \quad C\text{-}section_{jit} = \alpha + \sum_{k=-10}^{9} \delta_k time_{it}^k + \beta_1 phys_i + \beta_2 yq_t + \beta_3 Char_j + \varepsilon_{jit}.$$

[2]The characteristics used are age, race, insurance type and the following risk factors: previous C-section, breech position, multiple gestation, hypertension, early onset, hemorrhage, obesity, diabetes, polyhydramnios, oligohydramnios, anemia, distress, and feto.

In Equation (2), *phys*, *yq* and *Char* are vectors of physician dummies, of year-quarter dummies and of mother personal characteristics dummies, respectively. The variables of interest are the event time indicator variables *time*, dummies for the number of elapsed quarters since the adverse event, $k \in \{-10, ...-1, 0, ...9\}$. The indicator variable $time_{it}^{k} = 1$ if physician i experienced an adverse event in quarter $t-k$. For example, $time_{5,1995Q3}^{0} = 1$ if Physician 5 experienced an adverse event in the third quarter of 1995. In this specification, δ_k is the effect of an adverse event k periods after its occurrence.

Results. Figure VI plots the estimates of δ_k in Equation (2). The broken lines report the 95% confidence interval of the estimates. Column (1) of Table III reports, using a parsimonious representation of the findings in terms of elapsed years since the adverse event, the estimates and standard errors of the baseline specification, including physician and year-quarter fixed effects.

Figure VI shows that the estimates of δ_k before the adverse event are not statistically different from zero. Immediately after the adverse event C-section rates rise by 1 percentage point. Afterwards, they continue to increase until the estimate of δ_9, which estimates that the effect of an adverse event on C-section rates two and a half years after the adverse event, is 2.5 percentage points. The estimates in Column (1) of Table III square with the graphical evidence, showing increases of 1.1 percentage points in the first year after an adverse event, 0.13 percentage point in the second year, and 2.2 percentage points in the third year, all significantly different from zero.

One concern about the results is selection into the sample over time. Namely, the results may be capturing the upward trend in C-section rates that coincides with a set of adverse events at a given period. To address this concern, I divide the adverse events into four three-year groups according to their occurrence date.[3] Next, I add to the the baseline model a quadratic time trend for each of these groups.[4] Column (2) of Table III display the results of this specification. The estimates in this specification are similar to the results in Column (1), showing no evidence that the results are driven by selection into the sample over time.

Columns (3) and (4) of Table III add the demographic controls to the specifications in Columns (1) and (2), respectively.[5] The results with the demographic characteristics are smaller but qualitatively similar and statistically significant. These estimates show

[3]The groups are 1994-1996, 1997-1999, 2000-2002 and 2003-2006.

[4]I.e. I estimate the following variant of Equation (2):
$C\text{-}section_{jit} = \alpha + \sum_{k=-10}^{9} \delta_k time_{it}^{k} + \beta_1 phys_i + \beta_2 yq_t + \beta_3 Char_j + \sum_{g=1}^{4} \theta_g year + \sum_{g=1}^{4} \eta_g year^2 + \varepsilon_{jit}$.
Where θ_g and η_g estimate a quadratic time trend for each of the groups, $g \in \{1, ..4\}$.

[5]These include: a quadratic polynomial for age, dummy variables for race and for mother condition as follows: previous C-section, breech position, hypertension, early onset, hemorrhage, and oligohydramnios.

that physicians increase their C-section rates substantially after an adverse event and that the rates continue to rise over time as the lawsuit matures.

Placebo tests. A natural concern with my approach is that non-random selection into the sample may bias the results. For example, one may worry that adverse events tend to happen in times of a change in medical practice and increases in C-section rates, leading to spurious estimates of the treatment effect related to the adverse event. To test this hypothesis, I replicate my analysis for "placebo" physicians and check for a (spurious) treatment effect. More precisely, I first create a placebo panel by replacing each of the physicians in the adverse event panel by randomly selecting one of his "non-treated" colleagues who worked during the same five-year period in the same county. Using this panel, I then run the event study analysis in a manner analogous to the analysis in Table III, pretending that the placebo panel is the treatment panel. Next, using an F-test, I test the hypothesis that the adverse event had no effect on C-section rates: $H_0 : \delta_{year1} + \delta_{year2} + \delta_{year3} = 0$. I repeat this procedure a thousand times. I denote the results of this F-test $\hat{F}_p$, and define $G(\hat{F}_p)$ and $g(\hat{F}_p)$ to be their empirical cdf and pdf, respectively. Using $G(F)$ one can attach a p-value to the hypothesis that $F = 0$. Intuitively, if the adverse event had a significant effect on C-sections, I would expect the estimated coefficient to be in the lower tail of estimated placebo effects.

Figure VII displays the empirical pdf ($g(\hat{F}_p)$) that was generated by these placebo panels.[6] The dashed vertical line in Figure VII denotes F-statistics with a corresponding P-val=.05. The solid vertical line denotes the treatment effect reported in Column (1) of Table III. The figure shows that in roughly 87% of the placebo panels, the results were not statistically different from zero, i.e they had an F-statistic that corresponds to P-val>.05. More than 99.5% of the placebo panels had an F-statistic that was smaller than the F-statistic of the actual sample of adverse events. The results indicate that a sample of physicians who worked at the same time period and at the same location as the treated physicians is highly unlikely to produce results that are similar to the event study results. Overall, the results show no evidence of a spurious treatment effect.

III.B The "Very Long-Run" Effect of an Adverse Event - a Matching Approach

Now I employ a complementary approach based on a comparison between the treated-physician group and a control group. Identification in this case is based on the claim

[6]Note that I eliminated the cases in which the sum of coefficients was negative, and likely to be lower rather than higher than zero and therefore one can think about this distribution as an "upper bound" to the actual p-values of the placebo analysis.

that absent the adverse event the difference between the C-section rates of the treatment group and those of the comparison group would have stayed constant, i.e. they share a common trend. This assumption is supported by evidence showing that while there is substantial variation in C-section rates, *changes* in treatment styles over time at the local level are highly correlated across peers (Epstein and Nicholson, 2009). Of course, physicians who experience an adverse event may be different from their colleagues in a way that affects the manner by which they change their treatment patterns and therefore this assumption is not guaranteed.

Since the estimation of the impact of an adverse event is based on a different identification assumption, comparison with a non-treated control group, this approach tests the validity of the findings from the event study analysis in Section III.A. It also allows me to examine the effect of an adverse event on physicians' treatment patterns in the "very long-run" up to four and a half years after the event took place. Importantly, the results in this section are not perfectly comparable with those in the event study analysis: Here, each physician is considered an "observation" and the estimate is not weighted by the number of patients whom each physician treats, as in section III.A.

I expand the time span to seven years, ten quarters before the adverse event and eighteen quarters after, leaving a smaller sample of 338 physicians. I create the control group by matching each physician with colleagues who appear in the data throughout the relevant seven years.

To generate a control group that best controls for the factors affecting the treated physicians' C-section rates, physicians as close as possible to the treated physician should be chosen. There is a concern, however, that the adverse event has affected the physician's close peers (I study this issue below). With this trade-off in mind, I first conduct a "coarse matching" analysis using the set of physicians who come from the same county as the treated physicians, excluding physicians who work at the same hospital as the treated physician as a control group.[7]

Using the control group, I construct an estimator for the difference in C-section rates between the treatment and control groups. To make the visual representation clearer, I summarize the graphic results in six-month periods. Formally, for individual physician i, $i = 1, ..., N$, in six-month period t, $t \in \{-5, ... - 1, 0, ...8\}$

$$\tau_t = \frac{1}{N}\sum_{i=1}^{N}\{C\text{-}section_{it} - \frac{1}{J}\sum_{1}^{J} C\text{-}section_{jt}\} \tag{3}$$

[7]Same county is defined as the county in which most of a physicians' patients reside, same hospital is the hospital where most of a physician's deliveries are performed

where , $j \in \{1...J\}$ is the set of physicians in the control group.

Results. Figure VIIIa plots average C-section rates five six-month periods before and nine six-months periods after the adverse event for all 338 physicians who are included in the seven-year panel, and for the control group. The figure shows that before the adverse event, physicians in the treatment group tend to perform fewer C-sections than the average C-section rate in their county. This result is not surprising because, as Table I shows, the population of mothers in the panel tends to be higher in its socioeconomic status and lower in its incidence of risk factors. After the event, the treated physicians' C-section rate jump and the gap between the groups narrows from about 1% to less than 0.5%. The broken black vertical line indicates that two years passed since the adverse event, approximating the end of the statute of limitations period. after this time, 95% of the treated physicians were contacted and notified that they were facing a medical malpractice suit. After the end of first two years following the adverse event, the treated physicians' average rate converges toward the county average; four years after the adverse event, the rates are about equal.

To evaluate the very long-run effects of an adverse event, I estimate the average difference between the treatment and control group for the five six-month periods before the adverse event and the five six-month periods starting at the end of two years following an adverse event. Column (1) of Table IV summarizes the results. In the "before" period, there is a statistically significant gap of 1 percentage point between the treated physicians' average C-section rate and that of the county C-section. In the five six-month periods starting two years after the adverse event, the gap between the two average rates is very small and statistically insignificant.

Given that physicians who experienced lawsuits have lower pre-event C-section rates than members of the comparison group (Figure VIIIa), one may still worry that the two groups also differ in their trends. I attempt to make the identification assumption more plausible by conducting a "refined matching" analysis. specifically, in addition to the geographical location and time period, I match physicians conditional on two observable covariates: a physician's experience and a physician's treatment patterns. I therefore restrict the control group to include only physicians who have similar experience, defined as a gap of no more than three years from the treated physician, and physicians who use similar practice patterns, defined as less than a 10 percentage point gap in average C-section rate in the pre-event period. A valid concern is that using the pre-event C-section rate as a matching criteria may bias the results. For example, since the previous analysis showed that the treated physicians tend to perform less C-sections than their collogues, the matching procedure may include in the comparison group physicians who had a low "draw" of C-section rates in the pre-event period,

thereby biasing the results downward.

This restriction leaves 251 physicians for whom a control group exists. The results of this refinement are summarized in Figure VIIIb and Column (2) of Table IV.

Figure VIIIb shows that before the adverse event, average C-section rates for physicians in the treatment group and the comparison group are quite similar (by construction); additionally, per-period C-section rates in the pre-event period are very similar as well, providing support to the validity of the identification assumption. After an adverse event, however, the treated physicians' C-section rates jump, and 2.5-4.5 years after the event, their C-section rates exceed those of the control group by 2 percentage points. Column (2) of Table IV confirms the visual impression, showing a very small insignificant difference in C-section rates before the adverse event and a statistically significant difference of 1.7 percentage points between the treatment and control group, in the five six-month periods after the end of two years following an adverse event. These estimates support the preceding analysis that suggested a long-run increase of roughly 1.7 percentage point.

III.C Heterogeneity of the Response to an Adverse Event

I use the heterogeneity of the data to compare the response to an adverse event in subsets of claim types in order to learn about the mechanisms that underlie physicians' response to a medical error.

To which types of claims are physicians more responsive? I analyze physicians' response to successful versus unsuccessful claims. Assuming that claims that fail ex-post are less likely to be related to a medical error than claims that succeed ex-post, everything else being equal, a weaker response among physicians who experienced an unsuccessful claim supports the view that the analysis captures a response to a medical error rather than a change in treatment occasioned by an emotional or institutional reaction to the bad outcome that triggered the malpractice claim.

To examine this issue, I note that 69% of claims in the adverse event panel resulted in a payout (i.e. were successful) and that 31% of the claims resulted in zero payout (were unsuccessful). A comparison of successful and unsuccessful claims in terms of the adverse patient outcomes shows that the classes of claims are quite similar (e.g. the deaths rate in both groups is roughly 24%).

Figure IX displaying the event study estimates for successful and unsuccessful claims, shows that in successful claims average C-section rates rise by 1 percentage point immediately after the adverse event and continue to increase afterward bringing the cumulative upturn to 3 percentage points ten quarters after the adverse event. In

unsuccessful claims, there is no apparent increase in C-section rates in the first two years after an adverse event. In the third year, there appears to be a 1 percentage point increase.

Consistent with the graphic evidence, the estimates in Columns (1) and (2) of Table V show, for successful claims, statistically significant coefficients of 1.5, 1.9 and 2.6 percentage points, in the first, second and third year after the adverse event, respectively. For unsuccessful claims, the effect of an adverse event is small and insignificant in the first two years and 1 precentage point, not statistically different from zero, in the third year. Column (3) of Table V reports the p-values of a test of the null hypothesis that the estimates of the response in the two types of claims are equal. The hypothesis is rejected for Years 1 and 2 and is marginally insignificant in Year 3. Adding additional covariates in Columns (4), (5) and (6) of Table V, I obtain similar results. The difference between the estimates of the two claim groups supports the view that the physicians' response reflects a response to a medical error and is not driven by an emotional or institutional response to patient outcomes.

