Call the (Certified Nurse) Midwife: the Effect of Scope-of-Practice Laws on Hospital Costs and Patient Choice

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Abstract

The high cost of healthcare is a major driver of high medical spending in the United States. Reforming healthcare labor markets is an understudied and increasingly common cost-based intervention. To shed light on the effects of such reforms I use plausibly exogenous variation in the strictness of Scope-of-Practice laws for Certified Nurse Midwives (CNMs). Half of all states have relaxed their SOP laws to allow CNMs to practice and prescribe independently of a physician. I estimate the effect of granting CNMs full independence on hospital facility costs using administrative data from the Centers for Medicare and Medicaid Services (CMS) and inpatient discharge records from the Healthcare Cost and Utilization Project (HCUP). Using a two-way fixed-effects model I find that allowing CNMs to practice independently substantially reduces hospital facility costs per birth and the use of intensive procedures, such as cesarean sections. Procedures associated with negative maternal health outcomes also fall, suggesting that patient health improves overall. Cost reductions are concentrated in hospitals that are well-positioned to integrate CNMs into their practice. Using a structural choice model, I decompose the overall effect of the policy into savings generated from increased hospital efficiency and savings due to changing selection of patients into hospitals. I find that the savings are primarily driven by increased hospital efficiency for low-risk patients and higher-risk patients select into higher-cost hospitals after the law change. These effects are attenuated by market concentration and a high density of OBGYNs.

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1 Introduction

In many western European countries, midwives deliver the majority of babies (Emons and Luiten, 2001), while physicians attend only high-risk births. The U.S. takes a more intensive and physician-centric approach to infant and maternal healthcare. The most common non-physician providers, Certified Nurse Midwives (CNMs), attended fewer than 10 percent of all U.S. births in 2018. This difference is driven at least in part by Scope-of-Practice (SOP) laws for CNMs. In some U.S. states, the SOP laws require births to be supervised or attended by a physician. For instance, in Missouri all births must be supervised by a physician, whereas in Nevada mothers can choose to use only a CNM. This more intensive approach contributes to substantially higher spending per birth in the U.S. compared with peer countries, and it is unlikely that this high-cost approach improves outcomes.[1] Despite high expenditures, the U.S. has one of the highest cesarean-section (C-section) and infant and maternal mortality rates among comparable countries (Papanicolas, Woskie and Jha, 2018).

This paper estimates the effects of allowing CNMs to practice independently in the U.S. I consider the effect of CNM independence on the costs of delivering babies; the frequency of procedures such as C-sections; and the match between hospitals and patients based on patient risk, hospital specialization, and market characteristics. Even if CNM independence reduces costs, its effect on patients would be theoretically ambiguous. On the one hand, hospitals may pass along some of these cost savings in the form of charge reductions or quality improvements. On the other hand, patients in underserved areas may end up with less access to physician-led or intensive deliveries. To understand how relaxing constraints on CNMs can affect outcomes more broadly, I pair a staggered difference-in-difference analysis of the effect of changing SOP laws with a semi-parametric patient choice model and a novel decomposition technique.

My difference-in-difference study design is based on changes in SOP laws across states over time. The timing of these legal changes is plausibly exogenous, as they are not related to trends in cost or health outcomes and are likely due to idiosyncratic political factors (McMichael, 2017). I first use these changes to understand whether CNM independence makes giving birth less costly on average. I then decompose aggregate cost changes from CNM independence into components that include changes in the costs of giving birth at a given hospital, the impact on costs from patients choosing different hospitals based on their location and risk status, and hospital entry and exit. Finally, I investigate whether CNM independence results in a change in the frequency of medically intensive and other delivery procedures and in the specialization of procedures across hospitals, and whether there is more specialization in areas with substantial hospital competition. To evaluate these effects, I estimate two-way fixed effects and event study reduced-form specifications as well as a patient choice model. To avoid possible bias associated with the staggered nature of the

[1] Although C-sections and other invasive interventions are lifesaving in high-risk cases, they are associated with greater risk of maternal and infant complications and mortality (ACOG and SMFM, 2014). Baicker, Buckles and Chandra (2006) find that geographic variation in C-section use is greatly influenced by non-medical factors and is not associated with improved maternal or infant mortality.

treatment, I estimate the event study model using only non-treated states and separately by event cohort. I also use a new semi-parametric choice model to account for high-dimensional patient heterogeneity in preferences and costs.

I use administrative data on all hospital discharges in 13 different states from 2004–2014. This dataset, collected by the Healthcare Cost and Utilization Project (HCUP), provides detailed information on patient demographics, diagnoses, procedures, and charges for the universe of discharges in each state and year. It does not include information on the provider each patient sees. To calculate a measure of the cost per birth, I use hospital financial information from the Centers for Medicare and Medicaid Services (CMS) Hospital Cost Report Information System (HCRIS). These reports include hospital facility costs and charges for maternal and infant care. These costs and charges are for the use of hospital capital (e.g., operating room time, fMRI machine use) and labor (e.g., registered nurses but not CNMs or physicians). Covered by Medicare Part A, hospital facility costs account for a large portion of overall spending. In 2017, hospital facility costs accounted for 42 percent of total Medicare spending, or $293 billion (Cubanski and Neuman, 2018), and they have grown substantially faster than provider prices since 2014 (Cooper et al., 2019).

I leverage quasi-random variation in the strictness of SOP laws for CNMs across states and time to estimate the effect of the laws on hospital facility costs. Between 2004 and 2014, five states in my sample switched to allowing CNMs to practice and write prescriptions without the supervision of a physician, which I refer to as "CNM independence." In a difference-in- differences framework, I identify the causal effects of this policy change by comparing the change in outcomes for the hospitals in the treated states with the change in outcomes for hospitals in a group of control states. Following the recent literature on difference-in- differences with staggered event times (see e.g., Goodman-Bacon (2018); de Chaisemartin and D'Haultfœuille (2020)), I limit this control group to states that did not change their policy during the sample period (i.e., states that have not granted CNMs independence before 2014 or that granted it to CNMs before 1996).

I estimate a non-parametric structural choice model based on Raval, Rosenbaum and Tenn (2017) to explore the importance of changes in patient utility and choice of hospital. This model uses the detailed discharge data to flexibly allow for patient heterogeneity across many dimensions. Flexibly modeling patient heterogeneity is particularly important for two reasons. First, it is likely that the effect of being treated by a physician or CNM depends on patient characteristics (Chandra and Skinner, 2012; Daysal, Trandafir and van Ewijk, 2019). Second, patient utility and preferences depend on a wide range of hospital and patient characteristics as well as the interactions among these variables. For example, patients may generally prefer a hospital that is close to them. However, a preference for distance may interact with severity; higher risk patients may choose farther away but higher-quality hospitals. The choice model can take into account a large number of such interactions without restricting them to a particular functional form.

I then use the estimated choice probabilities before and after each law change to decompose the causal change in hospital facility costs into different mechanisms. To do so, I start with the decomposition used in Chandra et al. (2016), which splits cost savings over time into savings due to (a) within-hospital changes (e.g., through reducing intensive procedure use), (b) between-hospital changes (e.g., through patients choosing lower cost hospitals), (c) a cross term, and (d) net entry into the market.

I decompose the causal effect of the law by applying the decomposition to cost changes from the pre period to the post period separately for a treatment and control group. Then I subtract each component in the control group from the component in the treatment group. The contribution of each component to the causal change in costs is then the change in that component in the treatment group relative to the change in that component in the control group. This procedure identifies the causal contribution if the control group is a valid counterfactual for the treatment group.

I find that when states allow CNMs to practice independently, hospital facility cost per birth decreases substantially. These cost declines are concentrated in hospitals that are well-positioned to adapt to the law change. Hospitals without a large neonatal intensive care unit (NICU) and/or fewer births per obstetric bed experience much larger cost declines than other hospitals. I provide evidence that these cost declines are the result of a reduction in the intensity of care. Conditional on case-mix and hospital fixed effects, I find that CNM independence leads to a reduction in intensive procedures, like C-sections, and an increase in less intensive procedures that are associated with vaginal birth.

The effect of CNM independence on C-section use varies based on the risk-level of the mother and the relative prevalence of OBGYNs in a market. CNM independence does not significantly change the C-section rate for low-risk mothers. However, the C-section rate increases for high-risk mothers in underserved areas, and decreases the C-section rate for high-risk mothers in areas with many OBGYNs. At the same time, the rate of procedures associated with severe maternal complications does not change for the high-risk mothers in non-underserved areas and declines for all other groups. This result suggests that allowing CNMs to practice independently may better align intensive treatment with risk level.

I then decompose the overall cost declines into different mechanisms. Consistent with an efficiency story, within-hospital cost changes drive most of the reduction in costs. These could be due to better matching within-hospital to providers or a reduction in practice style across the board. However, these cost declines are mitigated by cost increases from patients moving to higher-cost hospitals. This result suggests that patients who need or prefer more intensive care are switching to those hospitals. Finally, the cross term indicates that costs are increasing at hospitals that gain market share. These results are consistent with patients switching to more intensive hospitals that provide more intensive care. This pattern is especially strong for high-risk cases, who would be most affected by a hospital specializing in low-intensive care.

Additionally, markets with fewer hospital choices have substantially less sorting. In competitive markets, both the within-hospital cost reductions and the cost increases due to moving to higher-cost hospitals and the cross term are larger than in concentrated ones. This result suggests that a lack of competition dampens the ability or incentive for hospitals to specialize in high- or low-intensive practice styles. Although they produce similar net cost savings, it is possible that the lack of specialization reduces the scope for quality improvements.

Consistent with work on nurse practitioners, relaxing SOP laws has a larger effect in places that are relatively underserved (Alexander and Schnell, 2019). Total cost declines are more than twice as large for patients living in counties with fewer OBGYNs per capita. They experience greater within-hospital gains and larger increases in cost, suggesting that the lack of OBGYNs leads to more specialization in the market. This effect may be due to taking on more low-risk cases, which allows OBGYNs to focus on higher risk patients. There are also large cost savings across risk levels due to net entry into these markets. This entry is likely due to hospitals opening new obstetrics departments.

