WHAT PASSED IS PAST? THE ROLE OF RECENT ADVERSE EVENTS IN PHYSICIAN TREATMENT DECISIONS*

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Abstract

In many areas of medical care, physician treatment decisions are made under substantial uncertainty. In the context of obstetrics, this uncertainty may predispose physicians to use decision-making heuristics when choosing between a cesarean or a vaginal mode of delivery. In this study, I examine whether obstetricians overreact to a prior patient’s adverse obstetric events when making subsequent delivery-mode choices, and if so, its effect on patient welfare. Using electronic health record data from a large academic hospital, I find that experiencing adverse obstetric events in one delivery-mode makes the physician more likely to switch to the other (and likely inappropriate) delivery-mode on the next patient, regardless of patient indication. Physician switching after adverse events is also associated with increased resource use by the physician and worse patient outcomes. I formally test and reject the hypothesis that observed physician behavior is consistent with Bayesian updating, and conclude that it is likely an overreaction to salient, negative events. These results highlight a source of cognitive bias in clinical settings, which may inform future efforts to improve physician decision-making through increased awareness or policy interventions.

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1 INTRODUCTION

Physicians often have to decide between competing treatments with limited information and under substantial uncertainty. According to Bayesian theory, which is commonly used to model physician learning (Coscelli and Shum, 2004; Crawford and Shum, 2005; Narayanan et al., 2005), physicians should incorporate all available information and weight all prior data points appropriately when making such decisions. However, research in psychology and economics shows that physicians, like most individuals, often deviate from Bayesian optimality in predictable ways (Croskerry, 2002; Elstein and Schwarz, 2002; Redelmeier, 2005) because they rely on decision-making heuristics under uncertainty (Dawes, 1979; Meehl, 1954). For instance, when making clinical decisions in controlled experiments, physicians have been shown to overweight recent information, (Bergus et al., 1998; Mamede et al., 2010), distracting but irrelevant information (Mamede et al., 2014), and the default option (Patel et al., 2014). Understanding how these heuristics affect clinical decisions is thus necessary to design interventions that can improve physicians’ treatment choices.

In this study, I examine the role of one such heuristic in physician decision-making: the availability heuristic. The availability heuristic may predispose physicians to overweight information that is easily accessible when making clinical decisions, such as recent information that triggers an emotional response (Tversky and Kahneman, 1973). To that end, I investigate whether obstetricians overreact to adverse patient outcomes in the obstetric ward, which is a particularly consequential clinical setting.

There is suggestive evidence that adverse events trigger the availability heuristic in non-clinical settings: investors overreact to surprising negative events and cause stock prices to dip further than rationally expected (Bondt and Thaler, 1985); a heavy snowstorm sharply increases the likelihood of consumers buying four-wheel-drive vehicles (Busse et al., 2015). The clinical literature, however, has been cautious about explicitly stating whether physician response to adverse events is a reaction or an overreaction.

Prior research has shown that physicians alter treatment patterns in response to adverse events such as patient death (Doctor et al., 2018; Kc et al., 2013), drug-related side-effects (Choudhry et al., 2006), malpractice litigation (Shurtz, 2013), and postoperative complications (Kanters et al., 2018). This response is not surprising; the adverse events in these studies are at least somewhat informative to the clinical decision and should thus be incorporated into subsequent physician decisions to some extent. However, the extent to which this response is optimal – that is, a form of Bayesian learning – is largely left undiscussed. Yet, this is not a trivial distinction. A change in physician behavior in response to new information is not by itself evidence of learning. For example, a person who gets into a car accident is expected to alter his driving style in response to it. However, if he
reverts to his usual driving style after a day, his response cannot be considered Bayesian. It is simply a temporary emotional response to a recent adverse event that did not result in learning.

I hypothesize that obstetricians will be susceptible to similarly biased thinking for two reasons. First, there is large uncertainty around the choice of delivery-mode due to the lack of high-quality evidence on the relative risks between vaginal and cesarean deliveries. Second, adverse obstetric events presumably elicit especially large emotional responses from the physician. Evidence suggests that clinical errors and adverse events cause significant distress and anxiety in physicians, and lead them to believe that they will make more errors in the future (Scott et al., 2009; Waterman et al., 2007; West et al., 2006). This response is likely exacerbated in the obstetric setting, since adverse obstetric events can seriously (and potentially irreversibly) harm both mother and child. As a result, any such events in a patient should be especially “available” to the obstetrician and affect their treatment choices for the next patient.

To test whether this occurs, I use 100% inpatient electronic health record data over three years (June 2015 – July 2018) from a large academic hospital to estimate: i) whether obstetricians’ choice of delivery-mode is influenced by the adverse clinical outcomes of their prior patient, ii) how prior adverse events impact subsequent treatment intensity and patient outcomes, and iii) whether the observed physician response to adverse events is consistent with Bayesian learning.

Using within-physician variation in care, I find that an obstetrician is more likely to switch delivery-modes following an adverse patient outcome (though this effect is only statistically significant when the adverse event occurs in a cesarean delivery), despite accounting for patient characteristics, physician practice style, and outcome expectedness. When physicians do switch delivery-modes after an adverse event, they are more likely to deviate from the expected delivery-mode as well. This switching behavior is in turn associated with increased treatment intensity and worse outcomes in the next patient. I formally examine a range of mechanisms that could reconcile observed physician switching behavior with a model of Bayesian learning. However, I find that physician treatment choices do not appear to be consistent with Bayesian updating and may instead be overreactions to salient, adverse events.

This study makes three primary contributions to a growing observational literature on cognitive biases in clinical settings like medication prescribing (Camacho et al., 2011), as well as in non-clinical settings like investments (Slovic, 1972), consumer choice (Meier and Sprenger, 2010), and judicial proceedings (Danziger et al., 2011). First, it shows that physicians respond to adverse events even if these events are not informative to the clinical decision. Previous studies have looked at how physicians respond to adverse events that are clearly informative; for example, Doctor et al. (2018) show that physicians prescribe fewer opioid prescriptions when they receive letters detailing their prior
patients’ opioid-related deaths. In their study, the adverse event warrants physician response. However, maternal hemorrhage (or even death) during a delivery has a large component of randomness to it, and arguably should not always precipitate a physician response. I find that not only do physicians react to these potentially uninformative events, they are likely to overreact as well.

Second, this study provides observational evidence of bias in the obstetric ward. This focus on the obstetric setting is important because, compared to commonly studied decisions like medication prescribing, choosing a delivery-mode is a high-stakes decision. The obstetrician only has one chance to perform a delivery, is unable to learn through repeated exposures to the same patient, and each decision has lasting effects on the health of both mother and child.

Third, and finally, this study contributes to a limited literature on how physician heuristics affect actual patient outcomes in clinical practice. This is an important contribution because, as previously mentioned, prior studies either use controlled laboratory experiments to study physicians’ cognitive biases or use empirical approaches to examine changes in physician behavior without explicit investigation of biases. As a result, either the effects of biases on patient outcomes cannot be studied, or any observed effects on patient outcomes cannot be attributed to biases, respectively.

My study is most closely related to the work of Van Gestel et al. (2018), who show that a prior patient’s death significantly improves the likelihood of the physician’s subsequent patient’s survival in the interventional healthcare setting. Our respective studies overlap in that they both show that physicians are likely to focus on the outcomes of recent patients when making clinical decisions, albeit in different clinical settings. In their study, this focus leads to a short-lived improvement in patient outcomes, based on which they conclude that adverse events are important to physician learning. However, like other studies that show a lack of persistence in physician response to adverse information (Ly, 2019), the transience of the response in the Van Gestel et al. (2018) study indicates suboptimal learning. I provide the counterpoint to their example by presenting evidence that physician overweighting of recent adverse events is unlikely to be a Bayesian response.

This study informs current discourse on the variation in, and misuse of, cesarean sections (Betrán et al., 2018; Currie and MacLeod, 2017; Rosenberg, 2016). There is wide variation in rates of cesarean sections across hospitals (Kozhimannil et al., 2013) and physicians (Goyert et al., 1989), with evidence suggesting that the recent increase in first-time cesareans is driven more by subjective indications than objective indications (Barber et al., 2011). My study builds on this research by highlighting a source of non-diagnostic, within-physician variation in cesarean use: the physician’s prior clinical outcome.

Moreover, this study points to a counter-intuitive takeaway. Physicians are significantly more likely to switch delivery-modes to a vaginal delivery after experiencing adverse events in a cesarean,
regardless of patient indication. So it is possible that in the immediate aftermath of an adverse cesarean event, there are patients who require cesareans but do not receive them, suggesting cesarean underuse by physicians.

The rest of this paper proceeds as follows. Section 2 explains the data, the construction of the variables of interest, and provides descriptive summaries. Section 3 provides evidence that prior adverse events affect the physician’s subsequent treatment choices and patient outcomes. Section 4 formally examines whether physician response to prior adverse events is consistent with Bayesian learning. Section 5 concludes.

2 DATA AND DESCRIPTIVE STATISTICS

2.1 Dataset

I use the universe of inpatient electronic health records at a large academic hospital’s obstetric ward over three years (June 2015 through June 2018). Figure I presents a histogram depicting the distribution of cesarean and vaginal deliveries over physicians. Deliveries by physicians who are not OB/GYNs or family medicine physicians are excluded (≤ 1% of the sample) from the analytic dataset.

Though the data is from a single institution, it is unlikely that physicians in this hospital behave significantly differently from physicians in other hospitals. Importantly, the rich, granular detail provided by this dataset allows me to examine physician decision-making in a way that is not
possible with other commonly used databases. For instance, it captures each patient’s movement through various wings of the hospital, allowing me to use the time at which the patient is admitted to the labor and delivery ward (instead of the time they arrive at the hospital) to queue patients in the order that they are seen by each physician. Additionally, the data provides within-team information such that for each delivery, I can observe the specific duties performed by each provider, be it nurse or physician. Using this information and the primary physician listed on the billing claim, I can identify the physician with primary responsibility of the delivery. According to my hypothesis, any adverse clinical events will be particularly available to the physician in charge of that delivery, causing her to influence the delivery-mode of the next delivery she is responsible for – even if she is working in a team. This focus on a single obstetrician having disproportionate influence over a delivery-mode choice is consistent with the notion that malpractice lawsuits are commonly filed against single obstetricians, not clinical teams. Moreover, to the extent that working in teams dilutes the effects of the availability heuristic, this additional random noise should only bias against my results.