III.D Selection around an Adverse Event

Although I analyze a balanced panel of physicians, there is reason for concern that the estimates of the effect of an adverse event reflect a change in the composition of the sample of mothers after such an event. To address the matter, I check whether the composition of observable characteristics of the sample change after an adverse event in a way that may be associated with a change in C-section rates. Figure X, plotting per period birth numbers, shows no apparent change in the sample size around the adverse event.

Next, I estimate a linear probability model for the effect of age, high-risk factors[8], and type of insurance on the probability of undergoing a C-section in the pre-event period. The average predicted C-section rates using the model estimates for the entire panel decrease over time (Figure XI), notwithstanding a statistically insignificant 0.3 percentage point increase immediately after the adverse event (Table VI). Overall, the immediate impact of a medical error on C-section rates reflects a change in patterns of practice as opposed to a change in the characteristics of the sample of mothers after an adverse event. These results are consistent with Dranove et al. (forthcoming) who find that up to one year after the filing of a lawsuit, on average 3.5 years after the adverse

[8]High-risk includes the following diagnoses: Previous C-section, breech position, multiple gestation, hypertension, early onset, hemorrhage, obesity, diabetes, polyhydramnios, oligohydramnios, and distress (see a similar classification in MacDorman et al. (2008)).

event, a physician's patient composition remains quite stable. However Dranove et al. (forthcoming) find that afterwards, in the second year after the lawsuit, there is a change in patient volume and patient composition due to a demand-side response.

IV PEER'S RESPONSE TO AN ADVERSE EVENT

Another question that arises in this context is whether physicians' medical errors affect their peers. I attempt to answer by using the same method with which I studied the immediate response to an adverse event. Here, to reduce computation time, I aggregate inpatient discharge data and transform the unit of observation from patient-discharge to physician-quarter. The result is a five year balanced "peer panel" that resembles the adverse event panel except that instead of including the treated physicians, it includes all physicians who are affiliated with the treated physician's hospital (i.e. the hospital where a physician performs most of her deliveries) and appear throughout the relevant five-year period. The resulting data-set contains 45,440 observations, 558 physicians, some of whom appear more than once in the sample.

The specific question is whether or not there is a hospital-wide response to an adverse event. Figure XII depicting average hospital C-section rates ten periods before and ten periods after an adverse event, shows an upward trend in C-section rates in the peer panel. The trend appears to be smooth around the adverse event, implying no evidence of a hospital-wide response. The estimates in Column (1) of Table VII confirm this impression, showing a statistically insignificant coefficient of 0.001. It is important to note, however, that while this preliminary examination does not show evidence of a hospital-wide response to an adverse event, further examination of this important issue is left for future research.

V CONCLUSIONS

Little is known about the impact of medical errors on physician behavior. This study examined the issue for a special class of medical errors, medical errors that result in malpractice litigation.

The main findings are that after an adverse event, physicians increase C-section rates in the short-run by 4% and in the long-run, more than two years after the adverse event, by 8% in cumulative terms. Additionally, the effect of a medical error persists for at least four and a half years after the event. Finally, There is no evidence of a hospital-wide change in C-section rates after a physician's medical error.

In addition, physicians' response is concentrated among claims which are ultimately successful and hence are more likely to be associated with a medical error, supporting the view that the response is not occasioned by an emotional or institutional reaction to the bad outcome that led to the lawsuit.

The findings establish a relation between medical errors and treatment patterns. They show that an adverse event has a substantial and persistent impact effect on medical treatment. The evidence suggests that physicians' medical errors have a sizable impact of on their behavior, a result that corresponds to conventional wisdom but is not well documented in the literature.

Two selection issues pertain to this study. First, my estimates are specific to the sub-population of physicians who faced malpractice litigation; these physicians may be a selected group. Second, the sample of medical errors that result in litigation is clearly not a representative sample of medical errors; it may include medical errors that are relatively severe. Thus, the results may be difficult to generalize—an important issue that future research will have to examine.

Just the same, the results of this study are relevant for policy issues that relate to medical errors and malpractice litigation. The existence of a relation between medical errors and treatment patterns, even if it is peculiarly large in the sample of medical errors that I examined in this study, is important for policymaking that aims to reduce the incidence of medical errors. Furthermore, the evidence in this study suggests an interaction between physician behavior and medical malpractice law through exposure to medical malpractice litigation. This is a finding of interest for the discourse on the interaction between medical-malpractice law and a physician's own exposure to malpractice litigation; it may also have implications for the design of medical-malpractice law because it might shed light on the channels by which this area of law affects physician behavior.

THE HEBREW UNIVERSITY OF JERUSALEM

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Table I: Summary Statistics—Inpatient Data: All Sample and Adverse Event Panel

	Full Sample (1)	Adverse Event Panel (2)
Age (median)	27	27
Mother Hispanic	18.8%	12.4%
Mother African American	21.3%	18.5%
Mother other race	59.9%	69.2%
Anemia	8.4%	7.6%
Breech position	3.5%	3.6%
Diabetes	0.7%	0.6%
Early onset	7.5%	6.7%
Hemorrhage	1.9%	1.8%
Hypertension	4.8%	4.3%
Multiple gestation	1.1%	1.1%
Obesity	0.3%	0.2%
Oligohydramnios	2.4%	1.8%
Distress	3.3%	3.9%
Polyhydramnios	0.6%	0.5%
Previous C-section	14.1%	13.1%
Medicaid	41.7%	34.7%
Commercial	48.4%	56.9%
Physician #	2,307	459
Observations	2,981,742	403,336

NOTE. Table entries are means unless otherwise noted. Column (1) includes all the deliveries in the Florida Inpatient Data in the years 1992-2008. Column (2) includes all deliveries in the adverse event panel.

Table II: Short-Run Effect of an Adverse Event

	Baseline	Basic Controls	Full Controls
	(1)	(2)	(3)
Event dummy	0.0115	0.0090	0.0074
	(0.0047)	(0.0039)	(0.0036)
Patient characteristics	No	Yes	Yes
Physician, quarter FE	No	No	Yes
Number of physicians	459	459	459
Observations	403,336	403,336	403,336

NOTE. All columns report estimates of models akin to the baseline model specified in Equation 1. Column (2) includes, in addition to the baseline specification, a quadratic polynomial for age, dummy variables for race and for patient conditions as follows: previous C-section, breech position, multiple gestation, hypertension, early onset, hemorrhage, obesity, diabetes, polyhydramnios, oligohydramnios, anemia, distress and feto. Column (3) adds physician and year-quarter fixed effects. Standard errors clustered by physician shown in parentheses.

Table III: Long-Run Effect of an Adverse Event, Event Study Approach

	Baseline		Full Controls	
	(1)	(2)	(3)	(4)
Year1	0.011	0.011	0.008	0.008
	(0.003)	(0.003)	(0.003)	(0.003)
Year2	0.013	0.011	0.010	0.007
	(0.005)	(0.005)	(0.004)	(0.004)
Year3	0.022	0.016	0.018	0.012
	(0.006)	(0.006)	(0.005)	(0.005)
Year-quarter & physician FE	Yes	Yes	Yes	Yes
Quadratic trend by adverse-event period	No	Yes	No	Yes
Number of physicians	459	459	459	459
Observations	403,336	403,336	403,336	403,336

NOTE. Full controls include, in addition to the baseline specification, a quadratic polynomial for age, dummy variables for race and for mother condition as follows: previous C-section, breech position, hypertension, early onset, hemorrhage, and oligohydramnios. Standard errors clustered by physician shown in parenthesis.

Table IV: Matching Physician to Same-County-Colleagues, 7–Year Adverse Event Panel

Time of Event (Years)	τ_t All Physicians ("Coarse Matching") (1)	τ_t Close Match ("Refined Matching") (2)
Pre-period (2.5 - 0 years before event)	-0.0099	-0.0011
	(0.0024)	(0.0023)
Post-period (2.5 - 4.5 years after event)	-0.0030	0.0170
	(0.0028)	(0.0030)
F-test: $Prob(\tau_{pre} = \tau_{post})$	0.0006	0.0000
Number of physicians	338	251

NOTE. Column 1 includes all colleagues from the same county excluding colleagues from the same hospital ("Coarse Matching"). Column 2 includes all colleagues from the same county with less than a 3-year gap in experience and less than a 10 percentage point gap in C-section rate in the 10 quarter pre-event period ("Refined Matching"). Pre-event period is defined as the 5 six-months periods prior to the adverse event. 2.5-4.5 years after adverse event is the 5 six-month periods starting 2 years following the adverse event. Standard errors are calculated using bootstrapping; an analytic asymptotic variance estimator (Abadie and Imbens (2006)) shows very similar results.

Table V: Long-Run Effect of an Adverse Event, Successful and Unsuccessful Claims

	Baseline			Full Controls		
	Successful	Unsuccessful	F-Test Successful = Unsuccessful	Successful	Unsuccessful	F-Test Successful = Unsuccessful
	(1)	(2)	(3)	(4)	(5)	(6)
Year 1	.0155	.0002	0.0153	.01196	.0003	0.0205
	(.0034)	(.0053)		(.0028)	(.0041)	
Year 2	.0194	-.0019	0.0114	.0162	-.0035	0.0043
	(.0048)	(.0069)		(.0041)	(.0055)	
Year 3	.0268	.0094	0.0881	.0227	.0082	0.0925
	(.006)	(.0083)		(.0052)	(.0068)	
Year-quarter & physician FE	Yes	Yes		Yes	Yes	
Number of physicians	316	143		316	143	
Observations	403,336	403,336		403,336	403,336	

NOTE. Full controls include, in addition to the baseline specification, a quadratic polynomial for age, dummy variables for race and for patients conditions as follows: previous C-section, breech position, hypertension, early onset, hemorrhage, and oligohydramnios. Standard errors clustered by physician shown in parenthesis. Year 3 includes only the first two quarters of the third year.

Table VI: Selection around an Adverse Event - High-Risk Factors, Age, and Insurance Type

	Predicated C-section
Event dummy	0.0030
	(0.0026)
Number of physicians	459
Observations	403,336

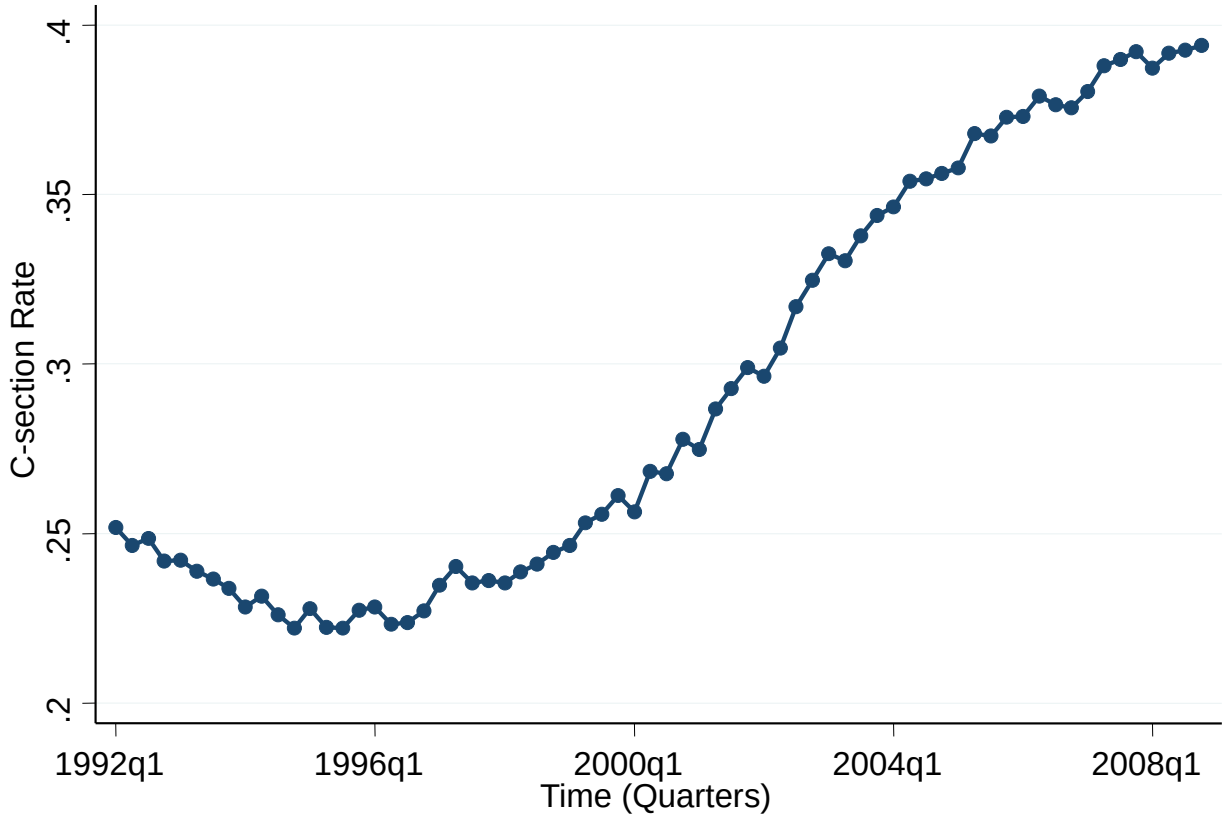
NOTE. The table reports estimates of a models akin to the baseline model specified in Equation 1, replacing C-section with predicted C-section. Standard errors clustered by physician shown in parenthesis.

