A demand-smoothing incentive for cesarean deliveries *

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Abstract

We study the demand-smoothing incentives for private hospitals to perform c-sections. First, we show that a policy change in Chile that increased delivery at private hospitals by reducing the out-of-pocket cost for women with public insurance increased the probability of a c-section by 8.6 percentage points despite private hospitals receiving the same price for a vaginal or cesarean delivery. Second, to understand hospitals' incentives to perform c-sections, we present a model of hospital decisions about the mode of delivery without price incentives. The model predicts that, because c-sections can be scheduled, a higher c-section rate increases total deliveries, compensating the forgone higher margin of vaginal deliveries. Finally, we provide evidence consistent with the demand-smoothing mechanism: hospitals with higher c-section rates are more likely to reschedule deliveries when they expect a high-demand week.

Keywords: health care, provider incentives, labor and delivery

JEL classification: I11, I13, I18

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1 Introduction

The rate of c-sections has increased worldwide in recent years. According to Betrán et al. (2016), the largest increase in c-section rates has occurred in Latin America and the Caribbean (LAC), where it went from 27% in 2000 to 42% in 2014. Recent studies in several countries suggest a correlation between delivery at for-profit private hospitals and c-sections (for example, see Hoxha et al., 2017). Figure 1 shows that both deliveries at private hospitals and c-section rates have increased in recent decades in Chile. [1]

If the correlation between deliveries at private hospitals and c-sections is causal, then the increase in c-section rates may be due to physician or hospital incentives rather than any change in medical conditions presented in pregnancy. This deserves attention given the extensive evidence that non-medically indicated c-sections are detrimental to the health of mothers and newborns (see Card et al., 2018, Costa-Ramón et al., 2018 or Borra et al., 2019, for recent examples). [2]

The literature on physician and hospital incentives has focused on the *price mechanism* to perform more c-sections, i.e. the physician or hospital receiving higher fees for a c-section than a vaginal delivery. A seminal paper in this literature is Gruber et al. (1999) and more recent examples are Allin et al. (2015) or Foo et al.

[1] This relationship was first documented qualitatively by Murray (2000), who found that women treated by private obstetricians are more likely to have c-sections than women treated by midwives or doctors in public hospitals. More recently, Borrescio-Higa and Valdés (2019) found an association between high c-section rates and women with health insurance giving birth at private hospitals.

[2] Several papers in medical journals also document that c-sections with cephalic presentation are associated with adverse maternal and newborn outcomes. These papers show a higher risk of morbidity and postpartum infections in the case of the mother (Villar et al., 2007), a higher risk of complications in future pregnancies (Ananth et al., 1997), a higher risk of injury for the newborn (Alexander et al., 2006), and a higher risk of a stay of 7 days or more in neonatal intensive care unit (Villar et al., 2007). For a review of the association between c-sections and health outcomes see Hyde et al. (2012).

