Electronic Medical Records and Medical Procedure Choice: Evidence from Cesarean Sections

Abstract: This paper examines how hospital adoption of Electronic Medical Records (EMRs) impacts medical procedure choice in the context of Cesarean section deliveries. It provides a unique contribution by tying the literature on EMR diffusion to the literature on the utilization of expensive medical technology and provider practice style. Exploiting within-hospital variation in three types of EMR adoption, we find that Computerized Physician Order Entry, an advanced EMR system that typically incorporates decision support, reduces C-section rates for low-risk mothers by 2.5%. Obstetric specific EMR systems and Physician Documentation have no statistically significant effect on C-section rates. In addition, we find that the CPOE effect occurs predominantly in hospitals that were already performing fewer C-sections, and does not change the behavior of already high-intensity providers.

Keywords: health information technology; medical technology; infant and maternal health

1. Introduction

Healthcare spending and utilization varies greatly across the United States, and this variation is often uncorrelated with health outcomes (e.g. Baicker et al., 2006; Fisher et al., 2003a,b; Fuchs, 2004; Skinner 2011). Recent research suggests that much of this variation is driven by supply side factors (Chandra et al. 2011), including practice style (Dranove et al. 2011, Epstein and Nicholson 2009, Molitor 2016) and physician beliefs (Cutler et al. 2018) that determine treatment choices for similar patients treated by different providers. Over the past decade, healthcare providers have increased their use of health information technology (HIT). HIT is intended to act as a complementary input to medical procedures, and proponents expect that further implementation of HIT is likely to improve healthcare quality while reducing costs (Hillestad et al. 2005). However, the evidence of the effect of HIT on patient health outcomes and healthcare costs has been mixed (e.g. Freedman et al. 2017, Agha 2014, McCullough et al. 2016).

This paper provides a unique contribution by tying together literature on HIT and the utilization of expensive medical treatment. We ask whether HIT can improve providers' ability to match patients with their most appropriate treatment. In our empirical context, we examine how hospital adoption of advanced Electronic Medical Record (EMR) applications impacts the utilization of Cesarean section deliveries for childbirth. C-sections are often considered an over-utilized procedure. C-sections are more expensive than normal delivery and can have negative health impacts for the marginal patient undergoing the procedure (Johnson and Rehavi 2016, Osterman and Martin 2013). Reducing unnecessary C-sections could also have additional benefits that would not be measurable in typical health and cost outcomes, such as a mother's quicker recovery time from the delivery and decreased chance of postpartum depression (Robertson et al., 2004).

EMRs may impact C-section decisions through a variety of mechanisms. For example, electronic patient information at the point of care may provide practitioners with better information about a patient's medical condition. Clinical decision support protocols built into some EMR systems may provide specific guidance and help providers make decisions based on real-time patient data.

The most similar study to ours, Meyerhoefer et al. (2016), finds that the exchange of electronic information between the outpatient and inpatient setting at a large, regional provider organization reduced C-section rates. Our study complements this work by exploring large-scale data on EMR use within hospitals across twenty-nine states and additional functionalities such as decision support. We exploit within hospital variation over time in EMR adoption and estimate the impact of EMR adoption on C-sections among a population of women for whom C-sections are most likely to be over-utilized. We also consider heterogeneous effects by a hospital's initial propensity to utilize C-sections. Lower intensity hospitals may be more committed to reducing unnecessary C-sections and may use EMR applications as a means to improve further. Alternatively, higher intensity hospitals may have more cases of clear overutilization that could be eliminated with an intervention such as EMR adoption.

Our analysis explores EMR applications that allow physicians to better document and communicate patient health conditions (Physician Documentation), applications that allow physicians to directly input orders electronically and often provide decision support protocols (Computerized Practitioner Order Entry), and an application designed and implemented specifically in an obstetrics unit of a hospital (Obstetric EMR).

We find consistent evidence that Computerized Practitioner Order Entry decreases the use of C-sections among low-risk women, particularly in hospitals that were already low-intensity. Relative to the mean low-risk C-section rate, we find it decreases C-sections by 2.5% in the full sample and 4.1% in low-intensity hospitals. We find some evidence that Physician Documentation may also decrease C-section rates among low-risk women, but this effect occurs with a lag and is not precisely estimated, and that Obstetric specific EMR systems reduce C-sections among the population most likely to be impacted by the ability to monitor and make decisions from real-time, obstetric-specific data.

We also consider the fact that changes in C-section rates could have ambiguous welfare effects. We examine how EMR adoption changes maternal health outcomes, examining the tradeoff between adverse events most associated with C-section delivery vs. adverse events most associated with vaginal delivery. We do find that decreases in C-sections among low-risk women are accompanied by increases in lacerations, most associated with vaginal delivery, and decreases in infections, which can be associated with either mode of delivery.

Our results suggest that hospitals more likely to be less intensively treating lower risk patients further decrease C-section rates for this group when implementing some EMR applications, particularly those most likely to incorporate decision support. However, the welfare effects of these changes are unclear given our findings of increases in some bad outcomes. These findings suggest that future research should explore more comprehensive cost and health outcomes for mothers and infants, both in the hospital and after the hospital stay.

2. Background and Previous Literature

A. EMR Technologies

Proponents of EMR adoption and increased investment in health information technology envision large improvements in the quality and cost of care (Hillestad et al. 2005). However, the empirical evidence to date has suggested difficulty in obtaining these goals. Several papers have found little impact of hospital EMR adoption on mortality among Medicare patients overall, and if anything increases in treatment costs (e.g. Agha 2014, McCullough et al. 2016). Effects on health outcomes, however, appear to be heterogeneous. McCullough et al. (2016) find that EMRs can decrease mortality for the highest severity Medicare patients through improved care coordination, and Freedman et al. (2017) find improved patient safety for younger and less severely ill patients through decision support mechanisms. Perhaps the most optimistic finding is evidence that EMR adoption decreases infant mortality (Miller & Tucker 2011). To our knowledge, our paper is the first large-scale study of the effect of hospital EMR adoption on treatment choices themselves.[1]

We focus our analysis on advanced EMR technologies that allow the provider to interact directly with the system at the point of care and which may provide additional input into treatment decisions beyond simply presenting patient data. We choose to focus on advanced systems because they exhibit much more variation in adoption during our study period than more basic systems, and because these are the systems found to improve outcomes in certain subpopulations (e.g. McCullough et al. 2016, Freedman et al. 2017). In particular, we estimate the effects of Computerized Practitioner Order Entry (CPOE), Physician Documentation (PD), as well as a specific Obstetrical System EMR (OB). CPOE gives physicians direct control over treatment orders which has the potential to reduce errors due to miscommunication. Rules based protocols, decision support, and error checks are often built into the CPOE user interface. Almost

---

[1] Lammers et al. (2014) finds evidence that electronic information exchange decreases repeated testing, but no other work has examined whether EMRs impact choice of intervention given a patient's diagnosis.

all CPOE systems include or interface with clinical decision support systems of varying sophistication (Kaushal and Bates, 2001), and they often provide real-time feedback about the appropriateness of orders, diagnostic or therapy protocols, and prompts about the adherence to clinical guideline (Sittig and Stead, 1994).[2] Physician Documentation allows physicians to directly input patient information, primarily used for billing and communication between providers (Dranove et al. 2014). Physician Documentation systems can include alerts and protocols at the point of care, but previous studies suggest CPOE is more likely to operate through decision support mechanisms and Physician Documentation through care coordination mechanisms (McCullough et al. 2016, Freedman et al. 2017).