2.2 Construction of Variables

Each physician \( j \) sees each patient (indexed by \( i \) in a set of patients \( I_j \)) sequentially in the order that patients are admitted to the labor and delivery ward. For example, a physician \( j \) sees a patient \( i \in I_j \) at time \( t \), patient \((i + 1) \in I_j \) at time \((t + 1)\) and so on\(^1\).

2.2.1 Independent variables

**Adverse Events** (\( AE_{ijt} \))

To be “available” to physicians, adverse events need to either signal the potential of harm to mother or child, or the potential for malpractice litigation. I thus identify such adverse events from the literature on obstetric care quality metrics (Mann et al., 2006) and news articles on obstetric malpractice lawsuits.

In the data, I classify the following six clinical events that could occur to the mother as maternal adverse events: maternal trauma, uterine rupture, third/fourth degree perineal tear, maternal hemorrhage, maternal admission to the ICU, and maternal death during delivery. I classify the following five clinical events that could occur to the mother’s neonate(s) as neonatal adverse events: newborn prematurity, APGAR score less than 7 at 5 minutes, neonatal injury/trauma, neonatal admission to the NICU, and neonatal death. Mann et al. (2006) argue that these events are plausibly sensitive

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\(^1\)There are three things to keep in mind about notation. First, since patient \( i \) can only be seen at time \( t \), patient \((i + 1) \) at time \((t + 1)\), and so on, I only use the subscripts for time (= \( t \)) to denote time fixed effects in my equations for simplicity. Second, the \( i \) subscript assigned to a patient is always associated with a specific physician and should be interpreted as patient \( ij \) (i.e., physician \( j \)’s patient \( i \)). Most importantly, patient \( i \) refers to the physician’s “current patient”, and patient \( (i − 1) \) refers to the physician’s “prior patient”. In other words, patient \( (i − 1) \) is prior to patient \( i \), and patient \( i \) is subsequent to patient \( i − 1 \). Analyses will largely focus on the effect of adverse events in a physician’s prior patient on the treatment choices made by that physician on her subsequent (i.e., current) patient.
to physician skill\textsuperscript{2}. Theoretically then, these adverse events should act as information shocks to the physician, i.e., feedback to the physician regarding their past clinical performance. This feedback, regardless of whether it is informative, should translate to observable changes in the delivery-mode choices of the physician. The extent to which these changes are Bayesian responses or overreactions to adverse events are discussed in the next few sections.

For each patient \( i \) in the dataset, I sum all maternal and neonatal adverse events in that encounter to create a count measure of adverse events (Figure C.1). A patient can have a maximum of eleven adverse events, though none have more than seven adverse events in my dataset. While I present results using the count variable, for the majority of this paper I use a categorical measure of adverse events with three categories (0, 1, and 2+ adverse events, Figure C.2) due to the relative rarity of more than two adverse events in a patient encounter.

**Mode of Adverse Event (\( \text{MoAE}_{ijt} \))**

For each patient with an adverse event, I identify the delivery-mode in which the adverse event is likely to have occurred using ICD codes, which I call the **Mode of Adverse Event**. \( \text{MoAE}_{ijt} \) is equal to 1 if the adverse event(s) occurred in a vaginal delivery, 0 if they occurred in a cesarean delivery. Importantly, mode of delivery is not always the same as Mode of Adverse Event. This stems from the fact that if a physician believes that adverse events provide relevant information, then this will cause her to change her behavior about the delivery-mode in which the adverse event occurred, and not the delivery-mode by which the baby was delivered. Thus, in encounters with an emergency cesarean, the Mode of Adverse Event is attributed to a vaginal delivery (because the emergency cesarean was likely conducted due to complications in the vaginal delivery), while the Mode of Delivery is classified as a cesarean (because the neonate was delivered via an emergency c-section)\textsuperscript{3,4}. Table I presents a summary of observed adverse events in vaginal and cesarean deliveries. As expected, there are no cesarean deliveries with associated maternal perineal tears because perineal tears occur exclusively in vaginal deliveries. The results are robust to excluding this specific adverse event (Appendix Table B.1).

\textsuperscript{2}Newborn prematurity is the only event that is not included in Mann et al. (2006)'s article. I include it in my measure of adverse obstetric events because: 1) there is a wealth of literature linking newborn prematurity to immediate and long-term morbidity for the baby (De Groote et al., 2007; Marlow et al., 2005); and 2) there are several examples of high-profile litigation cases on neonatal prematurity that were settled in favor of the patient. Moreover malpractice lawyers often have webpages dedicated to premature birth litigation, suggesting it is to some extent sensitive to physician skill as well.

\textsuperscript{3}Of the 3,012 individuals with a Cesarean Mode of Delivery, 1,095 first attempted a vaginal delivery.

\textsuperscript{4}There are two logical implications of this coding choice. First, there is no scenario in which an adverse event can be attributed to an emergency c-section. All adverse events observed in cesareans are only observed in planned/elective cesareans. While this assumption has anecdotal support in interviews with physicians, I test this assumption later on and find no difference in results (Appendix Table B.2). I also account for this issue by including an indicator for emergency c-sections. Second, there will be emergency cesareans without any associated adverse events (as defined by my measure). This only biases against my results, since those deliveries likely have adverse events that are not picked up by my measure, ought to induce subsequent switches in delivery-modes, but are coded as not having any adverse events. I also test this assumption in Appendix Table B.3 and find no differences in results.
## Table I
SUMMARY STATISTICS: MODE OF ADVERSE EVENT

<table>
<thead>
<tr>
<th>Maternal and Neonatal Adverse Events</th>
<th>Cesarean Deliveries (1)</th>
<th>Vaginal Deliveries (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maternal Trauma</td>
<td>16 (0.70)</td>
<td>26 (0.24)</td>
</tr>
<tr>
<td>Uterine rupture</td>
<td>10 (0.44)</td>
<td>6 (0.06)</td>
</tr>
<tr>
<td>Third/Fourth degree perineal tears</td>
<td>0</td>
<td>74 (0.69)</td>
</tr>
<tr>
<td>Maternal hemorrhage</td>
<td>130 (5.71)</td>
<td>735 (6.82)</td>
</tr>
<tr>
<td>Maternal admission to the ICU</td>
<td>45 (1.98)</td>
<td>52 (0.48)</td>
</tr>
<tr>
<td>Maternal Death</td>
<td>2 (0.09)</td>
<td>3 (0.03)</td>
</tr>
<tr>
<td>Neatnat prematurity</td>
<td>275 (12.09)</td>
<td>857 (7.95)</td>
</tr>
<tr>
<td>5-min APGAR &lt;7</td>
<td>324 (14.24)</td>
<td>1,339 (12.42)</td>
</tr>
<tr>
<td>Birth trauma/birth injury</td>
<td>60 (2.64)</td>
<td>325 (3.01)</td>
</tr>
<tr>
<td>Neonatal admission to the NICU</td>
<td>189 (8.31)</td>
<td>375 (3.48)</td>
</tr>
<tr>
<td>Neonatal death</td>
<td>12 (0.53)</td>
<td>15 (0.14)</td>
</tr>
<tr>
<td>Number of deliveries with 0 adverse event</td>
<td>1,517 (66.68)</td>
<td>7,746 (71.86)</td>
</tr>
<tr>
<td>Number of deliveries with 1 adverse event</td>
<td>546 (24.00)</td>
<td>2,424 (22.49)</td>
</tr>
<tr>
<td>Number of deliveries with 2+ adverse events</td>
<td>212 (9.32)</td>
<td>610 (5.66)</td>
</tr>
<tr>
<td>Total observations (N)</td>
<td>2,275</td>
<td>10,780</td>
</tr>
</tbody>
</table>

Note: All entries are counts (and percentages in parentheses), unless stated otherwise. Column (1) denotes adverse events that occur in a cesarean delivery; and column (2) denotes adverse events that occur in a vaginal delivery.

### 2.2.2 Dependent variables

**Mode of Delivery (Modijt)**

I classify delivery-mode (vaginal versus cesarean) using ICD codes. Modijt is equal to 1 if physician j delivered neonate(s) in patient i via a vaginal delivery, 0 if the neonate was delivered via a cesarean delivery. Table II provides summary statistics for the two groups: women who have cesarean deliveries and women who have vaginal deliveries. Cesareans comprise about a third of all deliveries. Older women, black women, and insured women are significantly more likely to receive cesareans, as are women with prior cesareans and greater number of comorbid conditions.

**Switch in Delivery-Mode (Switchijt)**

A physician j switches delivery-modes for patient i if the physician’s prior patient’s Mode of Adverse Event is different than her current patient’s Mode of Delivery (i.e., if MoAEi−1j ≠ Modij). If so, Switchij is an indicator variable that is equal to 1 for patient ij.
### TABLE II
SUMMARY STATISTICS: MODE OF DELIVERY

<table>
<thead>
<tr>
<th></th>
<th>Cesarean Deliveries</th>
<th>Vaginal Deliveries</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>% (SE)</td>
<td>% (SE)</td>
</tr>
<tr>
<td>Age (mean)</td>
<td>30.81 (5.99)</td>
<td>28.92 (5.84)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>3.22 (17.65)</td>
<td>3.44 (18.23)</td>
</tr>
<tr>
<td>Black</td>
<td>77.09 (42.03)</td>
<td>71.96 (44.9)</td>
</tr>
<tr>
<td>Medicaid</td>
<td>22.90 (42.03)</td>
<td>18.00 (38.42)</td>
</tr>
<tr>
<td>Commercial</td>
<td>67.13 (46.98)</td>
<td>58.73 (49.23)</td>
</tr>
<tr>
<td>Elixhauser readmission index (mean)</td>
<td>2.99 (6.21)</td>
<td>2.02 (4.76)</td>
</tr>
<tr>
<td>Elixhauser mortality index (mean)</td>
<td>-0.57 (4.26)</td>
<td>-0.44 (2.99)</td>
</tr>
<tr>
<td># prior children (mean)</td>
<td>1.04 (0.21)</td>
<td>1.05 (0.23)</td>
</tr>
<tr>
<td>Length of stay, days (mean)</td>
<td>4.15 (3.36)</td>
<td>2.98 (1.93)</td>
</tr>
<tr>
<td>Previous cesarean</td>
<td>24.20 (42.83)</td>
<td>4.19 (20.04)</td>
</tr>
<tr>
<td>Total observations (N)</td>
<td>3,012</td>
<td>10,043</td>
</tr>
</tbody>
</table>

Note: All numbers are percentages, unless stated otherwise. Column (1) denotes babies delivered by a cesarean; and column (2) denotes babies neonates delivered vaginally.