This paper builds on the literature that studies occupational licensing laws by examining their effect on costs and patient utility. Occupational licensing requirements are common in the United States, where they govern about one third of all employees (Kleiner and Krueger, 2013). There is robust empirical evidence that occupational licensing, including SOP laws, increases prices or lowers supply (Kleiner and Kudrle, 2000; Schaumans and Verboven, 2008; Hotz and Xiao, 2011; Kleiner et al., 2016)(Kleiner and Kudrle, 2000; Schaumans and Verboven, 2008; Hotz and Xiao, 2011; Kleiner et al., 2016). Licensing requirements also impact the labor market of covered occupations, generally raising the wages and hours of the covered occupations (Stange, 2014; Kleiner, 2015; Gittleman and Kleiner, 2016; Gittleman, Klee and Kleiner, 2018). Within healthcare, the quality effects are mixed. Anderson et al. (2016) find that early licensing laws for midwives improved infant mortality. Studies of CNMs find that they have similar outcomes as physicians Newhouse et al. (2011) and that stricter SOP laws do not raise quality (Markowitz et al., 2017). Moreover, Traczynski and Udalova (2018) and Alexander and Schnell (2019) both found that relaxing SOP laws for nurse practitioners improves health outcomes, especially in areas with few physicians.

This paper also contributes to the literature on patient choice and productivity in healthcare by exploring how they are influenced by the provider choice set. Healthcare treatment, as measured by healthcare spending or the rates of invasive procedures (like C-sections), varies substantially across states even after accounting for differences in patient characteristics (Baicker, Buckles and Chandra, 2006; Skinner, 2011). This variation can be due to providers over or underproviding intensive procedures or to productivity differences across hospitals and providers (Chandra and Staiger, 2019). A primary focus of the literature has been on the determinants of physician decision-making, such as financial incentives (e.g., Gruber et al, 1999 and Johnson and Rehavi (2016)) and liability considerations (e.g., Currie and Macleod (2008)). The productivity literature has emphasized selection into hospitals and spillovers from other physicians (e.g., Chandra and Staiger (2007)). Differences across hospitals can lead to mismatches between patient type and provider practice style. I expand on this literature by finding that adding a different class of provider to the choice set can reduce costs and improve outcomes by better aligning the provision of intensive treatment with patient risk level.

This work adds to the literature on the effects of competition in the hospital market by examining how it moderates the effects of SOP laws. Hospital markets have consolidated rapidly, with 100 mergers per year between 2010 and 2014 (Schmitt, 2017). This consolidation likely raised prices without reducing costs (Dafny, 2009; Gowrisankaran, Nevo and Town, 2015; Schmitt, 2017). An overlooked consequence of this consolidation is the lack of incentives for hospital specialization. Specializing in treating patient types can lead to improvements in outcomes, but only if there are enough hospitals in the market. Moreover, I show that one way to encourage entry is to legalize alternative care models, such as CNM-led births.

This work also ties into the existing literature on the effect of practice style on infant and maternal health. To avoid selection issues, these papers often focus on discontinuities in the intensity of care generated by cutoff rules. For example, Almond et al. (2010) estimates the impact of increased care for newborns who weigh just below 1500 grams—the Very Low Birthweight (VLBW) cutoff. They find that VLBW newborns receive $4,000 more medical care than those just above the cutoff and a reduction in one-year mortality. Daysal, Trandafir and van Ewijk (2019) estimate the effect of midwife care on low-risk mothers and infants by examining births that occur just before or after 37 weeks of gestation in the Netherlands. Similarly, Freedman (2016) documents that short-term variation in the availability of NICU beds increases the probability of NICU admission for moderate birthweight infants. This work complements these papers by exploring the effects of a policy that influences births across the risk spectrum and market wide. It also examines changes in selection as a potential mechanism.

In section 2, I provide more information on CNMs and SOP laws, including a description of the change in SOP laws over time. Section 2 also develops a model of how SOP laws influence patient and hospital decision-making. Section 3 describes the data used in the paper. Section 4 describes the empirical methods used to estimate the effects of SOP laws on costs and procedures. It includes a description of the difference-in-difference research design and event study model. It also provides details on the patient choice model and decomposition of the effect of the policy change. Section 5 describes the results of the study, and section 6 concludes the study.

2 Background

Occupational licensing laws regulate which jobs an individual can perform. They generally specify a certain level of competence to practice in a given profession. By restricting entry into the field, occupational licensing laws hope to increase quality and reduce risks. At the same time, they restrict the available supply of professionals in a given occupation, raising wages and the costs associated with their services (see Kleiner (2015) for review). Recent work by Anderson et al. (2016) finds that licensing requirements for midwives lowered maternal and infant mortality.

Medical licensing laws are set at the state level and have two main components. The first component is that they specify minimum requirements to legally practice in a given occupation. The second component, Scope-of-Practice (SOP) laws, regulate the services each occupation is allowed to perform within their license. I focus on SOP laws that set the level of autonomy that Advanced Practice Registered nurses (APRNs) have to practice and prescribe. Relaxing SOP laws to give CNMs full practice autonomy means that they can practice without the supervision of a physician (though they often work in collaboration), although they remain unable to do so outside of their specialty.

There are four major types of APRNs, each with a different specialty.

- Nurse Practitioners (NPs) mostly perform primary and urgent care services.
- Certified Registered Nurse Anesthetists (CRNAs) administer anesthetics.
- Clinical Nurse Specialists (CNSs) specialize in service areas such as gerontology, psychiatry, and oncology.
- Certified Nurse Midwives (CNMs) perform obstetric services.

2.1 CNM SOP laws

Prior work on SOP laws has mostly focused on expanding the SOP for NPs. Kleiner et al. (2016) finds that less restrictive SOP laws for NPs increases NP wages and hours while reducing wages and hours for MDs and lowering prices for well-child visits. Increased prescribing authority and practice authority also leads to increased utilization of primary care (Stange, 2014; Traczynski and Udalova, 2018). Allowing NPs to prescribe independently further improves measures of population mental health and decreases mental-health-related mortal- ity in underserved areas (Alexander and Schnell, 2019). Recent work by Markowitz and Adams (2020) finds that less restrictive SOP laws also increase hours worked and self-employment for APRNs.

Recent work on CNMs finds no differences between CNMs and MDs in the quality of care that they provide for low-risk births. Newhouse et al. (2011) review the medical literature on CNM performance and find that they perform similarly to physicians on several measures. Additionally, Newhouse et al. (2011) find that CNMs utilize fewer resource-intensive services like cesarean sections, epidurals, and neonatal intensive care units (NICUs). Similarly, Markowitz et al. (2017) find that relaxing SOP laws for CNMs does not significantly affect quality of care but does reduce the use of more intensive procedures. Finally, Miller (2006) finds that when insurers are forced to reimburse CNMs at the same rates as physicians, infant mortality declines.

I use data on SOP laws in all states compiled by Markowitz et al. (2017). They track SOP law restrictiveness along two dimensions: practice authority and prescription authority. I use the most restrictive of the two authorities as my preferred measure of the SOP law in a given state. Markowitz et al. (2017) classifies the laws into four broad categories based on the level of barriers to independent practice. For simplicity, I collapse these categories into barriers and no barriers, but the results are qualitatively similar when I use the full set of categories. I consider a state to have granted CNM independence when CNMs have no barriers for both practice and prescription authority.

At the beginning of the sample period, 2004, 37 states had restrictive SOP laws. Over the next ten years, ten states relaxed their laws to allow CNMs to practice with full prescribing and practice authority. Figure 1 displays the variation in SOP laws across states and time. States that are orange did not grant full independence to CNMs before 2014. States that are purple granted full independence to CNMs before 2004. Magenta states granted independence during the sample period. Only states that are completely opaque are in my sample.

Table 1 displays the treatment status of the states in my sample. Five states—Colorado, Massachusetts, Maryland, Rhode Island, and Nevada—granted CNMs independence during the sample period: 2004–2014. Three states—Arizona, New York, and Washington—allowed CNMs to practice independently before 2004. And five states—California, Florida, Kentucky, North Carolina, and New Jersey—did not grant CNMs independence before 2014.

2.2 CNMs and Hospital Costs

To fix ideas, I present a stylized model of hospital costs. Patient i with characteristics z_i chooses between hospitals $j = 1, \ldots, J$ to maximize their utility:

$$U_{ij} = f(\delta_j, x_j, z_i) \tag{1}$$

where δ_j is a vector of fixed hospital characteristics (such as the presence of a NICU, location and average intensiveness), and x_j is the fraction of MD-attended births at the hospital.

Then the probability that patient i chooses hospital j is:

$$Pr_{ij} = E[U_{ij} > U_{ik}, \forall j \neq k \in J] \tag{2}$$

Hospital j chooses the fraction of doctor-attended births x_j. Before CNMs receive full practice autonomy, x_j is restricted to be 1 and can be adjusted after they are granted independent practice authority.[2]

The hospital charges consumer i a price $P_{ij}(x_j, z_i)$ and incurs costs $C_{ij}(x_j, z_i)$, both of which rely on the hospital's proportion of doctor-attended births and the patient's risk type.

Each hospital j then picks x_j to maximize its utility[3]:

[2]While hospitals do not directly assign CNMs or physicians to patients they can influence x_j in a variety of ways. They can always set it to 0 by denying CNMs admitting privileges to the hospital. They can also increase of decrease x_j by adopting policies that either attract CNMs or deter them. One way to think of x_j is that it is an index of the relative friendliness of the hospital to CNMs.

[3]Since a large portion of hospitals are non-profits it is important to allow hospitals to have a different objective than

$$\max_{x_j} \sum_{i=1}^{N} (P_{ij}(x_j, z_i) - C_{ij}(x_j, z_i))Pr_{ij} \tag{3}$$

This optimization problem yields the following first order condition:

$$\sum_{i=1}^{N} Pr_{ij}(\frac{\partial P_{ij}}{\partial x_j} - \frac{\partial C_{ij}}{\partial x_j}) + (P_{ij} - Cij)\frac{\partial Pr_{ij}}{\partial x_j} = 0 \tag{4}$$

The first term represents the change in profits the hospital achieves by changing their fraction of doctor-attended births, holding the probability that patient i chooses the hospital constant. Markowitz et al. (2017) outline the possible mechanisms for SOP laws to change clinical practice. Expanding the SOP laws for CNMs may lower overall costs by eliminating inefficiencies associated with supervision agreements. Additionally, they may allow CNMs to practice in a way that is less intensive. Finally, independent CNMs may generate spillovers that lead to cost reductions for patients seeing physicians. Increased CNM autonomy may allow busier physicians to spend more time on higher risk patients or may cause physicians to adopt a less intensive practice style (more similar to CNMs) for their lower-risk patients.