Obstetrical Systems (OB) provide an interface to manage the clinical services of labor and delivery and typically interact with devices such as fetal monitors. More efficient management of information and other aspects of obstetric care could improve treatment decisions. Our study is the first to explore the effects of these systems in large-scale data.

B. Cesarean Sections, "Practice Style," and Potential Impacts of Advanced EMRs

C-sections provide a unique context to examine the effect of EMRs on treatment choices in hospitals. First, there is a well-defined patient population observable in hospital inpatient data, since almost all U.S. births occur in hospitals. Second, whether the delivery ultimately occurs via C-section is highly salient, measurable, and has important implications for both health outcomes

---

[2] While we would ideally examine the adoption of clinical decision support applications directly, these applications are inconsistently reported in our data. We therefore follow McCullough et al. (2016) and Freedman et al. (2017) and use CPOE adoption as a proxy for advanced EMR capabilities that allow the provider to interact with the system at the point of care and likely have decision support built in.

and cost of care. Third, there is a consensus of over use in the U.S, providing scope for interventions such as EMR adoption to influence C-section rates.

From 1996 to 2011, C-section rates for singleton births in the U.S. increased from 19.7% to 31.3%. These trends occurred for births of all gestational ages, with some of the largest increases among full term births (Osterman and Martin 2013). The U.S. is well above the OECD average rate of 25.9% as of 2009 (OECD 2011). There is also a great deal of variation in C-section rates across the country. Baicker et al. (2006) finds that patient characteristics do not explain this variation, and higher rates do not improve patient health outcomes. Johnson and Rehavi (2016) calculate that reducing C-sections to their 1996 levels could save between $1 and $3 billion per year in direct medical costs. Additionally, mothers undergoing C-section deliveries have higher mortality rates, higher re-hospitalization rates for infections and other surgical complications, longer recovery times and hospital stays, and greater chance of future pregnancy complications (see Johnson and Rehavi 2016 for a detailed discussion).

A recent literature in health economics explores the extent to which overutilization and regional variation in medical care is driven by “practice style” (Dranove et al. 2011, Epstein and Nicholson 2009, Molitor 2016). Chandra and Staiger (2007) find that practice style, as defined by a provider’s propensity to prescribe and ability to perform high intensity treatment, may be an important explanation of why geographic variation in health care spending is not highly correlated with outcomes. Currie and MacLeod (2013) extend a similar idea to the context of childbirth. Physicians differ in both their ability to perform C-sections (procedure skill) and their ability to make appropriate decisions about what treatment is best for a patient (diagnostic skill). They find that increasing diagnostic skill decreases C-section rates among low-risk women, increases C-section rates among high-risk women, and improves outcomes for both groups as doctors become better at matching patients with their most appropriate procedure. Our paper tests whether EMRs change medical decision-making and the process by which providers match patients to procedures.

Additionally, EMRs may affect some of the key challenges to C-section decision making. First, literature suggests compliance with C-section practice standards is an important way to improve quality of care and reduce variation (Mackey and Lang 2011, Ransom et al. 2003). Accordingly, reviews of EMR adoption suggest that health information technology affects care quality mostly by increasing adherence to guideline- or protocol-based care (Chaudhry 2006). Second, computerized tools are increasingly used to overcome challenges in monitoring and interpreting fetal heart rate patterns, contraction patterns, and the progress of dilation. These factors are key to determining whether the infant is tolerating labor and to diagnosing dystocia, or slow labor. Computer models can be used to interpret these sources of data, detect anomalies, and predict labor curves that allow clinicians to potentially make better decisions about the course of labor, and therefore when to recommend a C-section (Hamilton et al. 2004). These EMR based tools may be particularly valuable while administering drugs that induce labor. During this process, the surveillance of contraction timing and trends is particularly important to ensure contractions do not become too frequent as to limit the fetus's oxygen supply (Smith et al. 2014). Medical studies of these tools are typically small-scale case studies, and our results provide causal evidence of these effects in large-scale data from hospitals in more than half of U.S. states.

One limitation of our data is that we do not observe precise information about how exactly hospitals utilize each application. For example, case studies of EMR implementation suggest that obstetrics is a specialty in which hospitals likely integrate aspects of decision support into CPOE systems (Wright et al. 2010). We are not be able to distinguish whether a hospital implements decision support through a hospital wide system like CPOE or through a specialty specific system like OB. We estimate the reduced form effect of each application.

3. Empirical Model

We consider the following two-way fixed effect regression model for patient *i* in hospital *h* and year *t*:

$$\boldsymbol{I(Csection_{iht}) = \beta_0 + \beta_1 EMR_{ht} + \beta_x X_{iht} + \gamma_h + \delta_t + \varepsilon_{iht}} \qquad (1)$$

The dependent variable is an indicator equal to one if a delivery is a C-section and zero otherwise. EMR_{ht} is a dummy equal to one in years in which hospital *h* has EMR installed and zero otherwise. $X_{iht}$is a vector of patient demographics, including mother's race/ethnicity categories, insurance coverage categories, and quartiles of mean household income in the mother's zip code; dummies for characteristics of the delivery including mother's age, weekend delivery, quarter of year, and the presence of other comorbidities;[3] and a measure of price differences between C-sections and vaginal delivery at the hospital-year level, discussed in more detail below. γ_h and δ_t are hospital and year fixed effects. Standard errors are clustered at the hospital level to allow for correlated errors within hospitals.[4]

Our identification strategy exploits within-hospital changes in EMR availability through a generalized difference-in-differences model with staggered treatment timing. In other words, we identify the effect of EMR adoption on C-section rates by comparing changes in C-sections rates

---

[3] As discussed below, our analysis sample of low-risk deliveries excludes women with previous C-sections and multiple births, so we do not control for these typical determinants of C-sections. We control for presence of a sexually transmitted disease, anemia, incompetent cervix, pregnancy related hypertension, and hemoglobinopathy, which are the only comorbidities listed in Table A1 that appear in our low-risk sample.

[4] In Appendix Table A3 we show that our main results are robust to estimating a logit model.

in adopting hospitals around the adoption year to concurrent changes in C-section rates occurring in both non-adopting hospitals and adopting hospitals that adopt at other points in time (Goodman-Bacon, 2018). We therefore assume hospitals adopting at different points in time share common trends with each other and with non-adopting hospitals absent EMR adoption. This identification strategy has been utilized in many studies of the effect of EMR adoption on health outcomes (e.g. Agha 2014, McCullough et al. 2016, and Freedman et al. 2017), and in Section 5 we provide a variety of tests of our identifying assumption.

4. Data

A. Inpatient Data

Our primary data sources are the Nationwide Inpatient Sample (NIS) and the Health Information and Management Systems Society (HIMSS) Analytics Database from 2003-2011. The NIS is an annual 20%, nationally representative, stratified sample of U.S. community hospitals.[5] Within each sampled hospital we observe the universe of patient discharge records in that year. For each record we observe diagnosis codes, procedure codes, patient demographics, and other information about the hospital stay. We extract all records for women hospitalized for childbirth. We use ICD-9 diagnosis codes to identify comorbidities that might determine C-section delivery, discussed in more detail below. We also observe demographic characteristics of the mother. As in Currie and MacLeod (2013), we construct a proxy for the difference in reimbursement between C-section delivery and normal delivery by calculating the difference in the mean charges within a hospital-year for patients whose only procedure code is a C-section delivery and those whose only procedure code is a normal delivery.

---

[5] Our analysis data comes from 29 states which participate in the data set and provide hospital identifiers for linking to other data sources.

