

Understanding Variation in Cesarean Section Use: Supply-Side Drivers and Maternal Health Effects

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(Job Market Paper)

October 21, 2025

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Abstract

We estimate the causes and consequences of regional variation in healthcare utilization in the setting of Cesarean sections (C-sections), the most common inpatient surgery in the United States. C-section rates differ up to 10-fold across hospitals, with substantial variation even for clinically similar patients. Using nationwide Medicaid administrative claims data, covering 42% of all US births, we leverage physician mobility across hospitals to disentangle the role of physician practice style from hospital environment. We find that differences in physician practice style can explain over one quarter of the across-hospital differences in C-section rates. This variation in practice style has meaningful consequences for patient health: low-risk patients quasi-randomly assigned to more C-section-intensive physicians are 10% more likely to deliver via unplanned C-section, leading to worse maternal health outcomes without measurable improvements in infant health. Our findings highlight physician practice style as an important driver of variation in obstetric care with direct consequences for maternal health. **JEL Classification:** I10, I18

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We thank our advisors Ran Abramitzky, Liran Einav, Petra Persson, Maya Rossin-Slater, and Heidi Williams for their support and advice. We thank Lea Bottmer, Stuart Craig, Mariana Guido, Harsh Gupta, Caroline Hoxby, Maria Polyakova, Heather Royer, Adrienne Sabety, Isaac Sorkin, and Jason Weitze, as well as participants of seminars at ASHEcon 2025 and Stanford University for valuable feedback. We are grateful for the expertise and guidance of several obstetricians and gynecologists, midwives, and labor and delivery nurses, including Elliott Main and Judith Forster. This project was supported by a Stanford Population Health Sciences Spectrum Grant.

Data for this project were accessed using the Stanford Center for Population Health Sciences Data Core. The PHS Data Core is supported by a National Institutes of Health National Center for Advancing Translational Science Clinical and Translational Science Award (UL1TR003142) and from internal Stanford funding. The content is solely the responsibility of the authors and does not necessarily represent the official views of the NIH.

1. Introduction

In the United States (US), healthcare spending and utilization vary sharply across regions, even after adjusting for differences in patient health (Skinner, 2011). In many cases, higher treatment intensity is not accompanied by improvements in health outcomes, suggesting that reducing unnecessary utilization could lower healthcare costs without harming health (Doyle et al., 2017; Einav et al., 2023). While the literature has explored the determinants of this geographic variation in healthcare spending, relatively little work has directly examined the health consequences of this variation. Additionally, most existing work focuses on the over-65 Medicare population, necessarily excluding critical specialties such as obstetrics (Badinski et al., 2024; Finkelstein et al., 2016).

Cesarean sections (C-sections) provide a natural setting to study variation in treatment intensity, given their frequency and the substantial heterogeneity in utilization. Childbirth is the most common reason for hospitalization in the US, and the C-section is the most commonly performed inpatient surgery (Osterman et al., 2025). Roughly one in three US births (32.3%) are delivered by C-section, with rates varying dramatically across hospitals, from as low as 7% to as high as 70%.¹ Beyond concerns over variation in utilization, there is widespread concern that the C-section rate in the US is higher than medically indicated.² While a C-section can be life-saving when medically necessary, it is a major abdominal surgery involving health risks for mothers and infants, a longer recovery time, and higher costs.³

In this paper, we quantify the contribution of the primary supply-side agents in healthcare—physicians and hospitals—to variation in C-section use across the US, and estimate the health consequences of variation in physician practice style. We use full-count nationwide Medicaid claims data from 2015-2019, which cover 42% of all US births, and focus our analysis on unplanned C-sections among low-risk, first-time deliveries, a group for whom C-sections

¹This variation cannot be fully explained by differences in underlying patient health; even among lower risk births (singleton, non-breech, full term) hospital-level rates range from 2.4% to 36.5% (Kozhimannil et al., 2013).

²For example, the Healthy People 2030 goals include reducing the C-section rate among low-risk women with no prior births to a target of 23.6%. Rather than declining, the rate has increased from 25.9% in 2018 (when the goal was set) to 26.6% in 2023 (ODPHP, 2025)

³C-sections cost 40-50% more than vaginal deliveries, across insurance types (Truven Health Analytics, 2013; Valencia et al., 2022).

are most likely to be marginal.⁴ Our empirical approach combines two complementary sources of variation. Physician mobility across hospitals allows us to disentangle the role of physician practice style in C-section rates from the hospital environment. Additionally, the quasi-random assignment of patients to on-call physicians enables us to estimate the causal effect of physician practice style on maternal and infant health. We find that physician practice style explains a meaningful share of the variation in C-section use across hospitals, and that physicians with a more C-section-intensive practice style negatively impact maternal health outcomes for low-risk patients.

To decompose the variation in C-section use, we estimate an AKM-style model that separates out the roles of the physician, the hospital environment, and underlying patient health risk (Abowd et al., 1999). Estimating the determinants of C-section use is complicated by non-random patient sorting across physicians and hospitals. To address this, our model uses two sources of variation. First, physician mobility across hospitals, from both traditional movers (physicians who shift all of their practice from one hospital to another) and “multi-homers” (physicians who practice at multiple hospitals simultaneously), enables us to isolate the physician contribution separately from the hospital environment. Second, the spontaneous onset of labor for patients in our sample, combined with rotational variation in physician shifts, creates quasi-random patient-physician matching within hospitals.

We find that approximately 65% of the difference in unscheduled C-section rates between above- and below-median hospitals can be explained by differences in the hospital environment, and 29% of the difference can be explained by differences in physician practice style.⁵ This suggests that institutional factors—for example, clinical protocols, staffing ratios, and surgical capacity—contribute most to the observed variation across hospitals. However, there is a strikingly strong role of physicians, with differences in physician practice style explaining over a quarter of the gap in C-section rate across high vs. low C-section hospitals. This magnitude is notable given that, in prior work on cardiology, physician practice style explains

⁴Specifically, we restrict our sample to nulliparous (first-births), term (gestation ≥ 37 weeks), singleton, and vertex (dropping breech pregnancies), which we denote with the acronym NTSV. We restrict to first births because the delivery method of the first birth is highly predictive of subsequent deliveries. We additionally drop all scheduled C-sections, focusing only on unplanned or emergency C-sections. The focus on NTSV births is standard in the existing C-section literature.

⁵The remaining 6% is driven by differences in patient health risk

relatively little of the variation across hospital referral regions (HRR) (Molitor, 2018). Our estimates are closer in magnitude to those found for primary care utilization, suggesting that, although obstetrics is a surgical specialty, there remains substantial scope for physician discretion relative to other surgical fields (Badinski et al., 2024). Moreover, physicians do not appear to sort into hospitals based on C-section intensity, leaving substantial variation in physician C-section intensity even within hospitals. Taken together, our results indicate that existing policies, targeted primarily at hospital- or state-level interventions, are unlikely to fully address the geographic variation in C-section use.

Moving beyond identifying the drivers of C-section use, we estimate the causal effects of physician practice style on maternal and infant health outcomes. For identification, we adopt a judges-style design that exploits quasi-random assignment of patients to physicians within hospitals. Although patients can select their prenatal care provider, the unpredictability of labor and rotating physician shifts means that low-risk patients attempting vaginal birth are effectively delivered by whichever physician is on duty. We find that patients assigned to a physician with a 10 percentage point higher C-section intensity are 2.1 percentage points more likely to receive a C-section, an increase of about 10%.⁶

Beyond delivery method, we find that physician practice style has meaningful consequences for maternal health. Women quasi-randomly assigned to high C-section intensity physicians have higher rates of severe delivery complications, along with higher rates of postpartum infection, antibiotic use, and emergency room visits within 60 days of delivery. The adverse maternal health outcomes do not appear to be offset by improvements to infant health. We do not detect any statistically significant effects on neonatal outcomes, though the point estimates suggest a slight negative effect. Additionally, infants delivered by higher-intensity physicians have significantly higher rates of emergency room visits for respiratory illness during the first year of life. This is consistent with existing evidence linking C-section delivery to respiratory problems in infants (Card et al., 2023). We also find that women delivered by high C-section physicians have worse postpartum mental health outcomes and lower fertility rates. This result is noteworthy, given that mental health disorders are the leading cause of

⁶A 10 percentage point change in C-section intensity is roughly one standard deviation, or the effect of moving from a physician at the 25th to 75th percentile of the C-section intensity distribution.

maternal mortality in the postpartum period (Clarke et al., 2023). Taken together, these findings indicate that physician practice style plays a central role in determining C-section use and has meaningful consequences for both maternal and infant health.

We contribute to three related literatures. First, we build on the extensive literature in health economics documenting and examining geographic variation in healthcare use across the US. A growing body of research uses quasi-random changes in physician locations to disentangle demand- and supply-side drivers of healthcare utilization (Badinski et al., 2024; Finkelstein et al., 2016; Finkelstein et al., 2021; Fischer et al., 2023; Molitor, 2018; Song et al., 2010). Much analysis has been done on the Medicare 65+ population, which excludes large specialties such as obstetrics and pediatrics. We add to this literature by disentangling physician effects from hospital factors in obstetrics and linking variation in practice style to health outcomes. Childbirth is a particularly suitable context for this analysis, as the near universality of hospital delivery limits concerns about patient selection into treatment, the choice of delivery mode is binary, and the rate of surgical intervention is high.

We also contribute to a substantial body of literature examining the drivers of geographic variation in C-section utilization. It is well-documented that there is large geographic variation in C-section rates, even after adjusting for patient risk (Baicker et al., 2006; Card et al., 2023; Fischer et al., 2023; Robinson et al., 2023). Even within a geographic area, physicians differ in their propensity to perform C-sections on observably similar patients (Currie and MacLeod, 2017; Epstein and Nicholson, 2009; Goyert et al., 1989). One reason behind the large variation in C-section usage is that the decision to perform a C-section involves considerable physician discretion. Incentives have been found to influence decision-making at both the hospital and physician levels. Hospital characteristics, including capacity (Corredor-Waldron et al., 2024), management practices (La Forgia, 2023), malpractice environment (Currie and MacLeod, 2008), and ownership type (Johnson and Rehavi, 2016), have all been shown to influence mode of delivery. At the physician level, the decision to perform a C-section has been shown to respond to financial incentives (Allin et al., 2015; Gruber et al., 1999; Gruber and Owings, 1996; Keeler and Brodie, 1993), information asymmetries (Johnson and Rehavi, 2016), and outcomes of the preceding delivery (Singh, 2021). Even time of day (Son et al., 2020), day of week (Costa-Ramón et al., 2022), and holidays (Jacobson et al., 2021) have been found to

influence C-section rates.

However, parsing the role of patients, physicians, and hospitals in the overall geographic variation in utilization has been held back as data is typically either granular (observing all agents) but constrained to a smaller geographic region, or coarser (observing only patients and counties) but covering the whole of the US. Moreover, many data sources are restricted to inpatient or delivery records, limiting information on postpartum patient outcomes. The granularity *and* nationwide coverage of the Medicaid data allows us to build on this literature and separately estimate the contribution of both physicians and hospitals to differences in C-section use. Our paper is most closely related to contemporaneous work by [Deibler et al., 2025](#), which leverages physician movement and firm acquisition to estimate the role of doctors, firms, and facilities in C-section rates using commercial healthcare claims from 14 states. Our paper differs along several dimensions. First, we use a national sample of Medicaid claims, a particularly policy-relevant sample given Medicaid is the largest payer for maternity care in the US. The second key difference is that we extend the analysis of variation to estimate the causal effect of physician practice style on maternal and infant health outcomes, both during delivery and postpartum.

We also contribute to the broader literature on the health implications of C-sections. The health consequences of marginal C-sections are somewhat inconclusive and depend strongly on both the context and the risk of the patient. [Corredor-Waldron et al., 2024](#) find that reductions in unscheduled C-sections for low-risk mothers, driven by variation in hospital capacity, lead to lower infant and maternal complications, while reductions in unscheduled C-sections for high-risk mothers have little effect on maternal complications but increase infant complications. On the other hand, [Card et al., 2023](#) find that births at hospitals with a higher C-section rate have fewer delivery complications for infants, potentially outweighing small negative consequences for maternal health. We estimate the causal effects of being treated by a high C-section intensity physician for low-risk patients, keeping the hospital environment fixed, and find negative implications for maternal health without compensating benefits to newborns. This suggests that reducing marginal C-sections through policy targeting physician practice style could have positive health benefits. Another key contribution of our findings is the ability to observe long-run postpartum care outcomes for both mothers and infants. We

provide novel evidence that marginal unplanned C-sections are associated with a higher risk of maternal mental health complications postpartum, an important finding given that mental health disorders are a leading cause of postpartum maternal mortality.

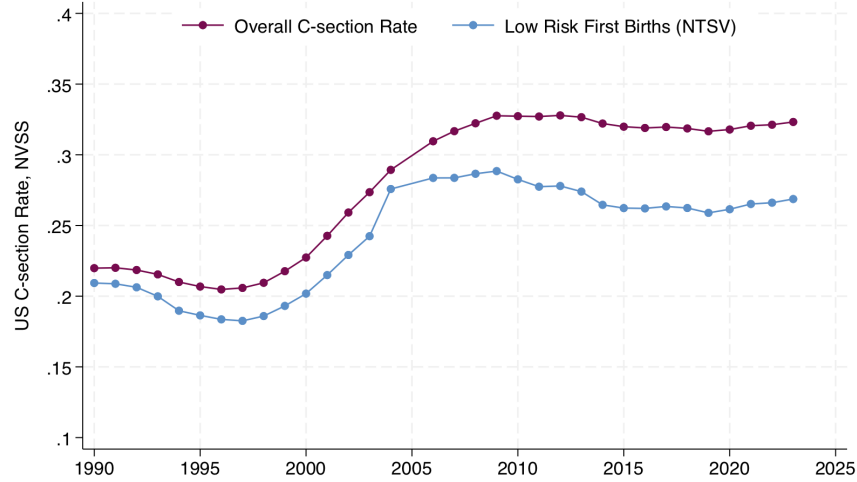
The rest of the paper proceeds as follows. [Section 2](#) provides background on maternal healthcare in the US and outlines the decision framework for C-sections. In [Section 3](#), we outline our data and summarize the geographic variation in C-section rates. Our empirical strategy, exploiting physician migration to separate the role of physician practice style from hospital environment, is detailed in [Section 4](#). We present additive decomposition results in [Section 5](#). In [Section 6](#) we explore the causal effect of the variation in physician practice style on delivery method and maternal health outcomes. Results are shown in [Section 7](#). In [Section 8](#) we discuss the implications of our findings and conclude.

2. Institutional Setting

The US C-section rate has risen significantly since the late 1990s ([Figure 1](#)), without accompanying improvements in maternal mortality or morbidity. This increase has raised concerns of excessive use, particularly for low-risk pregnancies. The Department of Health and Human Services, for example, in its Healthy People 2030 project, set a goal to reduce C-sections among low-risk first-time births, from the 2018 rate of 25.9% to 23.6%. The most recent rate, as of 2023, is 26.6% ([ODPHP, 2025](#)). Moreover, there is evidence that C-sections are poorly targeted, with too many being used for low-risk deliveries and too few among high-risk deliveries, deviations that are even more noticeable among racial minorities ([Corredor-Waldron et al., 2024](#); [Robinson et al., 2023](#)).

While C-sections can be lifesaving in the face of complications, the procedure carries risks not present in vaginal delivery. For the mother, risks associated with C-section delivery include infection, surgical damage to bladder or other organs, blood clots, and excessive bleeding or hemorrhage ([Hall and Bewley, 1999](#); [NHS, 2017](#)). Given that it is major abdominal surgery, the recovery period is longer on average following a C-section compared to vaginal birth, and patients who have had a C-section are more likely to be re-hospitalized and to report prolonged pain after delivery (as high as 18% six months postpartum) ([Declercq](#)

Figure 1: United States C-section rate, 1990-2023



Note: Data on annual C-section rate from NVSS. The top maroon line shows the overall C-section rate. The blue line shows the C-section rate among low-risk first-births. Specifically, this sample is restricted to nulliparous, term, singleton and vertex (NTSV) deliveries.

et al., 2008; Lydon-Rochelle, 2000). C-sections also increase maternal health risks for future pregnancies, largely due to the formation of uterine scar tissue from the procedure (Alpay et al., 2008; Ananth et al., 1997; Ecker and Frigoletto, 2007).⁷ Following a C-section, a woman’s subsequent deliveries are very likely to also be C-sections, which compounds the risks.⁸

There are also well-documented risks for infants, primarily in the form of respiratory issues. C-section delivery is associated with risk of respiratory problems in infants immediately following delivery, and higher rates of asthma, allergies, and infections in the year following birth (Costa-Ramón et al., 2022; Liang et al., 2023; Wolf, 2018).⁹ On the other hand, prolonged labors also pose risks, including infection¹⁰, birth injury, or oxygen deprivation to the infant. The risk of maternal pelvic floor damage and severe laceration is also increased

⁷For example, a C-section increases the risk of placenta accreta: a condition where the placenta grows into the uterine wall and does not detach after childbirth, risking major hemorrhage (Clark et al., 1985)

⁸In 2018, the rate of vaginal births following a C-section delivery (VBAC) was 13.3% (Osterman, 2020).

⁹There are several theorized mechanisms. One is that vaginal delivery is important for the development of a baby’s gut microbiome, which assists the immune system in early life. Another is that vaginal delivery helps remove amniotic fluid from the newborn’s lungs, something a C-section delivery does not have a mechanism for.

¹⁰Bacterial infection of the amniotic fluid, membranes, placenta, or uterus during labor is known as chorioamnionitis. Risk increases with prolonged labor or ruptured membranes and can affect both mothers and infants.

with vaginal births. In sum, there are risks to both delivery methods, and the health effects of C-section delivery are dependent on the context.

The decision to perform a C-section can be made either before or after the onset of labor. Studies in the US and elsewhere suggest that the share of C-sections performed due solely to maternal request, absent a clear clinical indication, is extremely low.¹¹ In most cases, the decision to deliver via *scheduled* C-section is due to medical indication. In this paper, we drop all scheduled C-sections and focus only on the outcome of unplanned C-sections for patients who plan for a vaginal birth and undergo a trial of labor.¹² [Table 1](#) shows the share of Medicaid deliveries occurring via scheduled and unplanned C-sections. After delivering via C-section in a prior birth, most patients will have scheduled C-sections for all subsequent births. Thus, the share of C-sections that occur after trial of labor is much higher for first-time (nulliparous) deliveries. In medical claims, all unplanned C-sections must have a diagnosis code that indicates the medical indication for the C-section. [Table 2](#) shows that the most commonly diagnosed indications for unplanned C-sections are fetal distress and inadequate contractions.

Table 1: Rate of scheduled vs. unplanned C-sections in Medicaid 2015-2019

Delivery type	All patients	Low-risk first-births
Scheduled C-section	1,483,015 (19.0%)	63,414 (4.6%)
Attempted vaginal delivery	6,337,837 (81.0%)	1,312,624 (95.4%)
Unscheduled C-section	817,195 (10.4%)	248,426 (18.1%)
Vaginal	5,520,642 (70.6%)	1,064,198 (77.3%)
Total births	7,820,852	1,376,038

Notes: Table reports the count, and percent, of delivery type. Estimates from Medicaid 2015-2019. Unscheduled C-sections are defined as C-section deliveries following a trial of labor. We define trial of labor following [Gregory et al., 2002](#), see [Appendix B](#) for more details. In column 3, we restrict to low-risk first-births (NTSV).

¹¹ACOG estimates the share of all births that fall into this category is 2.5% ([ACOG, 2019](#)). See also [Weaver et al., 2007](#). Even among patients with a previous C-section, surveys suggest that at term the majority prefer an attempted VBAC ([Emmett et al., 2011](#)).

¹²We use emergency, unscheduled, and unplanned C-section interchangeably to refer to any C-section delivery occurring after a trial of labor. Trial of labor is defined following ([Gregory et al., 2002](#)), see [Appendix B](#) for more details.

Table 2: Diagnosed medical indications in unplanned C-sections

Reason	All patients	Low-risk first-births
Fetal distress	64.30% (47.91)	60.49% (48.89)
Inadequate contractions or uterine fatigue	33.21% (47.10)	44.20% (49.66)
Umbilical cord complications (e.g. prolapse)	16.36% (36.99)	16.18% (36.82)
Obstructed labor (e.g. shoulder dystocia)	15.63% (36.31)	14.53% (35.24)
Disproportion due to pelvis malformation or fetal size	5.63% (23.04)	7.62% (26.53)
Placenta separation	3.24% (17.72)	1.63% (12.65)
Prolonged labor	2.46% (15.50)	3.23% (17.68)
Fever or infection in labor	1.94% (13.80)	2.43% (15.41)
Maternal distress or exhaustion	1.10% (10.44)	1.41% (11.78)
Antepartum hemorrhage	0.41% (6.40)	0.18% (4.22)
None of above reasons specified	4.90% (21.60)	5.28% (22.37)
N	817,195	248,426

Notes: Percent (and standard deviation) of commonly diagnosed medical indications for all unplanned C-sections occurring after trial of labor in Medicaid, 2015-2019. Column 2 includes all Medicaid births with an unplanned C-section, column 3 restricts to low-risk first-time births (NTSV). Note that diagnoses are not mutually exclusive. The final row reports the share of unplanned C-sections for which none of the above diagnoses are present.

2.1 Patient-Provider Assignment

The allocation of an outpatient clinic (for prenatal care) and a hospital is typically the patient’s choice. There are several factors, specific to Medicaid, that shape this matching. First, Medicaid tends to reimburse at lower rates relative to other forms of insurance, meaning patient choice over providers is often more limited. Second, managed care programs within Medicaid can also restrict the networks of available practices and hospitals. Moreover, because Medicaid coverage is systematically more generous for pregnant patients than non-pregnant patients, many patients will become eligible during pregnancy, and only then search for a provider for prenatal care, meaning they will have minimal history with a given practice. Because patients will typically need to see a provider soon after becoming pregnant, the search is urgent and often means that matching is subject to clinics’ capacity constraints; in other words, which clinic has availability when the patient becomes pregnant. Several obstetricians and gynecologists told us in interviews that, in practice, most Medicaid patients will have “one option” for prenatal care and delivery in their local area.

Patients in spontaneous labor typically present to a predetermined hospital after the onset

of labor. While the estimated gestation length is 40 weeks, the exact date of delivery is highly unpredictable.¹³ Even when labor is induced, rather than occurring spontaneously, the exact date of delivery is unpredictable. Most inductions are for medical reasons (e.g., preeclampsia, gestation after 41 weeks), and are usually relatively urgent with limited flexibility in scheduling. If induction occurs due to maternal preference, scheduling is subject to hospital capacity constraints, which can impact the date and time.¹⁴ Moreover, medical induction of labor (from administering induction to delivery) can take anywhere from a few hours to two or three days.