Whether lowering x_j reduces costs per birth depends on a hospital's cost function, C_{ij}. It is likely that $\frac{\partial C_{ij}}{\partial x_j}$ is small or positive for hospitals that have large amounts of physician-specific capital, such as a large NICU. Additionally, it may be small or positive for hospitals that are limited in their ability to add CNMs. These could be hospitals with relatively few spare beds or those with a large number of OBGYNs relative to their patient population. In these cases, a hospital may keep x_j at 1 or close to 1 even after the policy change.

The second term is the selection effect. As hospitals reduce their fraction of doctor-attended births, the probability that patients go to the hospital may also change. This change in selection may alter a hospital's cost per birth by changing its case-mix, even while holding patient i's cost constant. For example, higher-risk patients may prefer to go to a hospital with a NICU and fewer CNMs than a hospital that has a large CNM practice and no NICU. This could lower costs for both the CNM practice and the NICU hospital by allowing them to specialize.

Market concentration may reduce $\frac{\partial Pr_{ij}}{\partial x_j}$ by reducing the choice set of patients. In this case, the potential for cost reductions from better matching of patients to hospitals is reduced. With few competitors, hospitals are constrained in their ability to specialize in either high- or low-risk births, limiting the potential for within hospital efficiency gains as well.

The density of OBGYNs in a market may also moderate the effects of CNM independence. First, markets with a high density of OBGYNs may have relatively few practicing CNMs. Their relative

maximizing profits. For example, a non-profit hospital may want to serve as many people as possible (conditional on breaking even). In this framework, the hospital would have a cost function in which marginal cost is decreasing with the number of patients served.

scarcity may limit the immediate effects of CNM independence. Additionally, in a market with enough OBGYNs, mothers may have sufficient access to providers with an intensive practice style but a shortage of providers with a less intensive practice style. In this case, CNMs and hospitals may drive cost savings by offering a less intensive practice style. CNM independence, then, may result in a reduction in C-sections and other intensive procedures and lead to improvements in quality. In contrast, in underserved markets, there may be a shortage of intensive care for high-risk births. In these markets, CNMs and hospitals can specialize in low-risk births and free up time for OBGYNs to attend higher-risk cases. This specialization may increase C-sections for mothers who need them and improve quality.

3 Data

To estimate the effect of SOP laws on hospital costs and patient choice I use individual administrative data from the Healthcare Cost and Utilization Project (HCUP). I merge this with detailed data on hospital finances from the Healthcare Cost Report Information System (HCRIS) as well as hospital characteristics from the Centers for Medicare and Medicaid Services (CMS) impact files and the American Hospital Association (AHA) survey. Finally, I use market-level data from the Surveillance, Epidemiology, and End Results (SEER) and the Dartmouth Atlas. I describe each data source below.

I extract information on individual patients from 13 state inpatient databases (SIDs) distributed by HCUP, a subdivision of the Agency for Healthcare Research and Quality (AHRQ). This administrative dataset contains the universe of hospital discharges in each state. States have different availability across time, but the longest panel is from 2004–2014.[4] They contain detailed information on each patient, including current diagnoses, procedures, stay length, payor type, total charges, and birth weight. Since the data are de-identified and at the discharge-level I do not observe a patient's prior medical history, except through previous diagnoses. Additionally, mothers and infants have separate discharge records that cannot be linked in my sample of states.

The discharge data report gross charges for the discharge. Gross charges are the amount billed for a service, not the amount paid. Insurers typically negotiate large discounts so that actual prices are lower than the charges. I calculate a measure of facility costs by merging hospital financial information from HCRIS on to the discharge data.

Every Medicare-certified provider must submit detailed financial reports to HCRIS every year. These reports include information on facility characteristics, utilization, and hospital costs. Facilities must report facility costs and charges for their total population at the cost-center level but are not required to report provider costs (e.g., doctor or APRN salaries) at that level. Cost-centers are defined by CMS, and the facility must allocate each service to one of them. Following Salemi

[4]Sample years for Florida, Massachusetts, Maryland, New Jersey, New York, Rhode Island, and Washington covers 2004–2014; California: 2004–2011; Colorado: 2004–2012; Kentucky: 2005–2014; North Carolina: 2008–2014; Nevada: 2009–2014.

et al. (2013), I aggregate these cost-centers into 12 hospital departments. For example, the Nursery department includes the Nursery and Labor and Delivery rooms. Any cost-centers that cannot be allocated to a department are dropped.

HCRIS switched reporting forms in 2010, though some hospitals used the new forms in 2009 and some continued to use the old forms in 2011. A few hospitals used both forms, in which case I used the 2010 version. The form change altered the listed cost centers and I use a CMS provided crosswalk to map the new cost-centers to the old ones to consistently allocate cost-centers to departments. Additionally, the cost reports cover a hospital's financial year which may not align with the calendar year. I adjust HCRIS variables to the calendar year by assuming costs and charges are uniform across time.

The cost and charge data in HCRIS only pertain to hospital facility costs. For example, when a patient has an ultrasound, the HCRIS data include the cost to run the ultrasound machine, the salary of the ultrasound technician, and the salaries of the support staff (e.g., custodial staff, the front desk, and maintenance). It does not include provider costs, such as the salary of the CNM or the physician who orders and interprets the ultrasound. Consequently, I only observe cost savings associated with efficiency gains from independent practice as well as the savings from lower capital utilization by CNMs. I do not observe cost reductions associated with changes in the wages or salaries of primary providers.

Hospitals in HCUP do not report their CMS identifiers but do report identifiers from the American Hospital Association (AHA) survey, which contains CMS identifiers. I construct a crosswalk between HCUP, AHA, and CMS identifiers to merge the cost and charge data from HCRIS to HCUP. In some cases, multiple facilities in HCUP and the AHA survey share the same cost report. In those cases, I calculate the discharge-weighted average of the hospital-level variables in HCUP and AHA survey.

With the merged data in hand, I calculate a measure of facility costs for patient i using the information from HCRIS as:

$$\text{Patient Cost}_i = \text{Patient Gross Charges}_i \times \underbrace{\frac{\text{Annual LDR Costs}_h}{\text{Annual LDR Gross Charges}_h}}_{\text{Cost-to-Charge Ratio}}$$

where Patient Gross Charges is the amount charged to the patient reported in HCUP. Patient Gross Charges are then multiplied by the ratio of total reported facility costs to total reported charges in HCRIS. Unlike Net Charges, Annual Costs and Annual Gross Charges are both reported at the cost-center level. I only use costs and charges from the Labor and Delivery Room, Nursery, and Neonatal Intensive Care Unit (NICU) to estimate costs. By using the cost-center specific costs and charges, I reduce measurement error from differences between the hospital-wide CCR and that for maternity cost centers.

I use detailed information on patient diagnoses and procedures in the HCUP data to estimate patient risk. Using ICD-9 diagnosis codes, I identify patients that have significant maternal risk factors, including pre-pregnancy diabetes, gestational diabetes, hypertension, gestational hypertension, preeclampsia, eclampsia, and being older than 40 or younger than 20. I also identify patients with a “V code” that indicates the pregnancy is high-risk. This set of codes is particularly helpful because it includes indicators for a mother’s obstetric history, which I otherwise do not observe. I combine these factors into one risk index by counting the number of risk factors. 83 percent of mothers have a risk level of zero (no risk factors), 15 percent have a risk level of 1, and 1.8 percent have a risk level of 2 or more.

I complement this risk index by identifying each mother’s Robson Ten Groups Classification System (TGCS) group. The TGCS is a global standard for comparing C-section rates within and across hospitals. It classifies women into one of ten mutually exclusive categories based on six commonly available characteristics: parity, number of fetuses, previous C-section, labor onset, gestational age, and fetal presentation (see: WHO (2017) for more information on the categories). Since the records are de-identified, I do not typically observe parity, and there is not a consistent way to identify whether the provider induced labor. Consequently, I merge categories 1–4 into one category, and merge categories 6 and 7 into their own category since the distinctions between them rely on either parity or labor onset. Generally, the larger group numbers are expected to have higher C-section rates.

To measure maternal outcomes, I estimate changes in the rates of Severe Maternal Morbidity (SMM). SMM are unexpected labor and delivery outcomes identified by the Centers for Disease Control (CDC) as diagnoses or procedures that can have a significant, negative impact on women’s health (CDC, 2020). They are a good measure of the quality of care because they are direct health outcomes that occur during labor and delivery and can be identified in the discharge data via ICD-9 codes.

I obtain data on hospital characteristics from the AHA Annual Survey and CMS Impact files. The AHA survey provides information on each hospital’s provider mix and NICU resources. Additionally, it contains the hospital’s CMS ID, which allows me to link the HCRIS data to the HCUP data for hospitals that report an AHA survey ID to HCUP. The CMS impact files contain information on the hospital’s overall labor costs, case-mix, and for-profit status.

To measure each hospital’s market power, I allocate each hospital to an HRR from the Dartmouth Atlas of Healthcare based on their primary address. Created in the early 1990s, HRRs are collections of zip codes constructed so that the majority of Medicare referrals for patients living in the zip codes are at hospitals also in those zip codes. They are a natural definition of a local hospital market, as they represent areas in which residents are more likely to go to a hospital within the HRR rather than outside it. I then calculate measures of hospital-market concentration at the HRR-level using the HCUP discharge data.

I source county demographic characteristics from the National Cancer Institute's Surveillance, Epidemiology, and End Results (SEER) program. I use SEER's county-level population by year, age, and race to calculate the fraction of the county that is under 40 and the fraction of the county that is white. I extract data on the health workforce in each county from the Area Resource Files (ARF) published by the Health Resource Services Administration (HRSA). I use the number of OBGYNs per capita as a measure of the availability of physicians for maternal and infant care. I use data from 2001, the latest year available before the start of my sample, since CNM independence may influence the number of OBGYNs in a county. I classify counties as underserved if they are in the bottom two-thirds of the distribution of OBGYNs per capita. This cutoff occurs at 7 OBGYNs per 100,000 people.

I restrict the sample to non-government owned hospitals with a valid HCUP and AHA identifier, at least 25 births in a year, those with positive Nursery charges, and a positive and finite cost-to-charge ratio. This last restriction eliminates hospitals that do not have a dedicated obstetrics department. Several hospitals with different cost reports in HCRIS may share an AHA ID. In these cases, I aggregate the HCRIS variables to the AHAID-year level by taking the average of the HCRIS variables weighted by total births at the hospital. Discharges must have information on gross charges, age, and payor. I eliminate discharges that were either transferred to or from a hospital, since I do not observe their full gross charges or costs. I winsorize cost-to-charge ratios at the 1st and 99th percentile. Finally, I convert all nominal dollar measures into 2017 dollars using the CPI and use the end of the hospital's fiscal year to date its cost report. After the merging process and sample restrictions there are 13,968,819 individual discharges at 838 unique hospitals. The average cost per birth is $7,170 and the C-section rate is 30 percent.