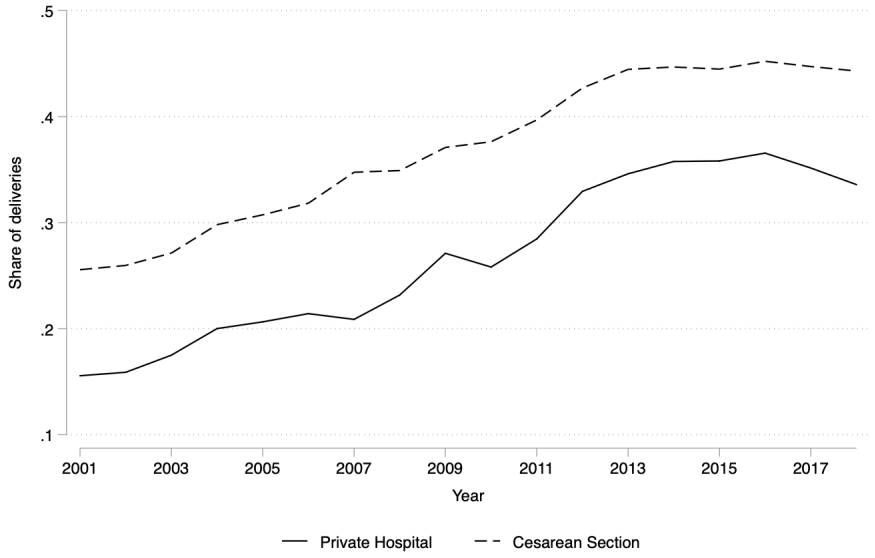


Figure 1: Share of deliveries at private hospitals and c-section rates in Chile
Source: Departamento de Estadísticas e Información de Salud (DEIS), Ministerio de Salud, Chile.

(2017). In this paper, we analyze a demand-smoothing mechanism: the scope to schedule of c-section deliveries, which is absent for vaginal deliveries. This flexibility may allow hospitals to schedule more deliveries and increase aggregate profits via a *quantity effect* even without price incentives. Therefore, we study whether this demand-smoothing mechanism can explain, at least in part, the high c-section rates of private hospitals when direct price incentives are not present.

To answer this question, in Section 2 we exploit a 2003 policy change in Chile that decreased the cost of delivery at private hospitals for women with public health insurance. Crucially, under this program, insurance pays private hospitals the same fee per delivery regardless of whether it is a vaginal delivery or a c-section. Using a difference-in-differences (DID) strategy exploiting the eligibility conditions for the program, related to insurance affiliation, we find that the policy increased the prob-

ability of delivery at a private hospital by 14.5 percentage points and the probability of a c-section by 8.6 percentage points.

After we show evidence that private hospitals perform more c-sections than public hospitals even without price incentives, in Section 3 we introduce a model of hospital decisions about the mode of delivery to understand the logic of the demand-smoothing mechanism. We model a profit-maximizing hospital receiving the same price for vaginal and cesarean deliveries, with the latter having a higher cost. However, while the hospital can schedule a c-section for a given period, a vaginal delivery arrives randomly either in the present or future period.

The model predicts that, at the margin, when the hospital increases the share of deliveries allocated to c-sections, the total number of deliveries increases (*a positive quantity effect*). This effect in equilibrium compensates for the higher margins of vaginal deliveries (*a negative price effect*). We conclude that, if vaginal deliveries have sufficient variation over time, a higher c-section rate may allow the hospital to more than compensate for the cost difference and to increase profits.

To quantify the importance of the demand-smoothing mechanism, we calibrate an extended version of the model with data and perform counterfactual experiments. The experiments suggest that constraining private hospitals to the c-section rate of public hospitals would decrease the capacity utilization of the former by 24% and reduce their profits by 12%. We then use the calibrated model, together with data on capacity utilization before and after the policy, to study if the demand-smoothing mechanism can explain, at least in part, the observed behavior in the c-section rates of PAD hospitals. The model replicates the positive correlation between changes in utilization and changes in c-section rates, providing further evidence that our

proposed mechanism may be behind some of the effects of the policy

Consistent with the demand-smoothing mechanism, in Section 4 we provide evidence that hospitals with higher c-section rates are more likely to reschedule a delivery when its due date (at a gestational age of 40 weeks) is expected to be a high-demand week. In particular, we find that the probability of an early-term birth (on week 37 or 38) is an increasing function of the expected demand at term (calculated as the number of deliveries that would have reached week 40 at the same time). This relationship holds only for private hospitals participating in the program, or hospitals with c-section rates above 40%.

Finally, in Section 5 we discuss our results and other possible mechanisms that may relate c-sections with physician/hospital incentives.