Physicians working on the labor and delivery ward can either be hospitalists (physicians who specialize in delivery and do not work in an outpatient clinic) or physicians on rotation from a group practice (with an outpatient clinic) or solo practice. Although obstetric hospitalists are growing in popularity, the vast majority of delivering physicians work in group practices and see patients both during outpatient clinic visits and in the hospital for delivery (ACOG, 2016). Typically, physicians will set hospital delivery shifts a couple of months in advance (the remainder of their time being spent in an outpatient clinic).¹⁵ Matching is therefore done in an emergent setting, based on the (unpredictable) delivery date and which physician is on-call.¹⁶ In our sample of low-risk (NTSV) and unplanned deliveries with Medicaid insurance, approximately half of all patients had never seen their delivering physician for any prenatal care.

¹³Less than 5% of all births occur on the estimated due date (Khambalia et al., 2013)

¹⁴For example, elective inductions are typically the first patients to be “bumped” due to capacity constraints. Anecdotally, many hospitals use wait-lists for non-urgent inductions, whereby patients scheduled for induction are on “standby” until a bed is available.

¹⁵Obstetricians and gynecologists we interviewed said that inpatient shifts would be set between one and three months in advance, and shifts are strictly followed. All were clear that patients would not be routed to a particular physician upon arrival in the hospital except in the rarest of circumstances. This is in part because if a patient had a particularly complex pregnancy, she would often be scheduled for a C-section, rather than waiting to go into labor. Instead, patients would be allocated the next available physician, either an obstetrician from their group practice or a hospitalist.

¹⁶In theory, this is done within the physicians in the group practice a patient attends. However, the pool of potential physicians is often extended in two ways. First, hospitalists are typically included in the pool (and comprise a growing share of obstetricians who perform deliveries) (Johnson et al., 2016). Second, group practices can form “alliances” for inpatient shifts, committing to deliver any patients from the pool of group practices when they arrive at the labor and delivery ward. This can ease the scheduling burden for smaller group practices and allow physicians to operate across multiple hospitals more easily.

3. Data and Descriptives

3.1 Medicaid Claims, 2015-2019

Our primary data source is the complete sample of nationwide Medicaid claims data from 2015-2019. Medicaid is a means-tested program providing health insurance to low-income individuals, and the largest payer for birth in the US, covering 42% of deliveries.¹⁷ Medicaid beneficiaries are a particularly policy-relevant population, as an estimated 80% of all maternal mortality occurs among women covered by Medicaid during pregnancy ([Hill and Sventek, 2025](#)). Medicaid claims are available in two formats. The Medicaid Analytic eXtract (MAX) files cover 1999 through 2015, while the Transformed Medicaid Statistical Information System Analytic Files (TAF) begin in 2015, coinciding with the transition from ICD-9 to ICD-10 coding. Our main analysis uses TAF claims from 2015 to 2019, although the 2015 TAF data are incomplete due to the transition. We also use MAX data from 2011 to 2015 to help verify parity (number of previous births).

Our data includes service-level claims for all inpatient and outpatient visits covering prenatal, delivery, and postpartum care. Each patient interaction covered by Medicaid (including all inpatient and outpatient visits) generates a claim with diagnoses and procedure codes, as well as the billing provider and physicians associated with the service. Hospitals typically bill for deliveries, allowing us to identify the hospital from the billing provider ID. See [Appendix B](#) for more details. We link physicians to the Center for Medicare and Medicaid Services' (CMS) National Provider and Plan Enumeration System (NPES) registry and the American Medical Association (AMA) masterfile, which gives us additional demographic, education, and specialty information for physicians. Medicaid also collects some demographic information on beneficiaries, including race and ethnicity. To address missing data in these fields, we assign to each beneficiary their most frequently reported race between 2011 and 2019.

To identify births in the Medicaid claims data, we follow the approach recommended by [Auty et al., 2024](#). We outline our process of identifying births and how we use the information

¹⁷This high share reflects, in part, more generous income thresholds for eligibility during pregnancy. We provide additional information on these, as well as the structure of Medicaid insurance, in [Appendix A](#).

associated with claims to code our variables of interest in [Appendix B](#).¹⁸ Medicaid provides summary tables of data quality concerns in the Medicaid files across years (DQAtlas), and both inpatient diagnosis and procedure codes are of high quality across most states.¹⁹ Because the variables we rely on are low- or medium-concern in most states, and because we are focusing on a relatively narrow subset of the Medicaid population (only claims for birth and postpartum), we opt to include all states and benchmark all estimates to the rates for Medicaid deliveries recorded in the CDC’s National Vital Statistics System (NVSS). The benchmarking exercise, both for the number of births and rates of key variables, is reported in [Appendix C](#). In four states (AR, MA, RI, TN), the number of Medicaid births reported in the CDC’s National Vital Statistics System (NVSS) differs from the number of births we identify in Medicaid claims data by more than 20%. All results are robust to dropping these states from our analysis.

For a subset of states, we are able to link mothers’ birth claims to newborn outcomes. We follow the deterministic linking algorithm developed by [Orr et al., 2024](#) to identify mother-infant dyads using a combination of case ID, date of delivery, ZIP of the delivering hospital, beneficiary residence ZIP, and race/ethnicity. We only include states in our newborn outcome analysis in which we find a unique match for over 75% of all births. See [Appendix B](#) for further discussion of the linking algorithm and match rates.

In our main analysis, we make several sample restrictions, outlined in [Table 3](#). First, we restrict to births for which we can identify an individual physician associated with the claim and the hospital of delivery.²⁰ We additionally require all delivering providers to have been observed on at least 100 delivery claims during the sample period. Given that the delivery method of higher order pregnancies is strongly correlated with the delivery method of prior

¹⁸Note that our sample of births, and associated outcomes, relies on diagnosis and procedure codes from the TAF inpatient (IP) files, supplemented with the “other services” (OT) files in light of findings from ([Auty et al., 2024](#)) that find some states have a considerable share of births recorded in the OT files.

¹⁹The exceptions to this are 1) MD procedure codes are flagged as “unusable” in all years and diagnosis codes “unusable” in 2016-2017, 2) TX procedure codes are “medium concern” in all years, 3) KY procedure codes are unusable in 2016, and 4) TN diagnosis codes are “unusable” in most years, however note that there is a known issue with leading zeros in TN ICD codes.

²⁰For details on variables used to identify the hospital and physician associated with a delivery, see [Appendix B](#). All analysis is restricted to births delivered by physicians with specialties in OB/GYN, family medicine, or general practice. Of our sample, 98% of physicians are OB/GYNs, and all results are robust to restricting to only OB/GYNs.

birth(s), we restrict our main analysis to only first births (nulliparous).²¹ In most of our analysis, we focus on a subset of births that are term (gestation of ≥ 37 weeks), singleton, and vertex. This sample of nulliparous, term, singleton, and vertex (NTSV) is a common classification often used in maternal healthcare research to indicate low risk. To mitigate selection concerns, we eliminate all scheduled C-sections from our analysis.²² The C-section rate for NTSV patients is especially policy relevant, as these procedures are more likely to be marginal and, due to the dynamic effects of delivery method, reducing C-sections for first births has compounding effects on subsequent deliveries.

Table 3: Sample restrictions

	% of Remaining Sample Dropped	Remaining N Births
All births		7,820,852
No hospital identified	25.61%	5,818,140
No delivering physician identified	31.78%	3,969,107
Physician with < 100 births total	14.92%	3,377,037
Not nulliparous	80.25%	666,850
Not term, singleton and vertex	6.93%	620,631
Scheduled C-section	4.18%	594,675
Single observation per physician-year or physician-hospital	3.69%	572,752
Total		572,752

Notes: Table details the share of data dropped with each sample restriction and resulting sample size. Data from Medicaid 2015-2019 T-MSIS (TAF) claims data. We use both the inpatient (IP) and other-services (OT) claims files to identify births and associated variables. See [Appendix B](#) for details on how we identify births, the delivering physician, and the hospital. Physicians are restricted to be either OB/GYN, family practice or general practice, 98% of our sample was delivered by an OB/GYN.

3.2 Variation in C-section Use

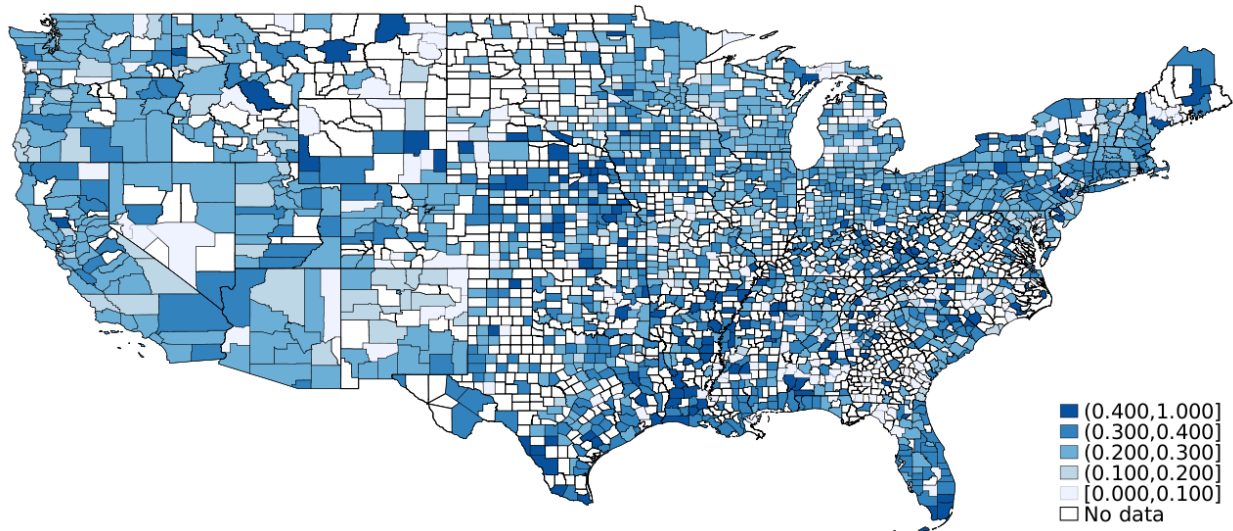
Alongside the rise in C-section rates, prior research has documented substantial geographic variation in C-section rates across the US ([Baicker et al., 2006](#); [Robinson et al., 2023](#)), and

²¹Note that we underestimate nulliparity in our sample. If we do not impose the nulliparous restriction, all results remain substantively the same, with more precision due to the increased sample size. We opt to use nulliparous births for our main specification to be conservative, due to potential concerns of patient selection into hospitals or physicians for higher-order births.

²²Specifically, we require all births to have evidence of trial of labor following ([Gregory et al., 2002](#)). See [Appendix B](#) for details.

even within healthcare markets (Epstein and Nicholson, 2009). This is evident in our data on Medicaid deliveries as well. Figure 2 shows the large variation in C-section rates by county for births covered by Medicaid. The variation observed at the county level is generated by both variation in C-section rate across hospitals and across physicians. We show distributions of C-section rates across both of these provider types in Figure 3.

Figure 2: County-level C-section rate, Medicaid 2015-2019



Notes: Data is from all deliveries in Medicaid claims, 2015-2019. The map shows the C-section rate based on the county where the birth occurred.

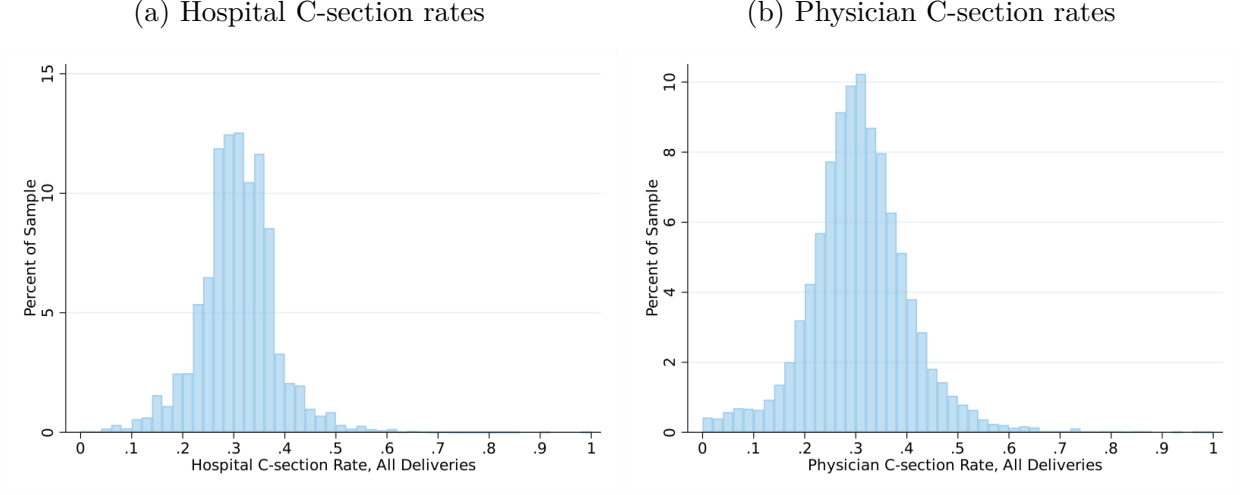
3.3 Predicting C-section Risk

Some share of the variation in C-section rates across hospitals and physicians reflects differences in underlying patient risk. In our analysis, we aim to isolate the role of hospitals and physicians, adjusting for differences in underlying patient risk across providers. As part of this, we control for each patient’s predicted C-section risk, following established practice in the literature (Currie and MacLeod, 2017; Robinson et al., 2023). We use a logistic model represented for patient i as:

$$\mathbb{P}(\text{C-section}_i = 1) = F(\beta X_i) \quad (1)$$

We include 29 clinical indications for C-section delivery in X_i . These covariates are listed

Figure 3: Distribution of C-section rates in Medicaid, 2015-2019



Notes: Sample includes all births where we can identify both a delivering physician and hospital. Physicians with less than 100 total births, or without at least one birth of each delivery method (cesarean/vaginal) are dropped from the sample. N hospitals = 3,084. Mean hospital C-section rate = 28.38% (std. dev. 20.05). Median hospital-level C-section rate 27.79%. N physicians = 15,243. Mean physician C-section rate = 28.65% (std. dev. 14.98). Median physician-level C-section rate 28.93%.

in [Table A1](#), with comparisons to previous literature. We draw on [Gregory et al., 2002](#), [Asch, 2009](#), [Currie and MacLeod, 2017](#), and [Robinson et al., 2023](#) to capture relevant comorbidities used to identify C-section appropriateness.²³

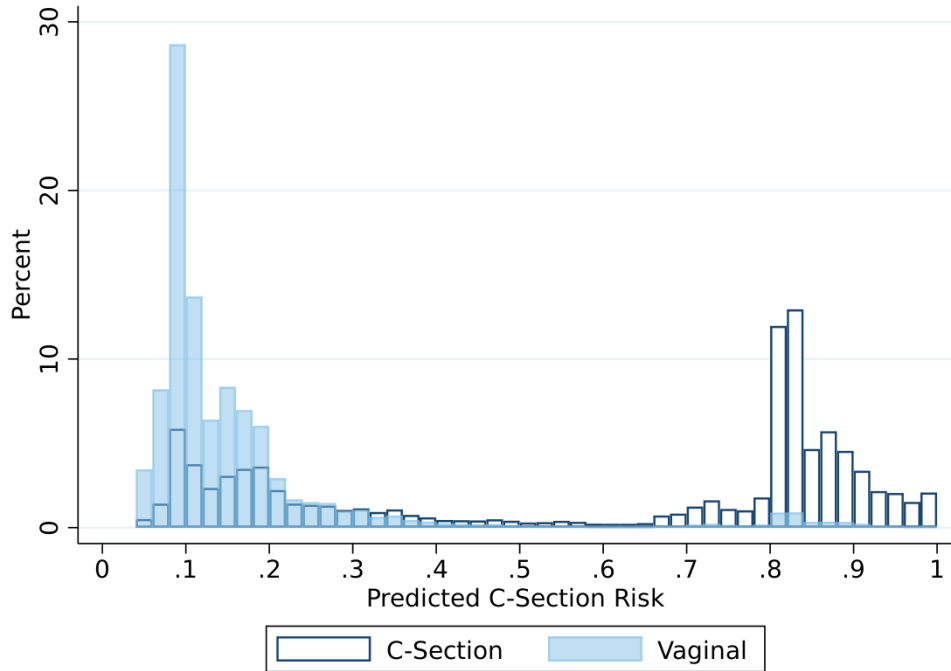
We estimate C-section appropriateness on the entire sample, comprising 7,820,852 deliveries over 2015-2019. As such, the estimates will be insensitive to any one physician’s behavior. Results are presented in [Table A2](#). All clinical indications are statistically significant at least at the 0.1% level. Estimates are clinically consistent in direction (e.g., C-section becomes more likely with age) and size (e.g., the largest coefficients are on previous C-section, vertex, and placenta previa).

We then use the estimated parameters from this model to provide an estimation of C-section risk for each patient, which we denote $\hat{h}_i$. This measure can be thought of as a measure of patient risk for C-section delivery, based on clinical observables. In [Figure 4](#),

²³[Gregory et al., 2002](#) and [Asch, 2009](#) provide guidance on identifying clinical indications from ICD codes, which we follow given we are using claims data. [Currie and MacLeod, 2017](#) and [Robinson et al., 2023](#) use birth record data. These vary in their level of detail; we have access to some variables unavailable in birth records and can also occasionally use more granular codings, but analogously the birth records data on occasion has access to information we struggle to code from claims.

we plot the distribution of the C-section appropriateness score by delivery type.²⁴ Vaginal deliveries are generally well-targeted, with almost all patients having a predicted C-section appropriateness below 0.5. C-sections, however, are much less accurately targeted. There is a notable mass of C-sections at higher risk levels; however, there is also a mass among low-risk patients. This is consistent with concerns about potential overuse of C-sections for low-risk patients.

Figure 4: Distribution of C-section appropriateness by delivery method



Notes: The histogram plots the distribution of the C-section appropriateness score separately by delivery type. Blue bars show the distribution for vaginal deliveries, white bars show the distribution for C-section births. The appropriateness score is estimated from a simple logit model (Equation (1)). The covariates included in the model, and their associations with C-section delivery, are reported in Table A2. Sample size is $N = 7,820,852$ deliveries.

4. Estimating the Role of Hospitals and Physicians

In this section, we outline our decomposition of C-section rates. We adopt an AKM-style model rooted in the labor economics literature (Abowd et al., 1999). Following applications

²⁴This figure is a replication of Currie and MacLeod, 2017, using Medicaid claims data.

in healthcare by [Finkelstein et al., 2016](#) and [Badinski et al., 2024](#) we use a fixed-effects model, which exploits physician mobility over hospitals to separately estimate the role of physicians and hospitals. This provides a macro perspective on the variation in C-section use in the US, comparing the role of physicians and hospital environment in explaining cross-facility variation in C-section usage.

4.1 Decision Framework for Unplanned C-sections

We begin by presenting a simple conceptual framework of C-section supply and demand, similar to [Finkelstein et al., 2016](#). The purpose is to clarify the determinants of delivery mode, outline the underlying assumptions of our empirical approach, and generate testable hypotheses.

On the demand-side, all pregnant patients i in labor will ultimately have either a vaginal birth or deliver via C-section: $c_i \in \{0, 1\}$. Patient i 's utility from a C-section is a function of clinical appropriateness for a C-section, $h_i \in [0, 1]$, which can evolve rapidly during labor and delivery. Higher values of h_i represent a higher-risk patient for whom a C-section delivery is more medically appropriate. Utility also depends on patient-specific preferences η_i . While all patients in our sample plan for vaginal birth, η_i captures how willing a patient is to deviate from the clinically appropriate delivery mode. This term also captures differences in patient i 's agency or ability to express her preferences in the delivery room. This may be influenced by access to information, language barriers, or the broader power dynamics in the delivery room.

We can write patient i 's utility as $u_i(c|h_i, \eta_i) = -\frac{1}{2}(c - h_i)^2 + \eta_i c$. Intuitively, the first term is a loss function capturing deviations from clinical appropriateness, and the second term captures patient taste. A C-section is preferred when $u(c = 1) > u(c = 0)$, which simplifies to $h_i + \eta_i > \frac{1}{2}$. We assume that in expectation $\eta_i = 0$ such that for any given h_i , the average patient prefers whichever delivery mode is most clinically appropriate. Note that we do not observe the true value of h_i , and predict a patient's clinical indication using clinical consensus for C-section estimated in [Equation \(1\)](#).

On the supply-side, physician j practicing in hospital b in month-year t chooses delivery method $c_i \in \{0, 1\}$ to maximize their perceived utility of patient i , $\tilde{u}_{jc}$, minus a hospital-

specific cost of performing a C-section HC_{bt} .

$$c_{itb} = \arg \max_c \tilde{u}_j(c|h_i, \eta_i) - HC_{bt}(c) \quad (2)$$

where the difference between a patient’s utility for a C-section and the physician’s perception of their utility captures the physician’s underlying propensity to perform a C-section, which we refer to as C-section intensity and denote γ_j . A physician’s C-section intensity is shaped by heterogeneous preferences for C-sections, which reflect a physician’s assessment of the benefits of C-section versus vaginal delivery. This may be influenced by a physician’s preferences, surgical skill, or clinical experience. For example, a more skilled surgeon may perceive the risks of surgical complications as lower and prefer to do more C-sections, all else equal (Currie and MacLeod, 2017). We assume that $\tilde{u}_j(c|h_i, \eta_i) = u_i(c|h_i, \eta_i) + \gamma_j c$, so that higher values of γ_j reflect higher C-section “intensity” physicians.

The hospital-specific cost $HC_{bt}(c) = c(\gamma_b + \gamma_t)$. We use the term “hospital environment” to capture all non-physician supply-side factors that vary at the hospital level and influence delivery decisions, which is represented by γ_b in our model. Many hospital-specific factors, including capacity constraints, malpractice environment, ownership status, the presence of midwives, and state-level initiatives, have all been shown to influence a hospital’s C-section rate (AHRQ, 2015; Baicker et al., 2006; Corredor-Waldron et al., 2024; Currie and MacLeod, 2008; Miller et al., 2025). The decision to perform a C-section may also depend on a time trend γ_t , which captures seasonality, changes to clinical guidelines, and/or time trends in births that affect all hospitals. Physician j chooses $c_{i(tb)} \in \{0, 1\}$ to maximize Equation (2). This yields that $c_{i(jb)}^* = 1$ if $h_i + \eta_i + \gamma_j + \gamma_b + \gamma_t > \frac{1}{2}$. In the next section, we take this model to the data and decompose average C-section rates into components driven by patient risk, physician C-section intensity, and hospital practice environment.