4 Empirical Methodology

I estimate the total effect of CNM SOP laws on patient costs and outcomes by comparing changes in the outcomes for hospitals in treated states to changes in the outcomes for hospitals in control states. I use a two-way fixed effects (TWFE) estimator to estimate the average treatment effect on costs and procedure use. I then estimate the dynamic effects of the policy before and after the policy change using an event study model. This model provides insight into whether hospitals require time to adjust to the new policy and provides a useful check on the validity of the estimate from the TWFE. Finally, I estimate a structural patient choice model and decompose the average treatment effect to investigate mechanisms.

To explore the average effect of CNM independence on hospital costs per birth, I estimate the following TWFE model:

$$Y_{hst} = \beta \mathit{Indep}_{st} + X_{hst}\theta + \gamma_s + \delta_t + \varepsilon_{hst} \tag{5}$$

for each hospital h in state s during year t. Y_{ht} is the outcome of interest, typically $\log$ costs per patient or $\log$ discounted charges per patient. $Indep_{st}$ is an indicator for whether CNMs can practice independently—i.e., whether they have full practice and prescription authority. β captures the effect of allowing CNMs to practice independently. γ_h and ρ_t are hospital and year fixed effects and ϵ_{ht} is an idiosyncratic error term. X_{ht} is a vector of time-varying hospital characteristics, which includes an indicator for whether the hospital is for-profit, the total number of births at the hospital in the base year, the fraction of people in the county under 40, the fraction of the people in the county who are white, the log of the county's population, and the hospital's wage index assigned by CMS. I cluster all standard errors at the state and year level to account for correlations between observations.

4.1 Identification

A key assumption of my empirical strategy is that states that change their laws have similar trends in the outcome of interest as those that did not. This assumption is violated if states pass laws in response to increases in costs or shortages of providers. Prior work has found little evidence that the timing of SOP law changes is related to the quality of health care (Markowitz et al., 2017; Alexander and Schnell, 2019). One reason to expect that the legal changes are exogenous is the exact timing of passage may be controlled by unrelated political factors. Lobbying groups, such as the National Association of Certified Professional Midwives (NACPM), have pushed continuously for relaxing the SOP laws in each state throughout this period. Their success in any one year may be mostly a result of political processes like elections or negotiation rather than directly related to trends in the cost of healthcare (McMichael, 2017).

Following Alexander and Schnell (2019), I test explicitly for this possibility by estimating the degree to which control variables are predicted by law changes. These balancing regressions presented in Table 2 can detect differences in pre-trends (Pei, Pischke and Schwandt, 2018). I find no economically significant differences. Additionally, I test for differential pre-trends before the event by regressing hospital facility costs per birth at the state-year level on state and year fixed effects and the covariates listed above (Hollingsworth and Wing, 2020). I plot the residuals of these regressions for each state. Control states (both never treated and treated before the sample) are in gray and treatment states are in color. Vertical lines indicate the event time for each treatment cohort. The residuals for treatment and control states are similar until the event when both treatment cohorts decline.[5]

Additionally, the event study estimates of CNM independence's effects for years before the law is changed (event time < 0) are an effective test of the identification assumptions. If CNM independence has an effect before the law changes, then that would indicate that the estimated effect is at least partially driven by different trends between treatment and control states. These differential pre-trends would bias the estimates of the causal effect of the program. As shown in Figure 3, I

[5]One control state, Kentucky, experiences a sharp decline in 2007 but returns to the same trend as before in 2008.

find no significant effect of CNM independence before the law changes. This result suggests that the identification assumptions are met.

4.2 Event Study Model

The difference-in-differences estimate averages the treatment effect across all post-treatment years and may miss the dynamic effects of SOP laws. For example, if it takes the hospital time to adjust its staffing in response to the law, then effects may only appear after a phase-in period. In this case, the difference-in-differences estimate will underestimate the true effect. I investigate these issues by estimating an event study in section 4.2. The event study model also serves as a check of the identification assumptions and to diagnose and correct for other sources of bias due to staggered adoption.

Recent work suggests that the TWFE model may be biased if the effect of the treatment changes over time. Dynamic treatment effects introduce bias in a staggered design because the TWFE uses previously treated units as controls for units that are newly treated. If the effect of the treatment is constant over time, then changes in the already treated units provide a valid counterfactual for changes that would have occurred in the newly treated unit if it were never treated. However, if the treatment effect changes over time, then changes in the recently treated states will be partly due to the treatment itself, making them an invalid counterfactual for the newly treated units (Goodman-Bacon, 2018; de Chaisemartin and D'Haultfœuille, 2020; Abraham and Sun, 2020). Intuitively, this bias is due to a misspecification in the original model, which assumes that the effect of treatment is constant and occurs exactly at the time of treatment.

The event study can diagnose and correct for bias from dynamic treatment effects by modeling them explicitly and by limiting the control groups to observations that have yet to be treated or were treated a long time ago. [6] The event study model detects dynamic treatment effects by estimating the effect of the treatment r periods before or after the treatment at event time e. If the effects change as r increases, then the treatment has dynamic effects that will bias the TWFE estimate (de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2018; Abraham and Sun, 2020).

Another source of bias that may affect the TWFE and the above event study specification comes from heterogeneity across treatment cohorts. A treatment cohort is a group of units treated at the same time. Both the TWFE and event study models implicitly assume that the treatment effect is the same across treatment cohorts. Abraham and Sun (2020) prove that this bias exists and develop a way to correct for it. Their correction involves first estimating treatment effects separately by treatment cohort. Heterogeneity across cohorts will suggest that this bias is large. They then derive a weighted average of the cohort-specific treatment effects that recovers the unbiased average

[6] By limiting the control groups in this way I avoid using already treated observations from different event times. Including states that are not-yet-treated yields similar results. Including not-yet-treated control groups is a generalization of the method in Fadlon and Nielsen (2019), where treatment groups are matched with controls who will experience the event in r more periods (event time $e + r$).

treatment (referred to as CATT—cohort-specific average treatment on the treated).

I estimate the event study model using a stacking algorithm implemented by Novgorodsky and Setzler (2019). This approach has several advantages. First, it uses all possible comparisons between treatment cohorts and selected control cohorts, increasing the precision of the results. Second, it can estimate effects for each treatment cohort to check for heterogeneity and combine them using the CATT defined by Abraham and Sun (2020) or under an assumption of homogenous treatment effects. Finally, it also provides a convenient way to include the never-treated states, which do not have a defined event-time with multiple adoption periods.

The algorithm creates a new dataset for every treatment cohort. This new dataset includes observations for the treatment cohort and all control cohorts. It then indexes time to the treatment cohort's event time (i.e., event time = $t-e$). Another way to think about this is that control cohorts receive a placebo event at time $t = e$. Then, for each dataset, the following equation is estimated:

$$Y_{it} = \beta^e \times Treat_i + \sum_{r \neq -2; r=-4}^{4} \gamma_r^3 + \sum_{r \neq -2; r=-4}^{4} \delta_r^e \times Treat_i + \lambda X_{it} + \varepsilon_{it} \tag{6}$$

$Treat_i$ is an indicator for being in the treatment cohort and X_{it} is a vector of controls including the unit and time fixed effects.[7] Now each β_t^e is the treatment effect for treatment cohort e, r periods before/after the event. These can then be combined using a weighted average derived by Abraham and Sun (2020) to estimate the ATT under homogeneity.

4.3 Estimating effects on procedure counts

A reduction in resource-intensive procedures is one of the primary ways that hospitals can reduce their costs per birth when their case-mix stays the same. Procedures such as induction, fetal rotation, and cesarean sections require substantially more resources relative to vaginal birth without any interventions. These costs include additional staffing for the procedures, the cost of pharmaceutical drugs or anesthesia, and operating room time. They may also lead to longer hospital stays and recovery times for new mothers.

Granting CNMs practice independence may reduce intensive procedures for a variety of reasons. First, once granted independence, CNMs have more autonomy over the cases they are directly attending and reduce the use of intensive procedures. Second, physicians may adopt a less intensive practice style, either due to learning from CNMs or to competition for patients. Finally, CNMs may advocate for changes to hospital policies that reduce the likelihood of an intervention. For example, they may increase hospital guidelines that specify how long to wait before inducing labor.

I calculated the procedure frequency per birth for each hospital-year to examine the effect of CNM

[7] The algorithm, as implemented, runs each regression simultaneously by including indicators for event cohort. This approach is equivalent but not presented for ease of exposition.

independence on the use of procedures.[8] I selected the 15 most frequent ones and put all other procedures into another category since there are many infrequently used procedures in the data. The 15th most common procedure was performed in 2 percent of births. The results are robust to including more procedures.

With the data at the procedure-hospital-year level, I estimated the following regression:

$$\log(\text{count})_{pht} = \beta_{Other}\textit{Indep}_{pht} + Proc_{pht}\lambda + \textit{Indep}_{pht} \times Proc_{pht}\beta_p + X_{ht}\theta_1 + \gamma_h + \delta_t + \varepsilon_{ht} \quad (7)$$

This is the same equation as equation 5 except it adds a p subscript for procedure and the variable $Proc_{pht}$, which is a vector of indicators for each procedure (excluding the indicator for the other category), and the interaction between $\textit{Indep}_{pht}$ and $Proc_{pht}$. Since the focus of this analysis is to isolate the efficiency effects of CNM independence, X_{ht} now includes variables to control for case-mix.[9] β_{Other} represents the effect of CNM independence on the (log) frequency of procedures in the other category, and $\beta_{Other} + \beta p$ is the effect of CNM independence on the (log) frequency of procedures for procedure p, conditional on case-mix.

I perform a Holm-Bonferroni Sequential Multiple Test Procedure to account for the fact that I am running 16 hypothesis tests of interest. As the number of hypothesis tests increases the probability that the null hypothesis is true, α, also increases, for a fixed critical region. This result implies that the individual cluster-corrected confidence intervals are too narrow. The Holm-Bonferroni correction takes into account the total number of tests and expands the confidence interval as needed to keep α at the desired level (Holm, 1979).