### 3 THE EFFECT OF PRIOR ADVERSE EVENTS ON PHYSICIAN DELIVERY-MODE CHOICE, TREATMENT INTENSITY, AND PATIENT OUTCOMES

#### 3.1 The impact of prior adverse clinical events on delivery-mode choice

In this section, I examine whether experiencing an adverse clinical outcome in the current patient causes the physician to switch delivery-modes on their subsequent patient. To do so, I provide two models. In the first model, the dependent variable is $Switch_{ijt}$. Using this model, I estimate the effect of prior adverse events on subsequent physician switching behavior, conditional on the prior patient’s Mode of Adverse Event. In the second model, the dependent variable is $MoD_{ijt}$. Here, I estimate how the effect of prior adverse events on the physician’s choice of subsequent delivery-mode depends on the prior patient’s Mode of Adverse Event.

I include the second model only to provide more detailed evidence that my estimates are identified and in line with my hypotheses. However, in subsequent sections (i.e., when estimating effects on treatment intensity and patient outcomes) I use the first model in my analyses to avoid explicating unwieldy three-way coefficients.

#### 3.1.1 Average likelihood of switching

The first set of bars in Figure II show the simple, unadjusted proportions of deliveries in which a physician switched delivery-modes after adverse events in the prior delivery. For instance, physicians switched delivery-modes for 31% of deliveries that had no prior adverse event. However, they switched
delivery-modes for 39% of deliveries with 2+ prior adverse events.

I estimate the following linear probability model to formally test this hypothesis:

\[ Switch_{ijt} = \beta AE_{(i-1)j} + MoAE_{(i-1)j} + \phi_i + \gamma_j + \tau_t + \epsilon_{ijt} \]  

where \( \phi_i \) is a vector of patient characteristics (specifically: an emergency c-section indicator variable, Elixhauser readmission and mortality indices [Moore et al. (2017)], age, race, ethnicity, insurance status, history of cesarean, and maternal parity), \( \gamma_j \) is a vector of physician fixed effects, \( \tau_t \) is a vector of year, month, and week fixed effects. Standard errors in all analyses are clustered at the physician level. The coefficient of interest on \( AE_{(i-1)j} \) indicates that a physician is 18.1 percentage points (\( p = 0.034 \)) more likely to switch delivery-modes for her current patient if her prior patient had 2+ adverse events (compared to no adverse event).

\[ \begin{array}{c|c|c|c|c|c}
\# of adverse events in prior delivery & 0 & 1 & 2+ \\
\hline
Switched delivery-mode & 0.31 & 0.32 & 0.39 \\
Switched to Expected delivery-mode & 0.67 & 0.65 & 0.61 \\
Switched to Unexpected delivery-mode & 0.33 & 0.35 & 0.39 \\
\end{array} \]

FIGURE II
Unadjusted Physician Response to Prior Adverse Events

Note: Unadjusted proportion of deliveries in which, after prior adverse events, the physician: a) switched delivery-modes (first set of bars), b) switched to the Expected delivery-mode (second set of bars), and c) switched to the Unexpected delivery-mode (third set of bars). The second and third sets of bars decompose the first set of bars.

Consistently switching delivery-modes after an adverse event is unlikely to be optimal behavior. However, even less optimal would be if prior adverse events led physicians to switch to the inappropriate delivery-mode. I provide some insight into this question by decomposing \( Switch_{ij} \) into “Expected” switches (e.g., the physician switched to an cesarean for patient \( i \) and the patient was expected to have a cesarean) and “Unexpected” switches (e.g., the physician switched to a cesarean
for patient $i$ and the patient was expected to have a vaginal). Using a simple regression of delivery-mode on patient characteristics, I identify instances in which the physician deviates from the Expected delivery-mode\(^5\). The Expected delivery-mode for patient $i$ is simply the average delivery-mode performed on patients who look like patient $i$ in the dataset. Deviations from expected in delivery-mode choices are suboptimal because they imply that adverse events may be causing physicians to use criteria other than what are used for most patients.

I identify Unexpected and Expected delivery-modes in the following way. First, I regress Mode of Delivery on patient characteristics and time fixed effects, as defined previously. I then use the fitted values of Mode of Delivery ($\hat{MoD}_i$) to identify whether the physician deviates from the Expected delivery-mode. However, since $MoD_i$ is a dichotomous variable and $\hat{MoD}_i$ is continuous one, I median-split the latter to assign predicted delivery-modes to each patient. Unexpected delivery-mode ($UnexpMoD_{ij}$) is equal to 1 if the observed Mode of Delivery is different from the (now dichotomous) predicted Mode of Delivery, 0 otherwise.

$$MoD_{it} = \phi_i + \tau_t + \epsilon_{it} \quad (2)$$

$$UnexpMoD_{ij} = 1[MoD_{ij} \neq 1(\hat{MoD}_i > m)] \text{ where } F_{\hat{MoD}_i}(m) = 0.5 \quad (3)$$

The second and third set of bars in Figure II are the decomposition of the first set of bars (which represent overall physician switching) into Expected switches and Unexpected switches, respectively. For example, a physician switches delivery-modes for 31% of deliveries that follow no adverse events, of which 67% are to the Expected delivery-mode, and 33% are to the Unexpected delivery-mode. However, after 2+ adverse events, a physician switches delivery-modes for 39% of deliveries, of which 61% are to the Expected delivery-mode, and 39% are to the Unexpected delivery-mode. Again, we see that increasing number of prior adverse events are associated with greater likelihoods of switching to the Unexpected delivery-mode and lower likelihoods of switching to the Expected delivery-mode on the next delivery.

### 3.1.2 Delivery-mode-specific likelihood of switching

The model discussed above is masking substantial heterogeneity in physician response to adverse events by the prior patient’s Mode of Adverse Events. I therefore estimate the following delivery-

\(^5\)Using patient characteristics to identify expected delivery-modes will lead to biased estimates of the effect of prior adverse events on subsequent switching only if a certain patient type is always following the occurrence of adverse events. This is unlikely to be the case.
mode-specific model:

\[ MoD_{ijt} = \beta_1 AE_{(i-1)j} + \beta_2 MoAE_{(i-1)j} \]
\[ + \beta_3 [AE_{(i-1)j} \cdot MoAE_{(i-1)j}] \]
\[ + \phi_t + \gamma_j + \delta_t + \epsilon_{ijt} \]  

(4)

Since Mode of Delivery can only either be a vaginal (=1) or cesarean (=0), there are two primary coefficients of interest. The first is \( \beta_1 \), which tells us the (within-physician) effect of an adverse event in a prior cesarean delivery on the probability of a current vaginal delivery. A positive value for \( \beta_1 \) would indicate that a physician is more likely to switch to vaginal delivery if the prior patient experienced an adverse event during a cesarean delivery (compared to no adverse event in the prior cesarean delivery).

The second coefficient of interest is \( \beta_1 + \beta_3 \), which informs us about the (within-physician) effect of an adverse event in a prior vaginal delivery on the probability of a current cesarean delivery. A negative value of \( \beta_1 + \beta_3 \) would indicate that prior vaginal adverse events increase a physician’s propensity to perform a cesarean delivery on the current patient (compared to no adverse events in a prior vaginal delivery).

I argue that these coefficients are plausibly identified. If present, the most likely source of endogeneity would arise from the presence of correlated omitted variables (e.g., if unobserved patient characteristics driving the choice of delivery-mode for the current patient are correlated with the occurrence of adverse events in the prior patient). However, I present three reasons that this is unlikely to be the case.

First, anecdotal interviews with physicians suggests that obstetric patients arrive at the hospital in a random manner, are assigned to the physicians on-call in a random manner, and the adverse obstetric events occur in a random manner as well (in that they cannot be predicted by the physician). This assumption finds support in latter sections (see Table IV).

Second, I limit the potential of such unobserved effects by using an interaction and physician fixed effects in my main empirical model. I estimate delivery-mode-specific and physician-specific effects to adjust for unobserved between-physician and between-delivery-mode heterogeneity in patient population and practice style. For example, Equation 4 would compare the [effect of adverse events in a cesarean delivery by physician \( j \)] to [no adverse events in a cesarean delivery by physician \( j \)], thereby isolating physician \( j \)’s response to an adverse event in a cesarean delivery-mode.

Third, the model examines two separate effects: (1) the effect of an adverse event in a prior cesarean delivery on the physician’s choice of a subsequent vaginal delivery, and (2) the effect of an adverse event in a prior vaginal delivery on the physician’s choice of a subsequent cesarean delivery.

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6Any physician discretion over scheduling elective cesareans occurs far in advance of the prior patient. In other words, even if physicians can schedule elective cesareans, they are unlikely to schedule a patient at a moment’s notice, and as a result elective cesareans are unlikely to be correlated with the immediately preceding patient.
Any correlated omitted variable would need to affect both of these relationships (and have an effect that lasts very briefly) to bias results. It is difficult to identify explanations, other than availability bias, that predict such a precise pattern of results.

In my baseline analysis, I restrict attention to deliveries where the mother has never had a prior cesarean before\(^7\). When the mother has a history of cesarean delivery, the physician will be predisposed to perform a cesarean on her and is unlikely to be influenced by prior adverse events. Later, in a falsification test, I estimate the effect of prior adverse events on women with histories of cesarean.

Results are presented graphically in Figure III for my baseline analysis, and formally in Table III\(^8\). The Y axis in the figure denotes the probability of a vaginal delivery in the current patient; increasing values of Y denote increasing probabilities of a vaginal delivery and decreasing values of Y denote increasing probabilities of a cesarean delivery. The X axis denotes the number of adverse events in the prior patient.

Note: Figure presents the effect of adverse events in a prior delivery on the physician’s choice of delivery-mode on their current patient, on women with no prior history of cesareans.