This model generates several testable hypotheses. First, all else equal, physicians with higher γ_j will perform more C-sections. If we assume that higher-skilled or more experienced surgeons have lower perceived costs of performing a C-section, we would expect γ_j to be higher for physicians with more years of experience (Currie and MacLeod, 2017). Second, physician C-section intensity (γ_j) will have a stronger impact on delivery method for patients

with $h_i \approx 0.5$. For patients with very-high or very-low clinical appropriateness for a C-section, heterogeneity in physician practice style will not influence outcomes as much. Further, among patients with $h_i \approx 0.5$, those without strong preferences (i.e., small $|\eta_i|$) will be more impacted by physician C-section intensity γ_j . Note that in this model, small absolute values of η_i could reflect patients who are truly indifferent between delivery types, or patients who are unable to express their preferences in the delivery room. We would expect patient groups with lower agency to have smaller $|\eta_i|$, and thus be more impacted by physician type.

4.2 Empirical Specification

Maximizing Equation (2) gives us our estimating equation for patient i delivering in month-year t with physician j at hospital b :

$$c_{ijbt} = \gamma_j + \gamma_b + \gamma_t + \beta h_i + \varepsilon_{ijbt} \quad (3)$$

where c_{ijbt} is an indicator equal to one if patient i received a C-section. We include fixed effects for physician (γ_j) and hospital (γ_b), our main parameters of interest, and include month-year (γ_t) to control for seasonality in births. Finally, we control for the decile of patient i 's C-section risk (h_i), described in Section 3.3. As outlined above, in our benchmark specification, we restrict our estimation to nulliparous and low-risk (NTSV) pregnancies without scheduled C-sections. We also require that every physician-hospital pair has at least five deliveries, and hospitals must have at least one moving physician; we do not include any hospitals where all physicians practice only at that hospital throughout our sample. Finally, we create an adjacency matrix representing the network of hospitals, connected via mobile physicians, and take the largest component that is fully connected.

We use an additive decomposition to estimate the relative contribution of physicians vs. the hospital environment. Let $\bar{c}_b$ denote the average low-risk (NTSV) unplanned C-section rate at hospital b . As in Equation (3), this average C-section rate is determined by patient health characteristics, the physicians performing deliveries, seasonality in births, and the hospital environment. Thus, the difference in average C-section rates across two hospitals b

and b' can be decomposed as follows:

$$\bar{c}_b - \bar{c}_{b'} = \underbrace{(\bar{\gamma}_{j(b)} - \bar{\gamma}_{j(b')})}_{\text{Physician component}} + \underbrace{(\gamma_b - \gamma_{b'})}_{\text{Hospital component}} + \underbrace{\beta(\bar{h}_{i(b)} - \bar{h}_{i(b')})}_{\text{Patient risk component}} \quad (4)$$

where the average physician fixed effect at hospital b , across all deliveries, is denoted $\bar{\gamma}_{j(b)}$ and the average patient C-section risk at hospital b across all deliveries is denoted $\beta\bar{h}_{i(b)}$. The sample analogue of each component comes from our estimation of Equation (3); if this is consistently estimated, it follows that the means and differences will be as well (Finkelstein et al., 2016). We can use each term above, over the difference in the hospitals' raw C-section rates, to calculate the contribution of each component to the difference in C-section rate. In practice, we calculate the difference between groups of hospitals (denoted B), which we stratify based on their unscheduled C-section rate for low-risk (NTSV) deliveries.

We also calculate the variance and correlation of the physician and hospital components to investigate physician sorting over hospitals based on practice style. Correlated sampling error in the physician and hospital components will lead to negative bias in the estimated correlation (Andrews et al., 2008; Card et al., 2013). To correct for this, we follow Finkelstein et al., 2016 and use a split sample approach. We randomly split physicians into two samples.²⁵ We then estimate the hospital ($\hat{\gamma}_b$) and physician ($\hat{\gamma}_j$) fixed effects in each sample. To calculate the variance of $\hat{\gamma}_b$ (or $\hat{\gamma}_j$), we find the covariance between the estimates in each subsample. The correlation between $\hat{\gamma}_b$ and $\hat{\gamma}_j$ is calculated as the average of the covariance between $\hat{\gamma}_b$ from one subsample and $\hat{\gamma}_j$, divided by the estimated standard deviation of $\hat{\gamma}_b$ and $\hat{\gamma}_j$.²⁶

4.3 Identification via Physician Mobility

Our estimated fixed effects for physicians and hospitals are identified by physician mobility across hospitals, which allows us to separate the relative contribution of the two. In effect, within-physician differences in risk-adjusted C-section rate between hospitals identify the relative contribution of the hospital and the physician. Consider a simplified example,

²⁵Non-movers are randomly split within hospital. Physician movers and multi-homers are randomized within hospital pairs (the two hospitals with the most observed deliveries).

²⁶Denoting the samples 0 and 1, the formula is: $\rho(\hat{\gamma}_b, \hat{\gamma}_{j(b)}) = \frac{\text{cov}(\hat{\gamma}_{b,0}, \hat{\gamma}_{j,0}) + \text{cov}(\hat{\gamma}_{b,1}, \hat{\gamma}_{j,1})}{2} \times \frac{1}{\sqrt{\text{var}(\hat{\gamma}_j)}\sqrt{\text{var}(\hat{\gamma}_b)}}$

abstracted from patient risk and time factors. There are three physicians, A, B, and C, and two hospitals, 1 and 2. Physicians A and B each practice at both Hospital 1 and Hospital 2, while Physician C practices only at Hospital 1. Because Physicians A and B practice at Hospitals 1 and 2, the difference in their C-section rates between the two hospitals reveals each hospital’s relative influence. The estimated fixed effect for Hospital 1 is identified from Physicians A and B moving across hospitals. This allows us to back out the fixed effect for Physician C, even though she does not move hospitals.

In obstetrics, physician mobility comes in two primary forms. First, physicians may hold admitting privileges and treat patients at more than one hospital within the same area and time period. This is a practice we refer to as multi-homing, following [Mourot, 2024](#). In our conversations with obstetricians, this was cited as a common practice; affiliations with multiple hospitals can help attract additional patients to physicians’ outpatient clinics. Second, physicians may relocate their practice entirely from one hospital to another. We define “traditional movers” as physicians who change hospital exactly once in our six-year sample period, and who are the attending for at least two births at each hospital.²⁷

In [Table 4](#), we categorize the physicians in our sample based on their mobility. We observe 58% of physicians deliver a patient at more than one hospital during the sample period, but only 3% meet our strict criteria to be considered a “traditional mover”.²⁸

4.4 Investigating Assumptions

The key assumption behind this model is the exogenous network assumption, common to the classical AKM literature. This requires that the assignment of patients to hospitals and physicians is exogenous conditional on patient risk h_i and the included fixed effects: hospital type γ_b , physician type γ_j , and time γ_t . Let $D_{ijbt} = 1$ denote assignment of patient i to

²⁷Further, we require that these physicians move in a year other than the first or final year of our sample, such that we have at least one full year in each location to observe them. Each physician mover therefore has two “shifts”, identified from the date of the first delivery to the date of the last delivery at each hospital. We allow such shifts to overlap by one month, given physicians who move hospitals within a reasonable radius may perform a “warm hand-off” and continue to treat patients nearing the end of their pregnancy.

²⁸To contextualize our sample, [Mourot, 2024](#) finds that 40% of cardiologists are observed at multiple hospitals, and [Molitor, 2018](#) estimates that approximately 15.5% of cardiologists in Medicaid move HRRs between 1998-2010. Note that we both have a more restrictive definition of mover compared to Molitor and a much shorter time window

Table 4: Types of physician mobility

Physician Mobility Type	N Physicians (%)	All Deliveries (%)	NTSV Deliveries (%)
One Practice Location	5,498 (41.45%)	1,213,278 (35.87%)	203,548 (35.54%)
Multiple Practice Locations	7,765 (58.55%)	2,169,509 (64.13%)	369,204 (64.46%)
Traditional Movers	404 (3.05%)	94,992 (2.81%)	16,711 (2.92%)
Total	13,263	3,382,787	572,752

Notes: Table outlines the number and percent of physicians and deliveries by physician mobility type. We define a “traditional mover” as a physician with exactly two practice locations, with at least 2 NTSV deliveries in each hospital, and with an overlap between hospitals of no more than one month. We drop any moves occurring in 2015 or 2019. NTSV sample includes patients who are nulliparous with singleton, term, vertex pregnancies, and who attempted vaginal delivery.

physician j in hospital b in month-year t .

$$\mathbb{E}[\varepsilon_{ijbt} | D_{ijbt}, h_i, \gamma_j, \gamma_b, \gamma_t] = 0$$

Under this assumption, the assignment of patients to physicians and hospitals, D_{ijbt} , can depend on patient observable risk h_i as well as physician, hospital, and time heterogeneity in C-section intensity. We separate selection concerns into two types: i) physician sorting across hospitals and ii) patient sorting into hospitals or physicians.

Physician sorting across hospitals would violate the exogenous networks assumption only if the moves are associated with unobservable shocks to practice style that influence their C-section rate. For physician movers who have one clean relocation, we report an event-study specification in [Section 5.1](#) and find no pre-trends in practice style prior to a move, suggesting physicians are not relocating based on preferences over C-section intensity. The majority of our variation, however, is driven by multi-homers, who deliver at multiple hospitals within the same time period. Hospital affiliation is driven by group clinic, and it is reasonable to assume that there are no changes in underlying physician preferences for C-section delivery that would coincide with their inpatient shift schedule across hospitals.

If there are match-effects, μ_{jb} between some physician-hospital pairs, such that physician j is uniquely more (or less) likely to perform a C-section at hospital b , these will be absorbed in the error term ε_{ijbt} . Match effects could include local protocols, team fit, or equipment that interact with physician j ’s practice style. The existence of match effects is not a problem

in itself, but we require that the realized assignment of patient i to physician j and hospital b to be exogenous to physician-hospital match effects μ_{jb} . In other words, physician j having idiosyncratic match effects at hospital b is only a threat to identification if the match effect is driving the location decision of the physician or correlated with unobservable patient risk. For traditional movers, this would be violated if physicians systematically move to destinations with higher match effects. For multi-homers, this would be violated if physicians could systematically route certain patients to hospitals where they personally have a positive match effect. In our setting, the decision to deliver at hospital b is driven by patients, not physicians. All patients in our sample are relatively low-risk, are attempting a vaginal birth, and we control for ex-ante risk of C-section. Further, the delivering physician is typically not the primary prenatal care provider, and would have no reason or ability to influence the delivery location of the patients they deliver.²⁹

A second type of selection concern would be patients sorting into hospitals or physicians. The exogenous networks assumption requires that the probability of patient i delivering at hospital b with physician j , conditional on h_i , does not depend on unobservable patient characteristics that influence the probability of C-section delivery. If some physicians are differentially more likely to treat high-risk patients, then the physician fixed effect would pick up differences in patient sorting across providers. In restricting our sample to unplanned C-sections among low-risk patients, we exploit spontaneity in the procedure (via the onset of labor), combined with rotational variation in on-call physicians, which generates quasi-random patient-physician matching within the hospital. We assess this assumption in [Section 6.3](#).

In our setting, it would also be a problem if patients select into hospitals based on unobservables that are correlated with the probability of C-section delivery. We condition on the predicted risk of C-section, a measure based on detailed health history. Still, we cannot rule out that unobservable preferences for C-sections may be driving selection. For example, a patient with strong preferences for vaginal birth may select into hospitals with lower C-section rates. In this case, a portion of the hospital environment term will capture unobserved differences in patients.

²⁹Note that for high-risk patients, or patients with scheduled C-sections, this assumption is less likely to hold. However, for our analysis, we focus on low-risk patients attempting vaginal birth.

If physician j has an equal practice share across hospitals, the mis-measurement in patient risk will be attributed entirely to the hospital fixed effects, and the physician component γ_j will be unbiased on average. However, if the exposure to hospitals is unbalanced, then the physician fixed effect will start to “inherit” whichever hospital’s bias dominates her case load. To address this concern, we report robustness to a sample of physician movers and multi-homers who practice more balanced caseloads across hospitals over the sample period. This restriction strengthens the credibility of our physician effect estimates by limiting the influence of unbalanced exposure to biased hospital effects.

Additionally, in [Section 5.1](#) we focus only on the small share of physicians with exactly one clean move over hospitals. By following the same physician across hospitals, we hold constant the physician fixed effect and attribute changes in practice style to differences in hospital effects. Because identification of physician effects relies on within-hospital quasi-random assignment of patients to on-call physicians, any between-hospital differences in unobservable patient composition will bias the hospital fixed effects rather than the estimated physician contribution to C-section use.

Finally, our model assumes that hospital and physician effects are time invariant, within the sample period studied. As we cover a five-year period, a relatively short time period in a physician’s career and a hospital’s tenure, we do not believe this presents a major concern. Our event study on physician moves also suggests that there are no substantial year-on-year changes in practice, for example, via learning or peer effects.

5. Results: Role of Hospitals and Physicians

We begin with an additive decomposition of the relative contribution of physicians and hospitals, comparing several sets of hospitals based on their raw C-section rates in [Table 5](#). In the first three rows of each table, we compare the difference in average low-risk (NTSV) unplanned C-section rates between hospitals in higher vs. lower quantiles. The first row shows the overall difference in C-section rate. The second and third rows report differences in average hospital and physician fixed effects, respectively. We use the latter to estimate the share of difference in C-section rates explained by differences in hospitals and differences in

physicians, which we show in the final two rows.

Table 5: Additive decomposition of cross-hospital C-section rates, NTSV births

	Estimator	Top vs. Bottom			
		50%	25%	10%	5%
Δ in C-section Rate...					
... Overall	$\hat{c}_B - \hat{c}_{B'}$	0.117	0.192	0.287	0.351
... Due to hospitals	$\hat{\gamma}_B - \hat{\gamma}_{B'}$	0.076	0.122	0.178	0.212
... Due to physicians	$\hat{\gamma}_{j(B)} - \hat{\gamma}_{j(B')}$	0.033	0.058	0.094	0.117
Share of Δ due to...					
... Hospitals	$\frac{\hat{\gamma}_B - \hat{\gamma}_{B'}}{\hat{c}_B - \hat{c}_{B'}}$	0.649*** (0.097)	0.637*** (0.097)	0.621*** (0.097)	0.603*** (0.102)
... Physicians	$\frac{\hat{\gamma}_{j(B)} - \hat{\gamma}_{j(B')}}{\hat{c}_B - \hat{c}_{B'}}$	0.285** (0.097)	0.303** (0.098)	0.327*** (0.097)	0.334*** (0.103)
N hospitals		1,245	624	251	132
N physician-hospital pairs		12,467	5,101	1,612	718
N deliveries		481,237	190,782	53,660	20,424

Notes: Reports results from Equation (4). Restricted to the largest set of connected hospitals. Quantiles (denoted B and B') are determined by a hospital's raw NTSV unscheduled C-section rate over the sample period. First row reports the difference in average C-section rate between hospitals in group B vs B' . The second row reports the difference in average hospital fixed effects among hospitals in group B vs B' . The third row reports the difference in average physician fixed effect among hospitals in group B vs B' . Standard errors (in parentheses) are calculated by bootstrap with 100 repetitions. Births are restricted to nulliparous, term, singleton, and vertex (NTSV) without a scheduled C-section. C-section rates at each percentile are: $5^{th} = 8.00\%$, $10^{th} = 10.71\%$, $25^{th} = 15.09\%$, $50^{th} = 19.49\%$, $75^{th} = 23.88\%$, $90^{th} = 29.03\%$, $95^{th} = 33.33\%$. * indicates $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

We first compare hospitals with above versus below median C-section rates, where the median hospital-level unplanned C-section rate for NTSV patients is 19.49%. The difference in average C-section rate between these two groups is approximately 12 percentage points. We find that approximately 65% of this difference is due to hospital-level variation, and 29% is due to physician-level variation. As we compare more extreme quantiles (such as the top and bottom quartiles, or top and bottom 5%), we find a similar share of variation explained by the hospitals and physicians. However, the physician share increases in importance at the most extreme quantiles.

In Table 6, we present the variance in, and correlation between, the physician and hospital fixed effects. There is a negative but insignificant correlation between physician and hospital components, suggesting minimal sorting on preferences for performing C-sections. This is

consistent with our event study on physician movers, which shows no pre-trends in physician C-section practice style prior to moving to a hospital with a different C-section intensity.

Table 6: Variance decomposition of cross-hospital C-section rates, NTSV births

	Estimator	Estimate
Cross-hospital variance of average...		
... C-section rate	$Var(\hat{c}_b)$	0.0063
... Hospital effects	$Var(\hat{\gamma}_b)$	0.0007
... Physician effects	$Var(\hat{\gamma}_{j(b)})$	0.0035
Correlation of hospital + physician effects	$\rho(\hat{\gamma}_b, \hat{\gamma}_{j(b)})$	-0.083 (0.093)
N Hospitals		1,067

Notes: Estimates are based on [Equation \(3\)](#). Standard errors calculated using bootstrap with 100 repetitions. A split-sample approach is used to address correlated sampling error when calculating the variance. Births are restricted to nulliparous, term, singleton, and vertex (NTSV). Hospitals are restricted to a connected set. The average hospital C-section rate is 20%. Note that the number of hospitals is lower than in [Table 5](#), this is because our split-sample approach requires more than one physician mover or multi-homer within each pair of hospitals.

In sum, we find that while the largest contributor to a hospital’s C-section rate is the hospital environment, the contribution of physician variation is substantial, explaining between one quarter and one third of the observed gaps. In comparison to existing estimates from cardiologists in Medicare, physicians in our sample of Medicaid deliveries play a significantly larger role.³⁰ C-sections present an interesting comparison. Similar to primary care, physicians can exercise substantial influence over the diagnosis, albeit in an emergent setting. But a C-section is a major surgery (a capital intensive process) more similar to cardiology in many ways. We find that the physician influence over cross-hospital differences is similar to primary care for hospitals, but hospital contribution is similar to the case in cardiology ([Badinski et al., 2024](#)). This fits with a story where hospitals with noticeable constraints—either in staffing or capital for surgery—might exercise a strong influence over treatment choices, alongside physicians’ diagnostic ability and surgical preferences. Physicians and hospitals jointly explain the majority of differences across institutions, with less than 10% of the

³⁰[Molitor, 2018](#) studies how cardiologists’ catheterization rate evolves after a move to a different HRR, and finds an adjustment of around 80% for a hospital move, suggesting factors specific to the clinical environment play a larger role. Similarly, [Badinski et al., 2024](#) finds that cardiologists’ practice style accounts for only 3% of differences in treatment intensity across HRR, compared to 19% for primary care utilization in Medicare.

across-hospital variation in C-section explained by differences in patient health risk (h_i). This is consistent with prior estimates of the role of supply-side healthcare provision (Fischer et al., 2023). The finding that patient risk contributes much less to observed differences in utilization compared with estimates from the Medicare population makes sense given the relatively healthy population in obstetrics and our focus on low-risk births. Additionally, there is essentially no role of patient selection into treatment, given the near universality of hospital delivery, further limiting the role of the demand side in this context.

5.1 Illustrative Event Study

In our main additive decomposition approach, the identifying variation comes from physician mobility, including both multi-homing, in which physicians practice at more than one hospital during a time period, and physician movers relocating their practice from one hospital to another. Here we present results focusing only on the latter—physician movers—and estimate how physician practice style changes following a move. Assuming no other changes that impact physician C-section use are correlated with the timing of the move, any shift in C-section use following a move can be attributed to the change in practice environment. This approach allows us to check for pre-trends in physician practice style, to better understand if mobility is related to physicians’ selecting into environments based on their C-section intensity.

To measure the change in the practice environment of each physician following a hospital move, we define the hospital C-section intensity as the hospital’s raw C-section rate minus the predicted C-section rate among its patients (based on clinical indications). This latter term is the mean risk score from our logistic model, Equation (1). For hospital b in year t with N_{bt} patients, we measure a hospital’s C-section intensity as:

$$\text{C-section Intensity}_{bt} = \frac{\sum_i^{N_{bt}} \mathbb{1}(\text{C-section}_i)}{N_{bt}} - \frac{\sum_i^{N_{bt}} \hat{h}_i}{N_{bt}} \quad (5)$$

This measure can be thought of as the hospital-level deviation in C-section use from clinical consensus. In our analysis, we aggregate this measure across the years in our sample, such that we have a time-invariant C-section intensity per hospital. We compute a weighted

average per hospital over all years, where weights are the number of patients that hospital sees in a given year. We measure the hospital risk-adjusted C-section intensity using all deliveries at that hospital in our sample.

For physician movers, we define a change in physician j 's practice environment b as:

$$\begin{aligned}\Delta_{b,j} = & (\text{Destination hospital C-section intensity})_j \\ & - (\text{Origin hospital C-section intensity})_j\end{aligned}\tag{6}$$

To avoid a physician's own C-section intensity directly impacting on the hospital C-section rate, we leave out physician j 's patients when calculating the hospital-level risk-adjusted average $\Delta_{b,j}$. [Figure 5](#) shows the distribution of hospital C-section intensity along with the distribution of $\Delta_{b,j}$ for all movers in our sample.