4.4 Decomposing the causal effect of CNM independence

The event study and TWFE models estimate the total effect of CNM independence on costs per birth. I decompose this effect into changes due to within-hospital cost changes ($\frac{\partial C_{ij}}{\partial X_{ij}}$), changes in patient selection into hospitals ($\frac{\partial Pr_{ij}}{\partial X_{Ij}}$), a cross term, and net entry using the following decomposition:[10]

[8] I grouped procedures by 3-digit ICD-9 code so that the count includes the 3-digit code and any of its children.

[9] To adjust for hospital case-mix, I include the hospital's total births, fraction of high-risk births, fraction of births paid for by Medicaid and Medicare, whether the hospital is for-profit, the hospital's wage index calculated by CMS, the fraction of the county that is under 40, the fraction of the county that is white, and the log of the total county population.

[10] This decomposition was originally developed by Baily et al. (1992) and used to understand productivity changes in manufacturing (Foster, Haltiwanger and Krizan, 2001; Foster, Haltiwanger and Syverson, 2008) and heart attack treatment (Chandra et al., 2016)

$$\Delta\bar{c} = \underbrace{\sum_{h\in C}\theta_{h,pre}\Delta c_h}_{Within} + \underbrace{\sum_{h\in C}(c_{h,pre}-\bar{c}_{pre})\Delta\theta_h}_{Between} + \underbrace{\sum_{h\in C}\Delta c_h\Delta\theta_h}_{Cross} + \underbrace{\sum_{h\in M}\theta_{h,post}(c_{h,post}-\bar{c}_{pre})}_{Entry} - \underbrace{\sum_{h\in X}\theta_{h,pre}(c_{h,pre}-\bar{c}_{pre})}_{Exit} \quad (8)$$

$\Delta\bar{c}$ is the average change in facility costs per birth between the post and pre period. It can be broken down into within, between, cross, entry, and exit components. The within component measures the within-hospital changes in cost per birth by holding patient preferences constant at the pre period level. The between component measures the cost changes due to movement of patients to hospitals that are relatively more or less costly in the pre period. Overall costs per birth will decline if hospitals with below average costs per birth gain share. The cross-term measures whether hospitals that experience cost changes gain or lose share. Average costs will decline if hospitals that lower their costs gain more patients or those that experience cost increases lose share. Finally, the last two terms measure cost changes due to entry and exit. Average costs decline if new entrants are lower cost than the average hospital in the pre period or exiting hospitals are higher cost than the average hospital in the pre period. Entry and exit can happen in two ways, since a market is defined by patient group . First, a hospital may enter/exit by starting/closing an obstetric unit and beginning/ceasing to provider services. Second, an existing obstetric unit could start/stop treating a patient group.

This decomposition decomposes the time-series change in average costs per birth. To decompose the causal impact of CNM independence, I calculate the change in facility costs and each component *relative* to a control group.

$$\Delta\bar{c}^{treat} - \Delta\bar{c}^{control} \quad (9)$$

As in the event study, the treatment group is composed of states treated at event time e and the control group is composed of any states that are never treated or treated before the sample period. Equation 9, then, is the semi-parametric DiD analog of Equation 8. To see this, we can break up both the treatment group and control group changes using the decomposition in Equation 8 and rearrange to get:

$$
\begin{aligned}
&\Delta\bar{c}^{treat} - \Delta\bar{c}^{control} = \\
&\underbrace{\sum_{h\in C^{t}reat} \theta_{h,pre}^{treat}\Delta c_h^{treat}}_{Within^{treat}} - \underbrace{\sum_{h\in C^{control}} \theta_{h,pre}^{control}\Delta c_h^{control}}_{Within^{control}} + \\
&\underbrace{\sum_{h\in C^{treat}} (c_{h,pre} - \bar{c}_{pre})\Delta\theta_h^{treat}}_{Between^{treat}} - \underbrace{\sum_{h\in C^{control}} (c_{h,pre} - \bar{c}_{pre})\Delta\theta_h^{control}}_{Between^{control}} + \\
&\underbrace{\sum_{h\in C^{treat}} \Delta q_h^{treat}\Delta\theta_h^{treat}}_{Cross^{treat}} - \underbrace{\sum_{h\in C^{control}} \Delta c_h^{control}\Delta\theta_h^{control}}_{Cross^{control}} + \\
&\underbrace{\sum_{h\in M^{treat}} \theta_{h,post}^{treat}(c_{h,post}^{treat} - \bar{c}_{pre}^{treat})}_{Entry^{treat}} - \underbrace{\sum_{h\in M^{control}} \theta_{h,post}^{control}(c_{h,post}^{control} - \bar{c}_{pre}^{control})}_{Entry^{control}} + \\
&\underbrace{\sum_{h\in X^{treat}} \theta_{h,pre}^{treat}(c_{h,pre}^{treat} - \bar{c}_{pre}^{treat})}_{Exit^{treat}} - \underbrace{\sum_{h\in X^{control}} \theta_{h,pre}^{control}(c_{h,pre}^{control} - \bar{c}_{pre}^{control})}_{Exit^{control}}
\end{aligned}
\tag{10}
$$

In each line, I subtract the component for the treatment group from the component in the control group. That is, I apply the DiD component-wise rather than just on the total change. So, the impact of the policy on costs via the within-component is the within component change for the treatment group relative to the within-component change for the control group. The benefit of this procedure is that it relies on the same identification assumptions as the overall difference-in-differences. If the change in costs for the control represents a valid counterfactual change for the treatment group overall, then it also represents a valid counterfactual for the change due to each component.

Equation 10 applies to the case with only one event time. I extend this to the staggered setting in the following way. First, I calculate the above decomposition for each event cohort, restricting the sample to just states in the event cohort and the control states. Then, for each component, I average the estimate across event cohorts, weighting by the number of births in the post period for the treatment group.

4.5 Choice model

The above decomposition implicitly assumes that patient preferences, θ, and costs per birth, c, vary only by hospital characteristics. This homogeneity is consistent with the original application of the decomposition to homogeneous goods in Foster, Haltiwanger and Syverson (2008). However, it is likely that there is substantial heterogeneity in patient preferences and costs. If the cost to serve a patient is correlated with their hospital preferences, then the above decomposition will treat any cost reductions from better matching of patients to hospitals as efficiency gains (reductions in average cost) rather than due to selection (costs don't actually change but patients go to the hospital that can treat them more cheaply). Moreover, this heterogeneity may be driving overall reductions in costs if patients prefer hospitals that can treat them at a lower cost.

I adapt the non-parametric choice model developed by (Raval, Rosenbaum and Tenn, 2017) to estimate patient-hospital specific preferences θ_{ij} and costs c_{ij} and plug them into Equation 10 to mitigate these issues. In the model, the utility patient i in group g gets from going to hospital j in period t (pre or post) is:

$$U_{ijt} = \delta^g_{jt} + \varepsilon_{ijt} \tag{11}$$

where δ^g_{jt} is the mean utility that patients in group g receive from hospital j in time t and ε_{ijt} is an individual specific idiosyncratic error term. Under the assumption that choice probabilities and substitution patterns are identical within group then the probability that a patient chooses hospital j is the share of the group θ_{gj} that picked that hospital. The patient's expected cost at hospital j is the average cost of group members who chose the hospital. The model allows for a flexible market definition: any hospital that a member of the group went to. I define the outside option as any hospital that is in a different state than the patient.

To estimate the model, patients with identical values across a set of characteristics are partitioned into a mutually exclusive group $g \in G$. If the group has more than 25 members, then their estimated choice probability is the share of the group that chose each hospital and their estimated cost at each hospital is the average cost of the group members that chose that hospital. All groups with fewer than 25 members are assigned to new groups based on all characteristics besides the last one and probabilities and costs are recalculated in the same way. This process is repeated until all patients are assigned to a group or there are no more characteristics left.

There is a tradeoff between bias and variance when picking the minimum group size and the variables that define groups. The smaller and more well-defined the groups are, the lower the bias in the choice estimates. The bias is lower because the group members are more similar to each other. However, as the group size decreases, the choice estimates become less precise.

Patients are grouped based on the following characteristics:

1. Time (Pre or Post event)
2. Patient state
3. Patient county
4. Admit type (Routine, Urgent, Emergency)

5. Modified Ten Group Classification System Group (1–4, 5, 6–7, 8, 9, 10)
6. Risk level (excluding age)
7. Presenting diagnosis (3-digit ICD-9 code)
8. Payor (Medicaid, Medicare, Private, Other)
9. Patient age band (< 20, 20–40, 40–50, > 50)
10. Patient race (White, Black, Hispanic, Asian or Pacific Islander, Native American, Other)

These characteristics yielded 64,012 groups larger than 25 patients. Less than .5% of patients were unable to be grouped.

The discharge data are particularly well-suited to this method as they have a large number of characteristics and a large number of patients. The large number of characteristics allow for the identification of narrowly defined groups that are more likely to be homogeneous. The large number of patients ensures that the groups are still large enough to provide statistical power.

Finally, this approach allows me to flexibly and non-parametrically model rich heterogeneity among patients. Parametric logit models are often restricted in their ability to model heterogeneity by the need to estimate the underlying utility parameters. Since the choice probabilities are estimated without estimating the underlying utility parameters, I can capture heterogeneity with a large set of geographic, clinical, and patient demographic variables and include higher-order interactions between all of these factors. Flexibly modeling this heterogeneity is crucial, as more flexible models have been shown to better predict choices and may better describe substitution patterns across hospitals (Raval, Rosenbaum and Tenn, 2017).

I adapt this model by estimating choice probabilities in both a pre period and a post period. This model is typically estimated within a cross-section of patients and then used to estimate counterfactual patient distributions when a hospital is removed from the market, either through a merger or natural disaster (Raval, Rosenbaum and Tenn, 2017). The key assumption underlying these papers is that preferences remain stable before and after the event. However, since I am interested in how CNM independence influences preferences, I need to track how patient preferences change over time.

To estimate the pre and post period choice probabilities and expected costs, I first create a new dataset for each event cohort and all control states. Then, for each event cohort, I estimate the choice probabilities and expected costs for both the pre period and post period and average them across states within treatment and control groups. I then decompose the causal effect of CNM independence into the five components by plugging the above choice probabilities and estimated costs into equation 10. This approach yields estimates for 8,752 groups based on the patient characteristics.