Table VII: Short-Run Effect of an Adverse Event on All Peers from the Same Hospital

	All Same-Hospital Peers
	(1)
Event dummy	0.0010
	(0.0036)
Number of physicians	558
Observations	45,440

NOTE. The peer sample includes all the physicians from the same hospital who appear in the full deliveries data through the whole 5 years sample period. Standard errors clustered by physician shown in parenthesis.

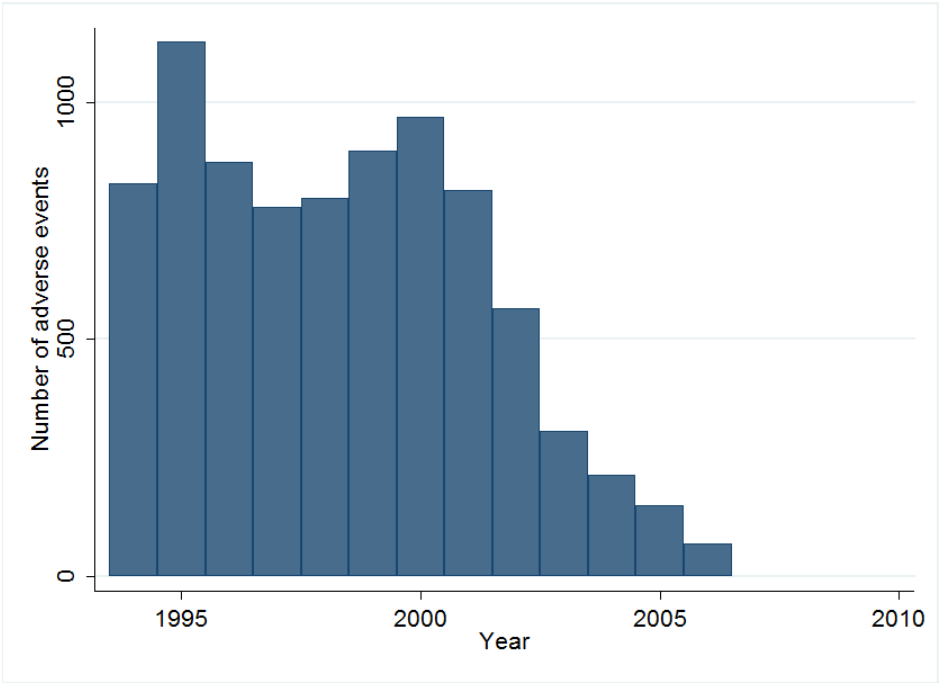
Figure I: C-section Rates 1992-2008, Florida



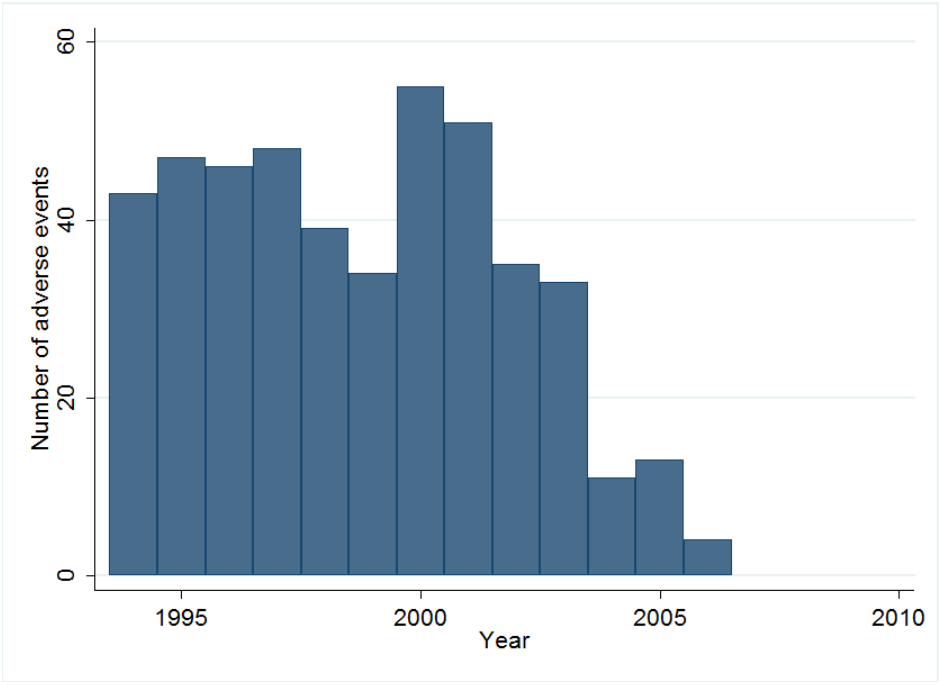
NOTE: The figure depicts C-section rates in Florida from 1992-Q1 to 2008-Q4. The sample consists of all deliveries in the Florida Hospital Inpatient Discharge Data in the relevant time period.

Figure II: Adverse events, Florida and Adverse Event Panel

(a) Adverse events per year, Florida

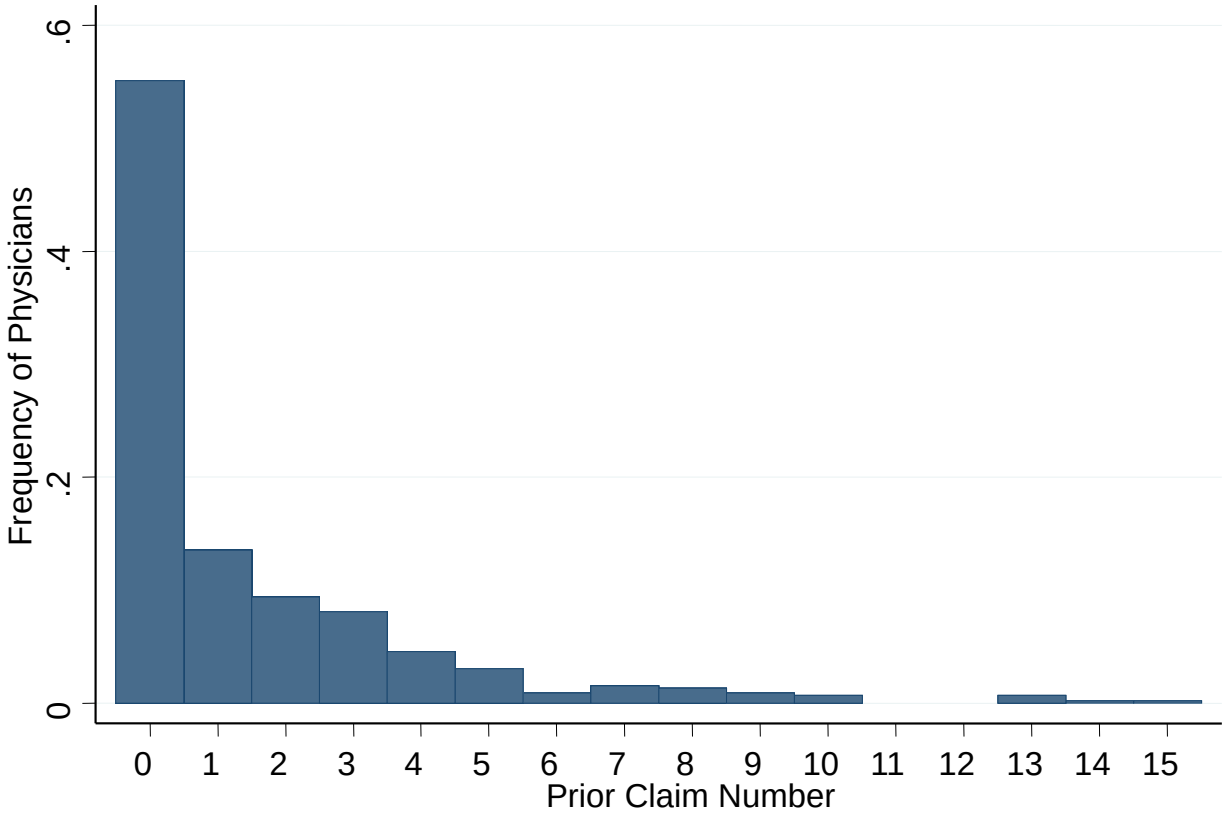


(b) Adverse events per year, Adverse Event Panel



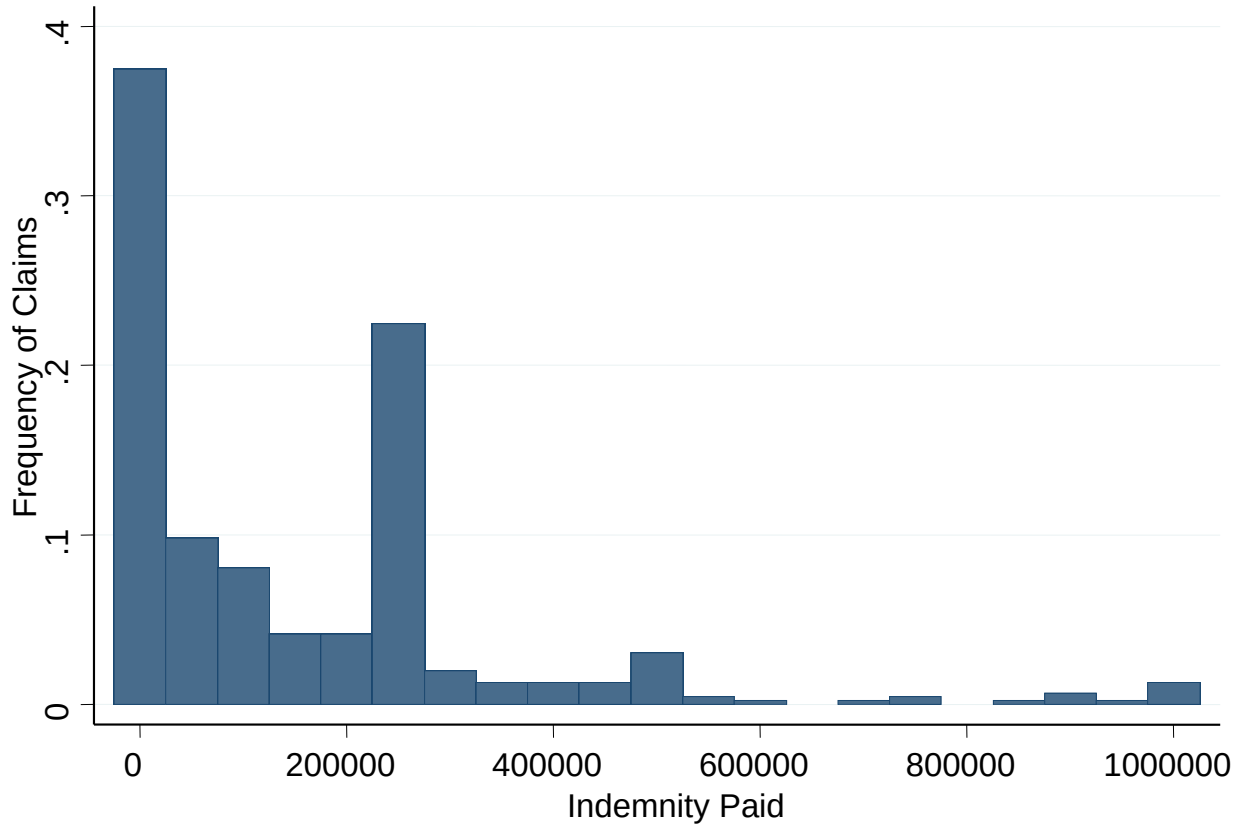
NOTE: Panels (a) and (b) of this figure depict the number of adverse events per year, during the period 1994Q2-2006Q3, in Florida and in the Adverse event panel, respectively.