B. Electronic Medical Record Data

The HIMSS Analytics Database is an annual survey of the information technology capabilities of over 3,000 hospitals nationwide. The HIMSS survey collects a wide range of information on over 100 different health information technology applications used in hospitals. Our analysis considers three EMR applications discussed above: CPOE, PD, and OB. We construct binary indicators for whether a hospital in a given year has the respective application installed.[6] We estimate separate versions of Equation 3 for each EMR applications for ease of interpretation; however, including the EMR adoption indicators in the same regression provides very similar results. CPOE is available for all years of our data (2003-2011), and OB and PD are available beginning in 2005.

Our full data set includes 5,105,525 delivery records from 1,525 unique hospitals that we are able to merge between the HIMSS and NIS data sources. Of these hospitals, we observe 975 in at least two years of data, allowing us to exploit changes in EMR adoption over time within these hospitals. While our sample is generally similar to the full set of hospitals available in the NIS, it is slightly more representative of large, teaching hospitals in urban areas.[7] Figure 1 shows the variation over time in each EMR application, plotting the fraction of births in our analysis sample that occur in hospitals with each application. CPOE diffuses from 7% of births in 2003 to

---

[6] We follow the guidelines given by HIMSS and consider an application installed if its status is live & operational, replaced, to be replaced or automated.

[7] Appendix Table A2 compares patient-level summary statistics of both patient and hospital characteristics for three different samples: all delivery patients in the NIS, a subsample of the patients who are in states with hospital identifiers and successfully merge to the HIMSS, and the subset of these patients that are in hospitals appearing in our data in more than one year. All three samples have very similar C-section rates and patient. Our analysis sample is more likely to be large, less likely be for-profit owned, more likely to be a teaching hospital, and less likely to be rural.

61% in 2011. PD increases from 23% in 2005 to 59% in 2011,[8] and OB increases from 45% in 2005 to 87% in 2011.

C. Sample Construction: Distinguishing Medical Risk and Hospital Intensity

Our main sample of interest is low-risk deliveries for which C-sections are least likely to be appropriate. We follow Currie and MacLeod (2013) and measure a mother's medical risk as her predicted likelihood of a C-section delivery.[9] We pool our data across hospitals and estimate a logit model in which the dependent variable is C-section delivery and the independent variables are observable health characteristics listed in Appendix Table A1. We estimate this model separately in each year to allow general evolution in practice patterns over time. Based on these estimates, we then use predicted probability to rank women in terms of their medical appropriateness for a C-section. In other words, we use nationwide treatment patterns to uncover how the medical profession as a whole tends to rank appropriateness for a C-section based on observed medical characteristics.

One concern with this framework is that if EMR adoption impacts how hospitals make C-section decisions, EMR adoption could impact our definition of patient risk. We estimate various versions using only observations from hospitals without EMRs, only observations from hospitals with EMRs, and only observations from hospitals that do not change their EMR adoption during our sample period. The correlation coefficient between predicted C-section probabilities from our main model and these alternative models are all above 0.999.

Appendix Table A1 lists the means and the marginal effects of each variable from the Logit models from the first and last years of data. Figure 2 shows histograms of predicted C-

---

[8] Despite the similar adoption rates over time, the correlation coefficient between CPOE and PD is only 0.44.

[9] Chandra and Staiger (2007) and Currie et al. (2015) follow a similar procedure for cardiac care.

section rates separately for women who do deliver by C-section (in white) and who do not deliver by C-section (in blue).[10] The bulk of the distribution of women who do delivery by C-section have a propensity above 0.80 and the bulk of the distribution of women who do not deliver by C-section have a propensity below 0.20. We consider those with propensities below 0.20 to define the sample of low-risk women.[11]

Table 1 presents summary statistics of patient characteristics for all births in our data and among our low-risk sample. Overall 31% of all deliveries and 14% of low-risk deliveries occur via C-section. While low-risk women are more likely to be younger, there are no large differences in demographic composition. Relative to the full set of deliveries, low-risk deliveries are slightly less likely to occur in hospitals with each of the EMR applications that we study.

Figure 1 plots C-section rates over time among all deliveries and low-risk deliveries. Consistent with vital statistics data reported in Osterman and Martin (2014), we find increasing C-section rates for both groups during the 2000s, and a slight dip in C-section rates in 2010 and 2011.

We also separate hospitals based on their baseline C-section intensity. We may expect larger effects of EMR adoption in low-intensity hospitals if they are more committed to reducing unnecessary C-sections and therefore attempt to use EMR applications as an additional tool to further achieve this goal. Alternatively, we may expect larger effects in higher intensity hospitals since they have more cases of clear overutilization that could potentially be avoided with an intervention such as EMR adoption.

---

[10] These figures show similar patterns to similar figures presented by Currie and MacLeod (2013).

[11] This sample turns out to be almost identical to an alternative sample that defines low-risk women as those with singleton deliveries, no previous C-sections, and no other comorbidities. Our main sample includes all of these alternative low-risk women, plus an additional 47,678 (1.5% of our main sample) women. The mean C-section rate is also 14.0% in both samples. We now show results in Appendix Table A4 that our main results are almost identical with these alternative criteria.

To identify a hospital's intensity level, we estimate a series of patient level regressions of C-section delivery on dummies for deciles of the predicted C-section probability separately for each hospital in each year. We recover the constant term, the hospital's C-section rate among its lowest risk patients, and assign each hospital its intensity measure from the first year we observe it in the data. Hospitals differ greatly in their treatment intensity of low-risk patients. The gap between the 10th percentile and 90th percentile of hospitals in our sample is 14 percentage points, and the gap between the 25th and the 75th percentile is 7 percentage points. We separate hospitals into groups based on terciles of this intensity measure.

5. Results

A. Main Estimation Results

Column 1 of Table 2 presents the estimation results of Equation 1 for all low-risk deliveries. We find that CPOE reduces C-section utilization by a statistically significant 0.35 percentage points. Given that the mean C-section rate among low-risk women is 0.14, this point estimate implies a 2.5% reduction relative to this mean. The estimated effects of OB and PD are also negative, but smaller and not statistically different from zero. Columns 2 and 3 of Table 2 compare results for the top and bottom terciles of hospital intensity. We find that CPOE adoption decreases C-section rates for low-risk women delivering in low-intensity hospitals by a statistically significant 0.57 percentage points, or 4.1% relative to the mean C-section rate of low-risk women. The estimate in high-intensity hospitals is statistically insignificant and smaller than the point estimate in low-intensity hospitals. While these point estimates are not statistically different from each other, they suggest that CPOE adoption decreases C-section rates for low-risk women predominantly in low-intensity hospitals.[12] Estimates for the other EMR technologies are not statistically significant in either type of hospital.

B. Timing of Effects

We also implement an event study approach by replacing EMR_{ht} with a set of dummies that more specifically trace out the timing of effects.

$$\boldsymbol{I(Csection_{iht}) = \beta_0 + \sum_{p=-3,-2,0,1,2+} \beta_p I(EventTime = p)_{ht} + \beta_x X_{iht} + \gamma_h + \delta_t + \varepsilon_{iht}} \quad (2)$$

We identify the year in which a hospital adopts an EMR application, and then construct five dummies: 3 or more years prior to adoption, 2 years prior to adoption, the year of adoption, 1 year post adoption, and 2 years post adoption.[13] We exclude the year just prior to adoption as the reference group.