\(^7\)though adverse events in mothers with histories of cesareans are still allowed to affect subsequent delivery decisions because physicians should still have an emotional response to these events

\(^8\)The graph presents the estimates from the logit regression model whereas the tables present the result from the linear probability model for ease of interpretation. This does not significantly change effect sizes or statistical significance.
Results support my hypotheses. There is a dose-response relationship between number of prior adverse events and probability of switching delivery-modes for the current patient (Figure III). An adverse event in a prior non-emergency cesarean delivery increases a physician’s probability of switching to a vaginal delivery in the current patient by approximately 3 percentage points (Table III Panel A). This effect appears to be primarily driven by patients who have a greater number of adverse events, with physicians being 9.1 percentage points more likely to switch delivery-modes to a vaginal after 2+ adverse events in a prior cesarean (Table III Panel B). The converse effects are also seen directionally: 2+ adverse events in a prior vaginal delivery increases the physician’s probability of performing a cesarean delivery for the current patient by 1.3 pp, albeit insignificantly.

This asymmetric relationship, both in statistical significance and effect size, can be explained by two mechanisms. First, the statistical insignificance of the effect of prior adverse events in vaginal delivery may be due to a lack of power, as vaginal deliveries are less likely to have a very high number of adverse events. Second, the smaller magnitude of the effect of 2+ adverse events in prior vaginal deliveries (1.3 pp vs. 9.1 pp in prior cesareans) may be because physicians have more discretion over the decision to perform a (non-emergency) c-section, whereas a vaginal delivery is largely considered the norm. As such, adverse events in vaginal deliveries may elicit smaller emotional responses from physicians than those in cesarean deliveries.

Results from a falsification test, presented in Table III Panel C, are also consistent with my hypothesis. Prior adverse events have no effect on subsequent physician behavior for women with prior histories of cesarean deliveries. This suggests that subjectivity plays an important role in physician decision-making; as the clinical decision becomes less subjective, the physician is less likely to rely on personal criteria to make the decision.

### 3.1.3 Heterogeneities in Physician Switching Response

**Switching to the Expected vs. Unexpected delivery-mode**

In this section, I disentangle delivery-mode-specific likelihoods of physician switching to the Expected vs. Unexpected delivery-modes after a prior adverse event. I create a categorical variable with three values for indicating physician response (\(\text{Response}_{ijt}\)): equal to 1 if physician \(j\) did not switch delivery-modes on patient \(i\); equal to 2 if physician \(j\) switched to the Expected delivery-mode on patient \(i\); and equal to 3 if physician \(j\) switched to the Unexpected delivery-mode on patient \(i\). For instance, assume the prior patient had a cesarean. If the current patient has a cesarean, then \(\text{Response}_{ij} = 1\). If the current patient has an Expected or Unexpected vaginal delivery, then \(\text{Response}_{ij} = 2\) or 3, respectively.

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9Physicians arguably have some discretion over emergency c-sections as well, in that they may conduct one when it is not necessary and knowingly or unknowingly miscode it as medically necessary. This is discussed later in the paper (Appendix Table B.2).
### TABLE III
EFFECT OF PRIOR ADVERSE EVENTS ON DELIVERY-MODE CHOICE

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Dep Var: Vaginal delivery in patient $i$ (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td><strong>PANEL A: Effect of prior adverse events (count)</strong></td>
<td></td>
</tr>
<tr>
<td># adverse events in a cesarean for patient $i - 1$ (marginal effect)</td>
<td>0.0313*** &amp; (0.0091)</td>
</tr>
<tr>
<td># adverse event in a vaginal for patient $i - 1$ (marginal effect)</td>
<td>-0.0020 &amp; (0.0056)</td>
</tr>
<tr>
<td><strong>PANEL B: Effect of prior adverse events (categorical)</strong></td>
<td></td>
</tr>
<tr>
<td>1-2 (vs. 0) adverse events in a cesarean for patient $i - 1$</td>
<td>0.0106 &amp; (0.0218)</td>
</tr>
<tr>
<td>2+ (vs. 0) adverse events in a cesarean for patient $i - 1$</td>
<td>0.0099*** &amp; (0.0240)</td>
</tr>
<tr>
<td>1-2 (vs. 0) adverse events in a vaginal for patient $i - 1$</td>
<td>-0.0026 &amp; (0.0104)</td>
</tr>
<tr>
<td>2+ (vs. 0) adverse events in a vaginal for patient $i - 1$</td>
<td>-0.0035 &amp; (0.0157)</td>
</tr>
<tr>
<td><strong>PANEL C: Effect of prior adverse events (falsification test)</strong></td>
<td></td>
</tr>
<tr>
<td>1-2 (vs. 0) adverse events in a cesarean for patient $i - 1$</td>
<td>0.0113 &amp; (0.0186)</td>
</tr>
<tr>
<td>2+ (vs. 0) adverse events in a cesarean for patient $i - 1$</td>
<td>-0.0196 &amp; (0.0318)</td>
</tr>
<tr>
<td>1 (vs. 0) adverse events in a vaginal for patient $i - 1$</td>
<td>0.0074 &amp; (0.0077)</td>
</tr>
<tr>
<td>2+ (vs. 0) adverse events in a vaginal for patient $i - 1$</td>
<td>-0.0132 &amp; (0.0170)</td>
</tr>
<tr>
<td><strong>PANEL D: Duration of effect of prior adverse events</strong></td>
<td></td>
</tr>
<tr>
<td>1-2 (vs. 0) adverse events in a cesarean for patient $i - 2$</td>
<td>0.0112 &amp; (0.0187)</td>
</tr>
<tr>
<td>2+ (vs. 0) adverse events in a cesarean for patient $i - 2$</td>
<td>-0.0199 &amp; (0.0321)</td>
</tr>
<tr>
<td>1 (vs. 0) adverse events in a vaginal for patient $i - 2$</td>
<td>0.0074 &amp; (0.0077)</td>
</tr>
<tr>
<td>2+ (vs. 0) adverse events in a vaginal for patient $i - 2$</td>
<td>-0.0132 &amp; (0.0170)</td>
</tr>
<tr>
<td><strong>PANEL E: Effect of unexpectedness of prior clinical outcome</strong></td>
<td></td>
</tr>
<tr>
<td>Effect of unexpectedness when patient $i - 1$ has a cesarean with:</td>
<td></td>
</tr>
<tr>
<td>0 adverse events</td>
<td>0.0121 &amp; (0.00924)</td>
</tr>
<tr>
<td>1 adverse events</td>
<td>0.1633 &amp; (0.1202)</td>
</tr>
<tr>
<td>2+ adverse events</td>
<td>0.0516 &amp; (0.0802)</td>
</tr>
<tr>
<td>Effect of unexpectedness when patient $i - 1$ has a vaginal with:</td>
<td></td>
</tr>
<tr>
<td>0 adverse events</td>
<td>0.0227 &amp; (0.00465)</td>
</tr>
<tr>
<td>1 adverse events</td>
<td>0.0128 &amp; (0.00284)</td>
</tr>
<tr>
<td>2+ adverse events</td>
<td>-0.0826 &amp; (0.01030)</td>
</tr>
</tbody>
</table>

Demographic controls: Y Y Y Y Y
Physician fixed effects: Y Y Y Y Y
Time fixed effects (Year, Month, Week): Y Y Y Y Y
N: 11,855 11,855 11,127 11,812 11,843

All entries are effect sizes. Controls include emergency c-section indicator, age, race, ethnicity, Elixhauser comorbidity scores, insurance status, and maternal parity. Heteroskedasticity-robust standard errors are clustered at the physician level.

*: p < 0.10; **: p < 0.05; ***: p < 0.001
I estimate the following multinomial logit equation separately for prior cesarean deliveries and prior vaginal deliveries:

$$P(\text{Response}_{ijt} = K) = \frac{1}{1 + \sum_{k=1}^{2} e^{\beta_k AE(i-1)j + \phi_i + \gamma_j + \tau_t}} \quad (5)$$

The values of $\beta_k$ are plotted separately for prior cesareans deliveries and prior vaginal deliveries in Figure IV. When the prior patient’s delivery-mode is cesarean and there are no adverse events, then the physician has a 27% chance of not switching delivery-modes (bottom left box), a 44% of switching to the Expected delivery-mode (bottom middle box), and a 29% chance of switching to the Unexpected delivery-mode (bottom right box) on the next patient. However, when there are 2+ adverse events in the prior patient’s cesarean’s delivery, then the physician has a 17% chance of not switching delivery-modes, a 43% of switching to the Expected delivery-mode, and a 39% chance of switching to the Unexpected delivery-mode on the next patient.

This analysis uses crude proxies for delivery-mode choice “appropriateness”. Moreover, I am estimating coefficients for 18 different groups (of which several have sparse data), due to which estimates are likely imprecise. Despite this, results from Equation 5 echo the results from sections 3.1.1 and 3.1.2: 1) physicians are more likely to switch overall, but especially to the Unexpected delivery-mode, after an adverse event in either delivery-mode; and 2) physicians are more responsive to adverse events in prior cesarean deliveries than prior vaginal deliveries.

**Duration of the effect of adverse events**

I examine the duration of the effect of an adverse event on subsequent physician delivery-mode choice. The results, presented in Table III Panel D Column (4), indicate that the effects of adverse clinical events last only for one patient, i.e., the physician’s delivery-mode choice for patient $i$ is influenced by patient $(i-1)$ but not patient $(i-2)$. The transient nature of this effect is an indication that physician switching is an emotional response to adverse events.

**Unexpectedness of adverse event**

I also examine whether physicians’ propensity to switch delivery-modes depends on the unexpectedness of prior adverse event. Physicians may be perfectly or imperfectly adjusting for risk factors when assessing why an adverse event occurred before updating their beliefs about the risk of a specific delivery-mode, and may thus respond differently to expected vs. unexpected adverse outcomes. Methods are presented in detail in Appendix A1. Results in Table III Panel E show that unexpectedness of prior adverse event does not moderate its effect on subsequent delivery-mode choice. However, it is possible that physicians may be risk-adjusting in ways that are not accurately captured by the EHR data and my model.
FIGURE IV
Physician Response to Prior Adverse Events, Further Decomposed into Expected and Unexpected Switches

Note: This graph presents the effect of adverse events in a prior vaginal delivery (top row) and a prior cesarean delivery (bottom row) on a physician’s likelihood of: 1) not switching delivery-mode (left column); 2) switching to the Expected delivery-mode (middle column); and 3) switching to the Unexpected delivery-mode (right column), on the subsequent patient.
3.2 The impact of prior adverse clinical events on treatment intensity and patient outcomes

If physicians are switching delivery-modes in response to adverse events, they are likely also changing other aspects of their care as well. For instance, in the immediate aftermath of an adverse event, they might ramp up the intensity of the treatment they provide subsequent patients to avoid incurring the next patient any harm and/or to avoid looking incompetent to regulators.