5 Results

I start by presenting the results from the TWFE model to estimate the average cost savings from CNM independence and the effects on different types of hospitals. I check these results by estimating an event study to examine the dynamic effects of CNM independence. I then present results on within hospital changes in the use of intensive procedures and on quality. Finally, I discuss results from the patient choice model and novel decomposition to identify the relative importance of within hospital changes and market-level changes.

In Table 3, I build up to the specification in equation 1 by starting with just the first term in column 1 and adding year and state fixed effects in columns 2 and 3. In column 4, I include time-varying hospital characteristics. In columns 5 and 6 I replace the state fixed effects with market and hospital fixed effects, respectively. Across the specifications with geographic and year fixed effects, the effect of full independence on hospital facility costs per birth remains steady.

In column 4, CNM independence reduces hospital costs per patient day in nursery departments by about 12 percent. In dollar terms, the law change results in a cost decrease of about $861 per birth. The estimated effect drops to 8 percent when including hospital fixed effects. The hospital fixed effects eliminate two market-level mechanisms for cost savings: reallocation of patients to lower cost hospitals and entry/exit of new OB departments. While the estimates are not statistically distinguishable, their difference suggests that these additional margins for adjustment may be important.

The TWFE presented in Table 3 estimates the average effect of the CNM independence in the post-period. Figure 3 presents estimates for the dynamic impact of the program. The model estimates effects for all available event times but I focus on the window with three periods before and after the event (not including the omitted time–2 years before the event) because most states have data during this window. For example, only Rhode Island has observations more than two years after the event. First, estimates for the effect of the policy in the pre period are relatively small and not statistically significant individually or jointly. This provides evidence that the control group provides a good counterfactual for the treatment group.

Second, there is an 8 percent reduction in costs per birth in the year of the event, which grows to 12 percent one year after. States often implement CNM independence in the middle of the year and, so, they are only partially treated at event time 0. The post period effects are not statistically different and are similar to the average effect from the TWFE model. This result suggests that there is little evidence of dynamic treatment effects in the short run. However, it is possible that cost savings may increase over longer periods if there is substantial lag in the ability of hospitals to adjust. This lag may be due to delays in the training of new CNMs or a redistribution of CNMs across markets.

5.1 Heterogeneity

The policy is likely to differentially impact hospitals based on their market position. Above, I implicitly assume that relaxing SOP laws has a uniform effect across all hospitals, conditional on the included covariates and fixed effects. In Table 4 I interact the treatment with hospital characteristics to investigate how different hospital respond to the policy change.

Column 1 of Table 4 replicates the overall model in Table 3. Column 2 adds an interaction for whether the hospital has a NICU unit with more than 25 beds. Column 3 adds an interaction with the fraction of patients at the hospital who live in a county with few OBGYNs. Finally, column 4 interacts CNM independence with the log of births per obstetric bed, a measure of utilization. All three measures are based on the first year that the hospital is observed since CNM independence might also change the measures themselves.

Overall, the results suggest that hospitals that were in a better position to adapt to the law experienced larger cost declines. In column 2, costs for hospitals with large NICUs declined by 3.6 percent relative to a 14 percent reduction for hospitals without a large NICU.[11] In column 3, the interaction term implies that a hospital that served only patients from underserved areas would experience an additional cost decline of 15.7 percentage points. Though the estimate is not statistically significant, it suggests that hospitals that serve more patients from underserved counties experience larger declines. This result is consistent with other research that shows that relaxing SOP laws for APRNs has greater effects in underserved areas (Alexander and Schnell, 2019). In this case, there is likely broader scope for cost reductions in hospitals with few existing physicians. Finally, hospitals that more intensively use their existing capital have smaller cost declines. For the average hospital, a 1 percent increase in births per obstetric bed reduces the cost savings by about 27 percentage points. The median hospital in my sample has 74 births per obstetric bed, which implies the total cost reduction of CNM independence on the median hospital is 9 percent. The 25th and 75th percentile hospitals deliver 55 and 98 births per obstetric bed and experience cost reductions of 17.7 percent and 2.2 percent, respectively.

5.2 Effects on Procedure use and Quality

A reduction in costly and intensive procedures is one of the primary mechanisms for CNM independence to reduce costs per birth. Figure 4 presents the marginal effect of CNM independence from the regression specified in Equation 7. Procedures are listed top to bottom by their average frequency per birth, which is denoted by the size of its point. Labels for the procedures are listed on the y-axis, and the x-axis contains the scale for the total effect. Each coefficient's uncorrected confidence interval surrounds the estimate. Estimates that are significant at the 5 percent level after the Holm-Bonferroni correction are teal, while those that are not are red.

[11] I classify a large NICU as one with at least 25 NICU beds, based on the AHA survey. Research suggests that NICU volume is a key predictor of NICU quality and I use it as a proxy for the NICU level (Phibbs et al., 2007).

Common and intensive procedures like manually assisted delivery (73.5), low cervical c-sections (74.1), and occlusion of the fallopian tubes (66.3) decline with CNM independence. Additionally, there are more procedures that are consistent with an increase in vaginal birth such as inserting a spinal catheter for infusion of therapeutic or palliative substances (03.9) and non-operative cleaning and irrigation (96.4). Only low cervical C-sections, occlusion of the fallopian tubes, and non-operative cleaning and irrigation survive the multiple hypothesis test. These results are consistent with the prior literature that suggests CNMs lower intensive procedures and have a less intensive practice style (Markowitz et al., 2017; Newhouse et al., 2011).

Although they are generally considered to be overused, C-sections are, in many cases, medically necessary. It is important to examine how reducing the use of C-sections influences overall quality. As an indicator of quality, I estimate the effect of CNM independence on the rate of SMM procedures. SMM procedures address serious and unexpected complications during labor and delivery (CDC, 2020). They often indicate that something has gone wrong and therefore can be used as an indicator of quality and outcomes. SMM procedures are relatively rare, occurring in about 1.6 percent of the sample. Additionally, the effects on C-section use and quality will likely be moderated by whether C-sections are currently over or underused and whether the mother is likely to need one or not.

To examine this heterogeneity Figure 5 displays the marginal effect of CNM independence by whether a mother is in a TGCS group that typically has a higher C-section rate (denoted in the graph as “High Risk”) and whether the hospital serves a larger than average fraction of patients from underserved counties. There is no significant effect on the C-section rate for mothers in the low risk group for both underserved and not underserved hospitals. CNM independence reduced each group’s rate of SMM procedures by approximately .002, or about 17 percent. CNM independence reduced the C-section rate at not underserved hospitals for mothers in the high risk group by .025, or 3 percent, with no significant effects on the SMM procedure rate. Conversely, high risk mothers going to underserved hospitals experienced a marginally significant increase in their C-section rate and a significant reduction in their SMM procedure rate.

Taken together, these results suggest that CNM independence improved outcomes and quality by expanding access to less intensive practice styles. First, quality improved for mothers that are less likely to require a C-section without a similar increase in C-sections. Second, mothers who are more likely to need C-sections but go to underserved hospitals, likely experienced an increase in C-sections and a decline in SMM procedures. This result suggests that C-sections were undersupplied before and that CNMs were able to free up OBGYN time for higher-risk cases. Finally, mothers who are indicated for a C-section going to hospitals that are not underserved experienced a reduction in C-sections. The absence of a decline in SMM procedures implies that C-sections were oversupplied in these hospitals.

5.3 Decomposition component estimates

The above results establish that CNM independence significantly reduces costs per birth. They also present evidence that these cost reductions are occurring at different hospitals through changes in procedure use for different types of patients. It is unclear, however, whether hospitals are treating the same patients more efficiently, if patients are choosing hospitals that are more suited to their risk type, or whether hospitals are opening new obstetric units.

To shed light on the relative importance of these mechanisms, Table 5 reports the results of the decomposition analysis. The values in the table are the average of each decomposition component for the whole sample and by risk level as a percent of the value in the pre-period. The total column is the total percent change cost per birth in the treatment group relative to the control group. The other four columns report the cost change due to each component. On average, patient groups in treatment states experienced a decline in costs of 6 percent. This decline was mostly due to within*hospital changes, which accounted for a decline of 8 percent. In other words, holding patient preferences constant, CNM independence reduced the average group's cost per birth by 8 percent. These gains were offset by cost increases due to the between and cross term. The increase in the cross term indicates that hospitals that gained share in the post period also experienced an increase cost per birth. This result suggests that they are treating patients more intensively than before.

This pattern is exacerbated by an increase in risk. Low-risk patients experienced a larger decline in costs (7 percent) than medium-risk (5 percent) and high-risk patients (2 percent). For each group, cost declines were driven by within hospital cost changes (7–8 percent decline for each group). However, higher-risk groups sought higher-cost care in the post period, reducing their cost savings more than the low-risk group. The between term, which measures cost changes due to movement between hospitals is 2 percent and 5 percent for the medium- and high-risk groups, respectively. The cross term for the medium- and high-risk group is 1 percent and 3 percent. These results suggest that higher-risk groups went to hospitals that treated them at a higher cost than in the pre period and that these hospitals became more intensive in the post period.

5.3.1 Market concentration

Given the importance of changing patient preferences, it is likely that cost savings will vary with the amount of competition in the market. Market concentration may restrict the ability of higher-risk patients to move to new hospitals in response to changes caused by CNM independence. This effect can dampen efficiency gains from better matching of patients to hospitals.

The first two panels of table 6 break out the sample by market concentration. The first panel presents results for patient groups that have an HHI of less than 2500, the FTC's standard for classifying a market as concentrated. The second panel presents results of the decomposition for patient groups that have an HHI greater than 2500.

Although the average total cost changes are similar in competitive and concentrated markets, their sources are different. Competitive markets see substantially larger declines due to within-hospital changes. For example, the within-hospital change for high-risk patients in competitive markets is -12 percent and only -4 percent in concentrated markets. However, the cost increases due to patient selection are also larger. Although the between terms are the same for high-risk patients, the cross term is 8 percent in competitive markets and -2 percent in concentrated markets. This pattern suggests that, in competitive markets, hospitals can deliver infant and maternal services at a lower cost, and patients who prefer a higher-cost or more intensive approach are able to move to a new hospital. In concentrated markets, patients have fewer hospitals to choose from, which reduces the ability of hospitals to lower costs by specializing.

5.3.2 OBGYN density

Hospitals that serve patients in areas with a high density of OBGYNs in the pre period experience lower cost reductions. This may be because physicians have substantial power in these markets and make it more difficult for CNMs to practice after the SOP law changes. It may also be because markets with a higher density of physicians have fewer existing CNMs, limiting the immediate gains from independence.