Figure 3 shows our event study estimates for each of the three technologies. In all of these figures, C-section trends are flat in the years prior to adoption, supporting our identification strategy. Panel A traces out low-risk patient C-section rates prior to and after CPOE adoption. The point estimates show a pattern consistent with Table 2 that CPOE reduces C-section rates. The only point estimate that is statistically significantly different from zero is during the year of

---

[12] We believe this differential effect for CPOE adoption is likely a function of how these hospitals make use of their EMR technologies rather than different rates of adoption itself. In Appendix Figure A1, we plot EMR adoption rates separately for low and high intensity hospitals. These figures suggest that there are not systematically different adoption rates or adoption trends that correlate with C-section intensity for CPOE and OB EMR. For PD, there is some evidence that low intensity hospitals started the sample with a lower rate of adoption, but adopted at a faster rate during the sample.

[13] While we do not observe each hospital in every year in the patient data, we do observe each year in the HIMSS data. We therefore use the HIMSS data to construct these dummies and attach them to the corresponding hospital-year groups available in the NIS data.

adoption, but C-section rates remain persistently lower through all post-adoption years. For PD we find a slight decrease in C-section rates that grows over time, though none of the point estimates are statistically different from zero. The trend after OB adoption follows no clear trend and is insignificant.

C. Additional Tests of Common Trends

To further explore the common trends assumption, we ask whether hospitals that adopt EMR systems at different times had differential C-section trends in the years prior to their adoption compared to trends among non-adopting hospitals. We separate hospitals into timing groups based on the year in which they adopted an EMR system in the HIMSS data, and we test whether each adoption year group had different trends in the years prior to adoption. We run regressions of the following form:

$$\begin{aligned}\boldsymbol{I}(\boldsymbol{Csection_{iht}}) &= \boldsymbol{\beta_0} + \sum\nolimits_{\boldsymbol{g}} \boldsymbol{\beta_g I}(\boldsymbol{AdoptionYear} = \boldsymbol{g})_{\boldsymbol{h}} * \boldsymbol{year_t} + \boldsymbol{\beta_x X_{iht}} + \boldsymbol{\gamma_h} \\ &+ \boldsymbol{\delta_t} + \boldsymbol{\varepsilon_{iht}}\ if\ year < AdoptionYear\end{aligned} \tag{3}$$

In this specification $\boldsymbol{\delta_t}$ represents the time path of C-sections among non-adopting hospitals over the full sample period. The $\boldsymbol{\beta_g}$ coefficients represent the difference from this time path based on a linear year trend for hospitals that initially adopted the EMR system in each year, $\boldsymbol{g}$. Note, we cannot include hospitals that had adopted in the first or second year of data for each application, since we need at least two years of pre-adoption data to estimate trends.

In estimates presented in Table 3, we show that none of these $\boldsymbol{\beta_g}$ coefficients are statistically different from zero for CPOE and PD, and an F-test does not reject the null that they are jointly zero for both. We do find some differences in trends for OB adoption. However, when we run our main specification for OB excluding the two timing groups with statistically different pre-trends, we obtain almost the same estimate as we report in Table 2. This test provides additional evidence that hospitals on different C-section treatment trajectories did not adopt EMR systems at different times.

Despite our findings that EMR adopting hospitals did not tend to exhibit differential pre-adoption C-section trends we also test whether our results are sensitive to controlling for trends in our regression specification in a variety of ways in the online Appendix Table 5. Our results are robust to controlling for hospital-specific linear trends, timing group specific linear trends, and to partialling out timing group pre-trends as suggested by Goodman-Bacon (2018).

D. Patient Composition

While the event study analysis suggests adopting hospitals do not have differential C-section trends prior to adoption, changes in patient characteristics may coincide with EMR adoption and lead to spurious results. We verify that there is no change in the composition of patients at the time of EMR adoption on observable dimensions with a regression of patient characteristics on EMR adoption. The test is similar in spirit to a test of balance on observables between the treatment and control group, but in the context of a difference-in-differences identification strategy (Pei, Pischke, & Schwandt 2018; Wing, Simon, Bello-Gomez 2018). Table 4 presents the effect of EMR adoption on patient characteristics. We find that CPOE adoption is correlated with small shifts in patient composition from Medicaid to private payers and a small increase in mothers over the age of 35. However, these magnitudes are small and suggest the patient population is changing in ways that would make C-sections more likely.

Importantly, there is no change in the probability of comorbidities. While we do not find meaningful effects of OB and PD on C-section rates, adoption is not associated with large changes in patient composition or health characteristics.[14]

E. Scheduled vs. Unscheduled C-Sections

This paper focuses on the use of EMR technology within the hospital.[15] As a result, we expect our results to be predominantly driven by C-section decisions that occur after the mother has been admitted to the hospital and not by C-section decisions scheduled prior to the hospitalization. A great deal of the variation in low-risk C-section rates is likely driven by decision making about the progress of labor (Main et al. 2011). Monitoring this progress may be an important mechanism through which EMRs, particularly decision support applications, may impact C-section decisions, as discussed above. We therefore explore the extent to which our results are driven by deliveries where monitoring labor is most likely to be relevant.

Our data do not allow us to directly separate scheduled C-sections from C-sections following a trial of labor. However, C-sections that follow labor are likely to follow labor with some type of complication. We therefore follow Henry et al. (1995), Gregory et al. (2002), and Johnson and Rehavi (2016), and identify C-sections that occur after an ICD-9 diagnosis code that indicates a complication during labor or an ICD-9 procedure code that indicates an intervention during labor as unscheduled C-sections. Among low-risk women in our sample, 5% have a scheduled C-section and 9% have an unscheduled C-section. We also further separate unscheduled C-sections into those that do and do not follow induced labor. When labor is

---

[14] In Appendix Table 6, we also show that the estimation results are not sensitive to the inclusion of control variables.

[15] We do not observe whether the mother's OB practice utilize EMRs in the outpatient setting or not.

induced, providers may pay closer attention to monitoring labor duration and contraction timing and interact more with the EMR system as they administer medication as labor progresses (Smith et al. 2014).

Table 5 presents results with scheduled C-sections and unscheduled C-sections as separate dependent variables. While the point estimate for unscheduled C-sections is larger than the estimate for scheduled C-sections, neither is statistically significant. However, we find the effect is largest and statistically significant when focusing on unscheduled C-sections following inductions. The OB adoption effect for unscheduled C-sections with induction is also negative and statistically significant at the 10% level.[16] These results suggest that EMRs impact C-section rates in the cases in which patients are being monitored the closest and through the applications most likely to include decision support and obstetric specific tools.

F. Additional Outcomes

While it is an interesting question in itself whether providers change their medical decision making in response to EMR adoption, it is difficult to evaluate the welfare impacts. While we cannot fully establish welfare impacts, we examine the extent to which health outcomes change concurrently with this change in utilization. Based on Srinivas et al. (2010) we classify five categories of negative maternal health. Three of these outcomes can occur during either a C-section or vaginal delivery, including hemorrhage, infection, and thrombotic/other. Among the other two outcomes, lacerations predominantly occur during vaginal delivery and operative outcomes predominately occur during C-sections. This set of outcomes allows us to detect the potential tradeoff that could occur from shifting deliveries from one method to the

---

[16] In results available upon request we find that EMR adoption does not impact the likelihood of inducing labor.

other. We note that these results are only suggestive of how EMR induced changes in C-section utilization may impact outcomes, since it is possible for EMR adoption to impact some of these outcomes through other possible channels in addition to changes in delivery type. For example, EMRs may change how nurses monitor potential infections in the postpartum period.[17] We therefore present reduced form estimates of the impact of adoption on these outcomes.