Any changes in physician care patterns induced by adverse events may also ultimately affect subsequent patient outcomes in unprecedented ways. In this section, I hypothesize that prior adverse events are associated with i) physicians increasing subsequent treatment intensity and ii) changes in subsequent patient outcomes. However, the direction of the latter effect is unclear because emotional responses may make the physician either more careful (and less likely to make mistakes, thereby improving patient outcomes) or less confident (and more likely to make mistakes, thereby worsening patient outcomes). To ensure that changes in patient outcomes are not driven by underlying trends in patient severity (e.g., due to potential patient selection efforts by the physician), I also report the effects of prior adverse events on subsequent patient Elixhauser readmission scores$^{10}$.

I estimate the following linear probability model:

\[ \text{Outcome}_{ijt} = \beta V a r + M o A E_{(i-1)j} + \phi_t + \gamma_j + \tau_t + \epsilon_{ijt} \]  

(6)

where \( \text{Outcome}_{ijt} \) captures measures of treatment intensity (charges per inpatient day, number of obstetricians and non-obstetrician specialists involved in the care encounter, and patient length of stay), patient health outcomes (90-day readmission, adverse obstetric events$^{11}$), and measures of patient acuity (Elixhauser readmission scores). The coefficient of interest is \( \beta \), whose interpretation depends on which of the three independent variables, described below, is being used.

3.2.1 The effect of an adverse event

I use the full patient sample to examine the effects of simply a prior adverse event on subsequent physician behavior and patient outcomes. Thus, in Equation 6, \( V a r = 1 (A E_{(i-1)j}) \). The results are presented in Table IV Panel A. The coefficient on the adverse event variable, 0.009, indicates that

$^{10}$ (which is a weighted sum of 29 comorbidities, with score values in this sample ranging from -4 to 51)

$^{11}$ This may at first glance appear similar to a dynamic optimization problem where the physician has to maximize patient outcomes over time, and may experiment with treatment choices in order to maximize learning over time (similar to theory outlined in Currie and MacLeod (2018)'s paper on physician prescription behavior). However, I argue that this argument is not valid in the obstetric setting because this is not a setting conducive to “experimenting”: the costs of experiments are likely too high (e.g., maternal/neonatal mortality and lifetime morbidity, high risk of litigation etc), there are not enough repeat chances with the same patient to learn, and it is a highly noisy setting where patient outcomes are not always informative signals of delivery-mode appropriateness. As a result, physicians are unlikely to be trading off current adverse events for improvements in long-term performance, making this unlikely to be a dynamic optimization problem from the physician’s perspective. In fact, it is interesting to simply consider whether an adverse clinical event pushes a physician into a type of “downward confidence spiral” which leads to a chain of bad patient outcomes.
patient charges are significantly about 1 percent higher if the prior patient treated by the physician experienced an adverse event. However, prior adverse events have no effects on other measures of treatment intensity or patient health outcomes. Moreover, it does not have any effect on patient comorbidity score, providing support for my identifying assumption that physicians are unlikely to be choosing clinically easier patients after adverse events.

**TABLE IV**

**EFFECT OF PRIOR AdVERSE EVENTS AND SWITCHING BEHAVIOR ON TREATMENT INTENSITY AND PATIENT OUTCOMES**

<table>
<thead>
<tr>
<th>Dependent Vars (for patient i)</th>
<th>Log charges per day</th>
<th># Non-OB specialists</th>
<th># OB specialists</th>
<th>Length of Stay</th>
<th>90-day readmission</th>
<th>Any adverse event</th>
<th>Comorbidity score</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. ( AE_{(i-1)jt} )</td>
<td>0.0098***</td>
<td>0.0056</td>
<td>-0.0254</td>
<td>-0.0310</td>
<td>0.0002</td>
<td>0.0024</td>
<td>-0.0541</td>
<td>12,995</td>
</tr>
<tr>
<td>(Adverse event in prior patient)</td>
<td>(0.0044)</td>
<td>(0.0130)</td>
<td>(0.0177)</td>
<td>(0.0439)</td>
<td>(0.0028)</td>
<td>(0.0088)</td>
<td>(0.0992)</td>
<td></td>
</tr>
<tr>
<td>B. ( Switch_{ijt} )</td>
<td>0.0491***</td>
<td>0.2049***</td>
<td>0.0872*</td>
<td>0.5618***</td>
<td>0.0108**</td>
<td>0.0795***</td>
<td>0.2762</td>
<td>3,782</td>
</tr>
<tr>
<td>(Switch delivery mode)</td>
<td>(0.0121)</td>
<td>(0.0312)</td>
<td>(0.0489)</td>
<td>(0.1334)</td>
<td>(0.0047)</td>
<td>(.0173)</td>
<td>(0.2534)</td>
<td></td>
</tr>
<tr>
<td>C. ( Switch_{ijt} \cdot Unexp_{ijt} )</td>
<td>0.0646**</td>
<td>0.1859***</td>
<td>-0.0782</td>
<td>0.0702</td>
<td>0.0055</td>
<td>0.0963**</td>
<td>-</td>
<td>3,782</td>
</tr>
<tr>
<td>(Switch to Unexpected delivery-mode)</td>
<td>(0.0217)</td>
<td>(0.0546)</td>
<td>(0.0868)</td>
<td>(0.1331)</td>
<td>(0.0133)</td>
<td>(0.0392)</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>

All entries are regression coefficients. Analyses in Panels B and C are limited to patients that are seen subsequent to an adverse event. Covariates include age, race, ethnicity, Elixhauser comorbidity scores, insurance status, history of prior cesareans, maternal parity and an emergency c-section indicator. Includes year fixed effects. Heteroskedasticity-robust standard errors are clustered at the physician level.

∗: p < 0.10; ∗∗: p < 0.05; ∗ ∗ ∗: p < 0.001

3.2.2 The effect of switching delivery-modes after an adverse event

Since switching delivery-modes is an observable response to prior adverse events, patterns of care and patient outcomes should theoretically change more when physicians switch delivery-modes than when they do not switch delivery-modes after an adverse event. I examine this question by limiting the dataset to only those patients who are seen after a prior adverse event, e.g., patient \( ij \) is only in the analytic sample if patient \( (i-1)j \) had an adverse event. The primary reason I limit it to this subset of patients is because I can reasonably assume from previous sections that physician switching behavior in this sample is driven by prior adverse outcomes. When there are no prior adverse events, physicians still have a baseline level of switching delivery-modes which may be driven by randomness or by unobservable adverse events – adding noise to the estimated effects of adverse events on physician behavior.
I examine the effect of switching delivery-modes on my outcomes of interest on this restricted sample, i.e., $Var = Switch_{ijt}$ in Equation 6. The results, presented in Table IV Panel B, suggest that a physician who switches after an adverse event behaves differently than when she does not switch after an adverse event. Specifically, when the physician does switch delivery-modes for a patient after a prior adverse event, that patient also has (significantly) about 5 percent higher daily charges, 0.2 more non-obstetric specialists, and a longer length of stay by 0.6 days. These effects do not appear to be driven by changes in underlying patient severity, as shown by the positive and insignificant effect of physician switching behavior on the current patient’s comorbidity score (which again suggests that physicians are exerting little influence on the order of patients). Finally, despite the lack of observable changes in patient acuity, switching delivery-modes significantly increases the probability of the physician’s current patient being readmitted within 90 days by about 1 percentage point, and the current patient’s probability of an adverse obstetric event by 8 percentage points. In other words, when a physician switches delivery-modes for patient $i$ after an adverse event in patient $(i-1)$, patient $i$ receives greater treatment intensity and experiences worse outcomes than when the physician does not switch delivery-modes.

### 3.2.3 The effect of switching to the Unexpected delivery-mode after an adverse event

Finally, I test whether treatment intensity and patient outcomes are different when a physician switches to the Unexpected delivery-mode versus when she switches to the Expected delivery-mode. Simply switching delivery-modes may be less indicative of an emotional physician response than an incorrect match between patient type and procedure. Thus, I again restrict the sample to only patients following a prior adverse event, and estimate Equation 6 with $Var = Switch_{ijt} \cdot UnexpMoD_{ijt}$. I do not calculate the effect of this interaction on patient comorbidity scores, since they are used for construction of the indicators for delivery-mode expectedness (i.e., $UnexpMoD_{ijt}$).

Table IV Panel C presents the results of this analysis. They solidify the results from prior panels by showing that the effects on treatment intensity and patient outcomes due to physician switching may be largely driven by the physician switching to the Unexpected delivery-modes. Specifically, switching to the Unexpected delivery-mode (vs the Expected delivery-mode) is associated with an increase in daily inpatient charges by 6 percent, number of non-obstetric specialists by 0.2, and increases probability of an adverse obstetric event by 9.6 pp.

### 3.3 Robustness checks

My methods do not account for time elapsed between a physician’s patients $ij$ and $(i+1)j$, i.e., they do not differentiate if consecutive patients are separated by one hour or by several days. Moreover, a
physician may be affiliated with other hospitals, meaning that there may be unobserved patients seen between the apparently consecutive patients in my dataset. To limit the extent to which time and unobserved patients dilute the estimated effect, I limit my dataset to only consecutive deliveries that overlap or begin within 27 hours of each other (to proxy for a single, long physician shift). The results from this analysis are presented in Appendix Table B.4. The results do not change in significance, though the switching response to adverse events increases in magnitude. This is consistent with my hypothesis, and suggests that physicians may be more prone to this bias when they are tired during long shifts, though “sleeping it off” attenuates it only slightly.