The lower two panels of table 6 report decomposed cost changes due to CNM independence for patients that live in counties with fewer or more than 7 OBGYNs per 100,000 people. Patients that live in areas with fewer OBGYNs per capita see much larger declines in cost per birth across risk levels. In low-density areas, CNM independence lowered the cost per birth by 13 percent for low- and medium-risk patients and 15 percent for high-risk patients. In high-density areas, CNM independence lowered the cost per birth by 5 percent for low-risk patients, 4 percent for medium risk patients, and 1 percent for high risk patients.

The cost declines in both areas are driven by within-hospital declines in cost. Higher-risk patients in low-density regions see larger within-hospital declines, which suggests that hospitals CNM independence may free up OBGYNs to treat higher-risk patients while CNMs take care of lower-risk patients. Entry is also a larger factor in cost declines in places with fewer OBGYNs, accounting for 5–6 percentage points of the cost declines across risk groups. Finally, both the between and cross terms are positive, suggesting that patients who are higher risk or prefer a more intensive treatment style may switch hospitals. This pattern may lead to better matching of patients to hospitals.

6 Conclusion

In this paper, I provide the first evidence of occupational licensing laws influencing firm costs and patient choice. Prior work has found that CNMs provide care that is of similar quality to doctors but is less capital-intensive. I find that granting CNMs full autonomy substantially reduces the marginal facility cost of obstetric services and that these savings are concentrated in hospitals with a large fraction of patients from counties with few OBGYNs and those without a large NICU. These savings are due, in part, to reductions in the use of low-cervical c-sections and other intensive procedures, suggesting that the cost savings come from providers adopting a less resource-intensive practice style. At the same time, most patients experience declines in procedures associated with negative maternal outcomes, suggesting that the reduction in intensive procedures did not harm patients overall.

In a decomposition, I find that within hospital-efficiency gains account for most of the cost savings and that some higher-risk patients move to higher-cost hospitals that treat them more intensively in the post period. These selection effects are larger in markets that are less concentrated or have fewer OBGYNs. Importantly, a large component of the savings in underserved markets occur due to entry of low-cost OB units.

These findings speak directly to current policy debates about how to reduce healthcare spending and make care more affordable. First, they show that significant cost savings can be achieved by expanding patient choice of provider type. These savings are especially large in areas with that have limited competition among providers. Second, a reduction in intensive procedures can reduce costs while improving outcomes. Expanding the patient's choice set may more efficiently allocate different types treatments to patients that would most benefit from them. Finally, the findings demonstrate that is important to take into account the existing market structure when estimating the effects of healthcare policy. In this case, hospital concentration reduces the potential for cost savings by reducing the scope for specialization.

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Tables

Table 1: State treatment status

Control States		Treatment States
Never Treated	Treated Before	
California	Arizona (1996)	Colorado (2010)
Florida	New York (<1991)	Massachusetts (2011)
Kentucky	Washington (<1991)	Maryland (2014)
North Carolina		Rhode Island (2007)
New Jersey		Nevada (2013)

Table 2: Balance Regressions

Dependent Variables:	$\%White$	$% Under 40	$\ln(CountyPop)$	CMS Wage Index	log(tot_births)	For-Profit
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Independent CNMs	-0.0004	0.0022	0.0379	0.0677	-0.0066	0.0182
	(0.0041)	(0.0017)	(0.0392)	(0.0515)	(0.0427)	(0.0259)
State	X	X	X	X	X	X
Year	X	X	X	X	X	X
Observations	6,904	6,904	6,904	6,684	6,904	6,904
Adjusted R^2	0.22989	0.24072	0.32423	0.52737	0.07125	0.15828

Each column represents a separate regression of the dependent variable on a policy indicator and state and year fixed effects. All standard errors are clustered at the state and year level.

Table 3: Specification Check

Dependent Variable:	$\ln(Cost/Birth)$					
Independent CNMs	-0.2663***	-0.2924***	-0.0787***	-0.1260*	-0.0821**	-0.0880***
	(0.0790)	(0.0728)	(0.0273)	(0.0713)	(0.0409)	(0.0228)
Year		X	X	X	X	X
State			X	X		
County Chars.				X	X	X
HRR					X	
Hospital						X
Observations	6,904	6,904	6,904	6,684	6,684	6,684
Adjusted R^2	0.05573	0.09035	0.13441	0.21275	0.3146	0.73093

Each column represents a separate regression of log(Cost/Birth) on the variables in the table. County characteristics include the fraction of the county under 40, the fraction of the county that is white, the log of the total county population, whether the hospital is for-profit, the total births at the hospital in the base year, and the CMS wage index. All standard errors are clustered at the state and year level.

Table 4: Heterogeneity by hospital type

Dependent Variable:	$\ln(Cost/Birth)$			
Model:	(1)	(2)	(3)	(4)
Variables				
Independent CNMs	-0.1260*	-0.1473**	-0.0963	-1.2563***
	(0.0713)	(0.0677)	(0.0876)	(0.3432)
Big NICU × Independent CNMs		0.1117**		
		(0.0553)		
% Underserved × Independent CNMs			-0.1570	
			(0.1008)	
$\log(Births/OBBeds)\times$ Independent CNMs)				0.2680***
				(0.0762)
Observations	6,684	6,684	6,684	5,498
Adjusted R^2	0.21275	0.21419	0.21645	0.21581

Each column represents a separate regression of log(Cost/Birth) on the variables in the table, the fraction of the county under 40, the fraction of the county that is white, the log of the total county population, whether the hospital is for-profit, the total births at the hospital in the base year, the CMS wage index, and state and year fixed effects. All standard errors are clustered at the state and year level.

Table 5: Decomposition by risk level

Risk level	Total	Within	Between	Cross	Net Entry
Overall	-0.07	-0.08	0.01	0.01	-0.00
Low Risk	-0.07	-0.08	0.01	0.01	-0.00
Medium Risk	-0.05	-0.08	0.02	0.01	-0.00
High Risk	-0.02	-0.07	0.02	0.03	-0.00

Presented effects are fractions of the base level of costs.

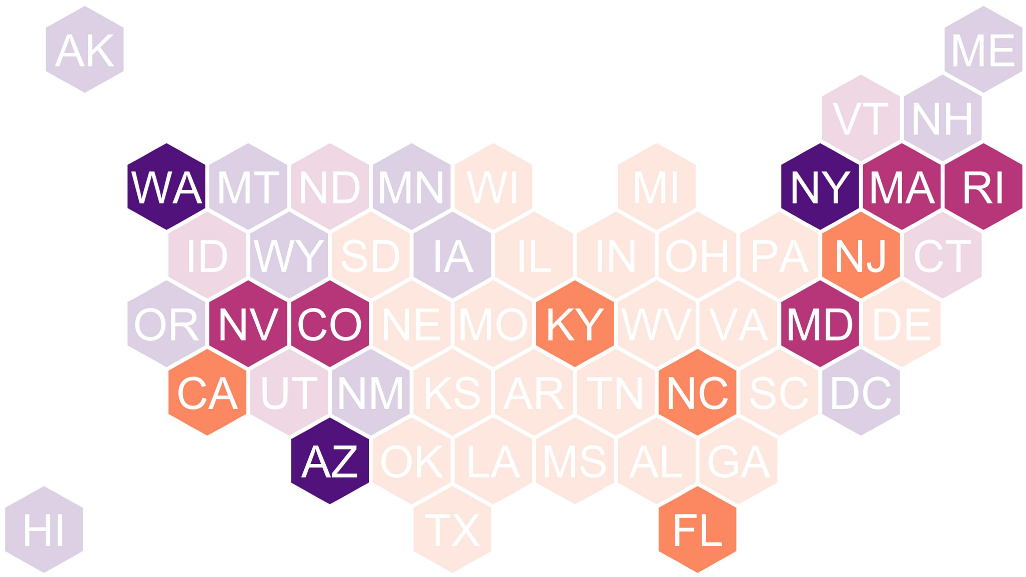
Table 6: Decomposition by hospital concentration and OBGYN density

Risk level	Total	Within	Between	Cross	Net Entry
Competitive (HHI $<$ 2500)					
Low Risk	-0.08	-0.11	0.01	0.02	-0.00
Medium Risk	-0.06	-0.11	0.04	0.01	0.00
High Risk	-0.00	-0.12	0.03	0.08	-0.00
Concentrated (HHI $>$ 2500)					
Low Risk	-0.06	-0.07	0.01	0.00	0.00
Medium Risk	-0.05	-0.06	-0.00	0.02	0.00
High Risk	-0.03	-0.04	0.03	-0.02	-0.00
Few OBGYNs per capita					
Low Risk	-0.13	-0.13	0.03	0.02	-0.06
Medium Risk	-0.13	-0.14	0.05	0.01	-0.06
High Risk	-0.15	-0.17	0.08	0.00	-0.05
Many OBGYNs per capita					
Low Risk	-0.05	-0.07	0.00	0.01	0.01
Medium Risk	-0.04	-0.07	0.01	0.01	0.01
High Risk	-0.01	-0.06	0.03	0.03	0.00

Presented effects are fractions of the base level of costs.