We then estimate the following event study:

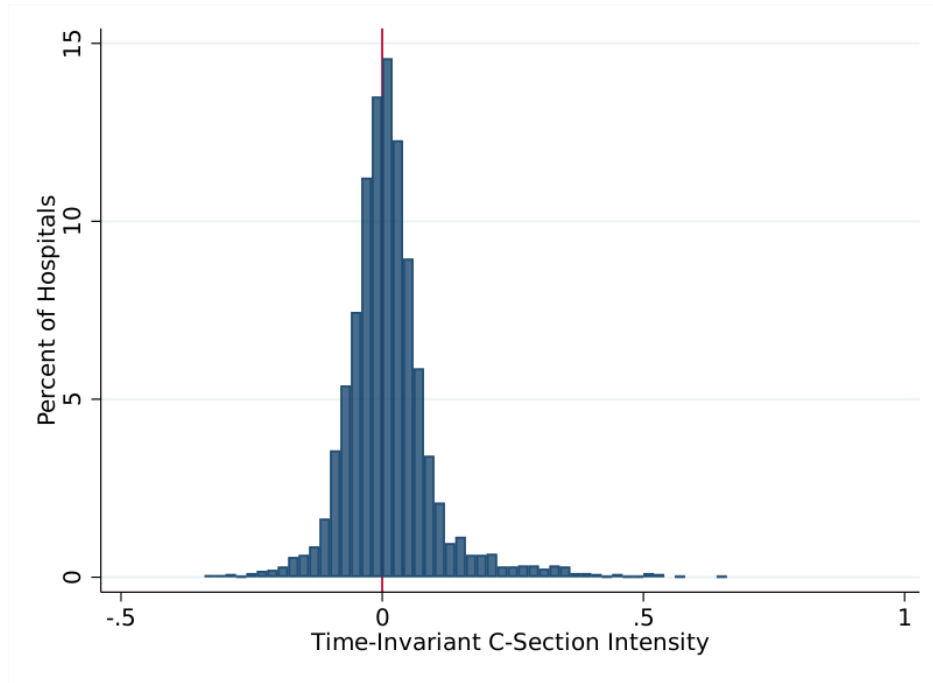
$$\text{C-section}_{ijt} = \sum_s [\alpha_t \mathbb{1}(s = t) + \beta_t \Delta_{b,j} \mathbb{1}(s = t)] + \gamma_j + \gamma_{mt} + \phi h_i + \varepsilon_{ijt}\tag{7}$$

Where C-section_{ijt} is an indicator for whether patient i delivered by physician j in year t received a C-section. We measure the change in the physician's environment (hospital) as $\Delta_{b,j}$, and our key parameters of interest are the coefficients on this variable interacted with a full set of time dummies $\mathbb{1}(s = t)$, where t indicates a year. We include physician fixed effects γ_j , as well as standalone event time dummies. Finally, we include fixed effects for calendar month and year (γ_{mt}) to control for changes in the C-section rate over time and predicted patient C-section risk (h_i) to control for observable characteristics related to appropriateness for C-section, but uncorrelated with regional treatment intensity. We estimate two-way clustered standard errors over the physician and hospital (of the observed delivery).

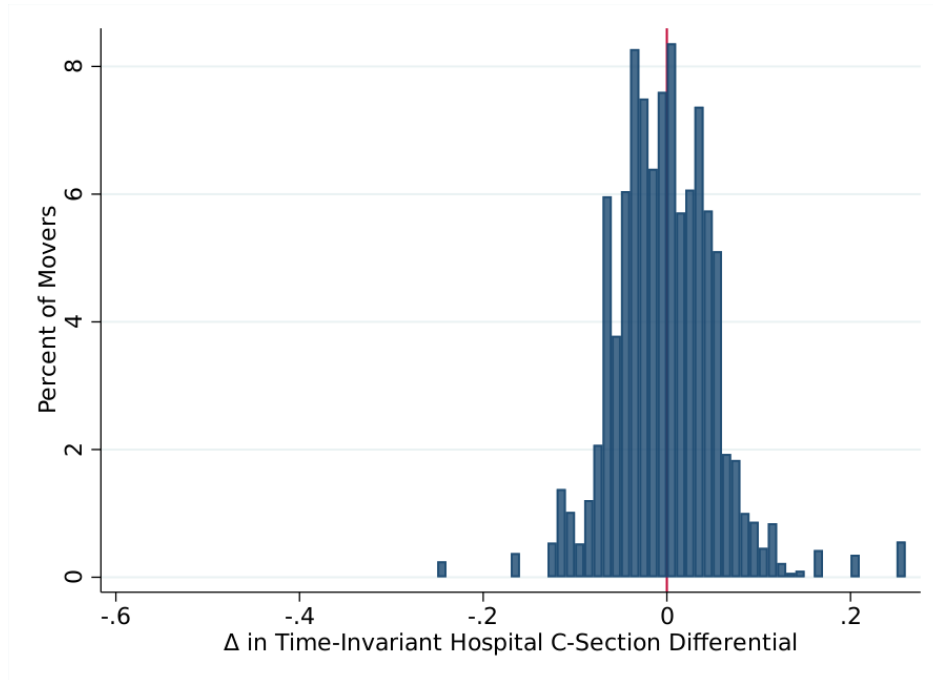
With the inclusion of physician fixed effects, our estimates can be interpreted as the change in physician behavior after the move, relative to behavior in a baseline period. We use the year prior to the move ($t = -1$) as the omitted base category, such that $\beta_t = -1$ is mechanically zero. The point estimates β_t prior to the move ($t < -1$) reflect differences in C-section intensity of movers relative to the change in C-section intensity of hospital environment Δ_t in the year of the move. If a physician's decision to move hospital is unrelated

Figure 5: Distribution of hospital C-section intensity for physician movers

(a) Time-invariant hospital C-section intensity



(b) Change in hospital C-section intensity, movers



Notes: Panel (a) shows the distribution of the time-invariant hospital-level C-section intensity (raw C-section rate minus predicted C-section rate) for all hospitals in our sample. Panel (b) shows the change in C-section intensity $\Delta_{b,j}$ between origin and destination hospitals for all physician movers. Red lines indicate zero. N movers = 404.

to the C-section intensity of the origin and destination hospital, we would expect $\beta_t = 0$ for all time periods before the move.

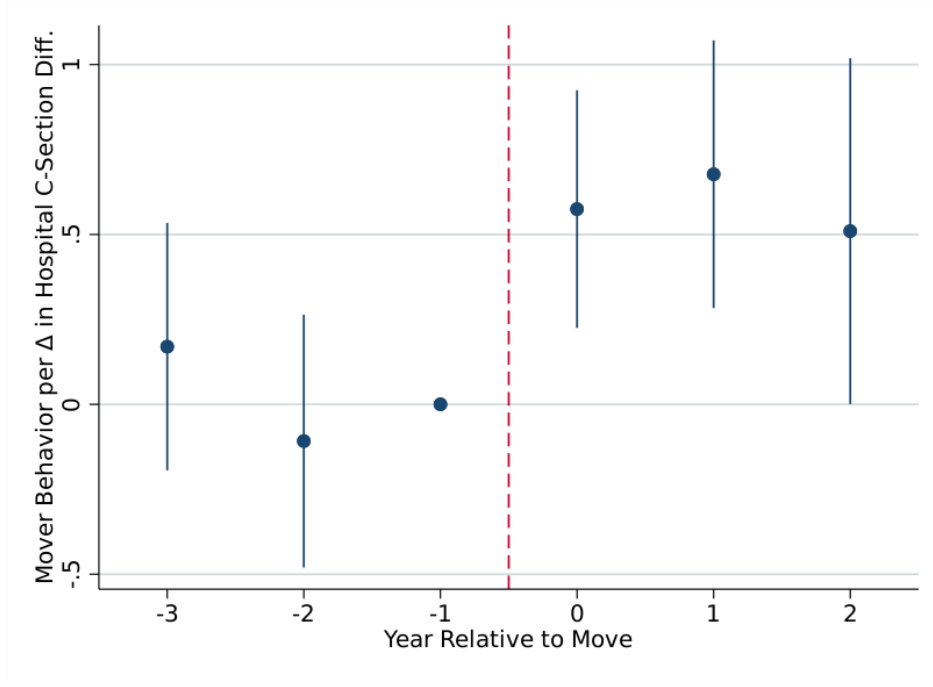
After the move, β_t estimates the change in a physician’s C-section rate relative to the change in C-section intensity of their environment. Values $\beta_{t>0} = 0$ would suggest physician risk-adjusted C-section rate is fixed and does not respond to changes in the hospital environment. Values $\beta_{t>0} = 1$ would suggest that a physician’s C-section intensity is fully determined by the hospital in which they practice. Before the move, β_t estimates whether the physician’s C-section intensity preemptively changes, suggesting selection into hospital location.

Results are displayed in [Figure 6](#). There is an immediate jump in the physician’s propensity to deliver via C-section after a move, with $\beta_{t=0} = 0.575$. This suggests that approximately 60% of the difference in risk-adjusted C-section rates across hospitals is driven by differences in hospital environment, and the remaining share is explained by physician practices. It is reassuring that these estimates are in line with our additive decomposition exercise. However, given the small sample size, our standard errors are large and we cannot rule out hospital contributions between 20% - 100%. An F -test for joint significance of the pre-period interactions has a value of $F = 0.873$ with a p -value of 0.419, presenting no evidence of a pre-trend in the physician’s C-section use (though the pre-period is short).

In [Figure 7](#), we plot each physician’s C-section intensity, as measured by the residuals in our within-hospital regression, by their mover status. For physician-movers, we compute their pre-move C-section intensity; for non-movers, we compute their C-section intensity over the entire sample period. The distributions are very similar, suggesting mobility is not associated with physicians’ C-section intensity. In [Table 7](#), we compare characteristics of “stayers”, multi-homers, and traditional movers.

For movers, the most notable difference is they tend to be younger and significantly more likely to be female. This is consistent with mobility being determined perhaps by personal factors (for example, co-location with a partner, or a move to a home state) and finding a long-term location from which to set up a practice. Their share of deliveries that are C-sections, and their C-section intensities, are not significantly different.

Figure 6: Response of physician C-section rate to change in hospital excess C-section rate



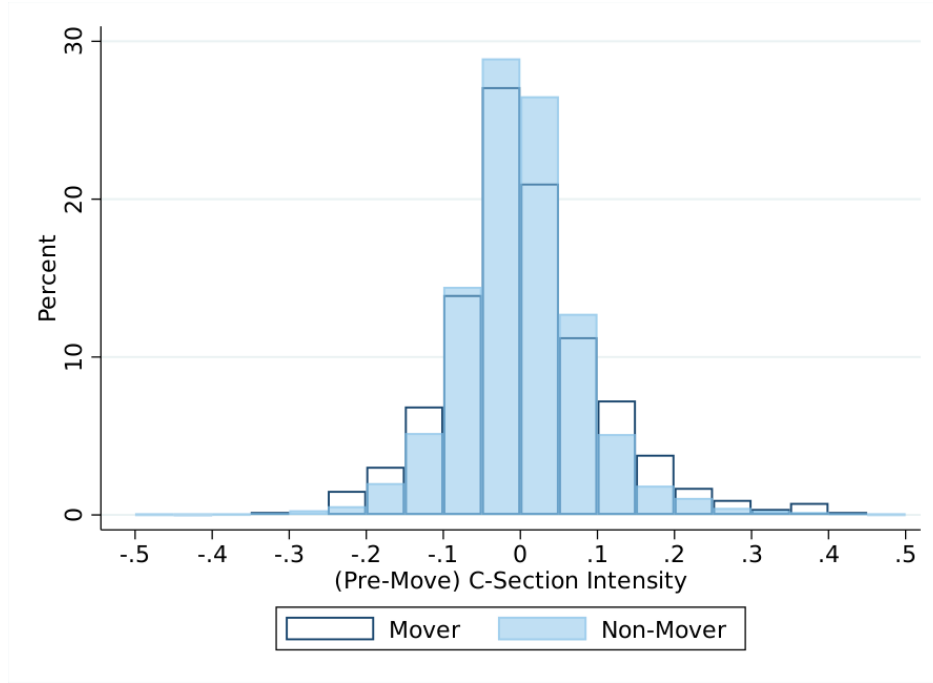
Notes: Figure shows coefficient estimates from a regression of C-section delivery on the change in clinical environment, as measured by the percentage point change in hospital C-section differential, see Equation (7). Time period zero is the first year of a move. We drop all moves occurring in 2015 or 2019. Identification comes from $N = 404$ with 16,313 deliveries. A coefficient of $\beta_{t \geq 0} = 0$ would suggest no impact of a change in hospital environment (hospital C-section intensity) on a physician's C-section rate. A coefficient of $\beta_{t \geq 0} = 1$ would suggest physicians fully adapt to the destination hospital's C-section intensity following a mover. We find $\beta_{t=0} = 0.575$.

Table 7: Physician characteristics by mobility type

	One practice location (1)	Multiple practice locations (2)	Traditional movers (3)	Difference: (1) - (2)	Difference: (1) - (3)
Age	47.29 (9.71)	46.64 (9.65)	41.46 (8.50)	0.65*** (0.22)	5.83*** (0.54)
Female	0.55 (0.50)	0.53 (0.50)	0.69 (0.46)	0.02** (0.01)	-0.14*** (0.02)
Years of experience	15.09 (9.81)	13.96 (9.58)	8.87 (7.87)	1.13*** (0.22)	6.22*** (0.51)
OB/GYN	0.94 (0.24)	0.97 (0.17)	0.98 (0.16)	-0.03*** (0.00)	-0.04*** (0.01)
MFM specialist	0.03 (0.18)	0.03 (0.16)	0.03 (0.16)	0.00 (0.00)	0.00 (0.01)
Annual Medicaid births	34.36 (26.23)	41.44 (34.67)	30.52 (20.44)	-7.08*** (0.53)	3.84*** (1.08)
% Births nulliparous with trial of labor	0.17 (0.09)	0.18 (0.08)	0.20 (0.09)	-0.01*** (0.00)	-0.04*** (0.00)
Overall C-section rate	0.29 (0.15)	0.30 (0.11)	0.30 (0.12)	-0.01*** (0.00)	-0.01 (0.01)
C-Section intensity	-0.00 (0.09)	0.00 (0.09)	0.01 (0.10)	-0.00** (0.00)	-0.01* (0.01)
% Patients Black	0.17 (0.20)	0.18 (0.17)	0.17 (0.18)	-0.00 (0.00)	-0.00 (0.01)
% Patients White	0.38 (0.27)	0.32 (0.24)	0.36 (0.26)	0.06*** (0.00)	0.01 (0.01)
% Patients Hispanic	0.21 (0.24)	0.27 (0.26)	0.24 (0.24)	-0.05*** (0.00)	-0.03** (0.01)
N	5,498	7,765	404	13,263	5,902

Notes: Table outlines the sample characteristics and differences between physicians based on mobility. Column (1) reports sample means for physicians with all deliveries in one hospital (standard deviations are reported below each mean). Column (2) reports sample means for all physicians with births in multiple hospitals (includes both traditional movers and “multihomers”). Column (3) reports sample means for “traditional movers”: physicians with exactly one move observed between 2016-2018. Note that the sample in column (3) is a subset of the sample in column (2). Movers must be observed at only two hospitals in the sample and overlap by no more than 30 days. Differences comparing the sample means of physicians with one practice location vs. those with more than one practice location are reported in column (4). The final column compares physicians with one practice location to traditional movers. * indicates $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Figure 7: Distribution of hospital C-section intensity by mover status



Notes: Histogram shows the distribution of C-section intensity by physician mover status. C-section intensity measured across all NTSV patients with spontaneous delivery, as detailed in [Equation \(9\)](#). N movers = 404.

6. Estimating Health Effects of Physician Practice Style

Relative to other medical fields, the contribution of physician practice style to cross-facility variation in C-section rates is substantial. Moreover, the lack of sorting suggests meaningful variation in physician practice style *within* hospital. We examine the consequences of this more closely using a so-called “judge leniency design” following [Dahl et al., 2014](#); [Dobbie et al., 2018](#); [Eichmeyer and Zhang, 2022](#), among others. We leverage quasi-random assignment of low-risk nulliparous patients to on-call physicians due to the spontaneous onset of labor combined with rotational variation in physicians’ hospital shifts. We are then able to estimate the causal effect of physician C-section intensity on delivery method and estimate the implied causal effect of a marginal C-section on health outcomes.

6.1 Defining Physician C-section Intensity

We construct a measure of each physician’s C-section intensity, leaving out a patient’s own delivery method. To do so, we estimate the following regression:

$$\text{C-section}_{ijbdt} = \alpha + \gamma_{bt} + \gamma_{bd} + \beta' X_i + \varepsilon_{ijbdt} \quad (8)$$

where C-section_{ijbdt} is an indicator equal to one if patient i , seen by physician j at hospital b in month-year t on day-of-week d , is delivered via C-section. This is regressed on hospital-month-year and hospital-day of week fixed effects, which reflect the assignment mechanism of patients to physicians, and flexibly control for seasonality in births, differences in hospital staffing throughout the week, hospital-specific policies (e.g., regarding VBAC) or facilities (e.g. number of operating rooms). All nulliparous deliveries, excluding scheduled C-sections, are used to estimate Equation (8).³¹ We control for salient patient observables (X_i) which may impact physician assignment, including term, vertex, singleton, induction, preeclampsia, eclampsia, advanced maternal age, obesity, diabetes, macrosomia (large baby), and an indicator for if the patient ever saw the delivering physician for prenatal care.³²

Under our assumptions regarding quasi-random patient-physician assignment on the ward, the individual physician’s contribution to the C-section decision is in the error term, ε_{ijbdt} . We then estimate the C-section intensity measure for a patient i seen by physician j in month-year t as the leave-one-out average of the residuals from Equation (8):

$$\text{C-section Intensity}_{i,jt} = \frac{1}{N_{-i,jt}} \sum_{i' \in \mathbb{J}_i} \hat{\varepsilon}_{i'} \quad (9)$$

Where $\hat{\varepsilon}_{i'}$ is the residual from Equation (8), $\mathbb{J}$ denotes the set of all deliveries performed by physician j within a year prior to t and a year after t , and $N_{-i,jt} = |\mathbb{J} \setminus i|$ is the count of those deliveries excluding patient i ’s delivery. This C-section intensity measure is interpreted as the average C-section rate of patient i ’s physician j , relative to other physicians delivering

³¹Note that the share of nulliparous patients who are not also term, singleton, and vertex is very low ($\approx 5\%$). Thus, whether we include these deliveries in the C-section intensity construction does not make a meaningful difference.

³²Results are not sensitive to the choice of controls included in X_i , alternative specifications available upon request.

at the same hospital within the same two-year period. Leaving out patient i 's delivery type prevents any mechanical bias in the physician's estimated C-section intensity from using patient i 's own delivery type (the outcome of interest) in its calculation.

We estimate the first-stage effect on a patient of seeing a physician with a higher C-section intensity. For patient i , seeing physician j at hospital b in month-year t , and day-of-week d .

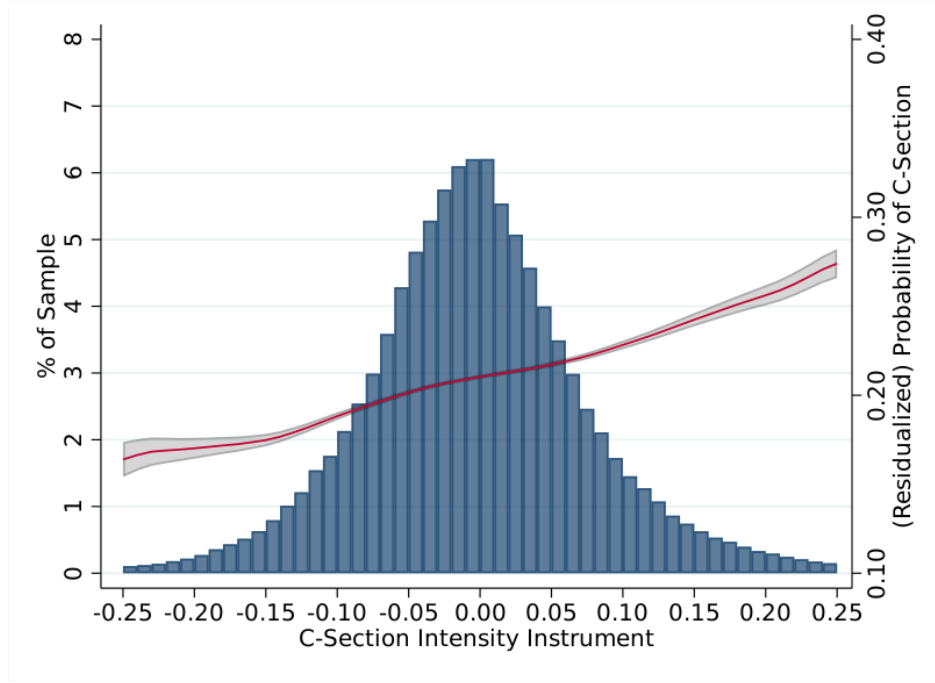
$$\text{C-section}_{ijbt} = \alpha + \beta \text{C-section Intensity}_{i,jt} + \gamma_{bt} + \gamma_{bd} + \beta X_i + e_{ijbdt} \quad (10)$$

C-section_{ijbt} is an indicator equal to one if patient i received a C-section, which is regressed on physician j 's leave-one-out C-section intensity measure for year t . We include fixed effects for interacted hospital-month-year (γ_{bt}) and hospital-day-of-week (γ_{bd}). Equation (10) is estimated on our main low-risk NTSV sample, thus term, singleton, and vertex are no longer included in X_i as controls. X_i includes indicators for induction, advanced maternal age, preeclampsia, eclampsia, macrosomia, obesity, and an indicator for whether patient i ever saw physician j for prenatal care. Standard errors are clustered at the physician level.

Figure 8 shows the relationship between C-section intensity and delivery method. On the x -axis we show the leave-one-out C-section intensity at the physician level. The histogram shows the distribution of this measure of physician practice style across deliveries, plotted with the left-hand y -axis. On the right-hand y -axis we plot a local-linear regression of the fitted probability of receiving a C-section on physician C-section intensity, after residualizing for the included fixed effects and patient characteristics. The graph shows the probability of a C-section rises steadily as a physician's C-section intensity increases, even after controlling for patient characteristics and the assignment mechanism of patients to physicians.

Table A7 presents estimates of the first-stage effect of a physician's C-section intensity on C-section delivery, within a hospital. If a patient is assigned a physician with a 10 percentage point higher C-section intensity (approximately one standard deviation), the likelihood of receiving a C-section increases by roughly 2.11 percentage points, off a base rate of 20.14%. For context, 10 percentage point change in C-section intensity roughly corresponds to the

Figure 8: Distribution of physician C-section intensity, and effect on probability of C-section



Notes: Histogram shows the distribution of the C-section intensity instrument on the x -axis against the percent of the sample on the left-hand y -axis. On the right-hand y -axis we plot a local linear regression of β from our first stage regression, [Equation \(10\)](#). An observation is a patient-physician pair associated with a delivery, where C-section intensity is a physician-level two-year average, leaving out patient i 's own delivery outcome. $N = 571,446$. $F\text{-stat} = 1391$. Graph is truncated at ± 0.25 . We find $\beta = 0.211$ (standard error 0.013), implying that being quasi-randomly assigned to a 10 percentage point more “C-section intense” physician increases the probability of C-section by 2.11 percentage points. A 10 percentage point increase in C-section intensity is roughly one standard deviation, or the difference between the 75th percentile and 25th percentile of the C-section intensity distribution. The base rate of C-section in this sample is 20.14%.

effect of moving from a physician in the 25th percentile to a physician in the 75th percentile.³³ The impact of moving from a 10th percentile physician to a 90th percentile physician is a 4.34 percentage point ($\approx 21\%$) increase in the probability of C-section delivery.