It is possible that the coding of the type of cesarean itself is subject to manipulation. Failed or prolonged labor is commonly cited to be a highly abused reason for emergency cesareans. If so, then the Mode of Adverse Event for an adverse event in an observed emergency cesarean will be classified as a vaginal delivery, when in fact the physician would be overreacting to an adverse event in a cesarean delivery (because she made the erroneous decision to conduct a cesarean when it was not necessary). I reclassify the Mode of Adverse Event for all emergency c-sections with failed or prolonged labor as cesarean deliveries, but again, results (presented in the Appendix Table B.2) do not change in significance.

4 IS PHYSICIAN RESPONSE TO ADVERSE EVENTS BAYESIAN?

In the last section, I presented evidence that prior adverse clinical outcomes cause a physician to switch delivery-modes and increase treatment intensity for the next patient, which is turn, is associated with worse patient outcomes. While these results suggest that physician switching behavior is not an optimal response in the short-run, I now formally examine whether these responses are consistent with Bayesian updating. Specifically, I derive qualitative predictions from a model of optimal Bayesian learning in 4.1, and then empirically test whether these predictions hold in the sample in Section 4.2.

4.1 Conceptual Framework

Suppose there are two patient-types $p \in \{a, b\}$ and two delivery-modes $d \in \{A, B\}$ in a two period model. The true match value of a delivery-mode for a patient-type is unobserved and denoted by $M_{dp} \in R$ where greater match values indicate greater appropriateness of delivery-mode choice for a patient-type. The physician has prior beliefs regarding the mean of the distribution of match values, which are distributed normally: $M_{dp} \sim N(\mu_{dp}, \sigma_{dp}^2)$, where $\sigma_{dp}^2$ is the uncertainty of the physicians’ beliefs about the match value. The priors for each patient-type and procedure are uncorrelated with
those for the others, i.e., updates in priors for one patient-type and one delivery-mode will not affect
the priors for the others.

Suppose, for example, in period 1, the physician observes patient-type $a$ and chooses the
delivery-mode which maximizes the expected value of $M_{dp}$. According to the physician’s initial priors,
since $\mu_A \geq \mu_B$ for patient type $a$, she chooses delivery-mode $A$ for the patient in period 1. Then, the
physician observes the patient’s clinical outcome $y_1$, which is a normalized measure such that positive
values denote positive outcomes and negative values denote adverse outcomes. In other words, the
physician observes the true match value with some error:

$$y_1 = M_{Aa} + \epsilon_1$$  \hspace{1cm} (7)

where the normally distributed, mean-zero error term $\epsilon \sim N(0, \sigma^2_\rho)$ means that the patient’s clinical
outcome $y$ depends in part on physician ability, such as how well she is able to identify patient
type and/or perform the chosen delivery-mode. The value of $\sigma^2_\rho$ is intrinsic to a physician, decreases
with increasing physician ability, and remains constant over time within- physician. Finally, prior
to choosing a delivery-mode for the next patient in period 2, the physician incorporates signal $y_1$ to
update her beliefs about the distribution of match values for delivery-mode $A$ over patient type $a$ to
yield a posterior distribution with the following parameters:

$$\mu_A(y_1) \equiv \frac{\mu_A \sigma^2_\rho + y_1 \sigma^2_A}{\sigma^2_\rho + \sigma^2_A}$$  \hspace{1cm} (8)

$$\sigma^2_A(y_1) \equiv \frac{1}{\text{var}(M_A|y_1,a)} = (\sigma^2_\rho + \sigma^{-2}_A)^{-1}$$  \hspace{1cm} (9)

If the next patient in period 2 is of type $a$, a physician will switch to delivery-mode $B$ if and only if
$E[M_B|y_1,a] > E[M_A|y_1,a]$. That is:

$$P[\text{Switch}_2|y_1,a] = P[\mu_B - (\mu_A|y_1,a) > 0]$$

$$= P\left[\mu_B - \frac{1}{\sigma^2_A + \sigma^2_\rho} (\mu_A \rho_A + y_1 \rho) > 0\right]$$

$$= P\left[\mu_B - \mu_A \left(\frac{\sigma^2_\rho}{\sigma^2_A + \sigma^2_\rho}\right) - y_1 \left(\frac{\sigma^2_A}{\sigma^2_A + \sigma^2_\rho}\right) > 0\right]$$

As $\sigma^2_\rho$ increases (= the physician becomes low ability), the Term I (which can range from 0 to 1)
approaches 1, and Term II (which can also range from 0 to 1) approaches 0. This increases the
weight the physician places on her priors when making the decision. As $\sigma^2_\rho$ decreases (= the physician
becomes high ability), Term I approaches 0, and Term II approaches 1. This increases the weight
the physician places on the data when making the decision. Therefore, increasing physician ability
decreases likelihood of switching delivery-modes over time because it is less dependent on data, and
more dependent on initial physician priors\textsuperscript{12}.

Extrapolating from this two-period model, if the physician has seen \( n \) patients of type \( a \), the
probability of the physician switching delivery-modes on patient \( (n + 1) \) who is also patient-type \( a \)
becomes:

\[
P[\text{Switch}_{(n+1)|y_n}] = P\left[ \mu_B - \mu_A \left( \frac{\sigma_a^2}{n\sigma_A^2 + \sigma^2} \right) - n\overline{y}_n \left( \frac{\sigma_A^2}{n\sigma_A^2 + \sigma^2} \right) > 0 \right]
\]  

(13)

As \( n \) increases (i.e., physician seen more patients), the data (= Term II) begin dominating the priors
(= Term I) in the physician delivery-mode decision. So if with the \( n^{th} \) patient, the physician observes
on average negative outcomes for patient-type \( a \) (i.e., \( \overline{y}_n \) dips below 0) she will be more likely to
switch delivery-modes on patient \( (n + 1) \). Assuming the clinical outcomes are informative, however,
the physician will converge to the “true” match value over time and eventually stop switching delivery-
modes for patient type \( a \). As suggested by Equation 12, this convergence is faster when the physician
is high ability compared to low ability\textsuperscript{13}.

The qualitative predictions from this model are simple, and can be deduced from Equations 12
and 13: 1) As the physician sees more patients, she will switch delivery-modes less frequently (assuming
the clinical outcomes are informative); and 2) low ability physicians will take longer to converge to
the “true” match values, and will thus switch more frequently than high ability physicians. I test
these predictions empirically in the next section. If physicians are Bayesian learners, then observed
switching response in the data should adhere to these predicted switching patterns.

4.2 Is observed physician switching behavior Bayesian?

4.2.1 Role of physician experience

To test the first prediction regarding differential rates of switching by number of patients seen, I use
a continuous measure of physician experience: years since the physician’s board certification.

Using the following linear probability model, I estimate the effect of the marginal year of

\textsuperscript{12}In this setup, I assume that confidence in one’s priors are an appropriate measure of physician ability in that they measure
uncertainty around unbiased estimates of the true match value. Of course, one can think of instances where this is an inappropriate
measure. However, to the extent that priors are biased estimates of the true match value, this will only cause the individual to
further deviate from Bayesian optimality.

\textsuperscript{13}This model predicts switching probabilities assuming the physician sees only one type of patient consecutively. That we
empirically observe physician switching behavior on consecutive patients is already indication that the physician is not behaving
in a Bayesian manner because it is unlikely that all the patients seen by the physician are of the same type.
experience \((Exp_j)\) on a physician’s likelihood of switching delivery-modes:

\[
Switch_{ijt} = AE_{(i-1)j} + Exp_j + \beta AE_{(i-1)j} \cdot Exp_j + \sum_{n=i-1}^{j} \phi_n + MoAE_{(i-1)j} + \tau_t + \epsilon_{ijt} \tag{14}
\]

If the observed switching behavior is a result of Bayesian learning, then the marginal year of experience should reduce a physician’s switching response to prior adverse events. In other words, \(\beta\) should be significantly negative. In Table V Panel A, I find that the marginal year of experience insignificantly reduces the physician’s likelihood of switching delivery-modes after an adverse event by 0.04 percentage points. I conclude that observed switching behavior on the marginal patient is inconsistent with the first prediction of the Bayesian updating model.

**TABLE V**
IS PHYSICIAN BEHAVIOR CONSISTENT WITH BAYESIAN UPDATING?

| Independent Variables | \(Switch_{ijt}\) & \(AE_{ijt}\) & \(90Readm_{ijt}\) |
|-----------------------|--------|--------|-------------|
| **Panel A**           |        |        |             |
| Adverse event in prior patient \((AE_{(i-1)j})\) | 0.0127 |        |             |
| Physician years of experience \((Exp_j)\) | -0.0007 |        |             |
| Adverse Event in prior patient \(\cdot\) Physician years of experience \((AE_{(i-1)j} \cdot Exp_j)\) | -0.0004 |        |             |
| **Panel B**           |        |        |             |
| Adverse event in prior patient \((AE_{(i-1)j})\) | -0.4150 |        |             |
| Physician ability \((\hat{Abil}_j)\) | -0.0329 |        |             |
| Adverse event in prior patient \(\cdot\) Physician Ability \((AE_{(i-1)j} \cdot \hat{Abil}_j)\) | 0.4081 |        |             |
| **Panel C**           |        |        |             |
| Physician propensity to switch \((\hat{PropSwitch}_j)\) | -0.0046 | -0.0015 |             |
|                     |        |        |             |
| **Panel D**           |        |        |             |
| Physician propensity to switch over time \((\hat{PropSwitch}_j \cdot Numpat_{ijt})\) | -0.0001 | 1.27e-06 |             |

All entries are regression coefficients. Covariates include age, race, ethnicity, Elixhauser comorbidity scores, insurance status, history of prior cesareans, and maternal parity. Analyses include year fixed effects. Heteroskedasticity-robust standard errors are clustered at the physician level.

*: \(p < 0.10\); **: \(p < 0.05\); ***: \(p < 0.001\)

### 4.2.2 Role of physician ability

To test the second prediction regarding differential rates of switching between high and low ability physicians, it is necessary to be able to distinguish intrinsic physician ability (that is unrelated to
experience). I use a crude measure - specifically, high rates of unexpected adverse events in early career physicians - to proxy for physician ability. This measures is likely highly noisy but should capture differences in behavior between low and high ability physicians on average. Since my chosen obstetric events are sensitive to clinical performance, their unexpected occurrence should signal poor physician performance.