Our paper fits within the literature that have linked c-sections with price incentives (Gruber et al., 1999), fear of liability risk (Dubay et al., 1999; Currie and MacLeod, 2008; Frakes and Gruber, 2020) or procedural skill (Currie and MacLeod, 2016). Our work is also related to research on the effects of the type of hospital on c-section rates. For example, Johnson and Rehavi (2016) compared c-section rates for HMO-owned hospitals and non-HMO-owned hospitals for physician and non-physician patients, using data for California from 1996-2005. They found that c-section rates for non-physicians are lower in HMO-owned hospitals than in non-HMO-owned hospitals, while c-section rates for physician patients do not depend on hospital ownership.[3]

This paper makes two main contributions. First, it demonstrates that a policy that increased access to private hospitals for women with public insurance had the

[3]Other examples are Shen (2002) and Lien et al. (2008).

unforeseen consequence of increasing the c-section rate. Second, our results suggest that hospitals/physicians have incentives to have a high c-section rate despite having a lower unit margin. Our results imply that future health policies may consider incentives other than price when designing contracts or payment systems.

2 Impact of easing access to private hospitals on C-Sections

2.1 Institutional Setting

Health insurance in Chile is mandatory for employees and retirees, but optional for the self-employed and economically inactive individuals. Health insurance buyers can choose between public or private insurance. In 2016, 74% of the population had public insurance, 19% had private insurance, and 7% were uninsured or had a specific type of insurance for the police and armed forces.[4]

Private insurance is supplied by private firms called ISAPRES (the Spanish acronym for *Institución de Salud Previsional*). Public insurance is administered by the *Fondo Nacional de Salud* (FONASA) and is financed by a 7% tax on enrollees' taxable incomes and government transfers.[5] Individuals with public insurance are assigned to one of four groups: A, B, C, or D. Group A includes only individuals who are below the indigence line, receive government subsidies or demonstrate they receive no income. The remaining three groups are classified by monthly income. In

[4]Source: FONASA (2017).

[5]The 7% tax on the enrollee's taxable income is up to a maximum of approximately 200 dollars.

2016, 18% of the population was in group A, 25% in B, 11% in C, and 20% in D.[6]

Individuals with public insurance have two options for receiving their benefits: *Modalidad Atención Institucional* (MAI), which involves the network of public providers, and *Modalidad Libre Elección* (MLE), which grants access to private hospitals for individuals in groups B, C, and D.[7] Under the MLE option, the government sets the hospital fees and copayments for all medical procedures (which do not vary by groups). Private hospitals choose whether or not to participate in the program, and individuals with public insurance can choose from among the available hospitals.

In 1996, the government made MLE more attractive by the introduction of a diagnosis-related group (DRG) payment system called PAD (the Spanish acronym for *Pago Asociado a Diagnóstico*). Under this system, both the patient's copayment and the hospital price are fixed amounts defined by FONASA for the treatment associated with a diagnosis, irrespective of the actual medical procedures performed.[8]

The PAD system includes a code for delivery that covers both vaginal and cesarean deliveries. Thus, with PAD delivery, a private hospital receives the same payment independent of the mode of delivery. The PAD delivery covers doctor and midwife fees, hospital stay, medical exams, medication and immunization costs, and postnatal care for 15 days after the patient is discharged. Importantly, to be eligible for PAD delivery, a woman with public insurance must: (i) be enrolled in group B, C, or D, (ii) expect a single baby, (iii) have a pregnancy with a gestational age of 37

[6]Individuals with incomes of less than 360 dollars are in group B, those with incomes between 360 and 530 dollars are in group C, and those with incomes greater than 530 dollars are in group D. These groups are important because the coinsurance rate in public hospitals (but not in private hospitals) depends on group affiliation: it is zero for individuals in groups A and B, 10% for individuals in group C, and 20% for individuals in group D.

[7]Private health insurance, on the other hand, only provides access to private hospitals, except in special cases like an emergency.

[8]For details of the evolution of the PAD program, see the Appendix.