Table 6 presents results for the effect of CPOE, PD, and OB on these outcomes. We find that CPOE, which decreases C-section use among low-risk women, has a statistically significant negative effect on infections. We also find a positive effect of CPOE on lacerations, though only statistically significant at the 10% level. This suggests a potential tradeoff between these two different adverse events for marginal C-section patients. When we estimate the effect of CPOE on length of stay in the hospital, also reported in Table 6, we find reductions, but small and not statistically significant. Given that C-section deliveries typically increase the length of stay by a day, it is possible that the marginal patient shifted away from a C-section experiences other complications that keep them in the hospital for the same length of time. Overall, our analysis of outcomes does not provide conclusive evidence of the welfare effects of changing treatment patterns but does suggest that there may be tradeoffs in outcomes for marginal patients that shift from one delivery method to another.

6. Conclusion

This paper explores the interaction of health information technology and medical treatment choices. We assess whether EMR adoption improves providers' ability to match

---

[17] For example, Freedman et al. (2017) find CPOE adoption reduces infections among surgical patients.

patients to procedures in a context where the procedure, C-section delivery, is thought to be over utilized among low-risk patients.

We find that CPOE decreases C-section utilization among low-risk mothers by 2.5%. We find suggestive evidence that this effect is largest in cases in which closer monitoring of the progress of labor is required. We do not find statistically significant effects of either PD or OB adoption on C-section rates; although, we find suggestive evidence OB reduces C-section rates when real-time labor monitoring is particularly important. Taken together these results suggest that EMRs most likely to impact procedure choice are those most tightly aligned with decision support capabilities.[18] While OB is specifically designed for obstetric units, it may not provide comprehensive tools to impact C-section decisions on its own.

Our analysis of delivery related health outcomes suggests that the marginal patients that shift delivery type may also be more likely to experience an adverse outcome. We find no change in length of stay, and cannot observe measures of well-being after discharge from the hospital, so it is unclear from our data if these women are better or worse off on net.

To put the magnitude of our results into context, we conduct a back of the envelope calculation of its implications for the cost of childbirth related care. Podulka et al. (2011) calculate that the cost of a maternal hospitalization for an uncomplicated C-section is $1,800 more than an uncomplicated vaginal delivery. Based on births we observe in the NIS data, we extrapolate that there are about 2.8 million low-risk deliveries per year nationwide. Our point estimate that CPOE reduces C-sections by 0.35 percentage points implies that if all hospitals implemented CPOE, it would save $17.64 million (2.8 million X $1,800 X 0.0035) in maternal hospital related expenses annually. This represents only 0.11% of the $16.1 billion spent

---

[18] This finding is consistent with Freedman et al. (2017)'s findings that CPOE reduces preventable, adverse events among surgical patients, but PD does not.

annually on maternal hospitalizations (Podulka et al. 2011). At the hospital level, the average hospital in our sample delivers about 1,000 births per year. Therefore, our estimates imply CPOE leads to 3.5 fewer C-sections per hospital per year, which would imply savings of $6,300 per hospital per year.

This paper has implications for understanding the role that EMR adoption may play in changing treatment decisions. However, the magnitude of this effect is quite small, and we only find these changes in certain hospitals: those that were already limiting their overutilization the most. Higher intensity hospitals are those where the system has the most to gain by reducing excessive over utilization. The marginal patient in these hospitals may also be more likely to have clearer welfare effects of decreased C-section rates. However, our results suggest these hospitals may have the most difficulty changing practice patterns. The characteristics that make high intensity hospitals the heaviest users of C-sections ex ante may also make these hospitals struggle to extract the most value from EMR adoption. For example, over utilization and the inability to harness EMRs to improve efficiency of care may both be correlated with management style or quality, physician training and practice style, or physician buy in to changes in practice organization.

Interestingly, our results suggest that EMR adoption may actually increase differences in treatment intensity across hospitals as low-intensity hospitals reduce C-section rates and high-intensity hospitals remain stable. These findings suggest that tools that might impact practice style are only likely to do so in provider organizations already committed to change. Our work shows that EMR adoption can impact treatment choices under certain conditions and suggests the need for more research around what these conditions are and how they can be modified.

References

Agha, L. 2014. The Effects of Health Information Technology on the Costs and Quality of Medical Care. *Journal of Health Economics* 34: 19 -30.

Baicker, K, Buckles, K.S., & Chandra, A. (2006). Geographic Variation in the Appropriate Use of Cesarean Delivery. *Health Affairs* 25(5): W355-W367.

Bates, D. W., Leape, L. L., Cullen, D. J., Laird, N., Petersen, L. A., Teich, J. M., ... & Vander Vliet, M. (1998). Effect of computerized physician order entry and a team intervention on prevention of serious medication errors. *Jama*, *280*(15), 1311-1316.

Cameron, A.C., & Miller, D.L. (2015). A Practitioner's Guide to Cluster-Robust Inference. *Journal of Human Resources* 50(2): 317-372.

Chandra A, Cutler DM and Z Song. (2011) "Who Ordered That? The Economics of Treatment Choices in Medical Care." In Handbook of Health Economics Volume 2. Eds M. Pauly, T. McGuire and Pedro P. Barros, North-Holland, 397-432.

Chandra, A. & Staiger, D. O. (2007). Productivity Spillovers in Healthcare: Evidence from the Treatment of Heart Attacks. *Journal of Political Economy* 115 (1): 103–140.

Chaudhry, B., Wang, J., Wu, S., Maglione, M., Mojica, W., Roth, E., ... & Shekelle, P. G. (2006). Systematic review: impact of health information technology on quality, efficiency, and costs of medical care. *Annals of internal medicine*, *144*(10), 742-752.

Currie, J. & MacLeod, W.B. (2013). Diagnosis and Unnecessary Procedure Use: Evidence from C-Section. (Working Paper No. 18977). National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w18977.

Currie, J., MacLeod, W.B., & Van Parys, J. (2015). Physician Practice Style and Patient Health Outcomes: The Case of Heart Attacks. (Working Paper No. 21218). National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w21218.

Cutler, D., Skinner, J., Dora Stern, A., & Wennberg, D. (2018). Physician Beliefs and Patient Preferences: A New Look at Regional Variation in Health Care Spending. *AEJ: Economic Policy*, forthcoming.

Dranove, D., Forman, C., Goldfarb, A., & Greenstein, S. (2014). The Trillion Dollar Conundrum: Complementarities and Health Information Technology. *American Economic Journal: Economic Policy,* 6(4), 239-270.

Dranove, D., Ramanarayanan, S., & Sfekas, A. (2011). Does the Market Punish Aggressive Experts? Evidence from Cesarean Sections. *B.E. Journal of Economic Analysis & Policy,* 11(2).

Epstein, A.J. & Nicholson, S. (2009). The Formation and Evolution of Physician Treatment Styles: An Application to Cesarean Sections. *Journal of Health Economics* 28: 1126-1140.

Fisher, E. S., Wennberg, D. E., Stukel, T. A., Gottlieb, D. J., Lucas, F. L., Pinder, E. L., 2003a. The implications of regional variations in Medicare spending. Part 1: The content, quality, and accessibility of care. Annals of Internal Medicine 138; 273-287.

Fisher, E. S., Wennberg, D. E., Stukel, T. A., Gottlieb, D. J., Lucas, F. L., Pinder, E. L., 2003b. The implications of regional variations in Medicare spending. Part 2: Health outcomes and satisfaction with care. Annals of Internal Medicine 138; 288-298.

Freedman, S., Lin, H., & Prince, J. (2017). Information Technology and Patient Health: Analyzing Outcomes, Populations, and Mechanisms. *American Journal of Health Economics,* Forthcoming.

Fuchs, V. R., 2004. Perspective: More variation in use of care, more medicine. Health Affairs; VAR104-VAR107.

Goodman-Bacon, A. (2018). Difference in Differences with Variable Treatment Timing. *NBER Working Paper #25018.* http://www.nber.org/papers/w25018.