I limit this analysis to early-career physicians because using adverse events as a proxy for ability in late-career physicians is likely endogenous. High ability physicians who have been practicing for many years may have distinguished themselves as particularly adept at obstetrics and may thus be assigned to the most difficult cases, which would spuriously make their adverse event rate high. However, this selection issue may be less severe for newly practicing physicians who get assigned cases at random because they have not yet had a chance to develop a reputation based on ability. As a result, in order to test the second prediction, I assume that high rates of unexpected adverse events in early-career physicians are more likely to be driven by low ability than selection effects. I conduct this analysis using a 2-stage regression. The first stage estimates ability, and the second stage examines the average effect of innate ability on physician likelihood of switching delivery-modes in response to prior adverse events.

In my first stage, I estimate a linear probability model on the entire sample of encounters (Equation 15) to calculate each patient’s likelihood of experiencing an adverse obstetric event. Then, after limiting the dataset to only encounters with physicians who have received their board certification in the last five years, I calculate $\hat{\text{Abil}}_j$ for each physician as a proxy for ability. $\hat{\text{Abil}}_j$ is the physician-specific mean residual probability of adverse events (i.e., how likely were the observed adverse events) for each physician $j$ who sees a total of $N_j$ patients (Equation 16). Specifically:

$$1(AE_i) = \phi_i + \tau_t + \epsilon_{it}$$  \hspace{1cm} (15)

$$\hat{\text{Abil}}_j = 1 - \frac{1}{N_j} \sum_{i=1}^{N_j} (1(AE_{ij}) - \bar{AE}_{ij})$$  \hspace{1cm} (16)

$\hat{\text{Abil}}_j$ is a continuous measure of innate physician ability. As the average residual term becomes more positive (i.e., the physician experiences more unexpected adverse events) and $\hat{\text{Abil}}_j$ becomes less positive, physician ability decreases. As the average residual term becomes less positive (i.e., the physician experiences more expected adverse events) and $\hat{\text{Abil}}_j$ becomes more positive, physician

---

14There is another advantage in using early career physicians. It is possible that knowledge of own low ability actually reduces the likelihood that a physician will switch delivery-modes because each adverse event relays less information and causes a smaller update of physician priors. However, early-career physicians are unlikely to know their own ability, and as a result, this counter-effect is likely to be absent in this analysis.

15I do not control for delivery-mode in the first stage because I wish to proxy a physician’s innate ability in identifying patient-type and performing the procedure. Conditioning on delivery-mode would inform me about the physician’s ability to perform a delivery-mode, but not necessarily her ability to identify patient-type.
ability increases.

In the second stage, I estimate Equation 14 where I substitute $\hat{Abil}_j$ for $Exp_j$, using bootstrapped standard errors to correct for 2-stage estimation error. In Panel B of Table V I present the results of the second stage equation and find that the increasing physician ability does not attenuate physician switching behavior. Specifically, increasing physician ability by 1 point insignificantly increases a physician’s likelihood of switching after an adverse event by 40 percentage points. This is contrary to the predictions from the Bayesian model.

4.2.3 Role of informativeness of clinical outcomes

The Bayesian model predicts that physicians should stop switching delivery-modes as they see more patients. However, this prediction is contingent on clinical outcomes being informative signals of match value. It is possible that observed clinical outcomes are highly noisy or biased, and therefore uninformative. If so, switching delivery-modes frequently, regardless of number of patients seen, may be a Bayesian response. While it is difficult to test whether the clinical outcomes are informative signals of match values, I can test whether switching behavior in this environment is a plausibly Bayesian response.

In the previous section, I examined predictions from the Bayesian learning model about which types of physicians should switch more than others. Those analyses focus on the heterogeneity in switching response. In this section, I instead look at the consequences (rather than the determinants) of switching. If switching in response to adverse events represents Bayesian learning, then such switching should manifest in improved patient outcomes over time. I test this hypothesis using a two-stage model to examine whether increasing physician propensity to switch affects the physician’s i) average patient outcomes during my data period, and ii) rate of change in patient outcomes over my data period. The former tests whether physicians who switch more have better outcomes on average. The latter tests whether physicians who switch more show the greatest improvements in patient outcomes over time.

The first stage in the regression estimates the standardized effect of prior adverse events on subsequent switching separately for each physician. The second stage estimates the relationship between the estimated stage I coefficient and patient outcomes (specifically, adverse obstetric events and 90-day readmission) for the whole sample of patient encounters\(^{16}\).

\(^{16}\)When the dependent variable in the second stage is adverse events, there may be reverse causality if the estimated coefficient from the first stage has a non-linear effect on physician switching response. Or, the relationship may simply be tautological. Physicians switch more because they have more adverse events to switch after, which then translates to them having a higher rate of adverse events than those who switch less. However, there are four reasons why this is not likely to be the case: 1) I test this assumption and find that the relationship is non-convex; 2) In my first stage equation, I compute a physician-specific, standardized value that measures a physician’s propensity to respond to an adverse event. This value is not influenced by the absolute number of adverse events seen by a physician, and therefore captures a relationship that is entirely different from what is captured by my second-stage equation; 3) The estimates presented in Table V are insignificant, which would not be the case were there some underlying mechanical relationship; and 4) I include another measure of patient outcomes - 90 day readmission - which should be free of such methodological issues. It gives the same types of results as when I use adverse obstetric events.
Specifically, for each physician $j$ I separately estimate Equation 17:

$$Switch_{it} = \beta AE_{(i-1)t} + \sum_{n=i-1}^{i} \phi_{nt} + MoAE_{(i-1)t} + \tau_{t} + \epsilon_{it}$$

Then I compute $\hat{PropSwitch}_{j} = \frac{\hat{\beta}_j}{\hat{\sigma}_{\beta_j}}$ (which is simply the t-statistic of the coefficient of interest).

In the second stage, I estimate the following linear probability model, using bootstrapped standard errors:

$$Var_{ijt} = \beta \hat{PropSwitch}_{j} + NumPat_{ijt} + \hat{PropSwitch}_{j} \cdot NumPat_{ijt} + MoAE_{ij} + \phi_{i} + \tau_{t} + \gamma_{j} + \epsilon_{ijt}$$

$Var_{ijt}$ is an indicator for either adverse obstetric events or 90-day readmission. Terms in the square brackets, where $NumPat_{ijt}$ signify number of patients seen by the physician thus far in the dataset, are added in additional models to estimate within-physician slopes of patient outcomes over time. The average effects of switching propensities on patient outcomes are presented in Columns (3) and (4) of Table V Panel C. The changes in patient outcomes over time are presented in Table V Panel D. The estimates for the main and additional models are statistically and economically insignificant, suggesting that physicians with greater propensities to switch after adverse events neither have better patient outcomes on average, or show significantly greater improvement in patient outcomes over time.

Section 3.2 showed that switching delivery-modes after adverse events results in worse patient outcomes on the next patient. This section provides additional evidence that frequently switching delivery-modes does not lead to better outcomes over time, invalidating the theory that physicians might be trading-off short-term costs for long-term learning (though as previously mentioned, the obstetric setting is not ideal for this type of trade-off because of the high short-term costs of experimentation). Taken together, the results from this section attest that switching behavior after adverse events is unlikely to be a Bayesian response.

5 CONCLUSION

Physicians wield considerable influence over their patients’ lives. They are entrusted with making serious, life-changing decisions that the patient is incapable of (or unqualified to be) making. As such, they are expected to base these decisions on diagnostic factors, such as patient symptomology and disease etiology, to provide care that is both efficient and equitable. However, in this paper, I examine physician decision-making in the obstetric setting and find evidence that physicians are influenced by non-diagnostic factors – such as recent, salient adverse obstetric events – in a way that

\[\text{i.e., NumPat}_{ijt} = 3 \text{ if patient } i \text{ is the third patient seen by physician } j \text{ in the dataset.}\]
is not consistent with Bayesian learning and actually harms patients.

These results have several implications for physician training and decision choice architecture. For instance, results suggest that physicians and patients might benefit from targeted organizational policies that nudge physicians into explicitly confront their biases (Emanuel et al., 2016), such as encouraging them to document their delivery-mode choices or via peer comparisons. However, physicians have expressed dissatisfaction with the ever-increasing burden of documentation (Newkirchen and Elsner, 2018) and an expansive literature also suggests that any increase in public monitoring induces distortions in physician behavior, such as cream skimming and provision of inappropriate care (Werner and Asch, 2005).

The results of this study can also be framed within the discussion of technology use in healthcare. Technology has already been used, both in research and practice, to improve a host of hospital processes and assist in clinical decision-making. One could argue that analytics and technology can be leveraged to reduce behavioral biases in clinical practice as well. However, the potential of this policy is once again underscored by evidence showing that physicians are often resistant to new technology, either due to mistrust or cumbersome technology design (Goldsmith, 2000; Wang and Huang, 2012).

Finally, and most importantly, the results speak to ongoing discussions about whether medical curricula should incorporate training in decision-making under uncertainty. Hall (2002) provides an anecdotal example in support of this inclusion: in a class taught on this topic, medical students were susceptible to almost all the behavioral fallacies and biases documented in decision theory. However, after being made aware of these errors in judgement, they were much less likely to make them again. The greatest contribution of this study may thus be to document and garner awareness of a decision choice that is susceptible to bias, which may in turn lead to improved physician decision-making over time.