This is a sizable effect relative to other interventions, which we outline in greater detail in Table A6. For example, a Cochrane review of midwife care suggests this can reduce C-section rates by around one percentage point (Sandall et al., 2024), and a meta-analysis of doula support suggested a reduction of 3.7 percentage points (Bohren et al., 2017). The effect of being a physician mother (and therefore reducing the information asymmetry between physician and patient) is 2.14 percentage point reduction (Johnson and Rehavi, 2016).

6.2 Empirical Framework

Reduced-form estimation: To estimate the effect of being assigned a higher C-section intensity physician on maternal and infant health outcomes, we use the following equation:

$$Y_{ijbdt} = \theta_0 + \theta_1 \text{C-section Intensity}_{i,jt} + \theta_2 X_i + \gamma_{bt} + \gamma_{bd} + \nu_{ijbdt} \quad (11)$$

where Y_{ijbdt} is an indicator for delivery complication or postpartum health outcome for patient i . All regressions include the same baseline controls as in the first stage for salient patient health observables X_i (induction, preeclampsia or eclampsia, advanced maternal age, macrosomia, obesity, diabetes, and an indicator for if patient i had prenatal visit with delivering physician j) and fixed-effects for hospital-month-year γ_{bt} and hospital-day of week γ_{bd} . Standard errors are clustered at the physician level.

Instrumental variables (IV) estimation: To estimate the health effects of the marginal C-section, we use C-section intensity of the delivering physician as an instrument for C-section delivery. We use the following 2SLS equations:

$$Y_{ijbdt} = \beta_0 + \beta_1 \text{C-section}_{ijbdt} + \beta_2 X_i + \gamma_{bt} + \gamma_{bd} + \varepsilon_{ijbdt} \quad (12)$$

³³We estimate the effect of moving a 25th to 75th percentile physician by scaling the coefficient β by the difference in C-section intensity between these percentiles of the C-section intensity distribution. The exact impact of moving from a 25th percentile physician to a 75th percentile physician is a 2.04 percentage point increase in probability of C-section.

$$\text{C-section}_{ijbdt} = \delta_0 + \delta_1 \text{C-section Intensity}_{i,jt} + \delta_2 X_i + \gamma_{bt} + \gamma_{bd} + \nu_{ijbdt} \quad (13)$$

The causal effect of C-section delivery on health outcomes is typically difficult to estimate due to endogeneity: delivery method is highly correlated with observable, and unobservable, patient characteristics. If our identifying assumptions, discussed in [Section 6.3](#), hold then using C-section intensity of quasi-randomly assigned physician as an instrument for C-section delivery provides causal estimates of the health consequences of the marginal C-section.

6.3 Identifying Assumptions

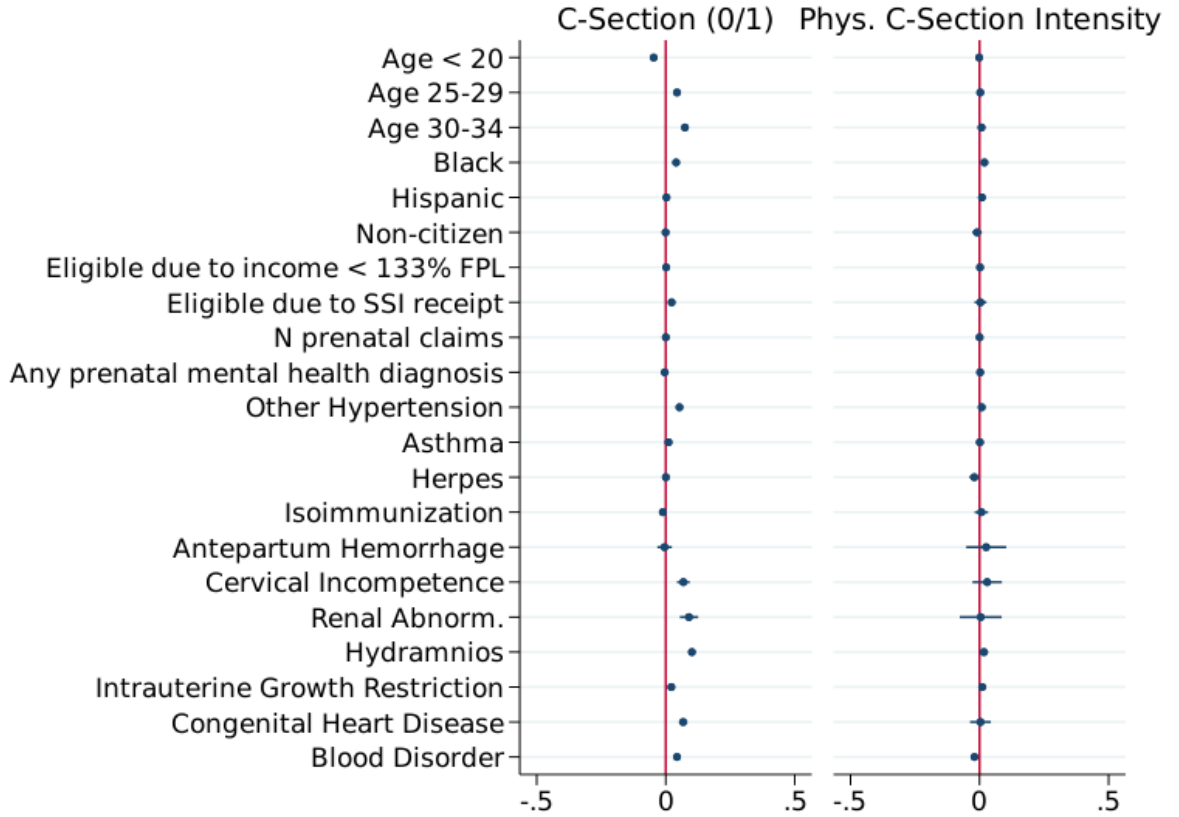
If physicians are quasi-randomly assigned to patients within hospitals, conditional on month-year, day of week, and patient observables X_i , then our reduced-form [Equation \(11\)](#) estimates the causal effect of physician C-section intensity on health outcomes. Violations of the randomness in our assignment mechanism might occur if some physicians are systematically more likely to be assigned to patients with higher ex-ante risk of C-section within a shift. We test this with the following specification:

$$\text{C-section Intensity}_{ijbdt} = \pi_0 + \pi_1 P_i + \pi_2 X_i + \gamma_{bt} + \gamma_{bd} + e_{ijbdt} \quad (14)$$

where γ_{bt} denote hospital-month-year fixed effects, γ_{bd} denote hospital-day-of-week fixed effects and X_i denote controls for the same salient patient characteristics used in constructing the instrument. If there is minimal selection or matching of patients to physicians based on the physician's C-section intensity, P_i should not be predictive of C-section intensity and π_1 should be zero. We plot these coefficients in [Figure 9](#). The left hand side shows patient characteristics P_i are strongly jointly predictive of delivering via C-section (F = statistic 294.908), but poor predictors of the delivering provider's C-section intensity (F statistic = 2.527). This is consistent with our assumption that low-risk patients attempting a vaginal birth are quasi-randomly assigned to an on-call physician.

For physician C-section intensity to serve as a valid instrument for estimating the causal effect of the marginal C-section delivery, three additional conditions must be satisfied: relevance, monotonicity, and the exclusion restriction. As shown in [Table A7](#), physician C-

Figure 9: Check of random assignment



Notes: The left hand side reports coefficients π_1 , and 95% confidence intervals, from a regression of C-section delivery on patient characteristics (P_i), with controls for hospital-month-year, hospital-day of week, and patient characteristics X_i . The right hand side reports the same coefficient estimates in a regression of physician C-section intensity on P_i , with the same controls (see [Equation \(14\)](#)). C-section intensity is standardized. Standard errors are clustered at the physician level. F-statistic for joint significance of P_i on the outcome C-section delivery is $F = 294.908$ and on the outcome physician C-section intensity is $F = 2.527$. This is consistent with our assumption that, conditional on controls, low-risk patients in labor are quasi-randomly assigned to a delivering physician.

section intensity strongly predicts C-section delivery, confirming relevance. The monotonicity assumption requires that higher C-section intensity physicians must at least weakly increase the probability of C-section for all patients. A violation of this would occur if a physician is relatively likely to perform a C-section on some set of patients, but relatively less likely for others. In [Table 13](#) we show the first-stage estimate for a variety of subsamples in column 3, confirming that higher C-section intensity physicians increase the probability of C-section delivery for different patient types.

The exclusion restriction requires that C-section intensity influences health outcomes Y_i only through the channel of delivery method. This is the strongest assumption of using physician C-section intensity as an instrument for the delivery method, and is less likely to hold for some health outcomes. Assignment to a high C-section intensity physician is a bundled treatment: high C-section intensity providers are more likely to perform C-sections, but they also differ along other dimensions. [Table 8](#) compares observable demographic and practice characteristics between physicians with higher vs. lower C-section intensity. Most notably, high C-section intensity physicians, on average, have more experience (completed residency earlier), are more likely to be male, and perform more scheduled C-sections. If other aspects of physician practice style are correlated with C-section intensity and with health outcomes, our IV results will be biased.

The majority of our relevant health outcomes are mechanically related to delivery method, and it is reasonable to assume that the exclusion restriction holds³⁴. However, for some outcomes, there is greater concern that other aspects correlated with C-section intensity could affect outcomes. For example, more highly experienced physicians may be better able to identify early onset complications and avoid severe delivery or postpartum complications. In this case, our IV results will be biased because they also capture the impact of other correlated dimensions of physicians on outcomes in addition to the C-section.

To test the mechanism behind the IV results, we control for other observable dimensions of practice style. We follow the same steps used to construct physician C-section intensity to create other measures of physician practice style. First, intervention intensity in vaginal births

³⁴For example, infection of the C-section incision is a common complication of C-section delivery, and is directly related to delivery method. It is improbable that a physician’s C-section intensity would influence postpartum infection for any reason other than their decision to perform a C-section.

Table 8: Characteristics of high vs low C-section intensity physicians

	(1) Above Median	(2) Below Median	(3) Δ
Average C-section appropriateness (of patients in main NTSV sample)	0.22 (0.04)	0.22 (0.03)	-0.00*** (0.00)
Year completed residency	2002.38 (9.83)	2002.96 (9.82)	0.58** (0.22)
Female	0.52 (0.50)	0.55 (0.50)	0.03*** (0.01)
MFM specialist	0.03 (0.16)	0.03 (0.16)	-0.00 (0.00)
Total Medicaid deliveries	304.39 (262.20)	308.82 (278.84)	4.43 (4.88)
Mean annual Medicaid deliveries	38.84 (29.67)	39.65 (33.15)	0.81 (0.57)
% Patients high C-section risk	0.21 (0.07)	0.19 (0.07)	-0.02*** (0.00)
% Patients NTSV	0.18 (0.07)	0.18 (0.07)	0.00* (0.00)
% Deliveries C-section	0.33 (0.10)	0.27 (0.10)	-0.06*** (0.00)
% of Patients with scheduled C-section	0.20 (0.08)	0.18 (0.07)	-0.03*** (0.00)
% Patients Black	0.20 (0.19)	0.20 (0.19)	0.00 (0.00)
% Patients White	0.38 (0.24)	0.38 (0.25)	-0.00 (0.00)
% Patients seen for prenatal care	0.46 (0.27)	0.47 (0.27)	0.01* (0.00)
N	6,153	6,153	12,306

Notes: Table presents sample means for physicians with above vs. below median C-section intensity. *t*-tests for differences in means are performed above vs. below median C-section intensity. We use this data to measure the year a physician completed residency. Note that physicians who completed residency after 2011 may not match to this file, in which case the year of residency completion is missing. Maternal Fetal Medicine (MFM) specialists have additional training in high-risk obstetrics care. * indicates $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

(use of vacuum or forceps), and second the tendency to use artificial rupture of membranes (AROM) for labor augmentation.³⁵ In our IV results, we test the extent to which our IV estimates change when controlling for aspects of physician practice style, which helps alleviate some concerns that physician C-section intensity is biased by other correlated dimensions of practice style. For all outcomes, we also present the reduced form effect of physician C-section intensity on health outcomes from [Equation \(11\)](#), which does not rely on the exclusion restriction for interpretation.

7. Results: Health Effects of Physician Practice Style

In this section, we present reduced-form results of the impact of physician C-section intensity from [Equation \(11\)](#), along with IV results from [Equation \(12\)](#) and [Equation \(13\)](#). The reduced-form coefficients show the causal effect of being assigned to a 10 percentage point higher C-section intensity physician, which is approximately the difference between a physician at the 75th percentile and 25th percentile of the C-section intensity distribution. IV results show the implied causal effect of the marginal unplanned C-section on the probability of health complications, expressed in percentage points. In column (3) we show reduced-form results are robust to including patient demographics and controls for ex-ante patient risk of complications: race/ethnicity, indicators for > 20 prenatal claims or no prenatal claims, prenatal mental health disorders, hypertension, and asthma.³⁶ In column (5) we show that IV results are robust to controlling for two other dimensions of physician practice style: physician intervention intensity in vaginal deliveries and physician propensity to use artificial rupture of membranes for induction (AROM).

For maternal health, we focus on three time windows: delivery complications reported on the delivery claim, postpartum health outcomes within 60 days of delivery, and postpartum health outcomes within one year of delivery. Federal law requires states to continue pregnancy-related Medicaid coverage for at least 60 days postpartum. During our sample period (2015-2019), a growing number of states opted to implement continuous coverage for women enrolled

³⁵Labor augmentation with pitocin is not recorded in the Medicaid claims data. We use AROM as a proxy for more intervention-intensive labor.

³⁶We chose these controls as they are most likely to correlate with our outcomes of interest.

in pregnancy-related Medicaid for 12 months postpartum (Eckert, 2020). In our sample of low-risk first-time births, 90% of beneficiaries are enrolled in Medicaid in the month following delivery, but only 44% remain continuously enrolled for one year postpartum. For outcomes within 60 days (one year) of delivery, we require the beneficiary to remain enrolled in Medicaid for at least one month³⁷ (one year) following delivery.

Table 9 reports maternal health outcomes during delivery and within 60 days postpartum. Lacerations (3rd or 4th degree) are complications of vaginal delivery, and we would expect high C-section intensity physicians to reduce complications of vaginal birth by avoiding more difficult labors. While the sign is negative, we do not find a statistically significant effect. Severe Maternal Morbidity (SMM) is a composite measure of severe complications, excluding blood transfusions. The medical literature has found C-sections are associated with a 2.7 times higher risk of SMM, and are estimated to contribute to 27% of all SMM cases (Leonard et al., 2019). We find a positive and marginally statistically significant relationship between C-section intensity and SMM; however, our estimated SMM rate is much lower than the estimated 1.5% incidence of SMM in the full population. This is because we have a healthier population than average and we focus on only SMM complications occurring on the delivery claim itself. Thus, in our sample, the majority of SMM complications are direct or indirect complications of the C-section surgery itself. Thus, the large estimated effect reflects the mechanical relationship between C-section and surgical complications.

We find that higher physician C-section intensity causes a statistically significant increase in complications within 60 days postpartum. It is well documented in the medical literature that postpartum infections are more common for patients who delivered via C-section, and particularly for unplanned C-sections (Boushra et al., 2025).³⁸ We find that a 10 percentage point increase in physician C-section intensity increases the probability of postpartum infection diagnosis by 0.08 percentage points, or 2.8%, and prescriptions for antibiotics by .22 percentage points, or 1.6%. Our IV results imply that an unplanned C-section leads to a 3.7 percentage

³⁷Specifically, we require beneficiaries to be enrolled in the month of delivery, and the month following delivery.

³⁸One mechanism for this is infection of the surgical site, which can only occur after a C-section, and has an estimated incidence of 3% to 15% in the medical literature (Zuarez-Easton et al., 2017). C-sections are also an open surgery, leading to an increased risk of upper reproductive tract infections. Additionally, because catheterization is standard, there is a higher risk of urinary tract infections.

Table 9: Implications for maternal delivery outcomes and postpartum physical health

	Mean (1)	Reduced form (2)	(3)	Instrumental variables (4)	(5)
<i>Delivery outcomes:</i>					
Laceration (3rd or 4th degree)	2.51%	-0.016 (0.029)	-0.013 (0.029)	-0.768 (1.380)	0.145 (1.370)
Severe Maternal Morbidity*	0.45%	0.022* (0.012)	0.022* (0.012)	1.054* (0.560)	1.074* (0.551)
<i>Postpartum health - within 60 days:</i>					
Postpartum infection	2.90%	0.080*** (0.030)	0.081*** (0.030)	3.688*** (1.390)	3.656*** (1.316)
Antibiotic prescription	13.51%	0.222*** (0.066)	0.230*** (0.066)	10.279*** (3.030)	11.689*** (2.882)
ER visit	14.10%	0.244*** (0.059)	0.237*** (0.059)	11.262*** (2.765)	12.382*** (2.597)
Urgent care visit	1.82%	0.017 (0.029)	0.019 (0.028)	0.803 (1.318)	1.140 (1.187)
Baseline patient controls		✓	✓	✓	✓
Additional patient controls			✓		
Physician practice style controls					✓
Hospital-month-year		✓	✓	✓	✓
Hospital-day of week		✓	✓	✓	✓

Notes: Column (1) reports the share of our sample with each complication. Columns (2) and (3) show the percentage-point change in each outcome associated with a 10 percentage-point increase in physician C-section intensity. Columns (4) and (5) report IV coefficients x 100, interpreted as the percentage point change in each outcome from a marginal C-section. Delivery outcomes reported for full sample, N=570,617. Postpartum health outcomes within 60 days are restricted to only those enrolled in Medicaid in the month following delivery, N=511,558. All regressions include baseline patient controls (induction, preeclampsia, eclampsia, advanced maternal age, macrosomia, obesity, diabetes, and an indicator for any prenatal care with delivering physician) and fixed effects for hospital-month-year and hospital-day of week of the delivery. Column (3) includes additional controls for patient demographic and risk characteristics: race/ethnicity, indicators for > 20 prenatal claims or zero prenatal claims, prenatal mental health disorder, hypertension, and asthma. Standard errors are clustered at the physician level. Column (5) includes controls for physician practice style: “intensity” in vaginal deliveries, and “intensity” of labor augmentation. Standard errors are clustered at the physician level. * indicates $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

* We use the CDC definition of severe maternal morbidity, excluding blood transfusion. SMM measure includes only complications occurring on the delivery claim. ([CDC SMM definition](#)).

point increase in the probability of infection, off a baseline rate of 2.9%, and a 10.2 percentage point increase off a base rate of 13.5% in our sample. We also find that the marginal C-section leads to a statistically significant increase in ER visits. Given barriers to access primary care among Medicaid beneficiaries, many of these visits are likely related to postpartum infections.

While it is expected that higher C-section utilization will have negative maternal health outcomes, the effects on newborns are less clear. [Card et al., 2023](#) find that high C-section hospitals improve outcomes for newborns by avoiding longer labor, but other papers, including [Corredor-Waldron et al., 2024](#), find that unplanned C-sections increase both maternal and infant complications in low-risk births. [Table 10](#) shows the reduced-form effect of a 10 percentage point increase in delivering physician C-section intensity on newborn health outcomes, along with the associated IV coefficients. We report outcomes at delivery, within 30 days of birth, and within the first year of life. We find a positive, although not statistically significant, association between high C-section physicians and increases in NICU admissions and birth trauma. We follow [Card et al., 2023](#) and report the effect on a composite measure of infant death within 30 days or hospitalization of six or more days, a proxy for “adverse health event”. We do not find a statistically significant effect of physician practice style on this measure, or an effect on hospitalization and ER visits within 30 days. In sum, we find that marginal C-sections in our sample have a negative, but not statistically significant, effect on newborn and neonatal health. We can rule out that high C-section intensity physicians cause a significant benefit to newborn or neonatal health by avoiding more difficult labors.

We also report infant outcomes related to respiratory illness within one year of delivery. This is in light of medical literature suggesting a link between C-section delivery and respiratory outcomes ([Liang et al., 2023](#); [Wolf, 2018](#)). The theorized mechanism for this relationship is exposure to maternal microbes during delivery, leading to differences in immune system development.³⁹ For newborns delivered by more C-section intensive physicians, we do see a statistically significant increase in ER visits within one year, primarily driven by visits for respiratory illness. Our IV estimates suggest that the marginal C-section is 15.8 percentage points more likely to visit the emergency room within the first year of life, and we find

³⁹Note that evidence on the causal relationship between C-section delivery and long-term respiratory effects is mixed; many papers find no relationship ([Jakobsson et al., 2014](#); [Magnus et al., 2011](#); [Salem et al., 2022](#)).

Table 10: Implications for infant health

	Mean (1)	Reduced form (2)	(3)	Instrumental variables (4)	(5)
<i>Newborn delivery complications:</i>					
NICU	12.95%	0.100 (0.089)	0.104 (0.088)	6.288 (5.476)	3.876 (5.312)
Birth trauma to newborn	6.26%	0.066 (0.060)	0.070 (0.060)	4.156 (3.780)	4.101 (3.649)
<i>Neonatal outcomes - within 30 days:</i>					
Any readmission	10.12%	0.032 (0.077)	0.034 (0.077)	2.487 (4.729)	2.006 (4.586)
Any ER visit	10.82%	-0.094 (0.077)	-0.111 (0.077)	-4.724 (4.721)	-5.202 (4.586)
<i>Infant health - within 1 year:</i>					
Any ER visit	56.64%	0.337* (0.191)	0.278 (0.186)	15.844* (9.181)	14.848* (8.881)
ER for any respiratory illness	28.71%	0.361** (0.167)	0.311* (0.164)	16.975** (7.970)	16.612** (7.732)
Any respiratory diagnosis	68.67%	0.193 (0.169)	0.186 (0.168)	9.076 (7.942)	11.040 (7.709)
Baseline patient controls		✓	✓	✓	✓
Additional patient controls			✓		
Physican practice style controls					✓
Hospital-month-year		✓	✓	✓	✓
Hospital-day of week		✓	✓	✓	✓

Notes: Column (1) reports the share of our sample with each complication. Columns (2) and (3) show the percentage-point change in each outcome associated with a 10 percentage-point increase in physician C-section intensity. Reported coefficients are measured in percentage-point changes in the outcome. Columns (4) and (5) report IV coefficients x 100, interpreted as the percentage point change in each outcome from a marginal C-section. Delivery outcomes reported for the full sample of linked newborns, N=268,324. Neonatal health outcomes restricted to only those enrolled in Medicaid in the month following delivery, N=248,207. Newborn health outcomes within 1 year of delivery restricted to those enrolled in Medicaid for a full year after delivery, N=134,772. All regressions include baseline (maternal) patient controls (induction, preeclampsia, eclampsia, advanced maternal age, macrosomia, obesity, diabetes, and an indicator for any prenatal care with delivering physician) and fixed effects for hospital-month-year of delivery. Column (3) adds controls for race/ethnicity, indicators for > 20 prenatal claims or zero prenatal claims, prenatal mental health disorder, diabetes, hypertension, and asthma. Column (5) controls for additional dimensions of physician practice style. Standard errors are clustered at the physician level. * indicates $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

this increase is being driven entirely by visits for respiratory illness. Newborns delivered via C-section are 17 percentage points (59%) more likely to visit the emergency room for a respiratory illness. While this estimated effect on infant respiratory illness is surprisingly large, it is somewhat similar to prior estimates in the literature. [Card et al., 2023](#)’s instrumental variables strategy using hospital C-section intensity finds that the marginal C-section increases ER visits by 40% within the first year for all births in California. Given the high rate of ER use among the Medicaid population, it is not surprising that we see a particularly strong effect on this outcome.