Figure III: Distribution of Physicians' Prior Claims



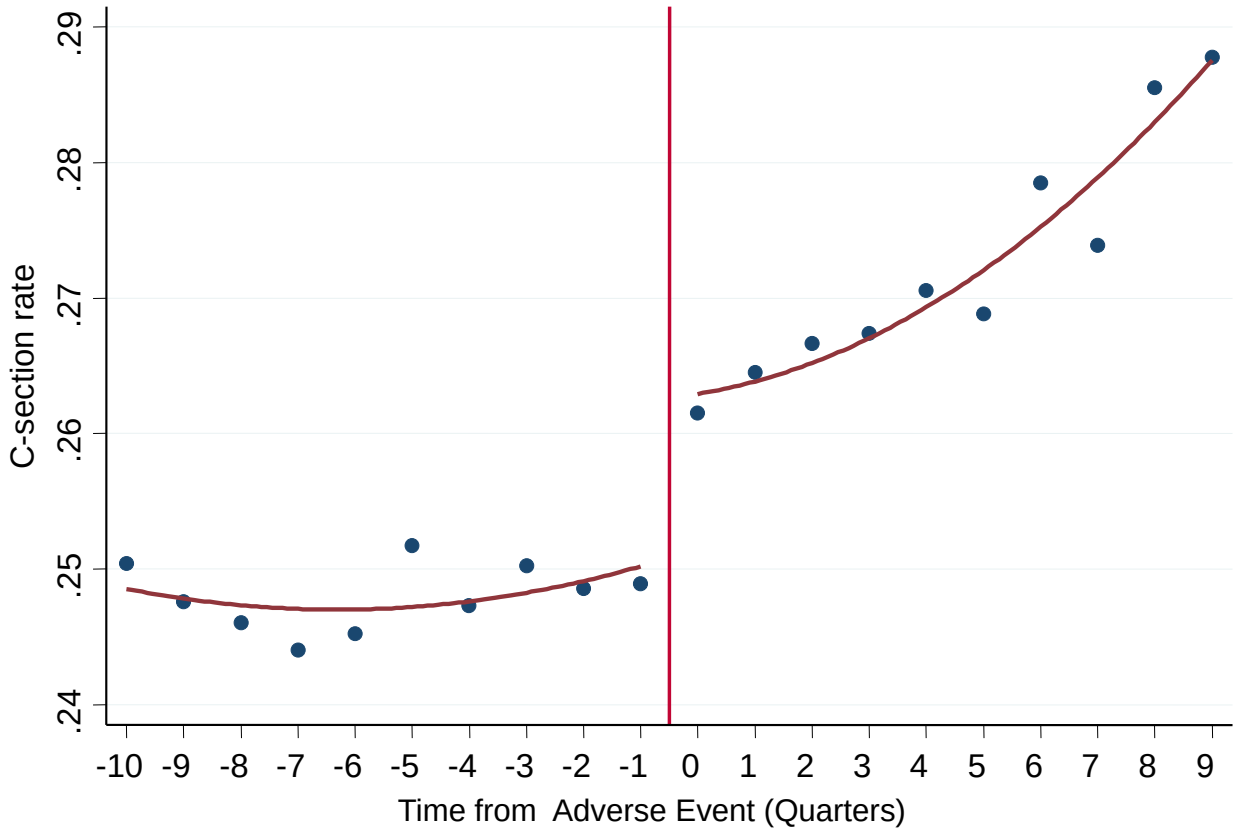
NOTE: This figure depicts the frequency of physicians by the number of claims they experienced prior to the adverse event. For example, 253 of 459 physicians, 55% of the physicians in the sample, did not experience prior claims. The Florida Medical Professional Liability Files were used to calculate the number of prior claims for each physician.

Figure IV: Distribution of Claim Payments



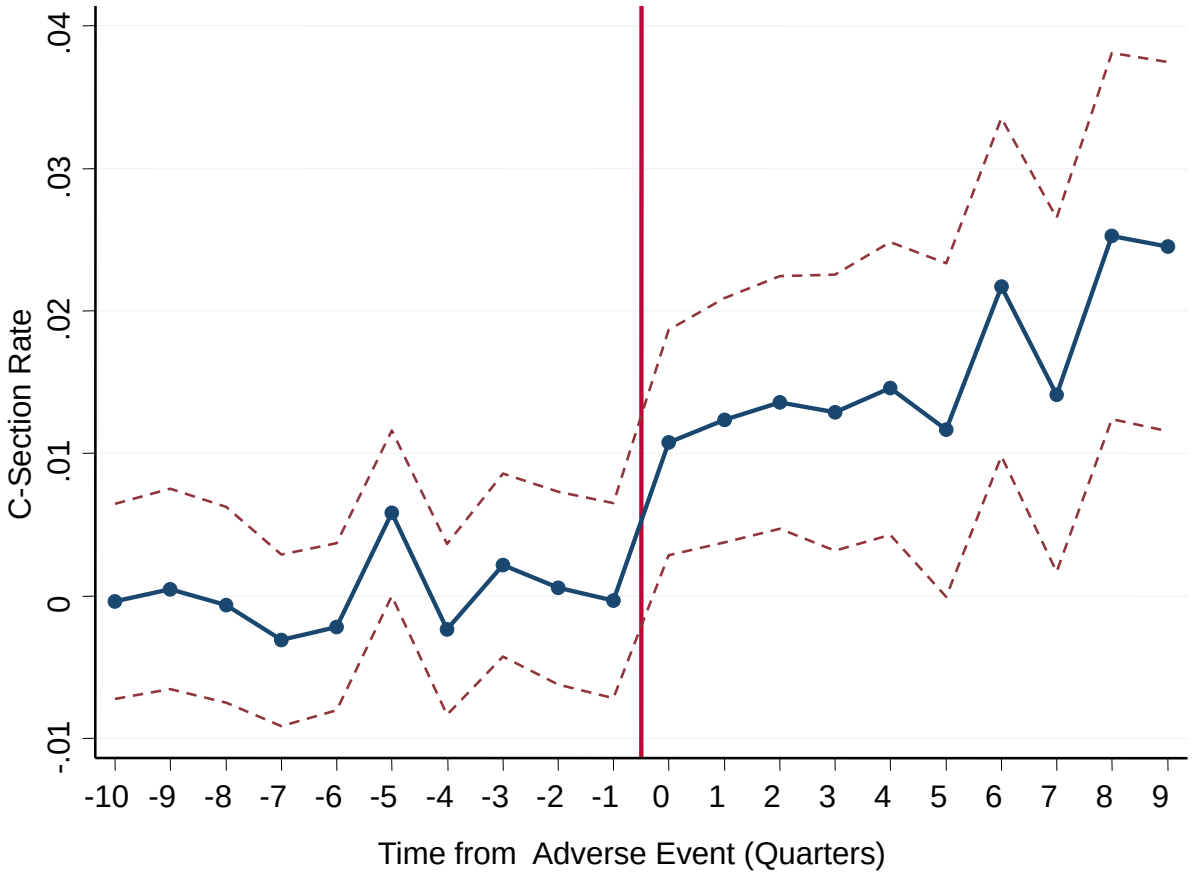
NOTE: This figure shows the frequency of claim payments rounded to the closest multiple of $50K, in the adverse event panel. The Florida Medical Professional Liability Files were used to generate the figures. Payments are in nominal terms.

Figure V: Short-Run Effect of an Adverse Event



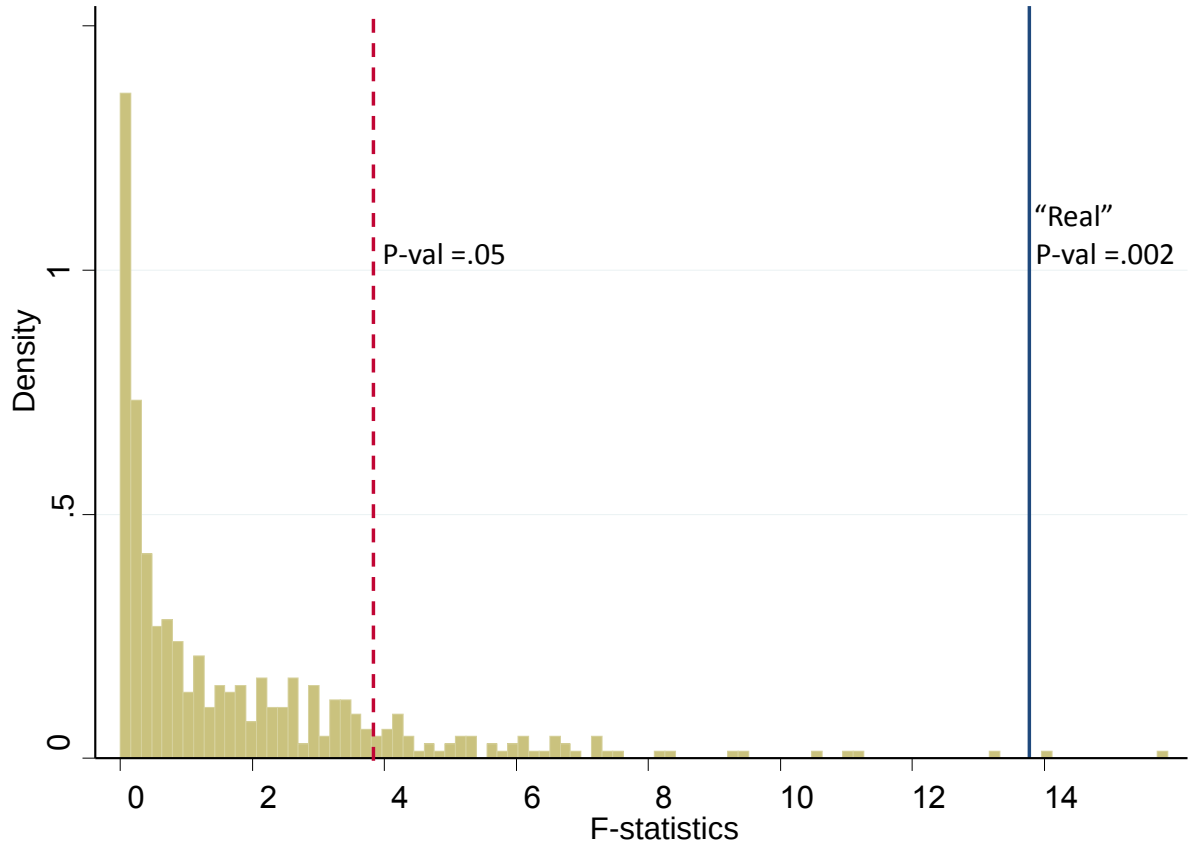
NOTE: The figure plots per-period C-section rates in the adverse event panel. The vertical line denotes the time of the adverse event.

Figure VI: Long-Run Effect of an Adverse Event, Event Study Approach



NOTE: This figure plots the coefficients of dummies for time from adverse event, obtained from an OLS regression with controls for physician and year-quarter fixed effects (Equation 2), imposing a constraint that sets the sum of the first 10 time coefficients (the "pre-period") at zero. The thin dashed lines report the 95% confidence interval of the coefficients.