This study raise several questions about physician decision-making that are yet to be answered. For example, it is unclear whether physicians are susceptible to similar biases in other high-pressure clinical environments with significant uncertainty, such as surgery and intensive care. If so, a relevant and natural next question would be to examine ways in which these biases can be attenuated. Another important question is whether such biases are simply a Bayesian response to the high cognitive load, malpractice environment, shortage of medical professionals, and burnout experienced by physicians. This would be in line with prior research suggesting that the use of some heuristics may be rational - or “adaptive” - in the long-term (Hart, 2005). Given that physicians are always juggling personal, organizational, and patient priorities at the same time, further research needs to be conducted into the extent to which these heuristics are adaptive and the extent to which they cause damaging but avoidable errors.
Bibliography


Brian J Moore, Susan White, Raynard Washington, Natalia Coenen, and Anne Elixhauser. Identifying


Amy D Waterman, Jane Garbutt, Erik Hazel, William Claiborne Dunagan, Wendy Levinson, Victoria J Fraser, and Thomas H Gallagher. The emotional impact of medical errors on practicing


APPENDICES

A Detailed Methods

A.1 The impact of unexpectedness of prior clinical outcomes on subsequent choice of delivery-mode

I first create a measure to account for the “unexpectedness” of (both positive and negative) clinical outcomes of the prior patient using a two-step process. In step 1, I regress all patients’ adverse outcome status on patient characteristics to extract the residual, i.e., the magnitude of the difference between the outcome that is observed and the outcome that is expected. Since the value of the residual captures a greater degree of unexpectedness the farther away it moves from zero in either direction (more positive values indicate more unexpectedly positive outcomes while more negative values indicate more unexpectedly negative outcomes), I take the absolute value of the residual to create a monotonically increasing measure of overall unexpectedness, regardless of valence: Step 1:

\[ AE_{ijt} = \phi_i + \gamma_j + \delta_t + \epsilon_{ijt} \]  \hspace{1cm} (A.1)

Using the residuals from this equation, I create \( \text{Resid}_{ijt} \) which is equal to \( \|AE_{ijt} - \bar{AE}_{ijt}\| \) calculated from Equation A.1. The greater the value of \( \text{Resid}_{ijt} \), the more “unexpected” the patient outcome is.

In step 2, I regress physician \( j \)'s current patient’s Mode of Delivery on the absolute value of their last patient’s residual (i.e., \( \text{Resid}_{(i-1)jt} \)), adverse event status, Mode of Adverse Event, and all their respective interactions. This allows me to see whether the effect of patient \( (i-1) \)'s clinical outcome on patient \( i \)'s Mode of Delivery depends on the “unexpectedness” of patient \( (i-1) \)'s clinical outcome. Specifically:

Step 2:

\[ MoD_{ijt} = \beta_1 AE_{(i-1)j} + \beta_2 MoAE_{(i-1)j} + \beta_3 Resid_{(i-1)j} \]
\[ + \beta_4 [AE_{(i-1)j} \cdot MoAE_{(i-1)j}] + \beta_5 [AE_{(i-1)j} \cdot Resid_{(i-1)j}] + \beta_6 [MoAE_{(i-1)j} \cdot Resid_{(i-1)j}] \]
\[ + \beta_7 [AE_{(i-1)j} \cdot MoAE_{(i-1)j} \cdot Resid_{(i-1)j}] + \phi_i + \gamma_j + \delta_t + \epsilon_{ijt} \]  \hspace{1cm} (A.2)

I am interested in the effect of unexpectedness of prior clinical outcome (i.e., the change in \( \text{Resid}_{(i-1)j} \)) on the probability of current vaginal delivery. If physicians are responding to unexpected outcomes more than expected outcomes: i) increasing the \( \text{Resid}_{(i-1)jt} \) of an adverse event in a prior cesarean should positively impact the probability of a current vaginal delivery; and ii) increasing the \( \text{Resid}_{(i-1)jt} \) of an adverse event in a prior vaginal should negatively impact the probability of a current vaginal delivery.
<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Dep Var: Vaginal delivery in patient $i$ (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td># adverse events in a cesarean for patient $i - 1$ (marginal effect)</td>
<td>0.0293***</td>
</tr>
<tr>
<td># adverse event in a vaginal for patient $i - 1$ (marginal effect)</td>
<td>-0.0028</td>
</tr>
<tr>
<td>1-2 (vs. 0) adverse events in a cesarean for patient $i - 1$</td>
<td>0.0106</td>
</tr>
<tr>
<td>3+ (vs. 0) adverse events in a cesarean for patient $i - 1$</td>
<td>0.0909***</td>
</tr>
<tr>
<td>1-2 (vs. 0) adverse events in a vaginal for patient $i - 1$</td>
<td>-0.0032</td>
</tr>
<tr>
<td>3+ (vs 0) adverse events in a vaginal for patient $i - 1$</td>
<td>-0.0154</td>
</tr>
<tr>
<td>Demographic controls</td>
<td>Y</td>
</tr>
<tr>
<td>Physician fixed effects</td>
<td>Y</td>
</tr>
<tr>
<td>Time fixed effects (year, month, week)</td>
<td>Y</td>
</tr>
<tr>
<td>N</td>
<td>11,855</td>
</tr>
</tbody>
</table>

Measure of adverse events has been computed without including perineal tears. All entries are effect sizes. Demographic controls include indicator for emergency c-section, age, race, ethnicity, Elixhauser comorbidity scores, insurance status, history of prior cesarean, and maternal parity. Analyses exclude physicians who see fewer than the first percentile of patients by volume, and mothers with prior history of cesareans.

*: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.001$
## TABLE B.2
MICSCODING OF EMERGENCY CESAREANS WITH PROLONGED LABOR

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Dep Var: Vaginal delivery in patient i (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td># adverse events in a cesarean for patient i − 1 (marginal effect)</td>
<td>0.0310***</td>
</tr>
<tr>
<td></td>
<td>(0.0069)</td>
</tr>
<tr>
<td># adverse event in a vaginal for patient i − 1 (marginal effect)</td>
<td>-0.0024</td>
</tr>
<tr>
<td></td>
<td>(0.0055)</td>
</tr>
<tr>
<td>1-2 (vs. 0) adverse events in a cesarean for patient i − 1</td>
<td>0.0150</td>
</tr>
<tr>
<td></td>
<td>(0.0215)</td>
</tr>
<tr>
<td>3+ (vs. 0) adverse events in a cesarean for patient i − 1</td>
<td>0.0954***</td>
</tr>
<tr>
<td></td>
<td>(0.0237)</td>
</tr>
<tr>
<td>1-2 (vs. 0) adverse events in a vaginal for patient i − 1</td>
<td>-0.0034</td>
</tr>
<tr>
<td></td>
<td>(0.0103)</td>
</tr>
<tr>
<td>3+ (vs. 0) adverse events in a vaginal for patient i − 1</td>
<td>-0.0138</td>
</tr>
<tr>
<td></td>
<td>(0.0152)</td>
</tr>
<tr>
<td>Demographic controls</td>
<td>Y</td>
</tr>
<tr>
<td>Physician fixed effects</td>
<td>Y</td>
</tr>
<tr>
<td>Time fixed effects (year, month, week)</td>
<td>Y</td>
</tr>
<tr>
<td>N</td>
<td>11,855</td>
</tr>
</tbody>
</table>

Mode Of Adverse Event for all emergency cesareans with prolonged labor have been recoded as Vaginal delivery. All entries are effect sizes. Demographic controls include indicator for emergency c-section, age, race, ethnicity, Elixhauser comorbidity scores, insurance status, history of prior cesarean, and maternal parity. Analyses exclude physicians who see fewer than the first percentile of patients by volume, and mothers with prior history of cesareans.

*: p < 0.10; **: p < 0.05; ***: p < 0.001
**TABLE B.3**  
MISCODING OF MODE OF ADVERSE EVENT FOR DELIVERIES WITHOUT ADVERSE EVENTS

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Dep Var: Vaginal delivery in patient $i$ (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td># adverse events in a cesarean for patient $i - 1$ (marginal effect)</td>
<td>0.0239** (0.0076)</td>
</tr>
<tr>
<td># adverse event in a vaginal for patient $i - 1$ (marginal effect)</td>
<td>0.0010 (0.0059)</td>
</tr>
</tbody>
</table>

1-2 (vs. 0) adverse events in a cesarean for patient $i - 1$  
3+ (vs. 0) adverse events in a cesarean for patient $i - 1$  
1-2 (vs. 0) adverse events in a vaginal for patient $i - 1$  
3+ (vs 0) adverse events in a vaginal for patient $i - 1$  

Demographic controls Y Y  
Physician fixed effects Y Y  
Time fixed effects (year, month, week) Y Y  
N 11,855 11,855

Mode Of Adverse Event for all emergency cesareans without adverse events has been recoded to be same as Mode of Delivery. All entries are effect sizes. Demographic controls include indicator for emergency c-section, age, race, ethnicity, Elixhauser comorbidity scores, insurance status, history of prior cesarean, and maternal parity. Analyses exclude physicians who see fewer than the first percentile of patients by volume, and mothers with prior history of cesareans.  
*: p < 0.10; **: p < 0.05; ***: p < 0.001
### TABLE B.4
**EFFECT OF TIMESPAN BETWEEN CONSECUTIVE PATIENTS**

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Dep Var: Vaginal delivery in patient i (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td># adverse events in a cesarean for patient i − 1 (marginal effect)</td>
<td>0.0297** (0.0118)</td>
</tr>
<tr>
<td># adverse event in a vaginal for patient i − 1 (marginal effect)</td>
<td>0.0074 (0.0100)</td>
</tr>
<tr>
<td>1-2 (vs. 0) adverse events in a cesarean for patient i − 1</td>
<td>0.0100 (0.0321)</td>
</tr>
<tr>
<td>3+ (vs. 0) adverse events in a cesarean for patient i − 1</td>
<td>0.0952*** (0.0275)</td>
</tr>
<tr>
<td>1-2 (vs. 0) adverse events in a vaginal for patient i − 1</td>
<td>0.0051 (0.0162)</td>
</tr>
<tr>
<td>3+ (vs 0) adverse events in a vaginal for patient i − 1</td>
<td>0.0103 (0.0226)</td>
</tr>
<tr>
<td>Demographic controls</td>
<td><strong>Y</strong></td>
</tr>
<tr>
<td>Physician fixed effects</td>
<td><strong>Y</strong></td>
</tr>
<tr>
<td>Time fixed effects (year, month, week)</td>
<td><strong>Y</strong></td>
</tr>
<tr>
<td>N</td>
<td>6,484</td>
</tr>
</tbody>
</table>

This analysis is on patients seen within 27 hours of the prior patient. All entries are effect sizes. Demographic controls include indicator for emergency cesarean, age, race, ethnicity, Elixhauser comorbidity scores, insurance status, history of prior cesarean, and maternal parity. Year, month, and week fixed effects included. Analyses exclude physicians who see fewer than the first percentile of patients by volume, and mothers with prior histories of cesareans.

*: p < 0.10; **: p < 0.05; ***: p < 0.001
C Figures

**FIGURE C.1**
Proportion of adverse events in vaginal and cesarean deliveries (count variable)

**FIGURE C.2**
Proportion of adverse events in vaginal and cesarean deliveries (categorical variable)