The final category of health outcomes we study is postpartum mental health; the results are presented in [Table 11](#). The postpartum period represents a particularly vulnerable time for mental health. In the United States, suicide accounts for 5–20% of all maternal deaths, and mental health disorders, specifically suicides and overdoses, are the leading cause of maternal mortality within one year of delivery ([Clarke et al., 2023](#)). The medical literature and qualitative studies have documented that unplanned C-section delivery is associated with higher rates of postpartum depression and post-traumatic stress disorder (PTSD) relative to vaginal deliveries or scheduled C-sections ([Grisbrook et al., 2022](#); [Orovou et al., 2025](#)). C-sections are also associated with longer recovery time postpartum, and in some studies, lower rates of breastfeeding, which has been hypothesized to increase the risk of developing mental health disorders ([Benton et al., 2019](#)). We find suggestive evidence that mental health diagnoses are increased by more C-section intensive physicians. A 10 percentage point increase in C-section intensity is associated with a 2% higher likelihood of anxiety diagnosis within 60 days postpartum, but small ($< 1\%$) and insignificant impacts on other measures of mental health. Within one year, we find a 10 percentage point increase in C-section intensity is associated with roughly 1% more mental health diagnoses and medication use, although only the outcome of any mental health diagnosis is statistically significant at the 95th percent confidence interval.

The corresponding IV estimates imply that the marginal C-section in our sample is associated with a 3 percentage point increase in anxiety diagnoses within 60 days postpartum, a nearly 100% increase relative to the 3.19% baseline rate. Within one year, we find approximately 10 percentage point increase in any mental health diagnosis, or a 42% increase

Table 11: Implications for maternal postpartum mental health

	Mean (1)	Reduced form (2)	Instrumental variables (3)	(4)	(5)
<i>Postpartum mental health - within 60 days:</i>					
Any mental health diagnosis	8.22%	0.036 (0.049)	0.026 (0.045)	1.659 (2.262)	1.718 (2.106)
Anxiety diagnosis	3.10%	0.062** (0.031)	0.056* (0.030)	2.864** (1.453)	2.752** (1.335)
Depression diagnosis	2.61%	0.018 (0.027)	0.013 (0.026)	0.850 (1.256)	0.289 (1.171)
Any mental health medication	6.43%	0.040 (0.042)	0.046 (0.041)	1.835 (1.916)	2.034 (1.777)
Antidepressant prescription	5.74%	0.037 (0.039)	0.043 (0.039)	1.727 (1.806)	2.002 (1.677)
Anxiolytic prescription	1.21%	0.017 (0.019)	0.017 (0.019)	0.764 (0.876)	0.872 (0.805)
<i>Postpartum mental health - within 1 year:</i>					
Any mental health diagnosis	24.70%	0.259** (0.115)	0.243** (0.106)	9.718** (4.328)	4.566 (2.882)
Anxiety diagnosis	12.56%	0.146* (0.087)	0.134 (0.083)	5.470* (3.257)	2.956 (2.066)
Depression diagnosis	10.38%	0.123 (0.079)	0.109 (0.075)	4.626 (2.967)	1.163 (1.881)
Any mental health medication	15.97%	0.138 (0.094)	0.152* (0.091)	5.185 (3.514)	3.240 (2.393)
Antidepressant prescription	13.86%	0.145 (0.089)	0.158* (0.086)	5.430 (3.325)	3.475 (2.245)
Anxiolytic prescription	5.34%	0.091 (0.058)	0.094* (0.057)	3.430 (2.169)	2.654* (1.357)
Baseline patient controls		✓	✓	✓	✓
Additional patient controls			✓		
Physician practice style controls					✓
Hospital-month-year		✓	✓	✓	✓
Hospital-day of week		✓	✓	✓	✓

Notes: Column (1) reports the share of our sample with each complication. Columns (2) and (3) show the percentage-point change in each outcome associated with a 10 percentage-point increase in physician C-section intensity. Columns (4) and (5) report associated IV estimates x 100, interpreted as the percentage point change in each outcome from a marginal C-section. Anxiety and depression are a subset of “any mental health diagnosis”. Anxiolytic refers to medications used to reduce anxiety, such as benzodiazepines (e.g., lorazepam). Postpartum health within 60 days is restricted to only those enrolled in Medicaid in the month following delivery, N=511,558. Postpartum health outcomes within 1 year of delivery is restricted to those enrolled in Medicaid for a full year after delivery, N=237,634. All regressions include baseline patient controls (induction, preeclampsia, eclampsia, advanced maternal age, macrosomia, obesity, diabetes, and an indicator for any prenatal care with delivering physician) and fixed effects for hospital-month-year of delivery. Column (3) adds controls for race/ethnicity, indicators for > 20 prenatal claims or zero prenatal claims, prenatal mental health disorder, diabetes, hypertension, and asthma.⁴⁸ Column (5) controls for other aspects of physician practice intensity. Standard errors are clustered at the physician level. * indicates $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

off the base rate of 24.7%. While large, these estimates are in line with the medical literature. [Xu et al., 2017](#)’s meta-analysis finds emergency C-sections are associated with 47% increase in postpartum depression.⁴⁰ However, of the outcomes presented, these IV results are most likely to be biased by unobserved dimensions of physician practice style. In column (5), we present IV results with additional controls for other dimensions of physical practice style (intensity of intervention in vaginal delivery and propensity to use artificial rupture of membranes to augment labor). Many of the point estimates are significantly smaller and no longer significant once we control for other dimensions of practice style. This suggests that other correlated dimensions of physician practice style may be driving the relationship between C-section intensity and mental health outcomes, in addition to C-section itself. Even if the magnitudes are accurate, a marginal C-section in our context may be particularly stressful for mothers. Potential mechanisms and discussion of compliers in this context are discussed in the next section.

Additionally, measuring postpartum mental health outcomes in the claims data is complicated by two confounders. First, many women are wary of taking medications while breastfeeding. While there are many safe and effective medications to treat postpartum depression and anxiety while breastfeeding, concerns over safety may still limit their take-up ([Lanza di Scalea and Wisner, 2009](#)). Rates of breastfeeding are lower on average for women with C-section deliveries ([Chen et al., 2018](#)). If C-section delivery causes lower success with breastfeeding, this could conflate the relationship between C-section delivery and medication use, particularly within 60 days postpartum. Second, providers often recommend a shorter follow-up window after a C-section to check on the healing of the incision, and on average, patients have more postpartum visits after a C-section delivery than after vaginal birth. This means that an increase in mental health diagnoses and prescriptions following a C-section could be evidence of worsened mental health, or of increased diagnosis and treatment of underlying mental health conditions.

In [Table A8](#), we show the relationship between physician C-section intensity and follow-up care. Patients seen by higher C-section intensity physicians are more likely to have a

⁴⁰Most studies included in this meta-analysis used the Edinburgh Postnatal Depression scale to define postpartum depression.

postpartum visit immediately following delivery, but there is no statistically significant effect on the overall probability of receiving postpartum care.⁴¹ We further examine the type of visit where mental health diagnoses are made (follow-up postpartum visits vs. emergency room visits), and find no statistically significant association with physician C-section intensity at either location. Taken together, these results suggest that differences in postpartum healthcare utilization are unlikely to explain the observed mental health effects.

7.1 Potential Mechanisms and Heterogeneity

When interpreting our results, it is important to consider our sample as well as the types of births and patients that are most impacted by physician C-section intensity. First, we are focusing only on unplanned C-sections among low-risk first-births. In general, unplanned C-sections typically have worse maternal health outcomes compared with planned C-sections because they occur after a trial of labor and are often emergent. Additionally, we are picking up the effect of C-sections only for deliveries that are influenced by physician C-section intensity. In Medicaid claims data, all unplanned C-sections must have a diagnosed medical indication, so we necessarily see higher C-section intensity physicians diagnosing patients with complications at higher rates. [Table 12](#) shows the association between physician C-section intensity and medical indications for C-section. The marginal C-sections are much more likely to be diagnosed with obstructed labor, disproportion, fetal distress, and inadequate contractions. These are the most common medical indications for unplanned C-section, and are also diagnoses for which there is more physician discretion. Thus, the IV results from this paper do not generalize to the average causal effect of a C-section for all patients. Rather, they provide insight into the health consequences of marginal unplanned C-sections among low-risk births. From a policy standpoint, this is the group where physician discretion is most influential, and thus the group that policies aimed at lowering C-section rates are likely to target.

The diagnoses associated with a marginal C-section are particularly important to consider

⁴¹Note that diagnoses codes differentiate between postpartum care for lactation, immediate care following delivery, and postpartum follow-up care. We only see an effect of physician intensity on immediate care following delivery.

Table 12: Impact of C-section intensity on medical indications for C-section

Outcome	Mean (1)	Reduced form	
		(2)	(3)
Inadequate contraction	10.82%	0.809*** (0.070)	0.806*** (0.070)
Long labor	1.72%	0.008 (0.024)	0.009 (0.024)
Obstructed labor	6.12%	0.393*** (0.046)	0.394*** (0.046)
Maternal distress or exhaustion	1.90%	0.062** (0.026)	0.064** (0.026)
Placental separation	0.57%	0.033** (0.013)	0.033** (0.013)
Cord complication	21.28%	-0.050 (0.077)	-0.041 (0.077)
Disproportion	1.77%	0.342*** (0.037)	0.343*** (0.037)
Fetal distress	29.49%	0.631*** (0.100)	0.618*** (0.100)
Infection in labor	1.65%	0.006 (0.021)	0.006 (0.021)
Antepartum hemorrhage	0.15%	0.005 (0.007)	0.004 (0.007)
Baseline patient controls		✓	✓
Additional patient controls			✓
Hospital-month-year		✓	✓
Hospital-day of week		✓	✓

Notes: Column (1) reports the share of our sample with each complication. Columns (2) and (3) show the percentage-point change in each outcome associated with a 10 percentage-point increase in physician C-section intensity. N=570,617. All regressions include baseline patient controls (induction, preeclampsia, eclampsia, advanced maternal age, macrosomia, obesity, diabetes, and an indicator for any prenatal care with delivering physician) and fixed effects for hospital-month-year of delivery. Column (3) adds controls for race/ethnicity, indicators for > 20 prenatal claims or zero prenatal claims, prenatal mental health disorder, diabetes, hypertension, and asthma. Standard errors are clustered at the physician level. * indicates $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

when interpreting our mental health results. From a medical perspective, most unplanned C-sections in our setting are fairly routine, and approximately 30% of all unplanned C-sections receiving a diagnosis of fetal distress. However, from the patient’s perspective, the diagnosis of fetal distress may generate fear for her baby’s safety. Thus, it is plausible that the mental health effects are in part driven by receiving a worrying diagnosis during labor, rather than the procedure itself.

For interpreting our results, it is also useful to consider who the “compliers” are in this setting. These are patients who would not have received a C-section if they had not been assigned to a low C-section intensity physician, but would deliver via C-section if assigned to a high C-section intensity physician. On the other hand, always-takers are patients who would always deliver via C-section, regardless of the physician they were assigned to. Vice versa, a never-taker would never deliver via C-section. This is equivalent to the group of patients who deliver vaginally, even when assigned to the highest intensity physician. We estimate the share of each patient type following the method from (Dahl et al., 2014; Dobbie et al., 2018; Eichmeyer and Zhang, 2022), where $\bar{z}$ is the most C-section intensive physician (top 1%) and $\underline{z}$ is the least intensive (bottom 1%).

$$\begin{aligned}\pi_{complier} &= P(c_{\bar{z}i} > c_{\underline{z}i}) = P(c_i \mid Z_i = \bar{z}) - P(c_i \mid Z_i = \underline{z}) \\ \pi_{always-taker} &= P(c_{\bar{z}i} = c_{\underline{z}i} = 1) = P(c_{\underline{z}i} = 1) \\ \pi_{never-taker} &= P(c_{\bar{z}i} = c_{\underline{z}i} = 0) = P(c_{\bar{z}i} = 0)\end{aligned}$$

In Table 13 we break our sample by patient demographics and characteristics of labor. We report in column (1) the share of the overall sample in each category and in column (2) the C-section rate of each category. In column (3), we report the first-stage coefficient, and in column (4), the share of compliers. One key takeaway is that “marginal” patients with predicted C-section appropriateness between 0.4 and 0.6, are much more impacted by physician practice style. This is consistent with the predictions of our model. Additionally, patients over the age of 35 (advanced maternal age) are more impacted, which is driven by the fact that this group is higher risk on average. A second key finding is that Hispanic patients are disproportionately influenced by practice style. Our model predicts that, all else

equal, physician practice style will matter more for patients with lower agency. If language barriers or cultural norms influence the ability of Hispanic patients to express preferences during delivery, this could explain our results. However, further work is needed to unpack the mechanisms behind this finding.

7.2 Implications for Subsequent Pregnancies

There are also strong dynamic effects of the delivery method. Although vaginal birth after cesarean (VBAC) rates are rising, most patients who deliver via unplanned C-section in their first birth deliver via scheduled C-section in their second birth.⁴² For a subset of our main NTSV sample, we can also observe a second birth during our sample period and estimate the following regression:

$$\text{C-section}_{ijbdt}^{\text{2nd birth}} = \alpha + \beta \text{C-section Intensity}_{i,jt}^{\text{1st birth}} + \gamma_{bt}^{\text{1st birth}} + \gamma_{bd}^{\text{1st birth}} + \beta X_i^{\text{1st birth}} + e_{ijbdt} \quad (15)$$

where the outcome is an indicator for C-section at the second birth, regressed on the C-section intensity of the physician assigned at the first birth. Baseline controls include health characteristics X_i , hospital-month-year γ_{bt} and hospital-day of week γ_{bd} , all defined based on health risks and delivery date of the patients' first birth. This estimates the relationship between the C-section intensity of the *first* delivering physician on the probability of C-section in their *second* birth.

Figure 10 shows the distribution of the C-section intensity instrument for this sample, and the local linear fit of β from Equation (15). As would be expected, the relationship between the intensity of C-sections of the physician assigned to a patient's first delivery also has a strong positive effect on the probability of C-section in her second birth. We find that being quasi-randomly assigned to a 10 percentage point more C-section intense physician for a first birth increases the probability that the second delivery is a C-section by 2.29 percentage

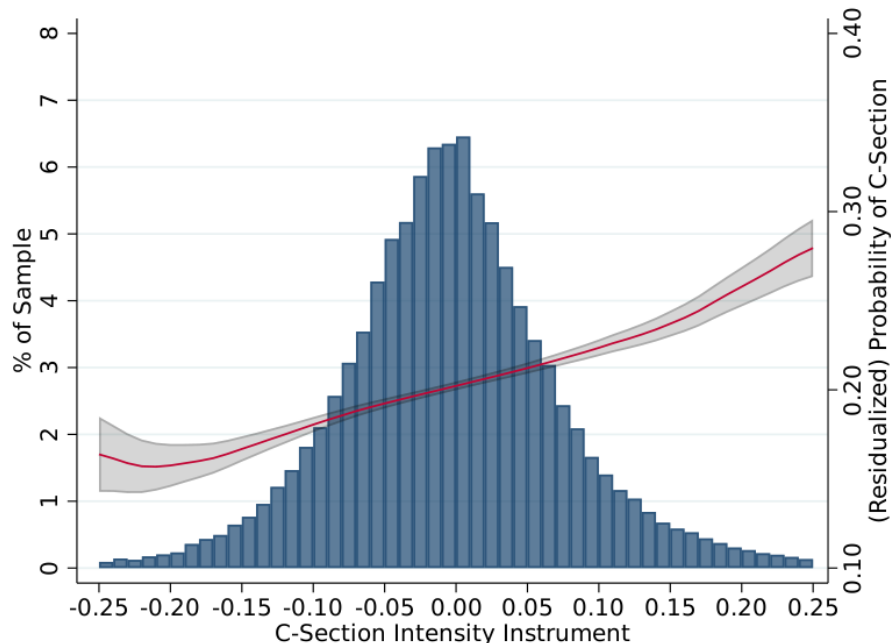
⁴²In our sample period, between 12-13% of all US births were VBACs (Osterman, 2020).

Table 13: Heterogeneity by patient type

Subsample (x):	Share of sample $P(X=x)$	C-section rate $P(c_i = 1 X = x)$	First stage β	Share compliers $P(\text{complier} X = x)$
Full sample		21.032	0.211*** (0.013)	7.697
White	34.802	18.971	0.129*** (0.019)	5.232
Black	19.286	23.566	0.177*** (0.023)	4.442
Hispanic	31.667	19.446	0.365*** (0.022)	10.165
Spanish speaker	7.937	18.276	0.414*** (0.040)	8.594
Non-citizen	6.802	21.004	0.278*** (0.041)	4.960
“Marginal” patients: $0.4 \leq h_i \leq 0.6$	4.803	44.057	0.359*** (0.071)	18.073
More than 20 prenatal visits	12.848	22.989	0.187*** (0.031)	6.222
Artificial rupture of membranes	21.714	12.751	0.120*** (0.018)	2.867
Advanced maternal age	3.250	32.717	0.306** (0.124)	12.834
Admitted on weekend	22.071	18.077	0.199*** (0.020)	5.882
Induction	24.737	24.984	0.211*** (0.022)	6.430
Saw delivering physician for prenatal care	53.370	20.968	0.200*** (0.017)	7.249

Notes: This table splits our full sample into subsamples based on demographics and patient risk. Column (1) reports the percent of our full sample in each subsample (x). Column (2) reports the C-section rate for each subsample. Column (3) reports the estimated first-stage coefficient β (standard error in parentheses). * indicates $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$. Column (4) reports the estimated % of each subsample that are “compliers” - i.e., the share who would not receive a C-section if assigned to the lowest-intensity physician but would if assigned to the highest-intensity physician.

Figure 10: Association between C-section intensity of physician in *first* birth on delivery method of *second* birth



Notes: This figure is based on the subset of our main sample for whom we can observe a second delivery in Medicaid: $N = 106,685$. The patient's *first* observed birth must be NTSV and unscheduled (either vaginal birth or unplanned C-section); however, no restrictions are placed on their second birth. The histogram shows the distribution of the C-section intensity of *first delivering provider* on the x -axis against the percent of the sample on the left-hand y -axis. Graph is truncated at ± 0.25 . On the right-hand y -axis, we plot a local linear regression of β from a regression of C-section delivery in the *second birth* on C-section intensity of *first physician*. Controls are included for health risks X_i , hospital-month-year, and hospital-day of week; all controls are defined in the patient's first birth. We find $\beta = 2.29$ (standard error = 0.24), implying that for women who deliver twice in our sample, being quasi-randomly assigned to a 10 percentage point more "C-section intense" physician increases the probability of C-section by 2.3 percentage points. C-section rate in this sample is 20.38%.

points off a base rate of 20.38%.⁴³ This implies that, in our sample of patients with two observed births, the large majority of patients with a marginal unplanned C-section in their first birth go on to have a C-section in their second birth, typically via scheduled C-section.

Table 14 compares characteristics between our main NTSV sample with and without an observed second birth in Medicaid. Patients for whom we are able to observe a second birth are younger on average, more likely to be white, and less likely to qualify for Medicaid based on income $< 133\%$ Federal Poverty Line (FPL). Patients with a second observed birth also

⁴³For comparison, the first-stage effect of a 10 percentage point increase in C-section intensity on delivery method in the *first* birth for the subsample of patients with a second observed birth in our data is 2.69 percentage point increase off a base rate of 17.93%.

had better health outcomes on average in their first birth: a lower rate of C-section delivery and were less likely to face complications such as fetal distress or inadequate contractions in their first birth. This reflects both differences in the demographics and health of patients who choose to have multiple children and/or children close in age, as well as causal effects from the outcome of their first birth. We would expect, on average, women with more difficult pregnancies and deliveries to delay future pregnancies or forgo having additional children altogether. Prior research from Austria has found women with unplanned C-sections in their first birth have a 13.6% reduction in lifetime fertility ([Halla et al., 2020](#)).

We test this relationship between unplanned C-sections and fertility in our sample by measuring the impact of physician C-section intensity on the likelihood of observing a second delivery in Medicaid between 2015 and 2019. [Table 15](#) reports the reduced-form effect of C-section intensity on fertility, along with the instrumental variables estimate of the causal impact of a marginal C-section. We find that in our sample, marginal C-sections reduce the likelihood of a second birth by between 5-6 percentage points, off a base rate of 20.38%. This implies a 28% reduction in fertility. This effect does not appear to be driven by differences in patients exiting Medicaid insurance: we find no effect of C-section intensity on the probability a patient remains enrolled in Medicaid for at least one year postpartum. However, the exact mechanisms for the fertility effect are unclear. The drop in fertility following a C-section could reflect changes in preferences for having additional children, impacts on infertility, an increase in spacing between children, or some combination of the three.