Gregory, K.D., Korst, L.M., Gornbein, J.A., and Platt, L.D. (2002). “Using Administrative Data to Identify Indications for Elective Primary Cesarean Delivery,” *Health Services Research,* 37, 1387-1401.

Hamilton, E., Platt, R., Gauthier, R., McNamara, H., Miner, L., Rothenberg, S., & Vintzileos, A. (2004). The Effect of Computer-Assisted Evaluation of Labor on Cesarean Rates. *Journal for Healthcare Quality, 26*(1), 37-44.

Henry, Olivia A., Kimberly D. Gregory, Calvin J. Hobel, and Lawrence D. Platt. (1995) “Using ICD-9 Codes to Identify Indications for Primary and Repeat Cesarean Sections: Agreement With Clinical Records.” *American Journal of Public Health*, 85, 1143-1145.

Hillestad, R., Bigelow, J., Bower, A., Girosi, F., Meili, R., Scoville, R., and Taylor, R. 2005. Can Electronic Medical Record Systems Transform Health Care? Potential Health Benefits, Savings, and Costs. *Health Affairs* 24: 1103-1117.

Johnson, E. M. & Rehavi, M.M. (2016). Physicians Treating Physicians: Information and Incentives in Childbirth. *American Economic Journal: Economic Policy*, 8(1), 115-41.

Kaushal, Rainu and David W. Bates. Computerized Physician Order Entry (CPOE) with Clinical Decision Support Systems (CDSSs). 2001. Agency for Healthcare Research and Quality Publication 01-E058.

Lammers, E.J., Adler-Milstein, J., & Kocher, K.E. (2014). Does Health Information Exchange Reduce Redundant Imaging? Evidence from Emergency Departments. *Medical Care* 52(3): 227-234.

Mackey, T. K., & Liang, B. A. (2011). The Role of Practice Guidelines in Medical Malpractice Litigation. *American Medical Association Journal of Ethic: Virtual Mentor 13*(1), 36.

Main, E.K., Morton, C.H., Hopkins, D., Giuliani, G., Melsop K, Gould J.B. (2011). Cesarean Deliveries, Outcomes, and Opportunities for Change in California: Toward a Public Agenda for Maternity Care Safety and Quality. *A CMQCC White Paper.*

McCullough, J. S., Parente, S. T., & Town, R. (2016). Health information technology and patient outcomes: the role of information and labor coordination. The RAND Journal of Economics, 47(1), 207–236.

Meyerhoefer, C., Deily, M., Sherer, S., Chou, S-Y., Peng, L., Sheinberg, M., and Levick. (2016). The Consequences of Electronic Health Record Adoption for Physician Productivity and Birth Outcomes, *Industrial and Labor Relations Review*, 69(4), 860-889.

Miller, A. and Tucker, C. (2011). Can Health Information Technology Save Babies? *Journal of Political Economy* 119: 289-324.

Molitor, D. (2016). The Evolution of Physician Practice Styles: Evidence from Cardiologist Migration. *NBER Working Paper #22478.*

OECD (2011). Caesarean Sections, in OECD, *Health at a Glance 2011: OECD Indicators*, OECD Publishing, Pairs. Retrieved July 3, 2015 from http://dx.doi.org/10.1787/health_glance-2011-37-en

Osterman, M.J.K. and Martin, J.A. (2013) Changes in Cesarean Delivery Rates by Gestational Age: United States, 1996-2011. *NCHS Data Brief 124*. Retrieved July 3, 2015, from http://www.cdc.gov/nchs/data/databriefs/db124.pdf

Osterman, M. J. K., & Martin, J. A. . M. P. H. (2014). Trends in low-risk cesarean delivery in the United States, 1990-2013. *CDC Stacks.* Retrieved from https://stacks.cdc.gov/view/cdc/26009

Patel, V. L., Kaufman, D. R., & Arocha, J. F. (2002). Emerging Paradigms of Cognition in Medical Decision-Making. *Journal of Biomedical Informatics*, *35*(1), 52-75.

Pei, Z., Pischke, J. (2018). Poorly Measured Confounders are More Useful on the Left than on the Right. *Journal of Business & Economic Statistics*, Forthcoming. Available at: https://doi.org/10.1080/07350015.2018.1462710.

Ransom, S. B., Studdert, D. M., Dombrowski, M. P., Mello, M. M., & Brennan, T. A. (2003). Reduced Medicolegal Risk by Compliance with Obstetric Clinical Pathways: A Case–Control Study. *Obstetrics & Gynecology*, *101*(4), 751-755.

Robertson, E., Grace, S., Wallington, T., Stewart D.E. (2004). Antenatal Risk Factors for Postpartum Depression: A Synthesis of Recent Literature. *General Hospital Psychiatry,* 26(3), 289-295.

Sittig, Dean F. and William W. Stead. 1994 “Computer-Based Physician Order Entry: The State of the Art.” *Journal of the American Medical Informatics Association* 1(2): 108-123.

Skinner, J. (2011) "Causes and Consequences of Regional Variations in Health Care." In Handbook of Health Economics Volume 2. Eds M. Pauly, T. McGuire and Pedro P. Barros, North-Holland, 45-93.

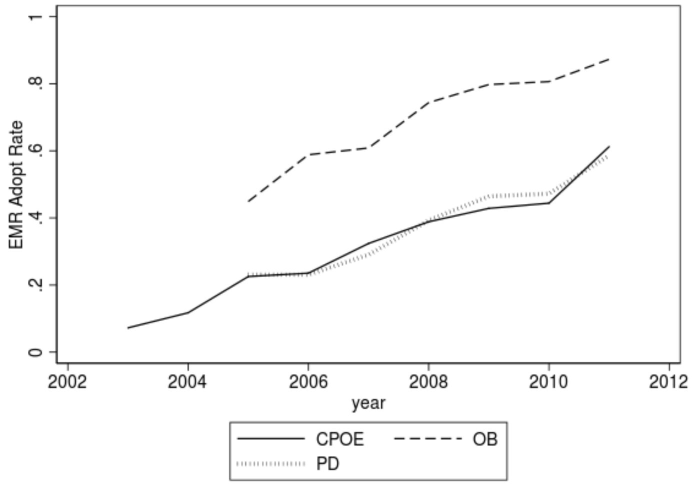
Smith, S., Bunting, K., & Hamilton, E. (2014). Using Intelligent Electronic Fetal Monitoring Software to Reduce Iatrogenic Complications of Childbirth: A Case Study. *The Journal of Healthcare Information Management*, 28(4), 28-33.

Wing, C., Simon, K., Bello-Gomez, R. (2018). Designing Difference in Difference Studies: Best Practices for Public Health Policy Research. *Annual Review of Public Health*, 39: 453-469.

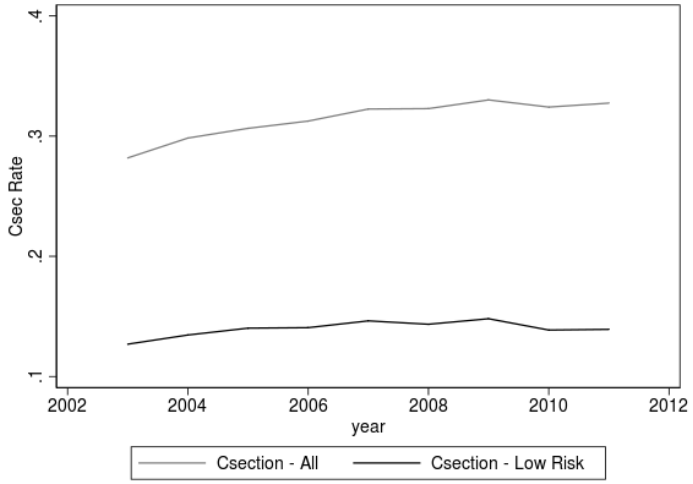
Wright, A., Sittig, D. F., Carpenter, J. D., Krall, M. A., Pang, J. E., & Middleton, B. (2010). Order Sets in Computerized Physician Order Entry Systems: an Analysis of Seven Sites. *AMIA Annual Symposium Proceedings*, *2010*, 892–896.