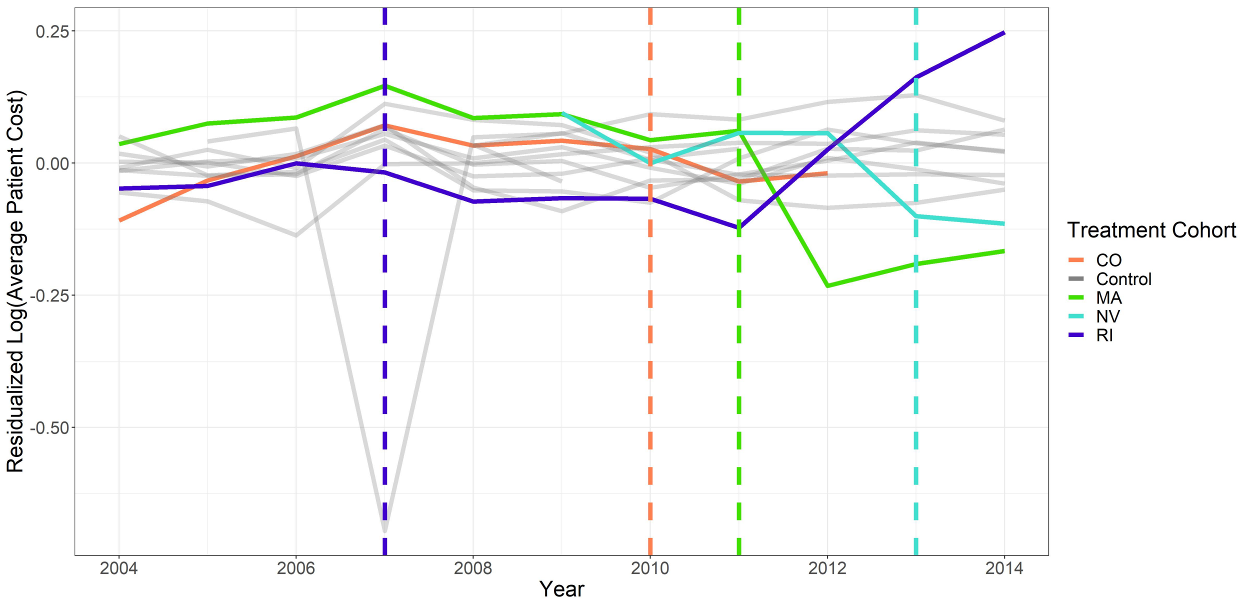
Figures

Figure 1: CNM Independence by state



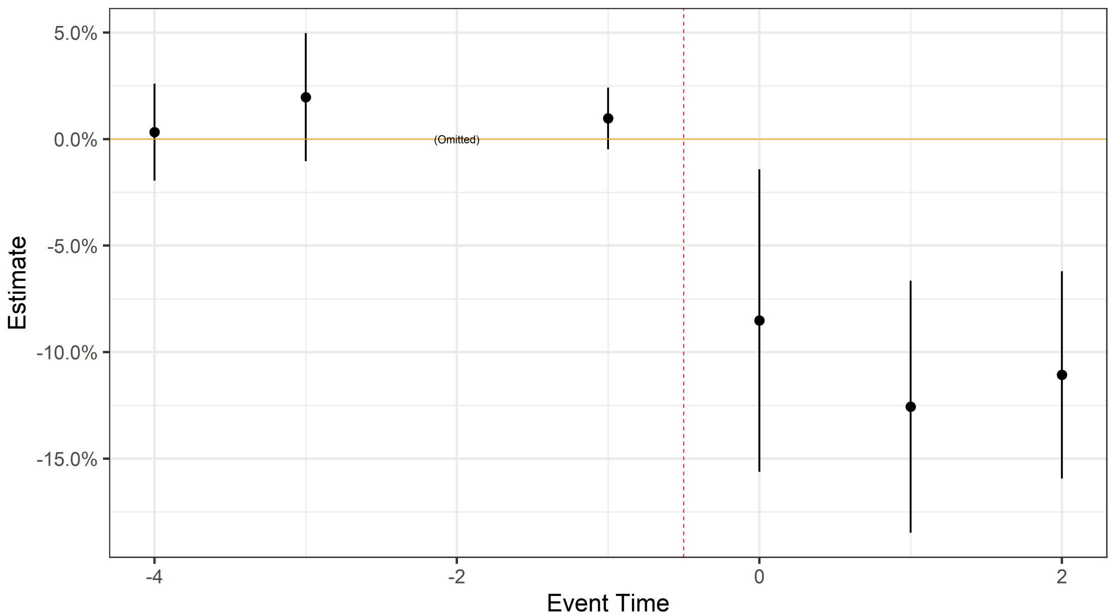
Map displaying CNM independence by state. Orange states did not grant CNM independence before the end of the sample period (2014—"Never treated"), purple states granted CNMs independence before the sample period (2004—"Treated before"), magenta states granted CNMs independence during the sample period ("Treated"). States that are grayed out are not in the sample.

Figure 2: Residualized Event Study



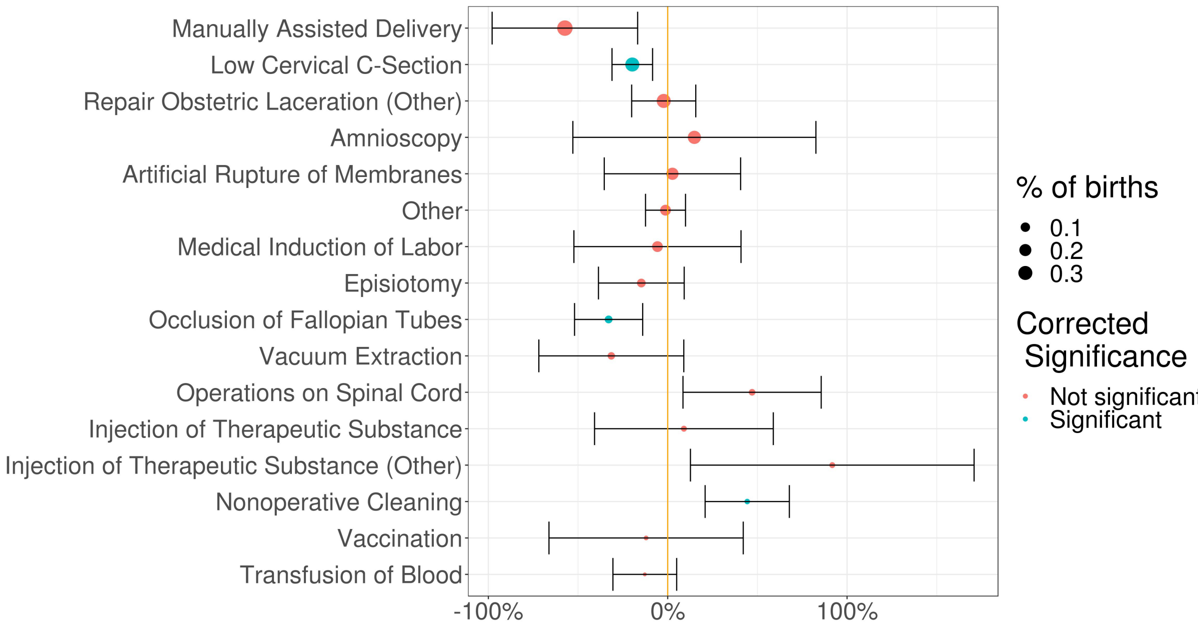
Average residuals from a regression of log(Cost/Birth) on state fixed effects, year fixed effects, and the percent of people under 40, percent of people who are white the total population of the county, whether the hospital is for-profit, and the total births at the hospital in the base year.

Figure 3: Event Study: log(Cost/Birth)



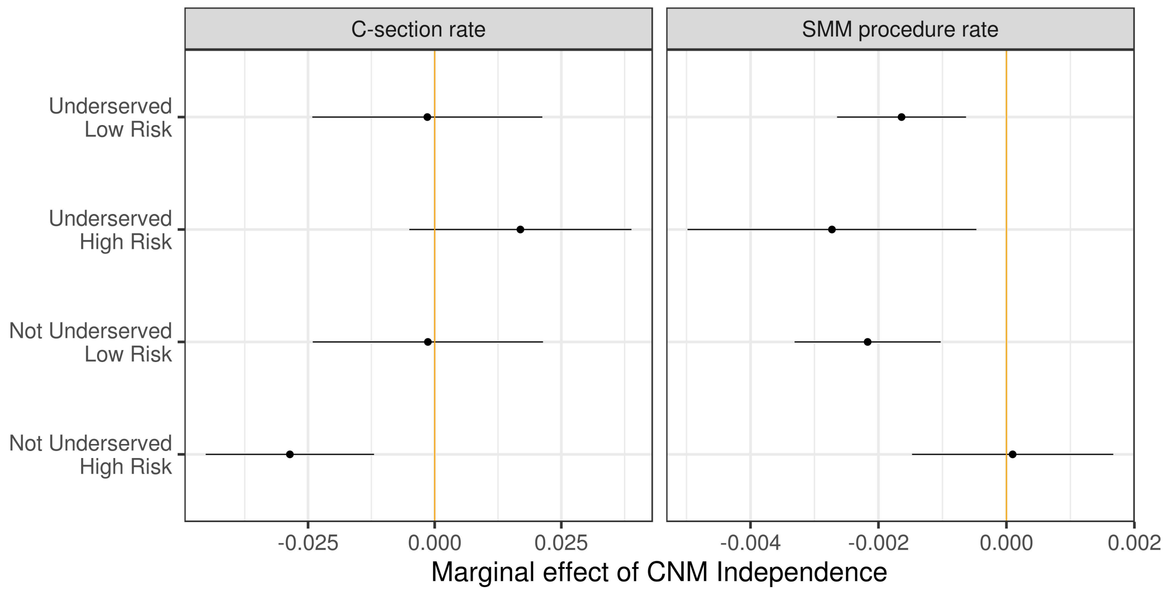
This figure plots estimated effects of CNM independence relative to 2 years before law passage. It includes the fraction of the county under 40, the fraction of the county that is white, the log of the total county population, the CMS wage index, whether the hospital is for-profit, the total births at the hospital in the base year, and state and year fixed effects. All standard errors are clustered at the state and year level.

Figure 4: Effects on procedure use



Each point in the above figure represents the estimated effect of CNM independence on the use of the top 15 most common procedures. They are regression coefficients from a regression of log(count) on indicators for procedure, total births at the hospital, the fraction of births at the hospital considered high risk, the fraction of births at the hospital that were paid for by Medicaid and Medicare, whether the hospital is for-profit, the fraction of the county's population under 40, the fraction of the county's population that is white, the log of the county's population, the level of the CMS wage index, hospital fixed effects, and year fixed effects. The size of the point indicates the average fraction of births in a year with the relevant procedure code. The teal points are statistically significant at the 5 percent level after a Bonferroni correction for multiple hypotheses. The confidence intervals shown are uncorrected. The standard errors are clustered at the state and year level.

Figure 5: Effects on C-section rate and SMM procedure rate by underserved status and TGCS group



This figure plots the marginal effect of CNM independence on hospital C-section and SMM procedure rates. Underserved indicates that hospital has a larger than average fraction of patients from underserved counties. Patients labelled as High Risk are from high C-section TGCS groups (groups 5–10), patients labelled as Low Risk are from low C-section TGCS groups. Each panel is a separate regression that includes the interaction of CNM independence, underserved, and high C-section TGCS group, the fraction of the county under 40, the fraction of the county that is white, the log of the total county population, the CMS wage index, whether the hospital is for profit, the total births at the hospital in the base year, and state and year fixed effects. All standard errors are clustered at the state and year level.