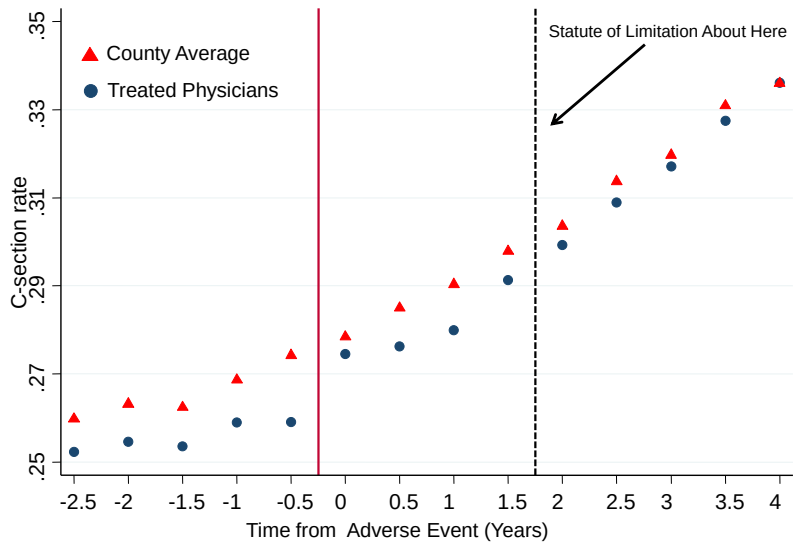
Figure VII: Placebo Tests, Event Study



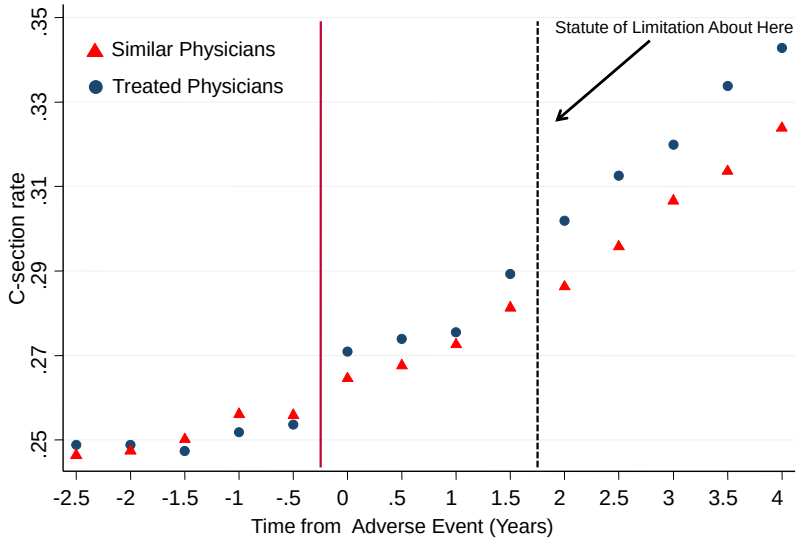
NOTE: This figure displays the empirical distribution of F-statistics that were obtained from testing the hypothesis: $H_0 : \delta_{year1} + \delta_{year2} + \delta_{year3} = 0$ on a random sample of a thousand placebo panels. The vertical solid line reports the F-statistic of the original analysis. The vertical dashed line reports the F-statistic that corresponds to P-value<0.05.

Figure VIII: "Very Long-Run" Effect of an Adverse Event, Matching Approach

(a) Coarse matching: treated physicians vs. all colleagues from their county

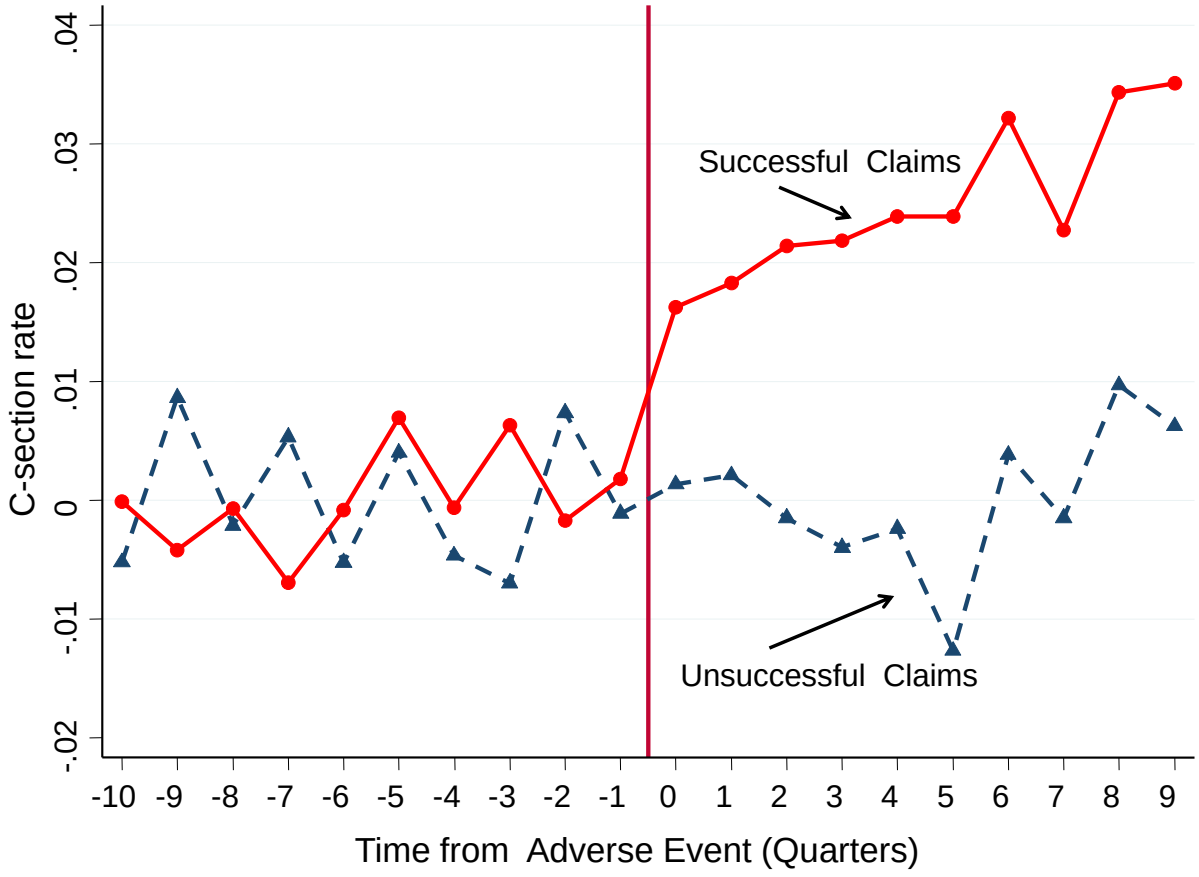


(b) Refined matching: treated physicians vs. only similar colleagues from their County



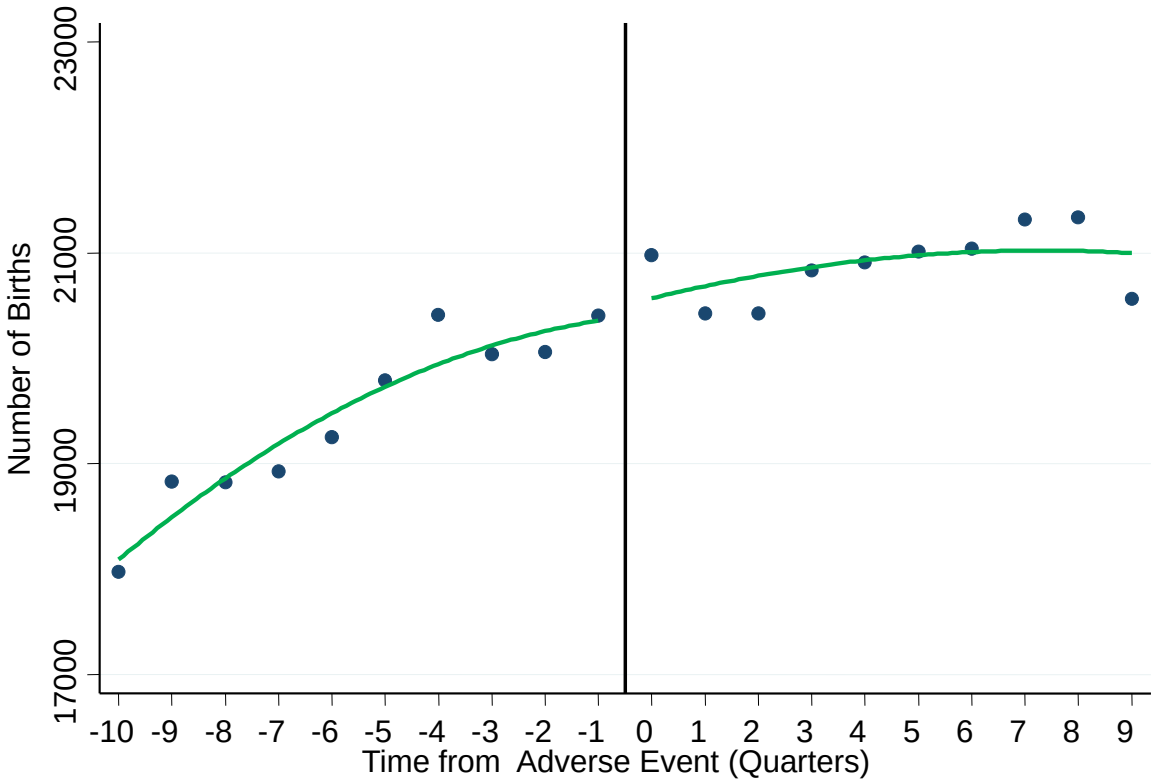
NOTE: Panels (a) and (b) of this figure depict the C-section rate in six-month periods 2.5 years before and 4.5 years after the adverse event. The control group in Panel (a) is comprised of physicians from the same county excluding physicians from the same hospital. The control group in Panel (b) is a subgroup of the Control group in panel (a), including only physicians with similar experience and similar pre-event C-section rates. The vertical red line denotes the time of the adverse event and the vertical dashed black line denotes the approximate end of the statute of limitations.

Figure IX: Long-Run Effect of an Adverse Event, Successful and Unsuccessful Claims



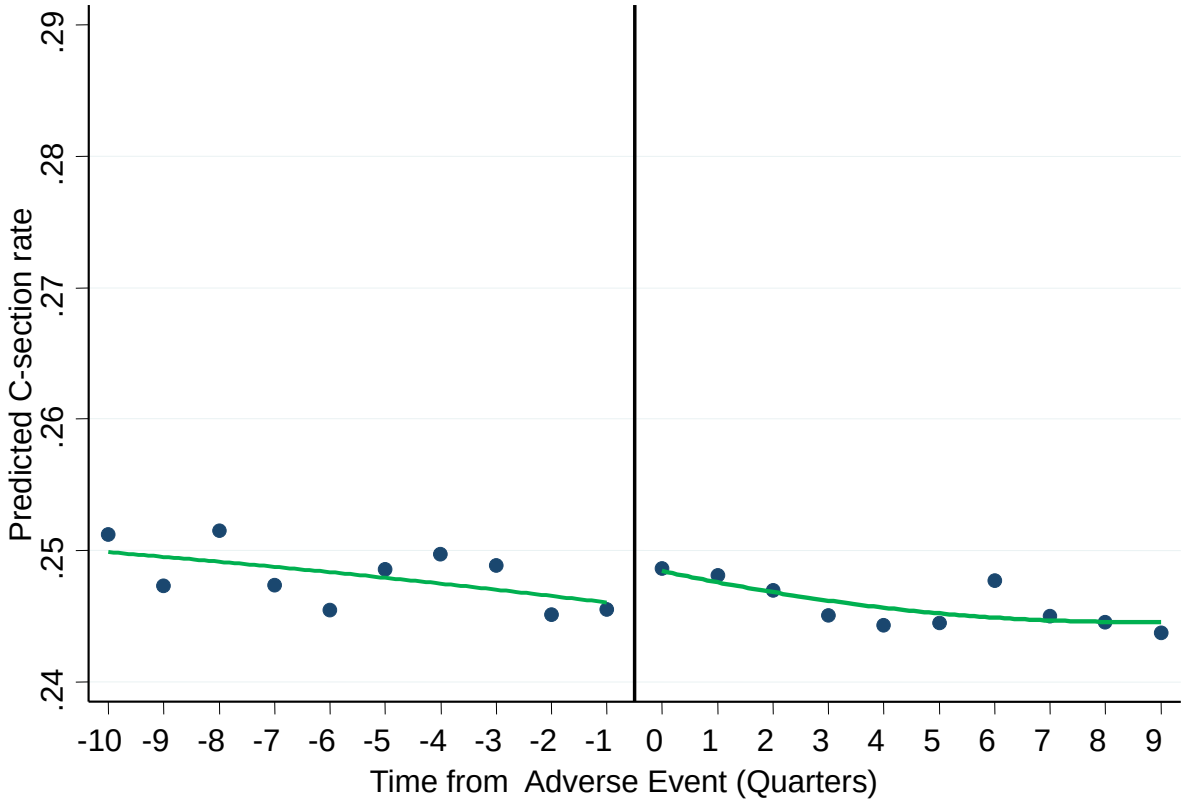
NOTE: This figure plots the coefficients of dummies for time from the adverse event for successful and unsuccessful claims, obtained from an OLS regression with controls for physician and quarter fixed effects interacted with claims success (Equation 2), imposing a constraint which sets the sum of the first 10 time coefficients (the "pre-period") at zero for each type of claim.