Figure 1: EMR Adoption and C-section Rates Over Time

Panel A: EMR Adoption Trends

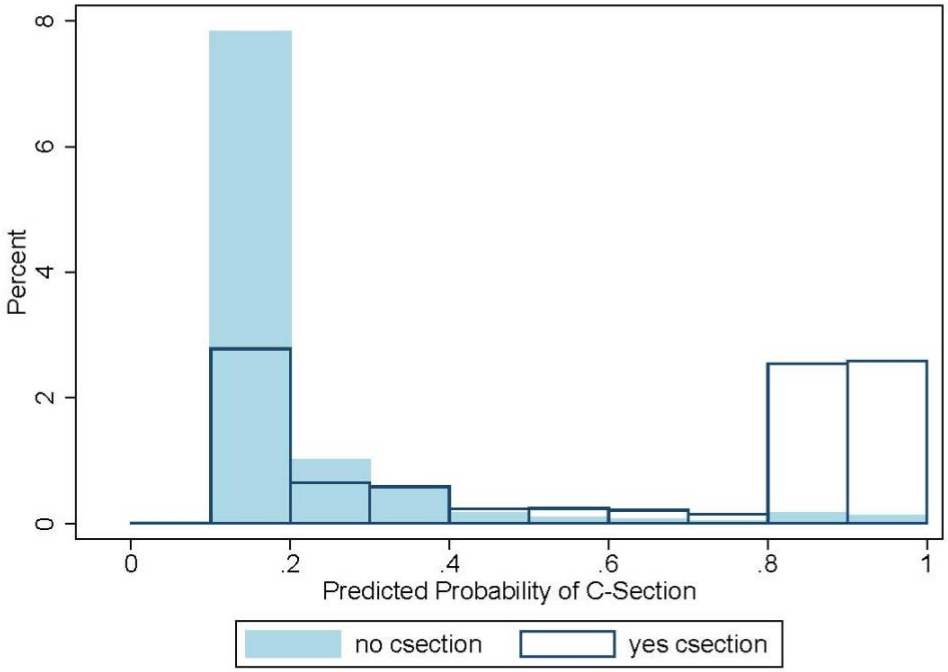


Panel B: C-section Trends



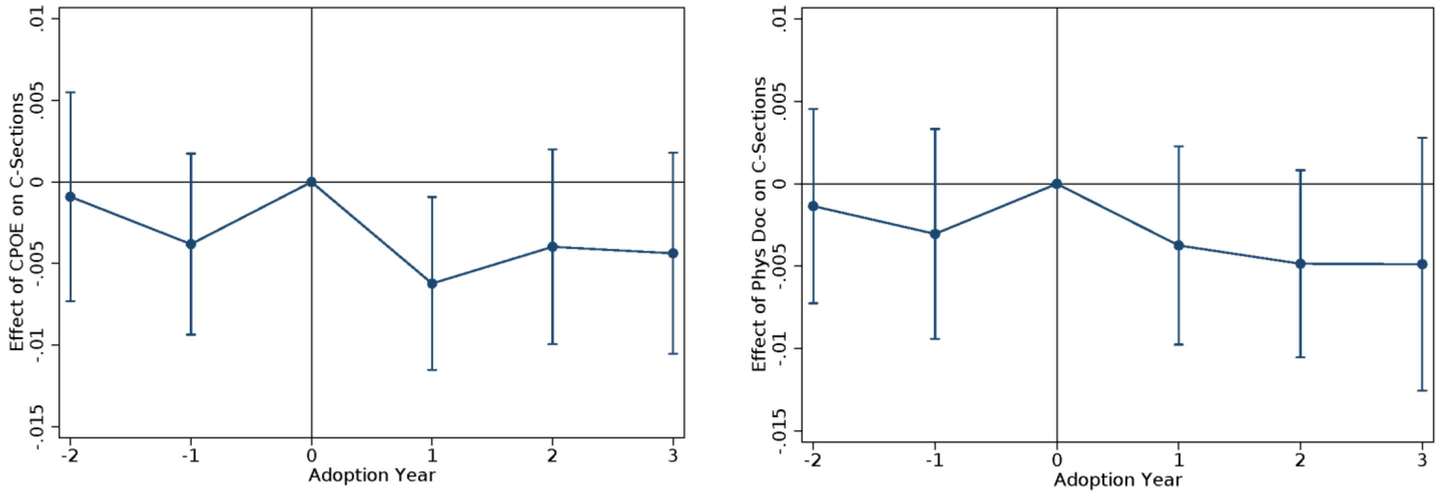
Notes: Authors calculations from NIS and HIMSS data. EMR rates represent the fraction of births in hospitals that have adopted these EMR technologies in each year.

Figure 2: Distribution of Logit Model C-Section Predictions



Notes: This figure graphs the distribution of the predicted probability of C-section based on the estimates in the Logit estimates in Appendix Table A1.

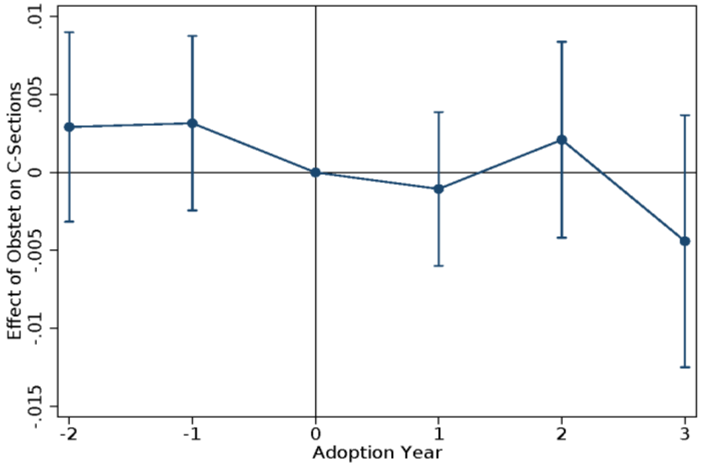
Figure 3: Event Study Estimation



Panel A: CPOE

Panel B: PD

Panel C: OB



Notes: These figures plot coefficients and 95% confidence intervals of event study estimation that traces out the trends in C-sections in EMR adopting hospitals from three years prior to adoption to 2 years post adoption. Zero corresponds to the adoption year and all coefficients are relative to the year prior to the adoption year.

Table 1: Summary Statistics

	All Deliveries	Low-Risk Sample
C-Section	0.314	0.140
Low Risk	0.626	
Age 20 - 25	0.089	0.105
Age 25 - 30	0.226	0.248
Age 30 - 35	0.273	0.283
Age > 35	0.248	0.234
White	0.422	0.426
Hispanic	0.195	0.195
Other Race/Ethn.	0.087	0.088
Missing Race/Ethn.	0.192	0.197
Medicaid	0.395	0.397
Private	0.542	0.539
Payer Missing	0.001	0.001
Weekend	0.198	0.224
OB	0.691	0.684
PD	0.314	0.304
CPOE	0.376	0.367
N	5,106,287	3,193,992

Notes: This table presents means from our analysis sample of deliveries occurring in hospitals merged between the NIS and HIMMS data sets.