Table 14: Comparison of demographics and *first birth* risk factors, for patients with and without a second observed birth

	(1) Patients with second birth	(2) Only one birth observed	(3) Δ
C-section	0.18 (0.38)	0.21 (0.40)	0.03*** (0.00)
Hispanic	0.32 (0.47)	0.32 (0.47)	-0.00 (0.00)
Black	0.19 (0.39)	0.19 (0.39)	0.00 (0.00)
White	0.37 (0.48)	0.34 (0.47)	-0.02*** (0.00)
Medicaid eligibility < 133% FPL	0.20 (0.40)	0.23 (0.42)	0.03*** (0.00)
Medicaid eligibility SSI	0.02 (0.13)	0.01 (0.12)	-0.00*** (0.00)
Age	22.14 (4.22)	23.28 (4.97)	1.13*** (0.01)
Over 20 prenatal visits	0.16 (0.36)	0.15 (0.35)	-0.01*** (0.00)
Fetal distress	0.26 (0.44)	0.30 (0.46)	0.04*** (0.00)
Inadequate contractions	0.09 (0.29)	0.11 (0.32)	0.02*** (0.00)
Obstructed labor	0.06 (0.23)	0.06 (0.24)	0.00*** (0.00)
Disproportion	0.02 (0.12)	0.02 (0.13)	0.00*** (0.00)
N	106,685	463,932	570,617

Notes: This table compares patients in our main sample of NTSV births, with and without a second observed birth in Medicaid 2015-2019. All characteristics reported are from the patients' *first* birth. Medicaid eligibility variables refer to patients eligible due to income below 133% of the Federal Poverty Line (FPL) and those eligible via Social Security (SSI) benefits due to disability. * indicates $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Table 15: Implications of unplanned C-sections on future fertility

	Mean (1)	Reduced form (2)	Instrumental variables (3)	(4)	(5)
Second birth in sample	20.38%	-0.124** (0.062)	-0.128** (0.062)	-5.879** (2.948)	-5.076* (2.910)
Enrolled in Medicaid for ≥ 1 year postpartum	43.51%	0.036 (0.068)	0.012 (0.067)	1.707 (3.221)	2.166 (3.210)
Baseline patient controls		✓	✓	✓	✓
Additional patient controls			✓		
Physician practice style controls					✓
Hospital-month-year		✓	✓	✓	✓
Hospital-day of week		✓	✓	✓	✓

Notes: “Second birth in sample” is an indicator for whether a given patient in our main sample has a second birth in Medicaid from 2015-2019. “Enrolled in Medicaid for $\geq$ year postpartum” is an indicator of whether the patient remains continuously enrolled in Medicaid for one year postpartum. Column (1) reports the mean of each variable. Columns (2) and (3) report the effect of a 10 percentage point increase in physician C-section intensity on each outcome. Columns (4) and (5) report associated IV estimates $\times 100$, interpreted as the percentage point change in each outcome from a marginal C-section. $N = 570,617$ * indicates $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

8. Discussion

The persistently high C-section rate in the United States has raised policy concerns about potential overuse of surgical delivery. Even after adjusting for patient risk factors, hospital-level C-section rates vary widely, suggesting that supply-side factors in healthcare provision play a central role in explaining this variation (Fischer et al., 2023; Kozhimannil et al., 2013). Most policy efforts to date have focused on state-level initiatives or hospital-level targets.⁴⁴ Our findings indicate that more than one-quarter of the variation in C-section use is attributable to physician practice style. This is a sizable share and underscores the importance of individual providers in shaping intervention rates. This suggests that while systemic reforms at the hospital or state level are crucial, they are likely to be incomplete solutions if they do not address a key source of variation: the behavior of individual physicians.

Within hospitals, we document substantial heterogeneity across physicians in their propen-

⁴⁴California’s CMQCC initiative is one example of a successful state-level effort to lower the C-section rate through hospital-level targets and quality-improvement programs in high C-section rate hospitals.

sity to perform C-sections on otherwise similar patients. Because patients are effectively randomly assigned to physicians through the onset of spontaneous labor and the shift rotation of on-call providers, we can causally estimate the impact of physician practice style on delivery method. We find large effects: being assigned to a physician with a 10 percentage point higher C-section intensity, roughly one standard deviation, increases the probability of C-section delivery by about 2.11 percentage points, or 10%. This effect is comparable to the difference between being treated by a physician at the 75th versus the 25th percentile of the intensity distribution.

Given that a C-section is a major abdominal surgery with elevated risks, it is not surprising that we find evidence that marginal C-sections have adverse consequences for maternal health, including higher rates of delivery complications, postpartum infection, and emergency room visits. We also do not find evidence that newborns benefit from higher physician C-section intensity. We observe negative but imprecise effects of marginal C-sections on neonatal outcomes, along with a statistically significant increase in severe respiratory infections within one year of birth. We also find important implications for maternal mental health. Patients quasi-randomly assigned to higher C-section intensity physicians are more likely to be diagnosed with mental health conditions within a year postpartum and have higher, although not statistically significant, use of mental health medications. These results are particularly salient given that mental health conditions are the leading cause of maternal mortality within one year postpartum (Clarke et al., 2023). Because C-sections have long-term consequences, most notably on the delivery method of subsequent births, these effects compound in future pregnancies. We also find strong effects on fertility: a marginal C-section is associated with a 28% reduction in the probability of observing a second birth during our sample period. This likely reflects both lower lifetime fertility and increased spacing between births.

Our analysis has several limitations. Since we rely on Medicaid claims data, we observe only a subset of births, and our findings should be interpreted within the Medicaid setting. The physicians and hospitals we focus on in our analysis deliver a large number of Medicaid patients, and may not be representative of healthcare providers more broadly. In addition, while we document clear physician effects, some of our estimates are imprecise, and we cannot rule out modest effects on other health outcomes. Finally, we do not observe the

counterfactual of what would happen if high-intensity physicians reduced their C-section rates, so we cannot make definitive welfare conclusions.

Although we establish that low-risk patients treated by high-intensity physicians experience worse health outcomes, we are unable to estimate the causal effects of practice style for higher-risk patients. Our identification strategy relies on quasi-random assignment of low-risk women in labor; we exclude all scheduled C-sections and higher-risk patients from our sample. It is plausible that high-intensity physicians could improve outcomes in such cases. Examining potential trade-offs of high-intensity physicians treating higher-risk patients is an important avenue for future research. Further work is also needed to identify which features of the hospital environment drive differences in C-section rates and how physician practice style is formed. In [Kissel and Roy, 2025](#), we assess the role of residency training in C-section use, among other dimensions of practice style, and find that the C-section intensity of a physician’s residency hospital is not a significant driver of post-residency practice style. A more complete understanding of the formation of physician practice style is critical for designing policies that effectively reduce unnecessary surgical interventions while maintaining high-quality care for mothers and infants.

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A. Supplemental Tables and Figures

Table A1: Covariates predicting C-section appropriateness

	This Paper	Currie and MacLeod, 2017	Robinson et al., 2023
Maternal Age	5-year bins	5-year bins	5-year bins
Term (37+ weeks)	✓	–	✓
Prenatal Visits	≥ 19	–	≥ 19
Nulliparous	✓	Birth order	✓
Singleton	✓	Multiples	✓
Vertex	✓	Breech	✓
Growth Restrictions	✓(intrauterine)	–	✓
Eclampsia	✓	–	✓
Preeclampsia	✓	–	✓
Other Hypertension	✓	✓	–
Asthma	✓	Chronic lung condition	–
Diabetes	✓	–	✓
Obesity	✓	–	–
Placenta Previa	✓	✓	–
Placental Abruption	✓	✓	–
Herpes	✓	✓	–
Hydramnios	✓	✓	–
Chorioamnionitis	✓	–	–
Cord Prolapse	✓	✓	–
Isoimmunization	✓	✓(Rh Sensitivity)	–
Macrosomia	✓	–	–
Antepartum Hemorrhage	✓	Uterine Bleeding	–
Previous C-Section	✓	✓	–
Previous Large Infant	–	✓	–
Previous Preterm	–	✓	–
Cardiac condition	✓+ congenital	✓	–
Blood disorder	✓	Anemia + Hemoglobinopathy	–
Cervical incompetence	✓	✓	–
Renal abnormalities	✓	✓	–

Notes: Age is classified into 5-year bins as follows: <20, 20-24, 25-29, 30-34, ≥ 35 . Isoimmunization is also known as Rh sensitivity (terminology used in Currie and MacLeod, 2017).

Table A2: Logistic regression model of C-section risk

	Beta	SE
Age < 20	-.1928386***	.004246
Age 25-29	.0288876***	.0027257
Age 30-34	.0893298***	.0030957
Age 35+	.2269394***	.0035983
Prenatal Claims ≥ 19	.1046772***	.0021831
Nulliparous	.7624481***	.0026043
Term	.0072586	.0048402
Singleton	-.6099307***	.0040694
Vertex	-3.056423***	.0057432
Intrauterine Growth Restriction	.5275533***	.005088
Eclampsia	1.432985***	.0264771
Preeclampsia	.8974775***	.0040323
Other Hypertension	.3488085***	.0036775
Asthma	-.0124584**	.0050635
Diabetes	.3131867***	.003878
Obesity	.4381966***	.0033706
Placenta Previa	1.426388***	.0112711
Placental Separation	1.443811***	.0083788
Herpes	.2789016***	.0058824
Hydramnios	.4656481***	.0048721
Chorioamnionitis	.8671536***	.0058849
Cord Complications	-.481389***	.0029228
Isoimmunization	-.0694652***	.0105647
Macrosomia	1.696111***	.0062682
Antepartum Hemorrhage	.7995364***	.0166766
Previous C-Section	3.744066***	.002855
Congenital Heart Disease	.4093788***	.0125014
Blood Disorder	.1283061***	.0028281
Cervical Incompetence	.1501317***	.0134766
Renal Abnorm.	.3903928***	.0242845
Constant	1.310074***	.0079258
Observations	7820852	

Notes: Table presents coefficients and standard errors from a logit regression of C-section delivery on patient characteristics.* indicates $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Table A3: Additive decomposition alternative specification: Without nulliparous restriction

	Estimator	Top vs. Bottom			
		50%	25%	10%	5%
Δ in C-section Rate...					
... Overall	$\hat{c}_B - \hat{c}_{B'}$	0.119	0.195	0.292	0.362
... Due to hospitals	$\hat{\gamma}_B - \hat{\gamma}_{B'}$	0.077	0.124	0.186	0.217
... Due to physicians	$\hat{\gamma}_{j(B)} - \hat{\gamma}_{j(B')}$	0.034	0.059	0.091	0.121
Share of Δ due to...					
... Hospitals	$\frac{\hat{\gamma}_B - \hat{\gamma}_{B'}}{\hat{c}_B - \hat{c}_{B'}}$	0.645*** (0.107)	0.635*** (0.100)	0.637*** (0.101)	0.598*** (0.106)
... Physicians	$\frac{\hat{\gamma}_{j(B)} - \hat{\gamma}_{j(B')}}{\hat{c}_B - \hat{c}_{B'}}$	0.287** (0.108)	0.305** (0.100)	0.310** (0.101)	0.334*** (0.105)
N hospitals		1,268	634	254	128
N physician-hospital pairs		12,584	5,098	1,593	700
N deliveries		485,676	190,726	52,745	20,161

Notes: Reports results from Equation (4), but *without restricting sample to nulliparous (first births)*. Sample includes all term, singleton, vertex deliveries with a trial of labor. Those attempting vaginal births following C-section (VBACs) are dropped. Restricted to the largest set of connected hospitals. Quantiles (denoted B and B') are determined by a hospital's raw NTSV unscheduled C-section rate over the sample period. First row reports the difference in average C-section rate between hospitals in group B vs B' . The second row reports the difference in average hospital fixed effects among hospitals in group B vs B' . The third row reports the difference in average physician fixed effect among hospitals in group B vs B' . Standard errors (in parentheses) are calculated by bootstrap with 100 repetitions. * indicates $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Table A4: Additive decomposition alternative specification: Dropping “stayers”

	Estimator	Top vs. Bottom			
		50%	25%	10%	5%
Δ in C-section Rate...					
... Overall	$\hat{c}_B - \hat{c}_{B'}$	0.141	0.230	0.344	0.427
... Due to hospitals	$\hat{\gamma}_B - \hat{\gamma}_{B'}$	0.100	0.176	0.238	0.294
... Due to physicians	$\hat{\gamma}_{j(B)} - \hat{\gamma}_{j(B')}$	0.033	0.042	0.083	0.107
Share of Δ due to...					
... Hospitals	$\frac{\hat{\gamma}_B - \hat{\gamma}_{B'}}{\hat{c}_B - \hat{c}_{B'}}$	0.711*** (0.094)	0.765*** (0.084)	0.693*** (0.090)	0.688*** (0.108)
... Physicians	$\frac{\hat{\gamma}_{j(B)} - \hat{\gamma}_{j(B')}}{\hat{c}_B - \hat{c}_{B'}}$	0.232** (0.094)	0.181** (0.083)	0.243*** (0.090)	0.250** (0.109)
N hospitals		1,245	629	256	128
N physician-hospital pairs		7,242	2,580	755	306
N deliveries		238,048	77,496	18,510	5,578

Notes: Reports results from Equation (4). In this alternative specification, we drop all physicians with only one practice location from the sample. Restricted to the largest set of connected hospitals. Quantiles (denoted B and B') are determined by a hospital’s raw NTSV unscheduled C-section rate over the sample period. First row reports the difference in average C-section rate between hospitals in group B vs B' . The second row reports the difference in average hospital fixed effects among hospitals in group B vs B' . The third row reports the difference in average physician fixed effect among hospitals in group B vs B' . Standard errors (in parentheses) are calculated by bootstrap with 100 repetitions. Births are restricted to nulliparous, term, singleton, and vertex (NTSV) without a scheduled C-section. * indicates $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Table A5: Additive decomposition alternative specification: Multihomers with more balanced patient shares

	Estimator	Top vs. Bottom			
		50%	25%	10%	5%
Δ in C-section Rate...					
... Overall	$\hat{c}_B - \hat{c}_{B'}$	0.115	0.189	0.282	0.344
... Due to hospitals	$\hat{\gamma}_B - \hat{\gamma}_{B'}$	0.072	0.103	0.133	0.202
... Due to physicians	$\hat{\gamma}_{j(B)} - \hat{\gamma}_{j(B')}$	0.036	0.073	0.133	0.121
Share of Δ due to...					
... Hospitals	$\frac{\hat{\gamma}_B - \hat{\gamma}_{B'}}{\hat{c}_B - \hat{c}_{B'}}$	0.624*** (0.135)	0.544*** (0.109)	0.472*** (0.121)	0.585*** (0.129)
... Physicians	$\frac{\hat{\gamma}_{j(B)} - \hat{\gamma}_{j(B')}}{\hat{c}_B - \hat{c}_{B'}}$	0.309** (0.135)	0.389*** (0.110)	0.470*** (0.122)	0.350** (0.130)
N hospitals		878	441	176	91
N physician-hospital pairs		10,057	4,179	1,312	578
N deliveries		378,987	152,911	44,527	16,938

Notes: Reports results from Equation (4). In this alternative specification, we only include “multi-homer” shifts at hospitals where at least 20% of a physician’s NTSV caseload. This limits concern over bias in the hospital environment component, leading to mis-measurement of the physician share. Restricted to the largest set of connected hospitals. Quantiles (denoted B and B') are determined by a hospital’s raw NTSV unscheduled C-section rate over the sample period. First row reports the difference in average C-section rate between hospitals in group B vs B' . The second row reports the difference in average hospital fixed effects among hospitals in group B vs B' . The third row reports the difference in average physician fixed effect among hospitals in group B vs B' . Standard errors (in parentheses) are calculated by bootstrap with 100 repetitions. Births are restricted to nulliparous, term, singleton, and vertex (NTSV) without a scheduled C-section. * indicates $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

Table A6: Review of policies, interventions, and other factors impacting C-section rates

Paper	Policy	Impact on C-Section Rate
Sandall et al., 2024	Midwife Care	-1 pp (16%→15%)
Main et al., 2019	CMQCC Supportive Vaginal Birth Collaborative participating hospitals ¹	-4.3 pp (29.3% → 25.0%)
	California C-section decline after CMQCC state-wide initiatives	-3.2pp
McGrath and Kennell, 2008	RCT of Doula support during labor ²	-11.6 pp (25.0% → 13.4%)
Bohren et al., 2017	Meta analysis on doula support in labor ³	-3.7% (14.6% → 10.9%)
Johnson et al., 2016	OBs delivering “own” patients ⁴	+4.7 pp (15.4% → 20.1%)
Johnson and Rehavi, 2016	Physician-mother’s own birth	-2.14 pp (base of 29.1%)
Johnson and Rehavi, 2016	Delivery at HMO-owned hospital	-5 pp ⁵

Notes: Table presents estimates from a literature review of policies, interventions, and other factors impacting C-section rates to contextualize our effect size.

¹California Maternal Quality Care Collaborative (CMQCC) partnered with 56 hospitals to lower NTSV cesarean delivery rate. A toolkit was provided including guidelines for active phase arrest, labor support techniques, transparency in C-section rate, along with other information aimed at reducing NSTV C-section rate.

²Effect of randomized doula support in labor among 224 nulliparous women with uncomplicated pregnancies in Cleveland, Ohio from 1988 - 1992

³ Meta analysis of 24 RCTS of continuous support during childbirth. The authors note this evidence is of low quality due to limitations of the study designs and large variation in effect size.

⁴ Patients for whom the OBGYN had a prenatal relationship with.

⁵ Approximately half of this difference is due to scheduled C-sections and the other half from unscheduled C-sections.

Table A7: Effect of physician C-section intensity on P(C-section delivery)

	(1) Dependent Variable: C-section Delivery (0/1)
C-section Intensity	0.211*** (0.0125) (0.0125)
Induction	0.0466*** (0.00187) (0.00187)
(Pre)eclampsia	0.103*** (0.00270) (0.00270)
Adv. Maternal Age	0.107*** (0.00392) (0.00392)
Macrosomia	0.333*** (0.00638) (0.00638)
Any prenatal visit w delivering phys.	0.00855*** (0.00165) (0.00165)
Obesity	0.150*** (0.00280) (0.00280)
Diabetes	0.0810*** (0.00308) (0.00308)
Constant	0.153*** (0.00111) (0.00111)
Mean of Dep. Var.	0.201
F-Statistic	1391.23
# Physicians (Clusters)	12,256
N	570,617

Notes: Table presents estimates from the first stage regression described in [Equation \(10\)](#). An observation is a delivery (patient-physician pair linked to a birth outcome). Fixed effects included for hospital-month-year and hospital-day-of-week. The coefficient on C-section intensity implies that a 10 percentage point increase in C-section intensity increases p(C-section) by 2.11 percentage points. A 10 percentage point increase is roughly equivalent to a one standard deviation increase, or moving from the 25th percentile to the 75th percentile of physician intensity. Standard errors in parentheses are clustered at the physician level. * p<.10, ** p<.05, ***p<.01

Table A8: Effect of Physician C-section Intensity on Postpartum Healthcare Utilization

Outcome	Mean (1)	Reduced form (2) (3)	
<i>Postpartum care visits (60 days):</i>			
Any lactation visit	15.67%	-0.020 (0.075)	-0.019 (0.075)
Any immediate postpartum visit	4.28%	0.323*** (0.086)	0.323*** (0.086)
Any postpartum follow-up visit	45.67%	0.092 (0.140)	0.100 (0.139)
N postpartum follow-up visits	0.60	0.335 (0.254)	0.343 (0.251)
<i>Place of mental health diagnosis (60 days):</i>			
Mental diagnosis at ER	0.48%	0.009 (0.011)	0.008 (0.011)
Mental diagnosis at postpartum follow-up visit	0.71%	-0.001 (0.015)	-0.001 (0.015)
<i>Place of mental health diagnosis (1 year):</i>			
Mental diagnosis at ER	3.06%	0.065 (0.045)	0.059 (0.044)
Mental diagnosis at postpartum follow-up visit	0.85%	-0.029 (0.025)	-0.029 (0.025)
Baseline patient controls		✓	✓
Additional patient controls			✓
Hospital-month-year		✓	✓
Hospital-day of week		✓	✓

Note: The ICD diagnosis codes differentiate between postpartum visits for lactation, “immediate” postpartum visits (often in the hospital following delivery), and “follow-up” postpartum visits (typically outpatient). The figure shows the effect of a 10 percentage point increase in physician C-section intensity on the probability of each postpartum visit type, as well as the total count of postpartum follow-up visits. Outcomes within 60 days restricted to only beneficiaries enrolled in Medicaid in the month following delivery, N = 511,558. Outcomes within 1 year restricted to only beneficiaries continuously enrolled for one year following delivery, N = 237,634. Controls are included for induction, preeclampsia, eclampsia, advanced maternal age, macrosomia, obesity, diabetes, and an indicator for any prenatal care with the delivering physician. Column 3 adds controls for race/ethnicity, indicators for > 20 prenatal claims or zero prenatal claims, prenatal mental health disorder, diabetes, hypertension, and asthma. Fixed effects for hospital-month-year of delivery are included. Standard errors are clustered at the physician level. * indicates $p < 0.10$, ** for $p < 0.05$, and *** for $p < 0.01$.

B. Variable Construction

B.1 Identifying Births in Medicaid Claims

We follow Approach 4 in [Auty et al., 2024](#) to identify live births, which they find achieves the best match for birth counts relative to CDC birth record data (NVSS). This method defines a “birth” claim as any claim with a diagnosis code in [Table A9](#) in either the Medicaid inpatient (IP) or other-services (OT) files. In 2015, Medicaid transitioned from reporting claims in MAX files to T-MSIS (TAF) files. In our main sample, we only use deliveries from the TAF files (this restriction only applies to the 2015 transition year). Due to data entry differences in the MAX and TAF files, the variable construction is slightly different between the files, leaving us cautious about using both data sources in the same analysis.

Table A9: Diagnosis codes associated with deliveries

Description	ICD-9 Diagnosis	ICD-10 Diagnosis
Encounter for care and examination of mother immediately after delivery	–	Z39.0
Encounter for full term uncomplicated delivery	650	O80
Cesarean delivery, without mention of indication	669.71, 669.70	O82
Single liveborn	V27.0	Z37.0
Single stillborn	V27.1	Z37.1
Twins, both liveborn	V27.2	Z37.2
Twins, one stillborn one liveborn	V27.3	Z37.3
Twins, both stillborn	V27.4	Z37.4
Other multiple birth, all liveborn	V27.5	Z37.5X
Other multiple birth, some liveborn	V27.6	Z37.6X
Other multiple birth, all stillborn	V27.7	Z37.7
Unspecified outcome of delivery	V27.9	Z37.9

When we observe multiple “deliveries” to the same beneficiary within seven days, we group these as one birth. To construct our patient health characteristics, we take the maximum value over all birth claims within seven days. For example, if a patient has two “birth” claims within seven days, if either claim has a billing code associated with C-section delivery, we code this patient as delivering via C-section. In cases when we observe two birth episodes within nine months, we only include the earlier observed birth.