Figure X: Per-Period Number of Births



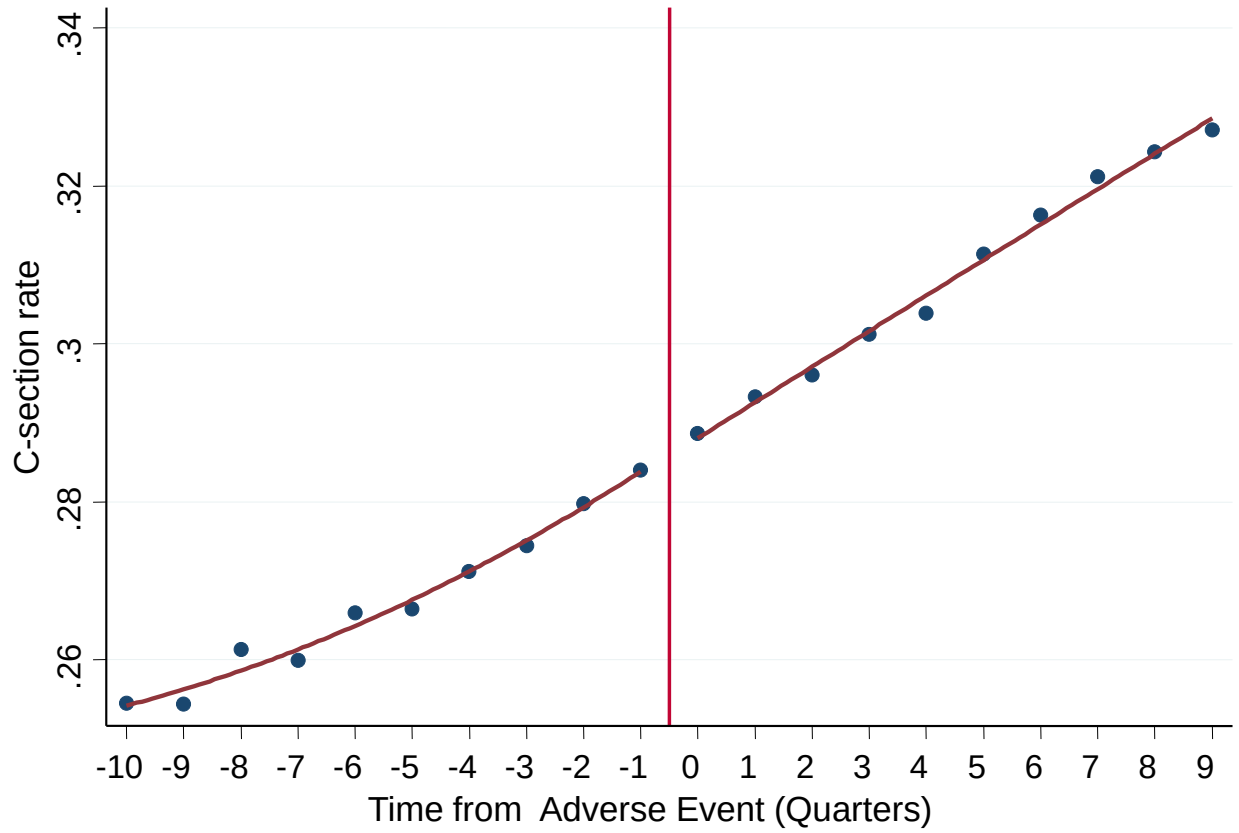
NOTE: This figure shows how the per-period number of births in the adverse event panel evolves around the adverse event.

Figure XI: Selection on Observables around an Adverse Event



NOTE: This figure shows predicted C-section rates in the adverse event panel. The vertical line denotes the time of the adverse event. The prediction was done by regressing, using OLS, C-section dummy on the high-risk covariates as well as age and insurance type dummies in the pre-reform period. The figure plots the average per period predicted C-section rate. Results are presented on the same scale as in Figure V.

Figure XII: Short-Run Effect of an Adverse Event on Same-Hospital Peers



NOTE: The figure plots per-period C-section rates in the peer panel, including all physicians who work at the same hospital as the treated physician and appear through the 5-year sample period. The vertical line denotes the time of the adverse event.

A Appendix (not for publication)

I.A THE DATA

Figures A.1a and A.1b show the number of lawsuits that were associated with adverse events in Florida and in the adverse event panel in 1994Q2-2006Q3, respectively.

I.B ECONOMIC FRAMEWORK

Consider a standard model of a physician's behavior in the presence of medical-malpractice law similar to Shavell (2007) and Currie and MacLeod (2008). Physicians' preferences assume the following form

$$U(\alpha, H, law) = B(\alpha) - H(law)\alpha, \tag{A.1}$$

where α is the probability of an error, $B(\alpha)$ is the benefit from treatment and $H(law)$ is the expected liability in the case of an error.

Next I add medical errors to the framework. A medical error may have a direct effect on physicians' marginal benefit from the treatment they provide irrespective of lawsuit. The effect may be gained via learning-by-doing, i.e., physicians learn from their error and consequently change their treatment patterns. Therefore:

$$B(\cdot) = B(\alpha, E) \tag{A.2}$$

where E is a medical error.

In addition, there are several mechanisms by which expected liability, $H(\cdot)$, may be affected by physicians' medical errors and subsequent exposure to malpractice litigation. One is a *salience mechanism*. Following a lawsuit, the costs of malpractice litigation become more salient to physicians. They realize that the costs of malpractice litigation are different from what they had thought and change their perception of expected liability in the case of a medical error, as suggested by Dranove and Watanabe (2010). Another is a *reputation mechanism*. Lawsuits change the cost of subsequent medical errors. Everything else being equal, physicians with prior exposure to lawsuit exposure face greater expected liability than to physicians who lack such prior exposure because it is easier to win a lawsuit against physicians who had prior history of malpractice suits (Quinn, 1998). Therefore:

$$H(\cdot) = H(law, E). \tag{A.3}$$

With these modifications, physicians' preferences are given by

$$U(\alpha, H, law, E) = B(\alpha, E) - H(law, E)\alpha. \tag{A.4}$$

Physicians' choose α^* to maximize utility:

$$0 = U_\alpha = B_\alpha(\alpha, E) - H(law, E). \tag{A.5}$$

To motivate the empirical analysis, consider the interaction between medical errors and α^* by differentiating the first-order condition

$$\frac{\partial \alpha^*}{\partial E} = (\frac{\partial H}{\partial E} - \frac{\partial B_\alpha}{\partial\ E})\frac{1}{B_{\alpha\alpha}}. \tag{A.6}$$

This simple derivation illustrates these two channels of response to medical errors, $\frac{\partial \alpha^*}{\partial E}$: a *learning-by-doing effect*, $\frac{\partial B_\alpha}{\partial E}$, the effect of a medical error on medical treatment via physicians' marginal benefit from having given the treatment, $B(\cdot)$; a *litigation effect*, $\frac{\partial H}{\partial E}$, the net effect of medical errors on medical treatment via a change in expected liability, $H(\cdot)$. The two channels of physicians' response are closely intertwined but to assess the interaction between a medical error and physician behavior more generally, absent litigation, an assessment of the learning-by-doing effect is important. In addition, in the context of the interaction between medical malpractice law and a physician's own exposure to lawsuits, the litigation effect is of interest since the learning-by-doing effect occurs regardless of the realization of a lawsuit. Therefore, in addition to quantifying the impact of medical errors on treatment patterns, this study seeks to examine the importance of the litigation effect separately from the learning-by-doing effect.

I.C Event study analysis Specification tests

An additional concern about the results is selection into the sample over time. Namely, the results may be capturing the upward trend in C-section rates that coincides with a set of adverse events at a given period. To address this concern, I divide the adverse events into four three-year groups according to their occurrence date.[9] Next, I add to

[9]The groups are 1994-1996, 1997-1999, 2000-2002 and 2003-2006.

the the baseline model a quadratic time trend for each of these groups:

$$
\begin{aligned}
&C\text{-}section_{jit} = \\
&\alpha + \sum_{k=-10}^{9} \delta_k time_{it}^k + \beta_1 phys_i + \beta_2 yq_t \\
&+\beta_3 Char_j + \sum_{g=1}^{4} \theta_g year + \sum_{g=1}^{4} \eta_g year^2 + \varepsilon_{jit}.
\end{aligned} \tag{A.7}
$$

where θ_g and η_g estimate a quadratic time trend for each of the groups, $g \in \{1, ..4\}$. Figure A.2 display the results of this analysis and Table A.2 shows the estimation results analogous to Table III. The results in Figure A.2 are quite similar to the results in Figure VI and the estimates in Table A.2 are very similar to those in Table III. These result provide no support to the hypothesis that the results in Figure VI capture the secular time-trend in C-section rates in a given period.

I.D Matching analysis Specification tests

Figure A.3 is analogous to Figure VIII, replacing C-section rates by "detrended" C-section rates. To generate the figure, I first ran a regression of C-section rates on year-quarter fixed effects using the entire Florida births sample. I then repeated the matching analysis replacing C-section rates with the residuals from this regression. The figures confirm that in the case of the Coarse matching sample, C-section rates in the pre-event period are roughly one percentage point lower in the treated physicians relative to the comparison group. in the post-period this gap is close to zero. In the refined matching sample, the pre-event C-section rates are similar on average by construction but reassuringly the per-period C-section rates in the pre-event period are almost identical, providing support for the identification assumption. In the post-event period, C-section rates in the treated group is about two percentage points higher than in the comparison group.

Figure A.4 is similar to Figure VIIIb. The figure includes in the comparison groups only physicians with 6 percentage points gap in average C-section rates in the pre-event period. The results appear to be quite similar but the sample size decreases by about 10% to 222 physicians.

Figure A.5 is similar to Figure VIIIb. The figure includes in the comparison groups only physicians with similar experience, defined as physicians with a gap of no more than three years from the treated physician (284 physicians). The results appear to be quite similar to the baseline analysis.

I.E Heterogeneity of the Response to an Adverse Event

What Role does Patients' Socioeconomic Status play? Another way to learn about the underlying mechanisms of the effect of a medical error is by analyzing physicians' response parsed by patients' socioeconomic status. A learning-by-doing effect is expected to induce a uniform response regardless of the patient's socioeconomic status. One reason to think that physicians may respond more strongly when treating patients of high socioeconomic status than when treating patients of low socioeconomic status, is that patients of the former class are considered less constrained in their choice of prenatal physician (Hoerger and Howard, 1995), magnifying the reputational aspects of a medical error.

I test the hypothesis that physicians are more responsive to an adverse event when treating patients of high socioeconomic status by using mothers' type of insurance carrier. Since Medicaid is a means-based program, the population of mothers under Medicaid is likely to be of lower socioeconomic status than that of privately insured mothers. Importantly however, there are obvious selection issues in this approach: physicians who treat primarily mothers under Medicaid may be different from those who treat primarily privately insured mothers in their characteristics and the circumstances under which they operate.

Figure A.6 plots the event study coefficients for privately insured and Medicaid insured mothers, respectively, and Table A.1 presents the estimation results much as in the specifications in Table V, using one regression with coefficients for the two patient types as well as separate physician and quarter fixed effects. Figure A.6 shows that for privately insured mothers average C-section rates rise by 2 percentage points immediately after an adverse event and by 3.5 percentage points two and a half years after the event. For mothers insured by Medicaid, a 0.5 percentage points increase occurs immediately after an adverse event and appears to persist for ten quarters.

Consistent with the graphic evidence, the estimates in Column (1) and (2) of Table A.1 show, for privately insured mothers, statistically significant coefficients of 1.5, 1.9 and 3 percentage points, in the first, second, and third years after an adverse event, respectively. For mothers insured by Medicaid, the point estimates of the effect of an adverse event are 0.5 percentage points in Year 1 and 2 and and 1.2 percentage points in Year 3; these estimates, however, are not statistically different from zero. Column (3) of Table A.1 reports the p-values of testing the null hypothesis that the estimates of the response in the two type of patients are equal. The hypothesis is rejected for Year 1, not rejected for Year 2 and not rejected for year 3 but with a marginal p-value for $\alpha = 10\%$. Adding the additional covariates in Columns (4), (5) and (6) of Table

A.1, I obtain smaller estimates for privately insured mothers and larger estimates for mothers insured by Medicaid and the hypothesis that the estimates are equal cannot be rejected for any of the years.

The results show some evidence that physicians respond more weakly when they treat Medicaid-insured mothers than when they treat privately insured mothers. This gap appears to widen with the passage of time, although for the full controls specification one cannot reject the hypothesis that physicians' response is similar in both mother types. The results are inconsistent with a pure learning-by-doing effect, which is expected to induce a uniform response to a medical error across mothers of different socioeconomic statuses and suggest that concern about damage to reputation plays a role in the response. Importantly however, one may offer an alternative interpretation: this result is driven by differences in behavior between physicians who treat primarily mothers who are insured by Medicaid and physicians whose main clientele is privately insured.