Table 2: Effect of EMR Adoption on C-Section Use

	(1) All Hospitals	(2) Low Intensity	(3) High Intensity
CPOE	-0.0035**	-0.0057**	-0.0030
	(0.0017)	(0.0024)	(0.0036)
	3,193,621	1,076,530	1,050,365
OB	-0.0019	-0.0033	0.0018
	(0.0023)	(0.0030)	(0.0046)
	2,450,417	802,198	839,715
PD	-0.0010	0.0011	-0.0062
	(0.0020)	(0.0025)	(0.0045)
	2,450,417	802,198	839,715
Csect Rate	14.0%	10.7%	17.5%

Notes: This table presents estimates of the coefficients of an indicator for whether a hospital has a particular EMR application installed. Standard errors are robust-clustered at the hospital level and are presented in parentheses. Observations for each estimate reported under standard-errors. Each set of rows present estimates from separate regressions for each EMR application. Each column presents regressions estimates for a given subset of hospitals. All regressions control for year and hospital fixed effects; comorbidities, demographics that include mother's race/ethnicity categories, insurance coverage categories, quartiles of mean household income in the mother's zip code, a weekend delivery indicator, and quarter of year indicators; and price differences measured as the difference in the mean charges within a hospital-year for patients whose only procedure code is a C-section delivery and those whose only procedure code is a normal delivery.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Test of Parallel Pre-Adoption Trends by Timing Group

	(1) CPOE	(2) OB	(3) PD
I(AdoptionYear=2005)*year	0.0088		
	(0.0058)		
I(AdoptionYear=2006)*year	0.0037		
	(0.0035)		
I(AdoptionYear=2007)*year	-0.0002	0.0030	-0.0131
	(0.0026)	(0.0072)	(0.0081)
I(AdoptionYear=2008)*year	0.0005	0.0012	0.0001
	(0.0022)	(0.0029)	(0.0034)
I(AdoptionYear=2009)*year	0.0002	0.0071***	0.0000
	(0.0020)	(0.0020)	(0.0019)
I(AdoptionYear=2010)*year	-0.0006	0.0053	0.0024
	(0.0037)	(0.0035)	(0.0034)
I(AdoptionYear=2011)*year	-0.0023	0.0070**	0.0020
	(0.0026)	(0.0033)	(0.0026)
P-Value of F-test of Joint Significance	0.496	0.011	0.473
Observations	1,910,020	635,701	1,319,401

Notes: This table presents estimates of the coefficients of interactions between indicators for adoption-year timing groups and a linear year trend. The sample includes observations in years prior to adoption, and excludes observations from the first two adoption groups, since a linear trend cannot be estimated for these groups. Standard errors are robust-clustered at the hospital level and are presented in parentheses. All regressions control for year and hospital fixed effects; comorbidities, demographics that include mother's race/ethnicity categories, insurance coverage categories, quartiles of mean household income in the mother's zip code, a weekend delivery indicator, and quarter of year indicators; and price differences measured as the difference in the mean charges within a hospital-year for patients whose only procedure code is a C-section delivery and those whose only procedure code is a normal delivery. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Effect of EMR Adoption on Patient Characteristics

	(1) White	(2) LOS	(3) Quarter 4	(4) Weekend	(5) Medicaid	(6) Private	(7) High Income	(8) Price Diff	(9) > Age 35	(10) Any Comorbs
CPOE	0.0116	-0.0004	-0.0025*	-0.0010	-0.0145***	0.0118**	0.0008	1.0095	0.0047***	0.0001
(N=3,193,621)	(0.0143)	(0.0087)	(0.0014)	(0.0012)	(0.0052)	(0.0057)	(0.0044)	(2.7016)	(0.0014)	(0.0001)
OB	0.0395**	-0.0012	-0.0018	0.0011	0.0046	0.0012	-0.0034	1.1951	-0.0001	0.0001
(N=2,450,417)	(0.0197)	(0.0067)	(0.0038)	(0.0014)	(0.0059)	(0.0058)	(0.0066)	(2.7638)	(0.0018)	(0.0002)
PD	0.0263	-0.0023	-0.0037*	0.0001	-0.0070	0.0085*	0.0016	-2.1816	0.0045**	0.0002
(N=2,450,417)	(0.0177)	(0.0091)	(0.0019)	(0.0014)	(0.0055)	(0.0047)	(0.0063)	(2.0874)	(0.0019)	(0.0002)

Notes: This table presents estimates of the coefficients of an indicator for whether a hospital has a particular EMR application installed on a patient characteristic. Standard errors are robust-clustered at the hospital level and presented in parentheses. Each set of rows present estimates for a different EMR application. All regressions control for year and hospital fixed effects; demographics (other than the outcome) that include mother's race/ethnicity categories, insurance coverage categories, quartiles of mean household income in the mother's zip code, a weekend delivery indicator, and quarter of year indicators; and price differences measured as the difference in the mean charges within a hospital-year for patients whose only procedure code is a C-section delivery and those whose only procedure code is a normal delivery. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Scheduled vs. Unscheduled C-Sections

	(1) Scheduled	(2) Unscheduled	(3) Unscheduled with Induction	(4) Unscheduled without Induction
CPOE (N=3,193,621)	-0.0014	-0.0021	-0.0030***	-0.0005
	(0.0010)	(0.0014)	(0.0010)	(0.0012)
OB (N=2,450,417)	-0.0003	-0.0016	-0.0017*	-0.0001
	(0.0014)	(0.0016)	(0.0011)	(0.0020)
PD (N=2,450,417)	-0.0003	-0.0007	-0.0009	-0.0001
	(0.0012)	(0.0014)	(0.0010)	(0.0016)

Notes: This table presents estimates of the coefficients of an indicator for whether a hospital has a particular EMR application installed on scheduled cesarean sections and on unscheduled cesarean sections for the low-risk sample. Standard errors are robust-clustered at the hospital level and are presented in parentheses. All regressions control for year and hospital fixed effects; comorbidities, demographics that include mother's race/ethnicity categories, insurance coverage categories, quartiles of mean household income in the mother's zip code, a weekend delivery indicator, and quarter of year indicators; and price differences measured as the difference in the mean charges within a hospital-year for patients whose only procedure code is a C-section delivery and those whose only procedure code is a normal delivery. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Effect of EMR Adoption on Outcomes

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Hemorrhage	Infection	Laceration	Operative	LOS
CPOE (N=3,193,616)	-0.0003	-0.0018**	0.0037*	-0.0000	-0.0017
	(0.0007)	(0.0008)	(0.0019)	(0.0001)	(0.0086)
OB (N=2,450,415)	0.0007	-0.0005	0.0023	0.0001	-0.0045
	(0.0008)	(0.0014)	(0.0021)	(0.0001)	(0.0068)
PD (N=2,450,415)	-0.0001	-0.0002	-0.0007	-0.0001	-0.0024
	(0.0009)	(0.0009)	(0.0023)	(0.0001)	(0.0090)

Notes: This table presents estimates of the coefficients of an indicator for whether a hospital has a particular EMR application installed on patient outcomes for the low-risk sample only. Standard errors are robust-clustered at the hospital level and are presented in parentheses. All regressions control for year and hospital fixed effects; comorbidities, demographics that include mother's race/ethnicity categories, insurance coverage categories, quartiles of mean household income in the mother's zip code, a weekend delivery indicator, and quarter of year indicators; and price differences measured as the difference in the mean charges within a hospital-year for patients whose only procedure code is a C-section delivery and those whose only procedure code is a normal delivery. *** p<0.01, ** p<0.05, * p<0.1