B.2 Identifying Delivering Physician and Hospital

For each birth claim, we identify the hospital and individual physician associated with the delivery. Claims in the IP file list operating provider, servicing provider, and billing provider. Each provider is identified by a National Provider Identifier (NPI). We link NPI to the Centers for Medicare and Medicaid Services (CMS) National Plan and Provider Enumeration System (NPES) database, which details the provider type (individual physician, group practice, or hospital) and taxonomy (e.g., OB/GYN).

We define the delivering physician on each claim as the servicing provider whenever this servicing provider is an individual physician. In cases where there is no individual servicing provider listed, we instead use the individual operating provider. In cases where there are multiple individual physicians listed, we keep the physician with taxonomy OB/GYN in the NPES records (if there is an OB/GYN listed). In our final data cut, we require the delivering NPI to be associated with an OB/GYN, family physician, or general practice physician. Of births in our final sample 98% are delivered by an OB/GYN.

To identify the hospital of delivery, we use the billing provider when this NPI is associated with an organization in NPES. We then map from billing provider NPI to a masterlist of all hospitals from the Agency for Healthcare Research and Quality (AHRQ) based on the NPES practice address. We use this strategy as hospitals can have more than one billing NPI. In our final sample, we only keep births that link to a known hospital from the AHRQ masterlist.

B.3 Delivery Method

[Table A10](#) shows the full list of all DRG, procedure and diagnosis codes we use to define C-section deliveries. We assume all births not coded as C-sections are vaginal deliveries. Note that this list includes several out-of-date DRG codes and should be used with caution if applied to other settings. We err on the side of including any possible C-section code, since all claims are first restricted to only delivery claims. This increases the likelihood that these codes refer to a C-section rather than another health outcome.

Table A10: ICD codes related to C-section delivery

Code Type	Code	Description
MS-DRG (est. 2008)	765	Cesarean section with complication (CCM/MCC)
MS-DRG (est. 2008)	766	Cesarean section without complication (CCM/MCC)
MS-DRG (est. 2017)	783	C-section w sterilization w MCC
MS-DRG (est. 2017)	784	C-section w sterilization w CC
MS-DRG (est. 2017)	785	C-section w sterilization w/o CC/MCC
MS-DRG (est. 2017)	786	C-section w/o sterilization w MCC
MS-DRG (est. 2017)	787	C-section w/o sterilization w CC
MS-DRG (est. 2017)	788	C-section w/o sterilization w/o CC/MCC
APR-DRG	540	Cesarean delivery
ICD-10 Procedure	10D00Z0*	Extraction of Products of Conception, Classical, Open Approach
ICD-10 Procedure	10D00Z1	Extraction of Products of Conception, Low Cervical, Open Approach
ICD-10 Procedure	10D00Z2	Extraction of Products of Conception, Extraperitoneal, Open Approach
ICD-9 Procedure	74.0	Classical C-section
ICD-9 Procedure	74.1	Low cervical C-section
ICD-9 Procedure	74.2	Extraperitoneal C-section
ICD-9 Procedure	74.4	C-section other type (NEC)
ICD-9 Procedure	74.99	C-section w no specific indication (NOS)
CPT Code	59510	Routine obstetric care including antepartum care, cesarean delivery, and postpartum care
CPT Code	59514	Cesarean delivery only

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Code Type	Code	Description
CPT Code	59515	Cesarean delivery only, including postpartum care
CPT Code	59618	Routine obstetric care including antepartum care, cesarean delivery, and postpartum care, following attempted vaginal delivery after previous cesarean delivery
CPT Code	59620	Cesarean delivery only, following attempted vaginal delivery after previous cesarean delivery
CPT Code	59622	Cesarean delivery only, following attempted vaginal delivery after previous cesarean delivery; including postpartum care
CPT Code	01961	Anesthesia for cesarean delivery only
CPT Code	01968	Anesthesia for cesarean delivery following neuraxial labor analgesia/anesthesia
ICD-9 Diagnosis	66970	Cesarean delivery, without mention of indication, unspecified as to episode of care or not applicable
ICD-9 Diagnosis	66971	Cesarean delivery, without mention of indication, delivered, with or without mention of antepartum condition
ICD-9 Diagnosis	64981	Spontaneous labor 37-39 weeks gestation, with delivery by (planned) cesarean section
ICD-9 Diagnosis	64982	Spontaneous labor 37-39 weeks gestation, with delivery by (planned) cesarean section, with postpartum complication

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Code Type	Code	Description
ICD-9 Diagnosis	V30.01	Single liveborn, delivered by cesarean section
ICD-9 Diagnosis	V31.01	Twin birth, mate liveborn, delivered by cesarean section
ICD-9 Diagnosis	V32.01	Twin birth, mate stillborn, delivered by cesarean section
ICD-9 Diagnosis	V33.01	Twin birth, unspecified whether mate liveborn or stillborn, delivered by cesarean section
ICD-9 Diagnosis	V34.01	Other multiple birth (three or more), mates all liveborn, delivered by cesarean section
ICD-9 Diagnosis	V35.01	Other multiple birth (three or more), mates all stillborn, delivered by cesarean section
ICD-9 Diagnosis	V37.01	Other multiple birth (three or more), unspecified whether mates liveborn or stillborn, delivered by cesarean section
ICD-9 Diagnosis	V39.01	Liveborn, unspecified whether single, twin or multiple, delivered by cesarean section
ICD-10 Diagnosis	O82	Encounter for cesarean delivery without indication
ICD-10 Diagnosis	O7582	Spontaneous labor between 37-39 weeks of gestation w delivery by (planned) C-section
ICD-10 Diagnosis	Z38.01	Single liveborn infant, delivered by cesarean
ICD-10 Diagnosis	Z38.31	Twin liveborn infant, delivered by cesarean
ICD-10 Diagnosis	Z38.62	Triplet liveborn infant, delivered by cesarean
ICD-10 Diagnosis	Z38.64	Quadruplet liveborn infant, delivered by cesarean

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Code Type	Code	Description
ICD-10 Diagnosis	Z38.66	Quintuplet liveborn infant, delivered by cesarean
ICD-10 Diagnosis	Z38.69	Other multiple liveborn infant, delivered by cesarean

* We find approximately 8,000 claims with code 10D00Z (non-existent billing code). These are assumed to be a C-section as well.

A note on DRG codes: Medical Severity Diagnosis Related Groups (MS-DRGs) are three digit codes that refer to the principal diagnosis or procedure, typically specifying whether there were comorbidities and complications (CCs) or major comorbidities and complications (MCCs). All Patient Refined Diagnosis Related Groups (APR-DRGs) are an alternative way to classify patients by primary diagnosis and the severity. Before Oct 1, 2007 the MS-DRG code associated with delivery were 370-375, with 370 and 375 referring to C-section with and without complications, respectively [HCUP Statistical Briefs, Table 4](#). After Oct 1, 2007 DRG codes 765 and 766 were used for C-section with and without complications, respectively. In fiscal year 2018-2019, MS-DRG 765 and 766 were deleted and subdivided by severity of complications (MCC vs CC) and with/ without sterilization. Codes 783, 784, 786, 787 now refer to C-sections with complications, while 785 and 788 refer to C-sections without complications [CMS Clinical Episode Construction Specifications Appendix A](#). Note that MAX OT does not contain DRG information.

B.4 Scheduled C-section

We consider a C-section to be scheduled if the billing claim(s) associated with delivery have no evidence of trial of labor. We drop all C-sections without evidence of trial of labor from our main analysis. We also drop any claim with a diagnosis of “onset of labor with delivery by (planned) cesarean section” (ICD-10: O75.82, ICD-9: 649.81, 649.82) or with a diagnosis of placenta previa on the delivery claim. [Table A11](#) shows all diagnoses included in our trial

of labor definition. This definition builds on the algorithm from [Gregory et al., 2002](#).

Table A11: Diagnoses used to define C-section occurring after trial of labor

Description	ICD-9 Diagnosis	ICD-10 Diagnosis
Obstructed labor	660.x	O64.x, O65.x, O66.x
Abnormalities of forces of labor	661.x	O62.x
Long labor	662.x	O63.x
Prolapse of umbilical cord	663.0x	O69.0x
Breech converted to cephalic	652.1x	
Disproportion in pregnancy, labor and delivery	653.x	O33.xx
Fetal distress	656.3x, 659.7x	O76, O77.x
Maternal distress	669.0x	O75.0
Delayed delivery after AROM	658.31	O75.5
Maternal exhaustion complicating labor		O75.81
Failed induction of labor	659.0x	O61.x
Use of forceps or vacuum extractor	669.5x	<i>included in O66</i>

Notes:([Gregory et al., 2002](#)) use the following diagnoses to indicate attempting vaginal birth: fetal distress, labor abnormalities (including disproportion, obstructed labor, abnormal forces of labor), cord prolapse, and breech converted to vertex. We add maternal distress or exhaustion during labor and delivery, delayed delivery after AROM, failed induction, and use of forceps or vacuum extraction. These are all conditions that indicate labor had been attempted prior to the C-section.

B.5 Induction of Labor

We follow [Main, 2016](#) advice for coding labor inductions, which gives guidelines on appropriate ICD-10-PCS billing codes for three categories of induction.

1. Oxytocin/Pitocin when used for labor induction should be coded as 3E033VJ. This code should not be used for oxytocin use in labor augmentation or for the prevention of hemorrhage.
2. Cervical ripening using cervical inserts should be coded as 3E0P7GC.
3. Cervical Dilators using mechanical methods (e.g. balloon) should be coded as 0U7C7ZZ (Dilation of Cervix, Via Natural or Artificial Opening) or 0U7C7DZ (Dilation of Cervix with Intraluminal Device, Via Natural or Artificial Opening).

A note that Artificial Rupture of Membranes (AROM) billing code 10907ZC makes no distinction between labor induction and labor augmentation. Given that AROM is mainly

used for augmentation we do not include this in our definition of induction, but use this as a proxy for augmentation of labor.

B.6 Nulliparous

We consider a patient to be nulliparous if any of the billing codes in [Table A12](#) are used during delivery or in any prenatal care claims.⁴⁵

Table A12: Nulliparous Definition

Description	Codes
Encounter for supervision of normal first pregnancy. Supervision of elderly (young) primigravida.	ICD-9 V22.0, ICD-10 Z34.00 - Z34.03 ICD-9 V23.81, V23.83, ICD-10 O0951.x, O09.6x

In cases where we identify a birth as a first pregnancy based on diagnosis codes, but observe a prior birth within our Medicaid claims data (2011-2019), this birth is not considered nulliparous. Note that our definition of nulliparous will be an underestimate, since we rely on providers' billing for supervision of a first pregnancy. See [Table A14](#) for comparison to NVSS rates.

B.7 Preterm

We define preterm birth to be gestation < 37 weeks (following the standard definition used in many settings, including NVSS). These are identified by birth claims with any of the following diagnosis codes:

- ICD-10 Z3A.X for pregnancy at X weeks of gestation where $X < 37$.
- ICD-10 codes starting with O60.1, refer to preterm labor with preterm delivery
- ICD-9 644.20, 644.21 - early onset of delivery.

⁴⁵Prenatal care claims in our setting are OT claims related to pregnancy within nine months prior to the patient's delivery.

B.8 Mother-Baby Linking

We link mothers to newborns using the multi-round deterministic algorithm in [Orr et al., 2024](#). Rounds 1–3 use unique matches that include the plan “Case ID” (with delivery/birth dates and facility constraints); later rounds (4–6) relax criteria by dropping Case ID to recover pairs with missing or inconsistent Case IDs. We retain a unique best link per delivery using the algorithm’s priority order. [Table A13](#) shows the match rate of the full sample of births by state. Our analysis only includes states where $\geq 75\%$ of births are successfully linked to an infant Medicaid beneficiary.

Table A13: Match rates by state for mother–baby linkage

State	Share of births matched (%)	
	Rounds 1–3	Rounds 1–6
AK	78.343	92.858
AL	55.119	69.426
AR	13.796	67.809
AZ	74.898	79.679
CA	35.876	38.620
CO	48.961	58.242
CT	0.131	57.503
DC	46.334	61.322
DE	85.624	96.006
FL	49.362	83.401
GA	63.219	80.468
HI	85.953	89.553
IA	81.266	94.461
ID	85.894	92.427
IL	78.327	87.154
IN	85.117	95.103

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State	Share of births matched (%)	
	Rounds 1–3	Rounds 1–6
KS	87.062	94.550
KY	76.899	92.895
LA	87.157	96.132
MA	52.089	80.411
MD	72.023	88.455
ME	82.821	93.807
MI	84.014	92.849
MN	39.926	54.343
MO	0.592	9.947
MS	93.356	97.441
MT	81.789	94.280
NC	0.618	60.528
ND	77.226	83.399
NE	61.450	77.188
NH	86.510	94.177
NJ	1.229	17.969
NM	90.012	96.344
NV	80.293	90.720
NY	84.778	93.869
OH	88.283	96.397
OK	81.888	94.298
OR	56.249	68.220
PA	88.725	95.678
RI	35.043	40.649
SC	0.882	45.838

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State	Share of births matched (%)	
	Rounds 1–3	Rounds 1–6
SD	79.326	92.189
TN	28.351	39.943
TX	0.208	48.230
UT	91.861	94.246
VA	71.663	90.151
VT	70.399	84.113
WA	0.339	14.776
WI	83.837	94.046
WV	62.251	73.657
WY	81.520	93.423

Notes: Column “matched rounds 1–3” reports links obtained from the strict Case-ID passes of [Orr et al., 2024](#). Column “matched rounds 1–6” reports the cumulative match rate after all passes, including those that do not use Case ID.

C. Benchmarking Health Outcomes Against National Vital Statistics Data

While claims data provides granularity and linkage to patients and physicians, many important pregnancy characteristics (e.g., gestation length, parity) are not directly coded. Instead, we rely on diagnosis and procedure codes to infer most health risk and outcome variables. In this section, we benchmark our sample against birth certificate records from the National Vital Statistics System (NVSS). After delivery, all mothers complete a survey with questions on demographics, lifestyle, and experience during pregnancy and childbirth. For each birth, the facility (typically a hospital) also completes a survey on maternal health during both prenatal care and delivery. In this data, insurance type is recorded, which allows us to compare our sample to the universe of all births in the US, and to all births funded by Medicaid as recorded in NVSS.

[Table A14](#) shows sample characteristics and differences for NVSS and Medicaid claims. Both samples are subject to different types of measurement error, but reassuringly, the differences between them on most variables are relatively minor. The number of deliveries also differs slightly. However, Medicaid insurance is under-reported in the NVSS data, because it is a self-reported question, and some beneficiaries incorrectly report insurance status or type.

More notable differences include a two percentage point gap in the C-section rate, suggesting we are slightly under-coding C-sections. We also have 10 percentage point lower induction rate in our sample, likely explained by our reliance on billing codes for induction using pharmacological means, rather than less invasive forms that may not be coded for billing. It is unsurprising that our nulliparous variable is also under-coded, given that we rely on diagnosis codes related to the supervision of a first pregnancy, recorded either during prenatal visits or delivery, to identify first-time mothers. This is a general billing code, and may not be used if a more specific procedure or diagnosis is the focus of the claim. Similarly, our definition of preterm birth relies on billing codes associated with delivery before 37 weeks of gestation (preterm). Since not all deliveries include information on gestational age, we

Table A14: Delivery characteristics of Medicaid births, birth certificate data (NVSS) vs. Medicaid claims data (TAF)

	Birth certificates (NVSS)	Medicaid claims (TAF)	Difference (TAF) - NVSS)
Age under 18	0.02 (0.15)	0.02 (0.13)	-0.01*** (0.00)
Advanced maternal age	0.12 (0.32)	0.12 (0.33)	0.01*** (0.00)
White	0.32 (0.47)	0.37 (0.48)	0.04*** (0.00)
Black	0.12 (0.32)	0.22 (0.41)	0.10*** (0.00)
Hispanic	0.27 (0.45)	0.27 (0.44)	-0.01*** (0.00)
Diabetes	0.07 (0.26)	0.07 (0.26)	-0.00*** (0.00)
Eclampsia	0.00 (0.05)	0.00 (0.03)	-0.00*** (0.00)
Induction	0.26 (0.44)	0.16 (0.37)	-0.10*** (0.00)
Cesarean	0.32 (0.46)	0.29 (0.46)	-0.02*** (0.00)
Nulliparous	0.33 (0.47)	0.20 (0.40)	-0.13*** (0.00)
Singleton	0.97 (0.17)	0.94 (0.24)	-0.03*** (0.00)
Term	0.86 (0.34)	0.95 (0.22)	0.09*** (0.00)
Vertex	0.97 (0.18)	0.97 (0.17)	0.00*** (0.00)
Share C-sections w trial of labor	0.25 (0.43)	0.36 (0.48)	0.11*** (0.00)
N	6,483,679	6,838,837	13,322,516

Notes: Table presents mean, standard deviation, and differences in means for all deliveries covered by Medicaid and recorded in the NVSS 2016-2019, versus deliveries recorded in Medicaid TAF claims 2016-2019. * indicates $p < 0.05$, ** for $p < 0.01$, and *** for $p < .001$. We use 2015 in our analysis, but eliminate it from this comparison, because we rely on only T-MSIS (TAF) claims. Since 2015 was a transition year from MAX to TAF, our 2015 sample is incomplete for some states.

underestimate the rate of preterm birth and overestimate term births. Our estimated rate of trial of labor goes in the opposite direction: we identify an 11 percentage point higher rate of C-sections occurring after trial of labor. Under-reporting of trial of labor is a known issue with the NVSS birth records data, as noted by [Card et al., 2023](#).

Table A15: Number of Medicaid births in birth certificate data vs. claims data

State	Birth certificate (NVSS) counts			Medicaid (TAF) counts			Percent difference		
	Total	Cesarean	Vaginal	Total	Cesarean	Vaginal	Total	Cesarean	Vaginal
Total	6481520	2046128	4433335	6794594	1998217	4796377	4.61	-2.40	7.57
AK	16102	3277	12825	16763	3128	13635	3.94	-4.76	5.94
AL	116539	39128	77411	113867	36914	76953	-2.35	-6.00	-0.60
AR	65697	22013	43684	50747	16333	34414	-29.46	-34.78	-26.94
AZ	167227	43938	123289	171208	43377	127831	2.33	-1.29	3.55
CA	783734	246010	537724	671242	184137	487105	-16.76	-33.60	-10.39
CO	99045	24324	74721	107621	24928	82693	7.97	2.42	9.64
CT	52334	17841	34436	61203	20490	40713	14.49	12.93	15.42
DC	16060	4974	11086	15522	4786	10736	-3.47	-3.93	-3.26
DE	19064	5957	13107	20419	6059	14360	6.64	1.68	8.73
FL	427121	153415	273528	439473	152932	286541	2.81	-0.32	4.54
GA	237313	79571	157450	276457	90128	186329	14.16	11.71	15.50
HI	21544	5460	16084	25089	5861	19228	14.13	6.84	16.35
IA	59462	18316	41146	69282	20144	49138	14.17	9.07	16.26
ID	31533	7693	23840	36549	8456	28093	13.72	9.02	15.14
IL	230635	67984	162572	261213	73366	187847	11.71	7.34	13.46
IN	131435	38854	92565	123775	31746	92029	-6.19	-22.39	-0.58
KS	45195	13742	31453	54087	15457	38630	16.44	11.10	18.58
KY	102929	35531	67286	113010	35874	77136	8.92	0.96	12.77
LA	150399	55400	94999	150885	54256	96629	0.32	-2.11	1.69

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State	NVSS Counts			TAF Counts			Percent Difference		
	Total	Cesarean	Vaginal	Total	Cesarean	Vaginal	Total	Cesarean	Vaginal
MA	79186	24937	54249	111761	33919	77842	29.15	26.48	30.31
MD	113158	37097	75983	128747	26376	102371	12.11	-40.65	25.78
ME	19040	5799	13241	17181	4543	12638	-10.82	-27.65	-4.77
MI	183718	58266	125398	188955	54134	134821	2.77	-7.63	6.99
MN	87046	23114	63932	94359	23079	71280	7.75	-0.15	10.31
MO	112774	33406	79208	121202	32138	89064	6.95	-3.95	11.07
MS	91862	34816	57046	85046	29561	55485	-8.01	-17.78	-2.81
MT	19118	5413	13685	20376	5448	14928	6.17	0.64	8.33
NC	202165	58684	143421	250485	68850	181635	19.29	14.77	21.04
ND	10351	2993	7358	10950	2989	7961	5.47	-0.13	7.57
NE	34331	10157	24174	36471	7976	28495	5.87	-27.34	15.16
NH	11865	3540	8325	10003	2707	7296	-18.61	-30.77	-14.10
NJ	123940	41273	82507	103264	27589	75675	-20.02	-49.60	-9.03
NM	51768	12458	39310	60249	12264	47985	14.08	-1.58	18.08
NV	64077	21523	42554	70478	23179	47299	9.08	7.14	10.03
NY	436055	137830	298120	411815	127079	284736	-5.89	-8.46	-4.70
OH	223706	69549	154107	259478	76380	183098	13.79	8.94	15.83
OK	104046	33330	70716	112692	34579	78113	7.67	3.61	9.47
OR	76388	21215	55173	79043	19966	59077	3.36	-6.26	6.61
PA	180800	54497	126303	227737	65537	162200	20.61	16.85	22.13
RI	20628	6205	14423	16288	4352	11936	-26.65	-42.58	-20.84
SC	112027	37033	74968	122285	37875	84410	8.39	2.22	11.19
SD	14469	3756	10713	16522	3948	12574	12.43	4.86	14.80
TN	156187	49575	106612	125720	31573	94147	-24.23	-57.02	-13.24
TX	730091	247858	481824	838081	281451	556630	12.89	11.94	13.44

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State	NVSS Counts			TAF Counts			Percent Difference		
	Total	Cesarean	Vaginal	Total	Cesarean	Vaginal	Total	Cesarean	Vaginal
UT	46333	11205	35128	52809	11662	41147	12.26	3.92	14.63
VA	121090	39405	81656	142180	44063	98117	14.83	10.57	16.78
VT	9343	2416	6927	9684	2409	7275	3.52	-0.29	4.78
WA	135198	36124	98943	149739	37192	112547	9.71	2.87	12.09
WI	92904	24397	68466	92279	22192	70087	-0.68	-9.94	2.31
WV	35869	12475	23394	40178	12200	27978	10.72	-2.25	16.38
WY	8619	2354	6265	10125	2635	7490	14.87	10.66	16.36

Note: Comparison of births reported as covered by Medicaid in CDC National Vital Statistics (NVSS) and births identified in Medicaid TAF data, 2016–2019. NVSS counts should not be considered “ground truth,” as there are known issues of under-reporting Medicaid insurance coverage in birth records data.