I.F Estimating the Litigation Effect

Here I produce a back-of-the-envelope calculation of the magnitude of the litigation effect separately from the learning-by-doing effect. I base the calculation on an assumption about the difference in the timing of the two effects: that the learning-by-doing effect takes place promptly after the adverse event and the medical error whereas the litigation effect enters only afterward, when the lawsuit comes about. Hence, the difference between the long-run and the short-run effects of an adverse event provides a measure for the litigation effect.

My assumption is bolstered by physicians' answers in surveys that indicate immediate changes in patterns of practice after a medical error (Wu et al., 1991, Wu et al., 1993). Furthermore, as the results in Section III.C show, lawsuits that ultimately fail and hence are unlikely to be associated with a medical error, do not lead to an increase in C-section rates in the short-run while successful claims do. In the long-run, however, C-sections rise in both types of lawsuits once the lawsuit comes about, providing additional support for this assumption.

I rely on the Florida statute of limitations which typically establishes a two-year time limit on the pursuit of legal remedy after an adverse event; this ensures that physicians are aware of an impending lawsuit two years after the event. Figure A.7 shows a histogram of the time frequencies between the adverse event and the report to the insurer. Consistent with the statute of Limitations, 95% of claims are reported to the insurer less than two years after the adverse event.

I use the difference between the estimates of the effects of an adverse event on treatment in the long-run, more than two years after the adverse event, and in the short-run, a year or less after an adverse event, to carry out a back-of-the-envelope calculation for the litigation effect. Using the point estimates of the effect of an adverse event in Year 3 and Year 1 from Columns (1) and (2), of Table III I estimate the litigation effect at 0.011 and 0.01 percentage point respectively. Furthermore, as the F-tests in Table III show, both are significantly different form zero.

The calculation suggests that half of the 2.2 percentage-point increase in C-section rates after a medical error, 1.1 percentage points, traces to the litigation effect and that the other half represents the learning-by-doing effect. Given that the base C-section rate is about 25%, this implies a cumulative increase of roughly 8% in C-section rates in Year 3 after the adverse event, half of which is due to the litigation effect. These findings reflect a substantial malpractice effect and clash with the existing literature which typically characterizes the litigation effect as weak and short-lived. The findings also provide evidence of a sizable learning-by-doing effect in the impact of a physician's medical error on subsequent medical treatment.

Table A.1: Long-Run Effect of an Adverse Event, Medicaid and Privatey Insured Patients

	Baseline			Full Controls		
	Medicaid	Private Insurance	F-Test Medicaid eq. Private	Medicaid	Private Insurance	F-Test Medicaid eq. Private
	(1)	(2)	(3)	(4)	(5)	(6)
Year 1	.0047	.01505	0.0777	.0069	.0099	0.5233
	(.0049)	(.0036)		(.0038)	(.0031)	
Year 2	.0076	.019	0.1800	.0084	.0145	0.3734
	(.0067)	(.0054)		(.0054)	(.0046)	
Year 3	.0128	.0302	0.1004	.0174	.0236	0.484
	(.0083)	(.0066)		(.0069)	(.0057)	
Quarter & physician FE	Yes	Yes		Yes	Yes	
Number of physicians	459	459		459	459	
Observations	369,739	369,739		369,739	369,739	

NOTE. Full controls include, in addition to the baseline specification, a quadratic polynomial for age, dummy variables for race and for patients conditions as follows: previous C-section, breech position, hypertension, early onset, hemorrhage, and oligohydramnios. Standard errors clustered by physician shown in parenthesis. Year 3 includes only the first two quarters of the third year.

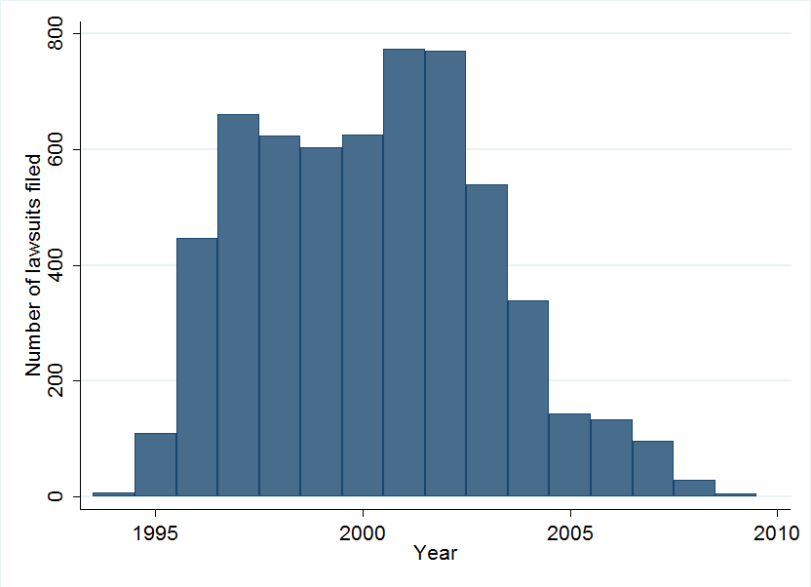
Table A.2: Event Study Approach, Specification Test

	Eq A.8 (1)
year1	0.010
	(0.003)
year2	0.010
	(0.005)
year3	0.016
	(0.006)
Year-quarter & physician FE	Yes
Quadratic trend by adverse-event period	Yes
Number of physicians	459
Observations	403,336

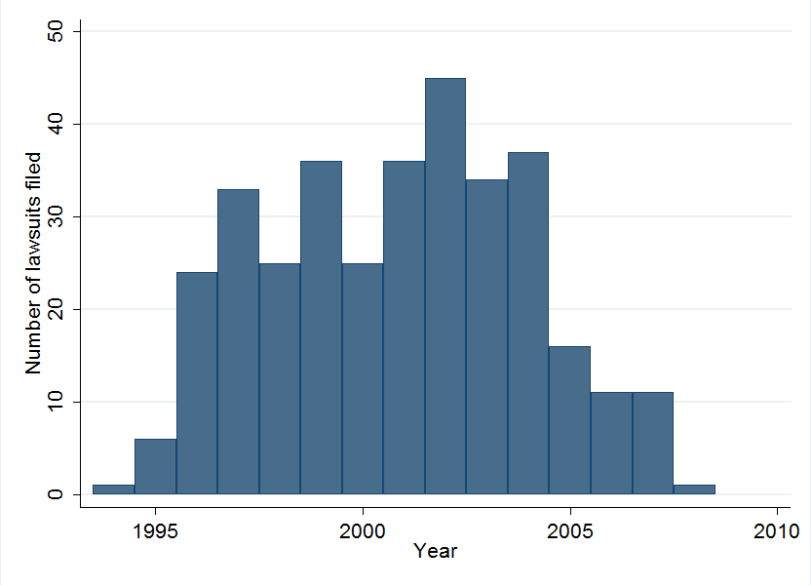
NOTE. The results in this table show the estimates of Equation A.8. Standard errors clustered by physician shown in parenthesis.

Figure A.1: Number of Lawsuits Filed 1994-2009, Florida and Adverse Event Panel

(a) Lawsuits filed, Florida

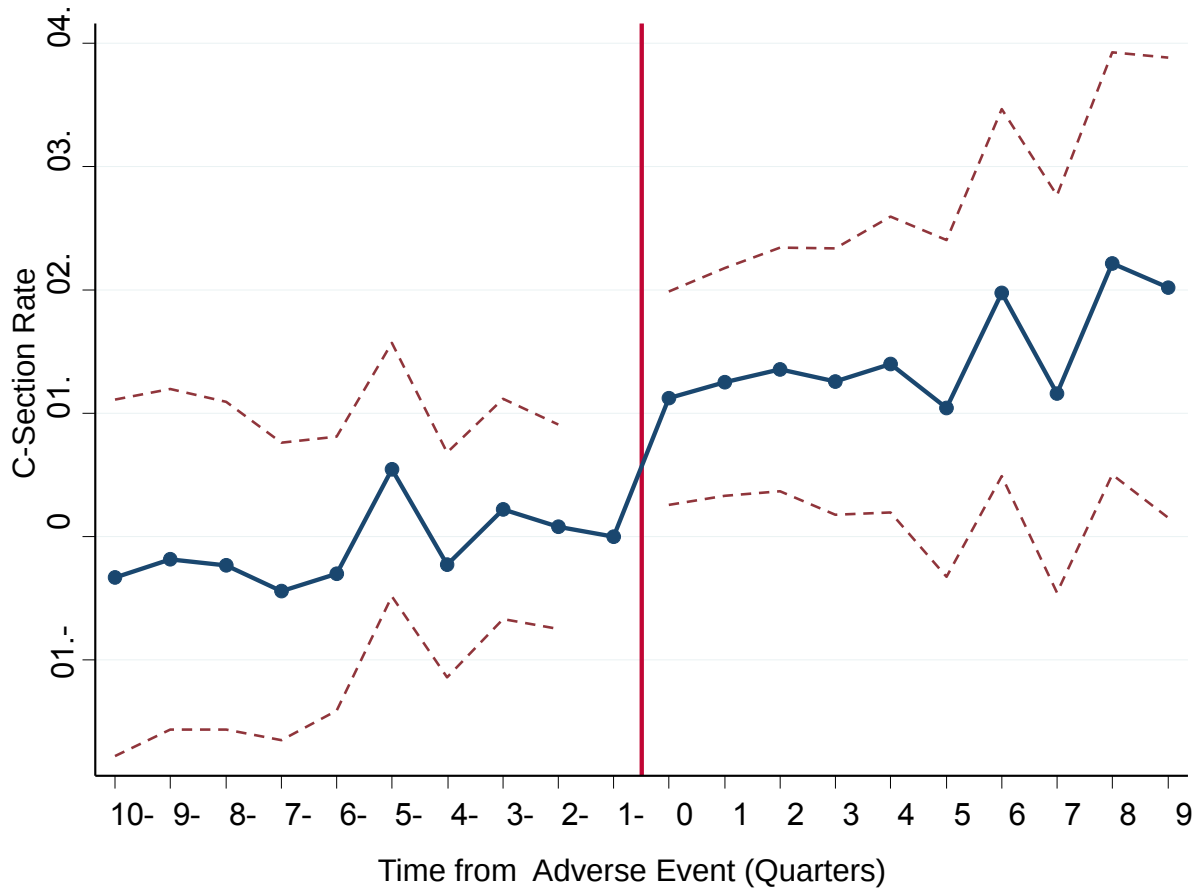


(b) Lawsuits filed, Adverse Event Panel



NOTE: Panels (a) and (b) of this figure depict the number of lawsuits arising from adverse events that happened between 1994Q2-2006Q3.

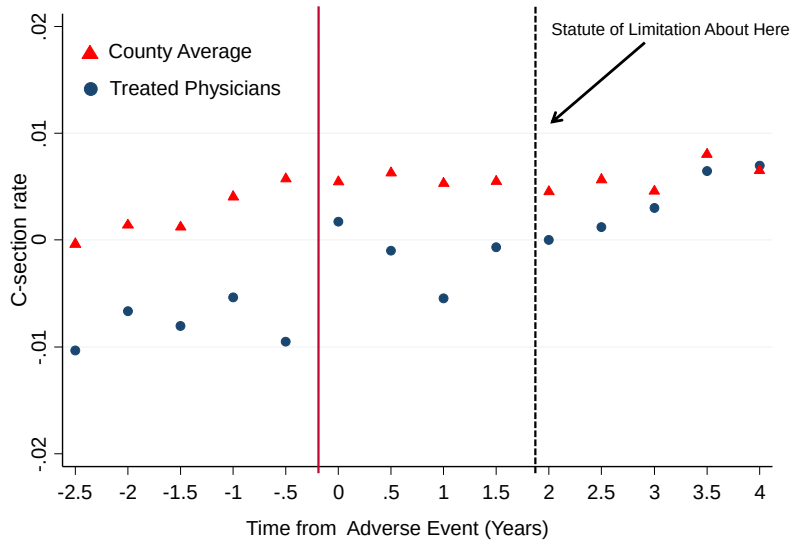
Figure A.2: Event Study Approach, Specification Test



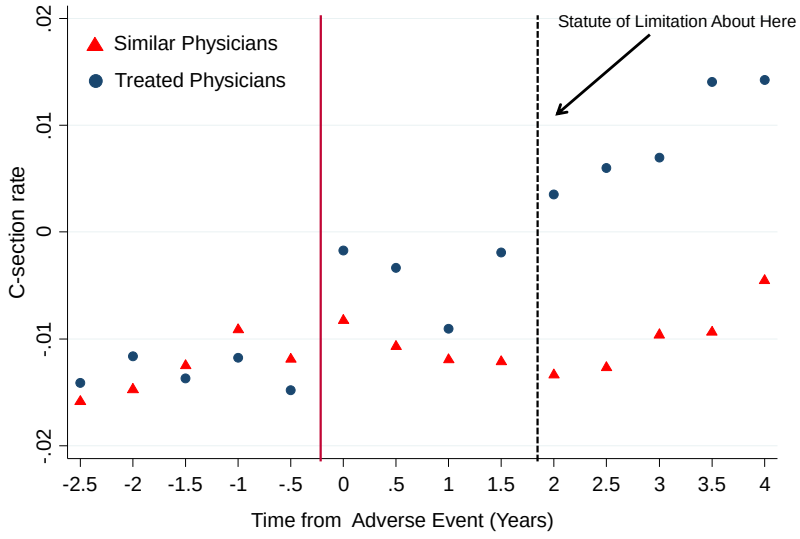
NOTE: This figure plots the coefficients of dummies for time from injury, obtained from an OLS regression with controls for physician and year-quarter fixed effects (Equation 2), imposing a constraint that sets the coefficient of $time_{-1}$ at zero. The thin dashed lines report the 95% confidence interval of the coefficients.

Figure A.3: Matching Approach with "Detrended" C-section Rates

(a) Coarse matching: treated physicians vs. all colleagues from their county

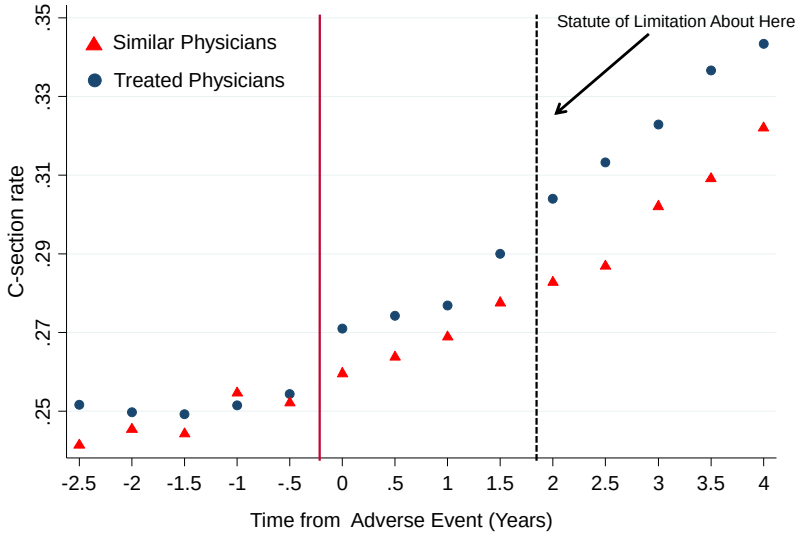


(b) Refined matching: treated physicians vs. only similar colleagues from their County



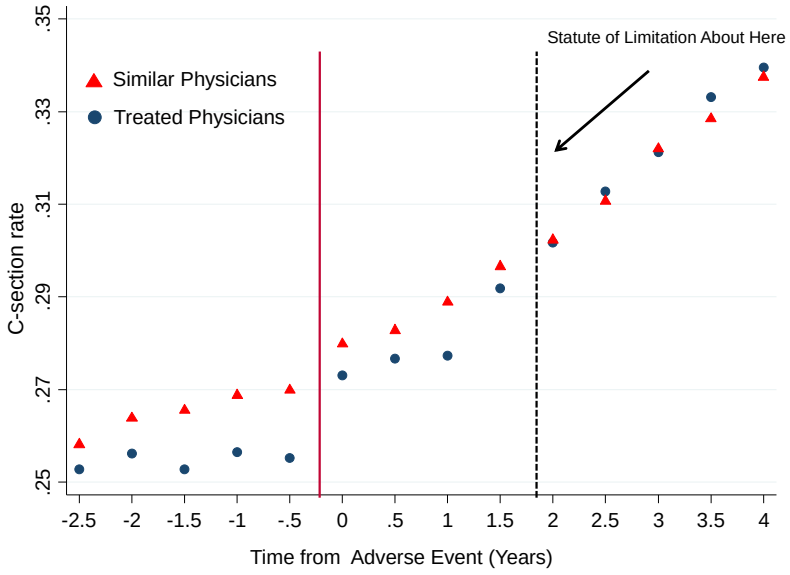
NOTE: This figure is analogous to Figure VIII. To create the figure I initially regressed C-section rates on year-quarter fixed effect and used the residuals rather than the original C-section rates. Panels (a) and (b) of this figure depict the (residuals of) C-section rate in six-month periods 2.5 years before and 4.5 years after the adverse event. The control group in Panel (a) is comprised of physicians from the same county excluding physicians from the same hospital. The control group in Panel (b) is a subgroup of the Control group in panel (a), including only physicians with similar experience and similar pre-event C-section rates. The vertical red line denotes the time of the adverse event and the vertical dashed black line denotes the approximate end of the statute of limitations.

Figure A.4: Refined matching: Pre period C-section rate within 6 percent and 3 year experience, specification checks



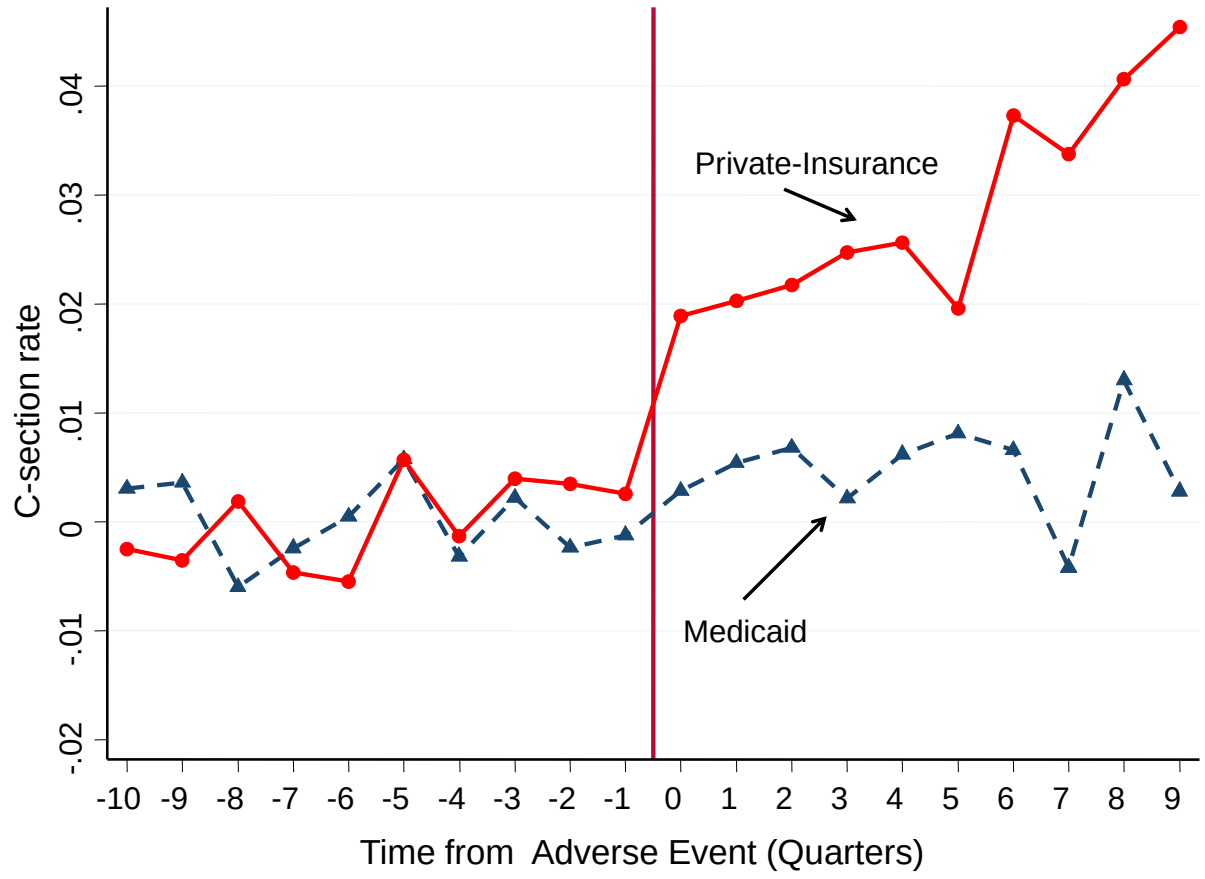
NOTE: Panel (b) is a subgroup of the Control group in panel (a), including only physicians with similar experience and similar pre-event C-section rates. The vertical red line denotes the time of the adverse event and the vertical dashed black line denotes the approximate end of the statute of limitations in this figure there are only 222 physicians and their control group.

Figure A.5: Refined matching: 3 years experience, no match on C-sections, specification checks



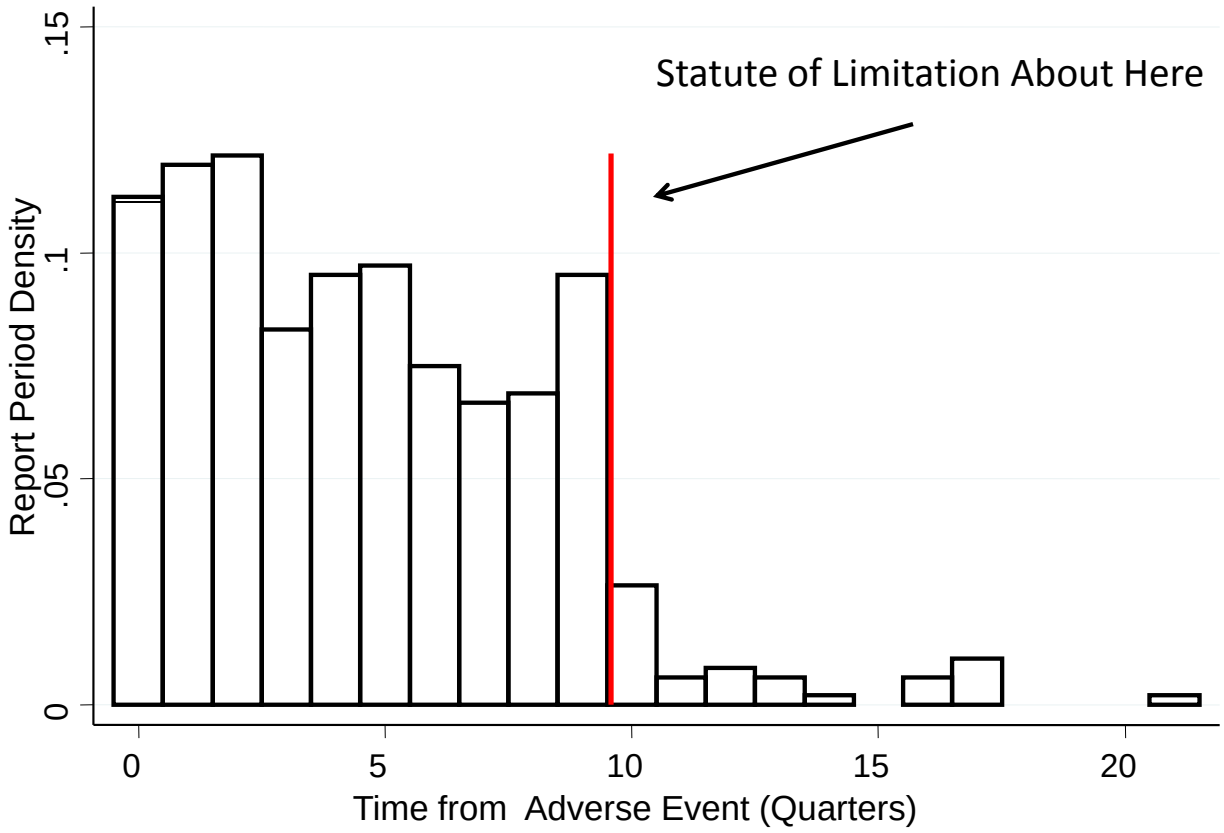
NOTE: This is a subgroup of panel (a) of Figure VIII, including only physicians with similar experience. The vertical red line denotes the time of the adverse event and the vertical dashed black line denotes the approximate end of the statute of limitations.

Figure A.6: Long-Run Effect of an Adverse Event, Medicaid and Privately Insured Mothers



NOTE: This figure plots the coefficients of dummies for time from the adverse event for Medicaid and privately insured mothers, obtained from an OLS regression with controls for physician and quarter fixed effects interacted with patient insurance type (Equation 2), imposing a constraint which sets the sum of the first 10 time coefficients (the "pre-period") at zero for each of the two types of patients.

Figure A.7: Distribution of Timing of Claims Report



NOTE: This figure depicts the frequency of claims by the timing of reporting to physicians' insurer relative to the adverse event.