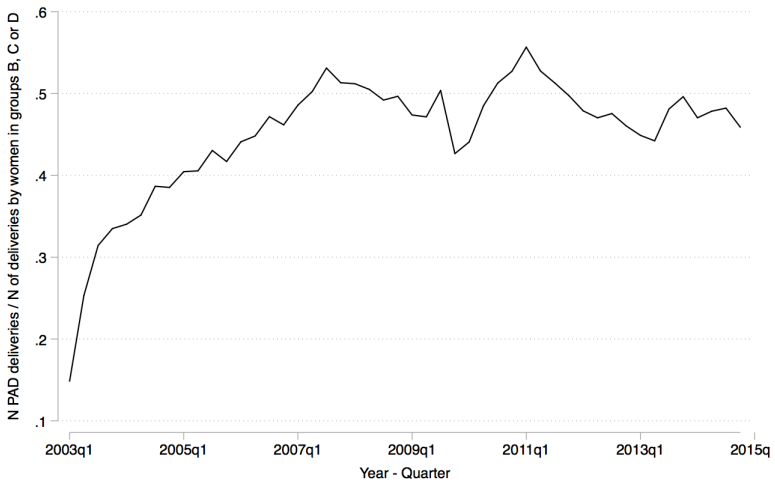


Figure 2: Share of deliveries by women with public insurance groups B, C or D financed with PAD delivery

Note: The number of PAD deliveries includes deliveries in private hospitals financed by PAD. Source: FONASA, Ministerio de Salud, Chile.

weeks or more (at the time of delivery), and (iv) have a non-high-risk pregnancy.[9]

Our policy of interest is a 2003 policy change that decreased the copayment for delivery from 60% to 25%. The decrease in the copayment for PAD delivery in 2003 was significant: it fell from 630 dollars in 2002 to 270 dollars in 2003.[10] After this change, the use of PAD delivery in private hospitals for women with public insurance B, C, or D increased from 10% in the 1st quarter of 2003 to 45% in the 1st quarter of 2008 (see Figure 2).

[9]To satisfy these eligibility requirements, on week 37, a woman must present a medical certificate about her pregnancy risk status in her chosen hospital. Since the high-risk status is loosely defined in the PAD requirements, the hospital can request additional tests for the patient and eventually reject the case. If the hospital accepts the case, the woman pays the copayment and gets PAD coverage.

[10]Decreto 48 of the Ministry of Health promulgated on February 11th, 2003, and came into force on April 2nd, 2003 (see http://bcn.cl/2bofl.).

2.2 Data and Descriptive Statistics

In our analysis, we use hospital discharge data from the Health Statistics and Information Department (DEIS) of the Ministry of Health, publicly available for the period 2001–2018. This dataset includes information on the discharging hospital, the discharge date, length of stay, the main diagnosis code (ICD-10 codes), whether the patient had surgery, and the patient's county of residence, age, gender, and type of insurance. We restrict the sample to women between 15 and 47 years of age with private or public insurance, giving birth in a hospital, with a hospital stay of fewer than 21 days, during the period 2001–2005.[11]

We use the ICD-10 codes and whether the patient had surgery to construct the variables vaginal delivery and c-section (codes 080–084).[12] We also construct variables to identify the type of hospital. We classify hospitals as *public hospitals*, private hospitals working with PAD delivery (*PAD private hospitals*), and private hospitals not working with PAD delivery (*non-PAD private hospitals*). Public hospitals belong to the public healthcare system while private hospitals do not. We consider that a private hospital is a PAD private hospital if it had at least one delivery financed by PAD delivery in 2001–2005. In 2005, there were 233 hospitals with positive deliveries: 61 PAD private hospitals, 9 non-PAD private hospitals, and 163 public hospitals. The hospitals identified as "non-PAD" have a share of around 3% of total deliveries through the period under analysis. Moreover, they work basically (more than 90%) with (upper-income) women with private insurance before and

[11] As we explain below, we restrict our sample to the period 2001–2005 to avoid contamination from confounding policies implemented after the policy of interest.

[12] Codes O80, O81, O83, O840, and O841, and codes O848 and O849 for women who did not have surgery are classified as vaginal deliveries, codes O82 and O842, and codes O848 and O849 for women who had surgery are classified as cesarean deliveries.

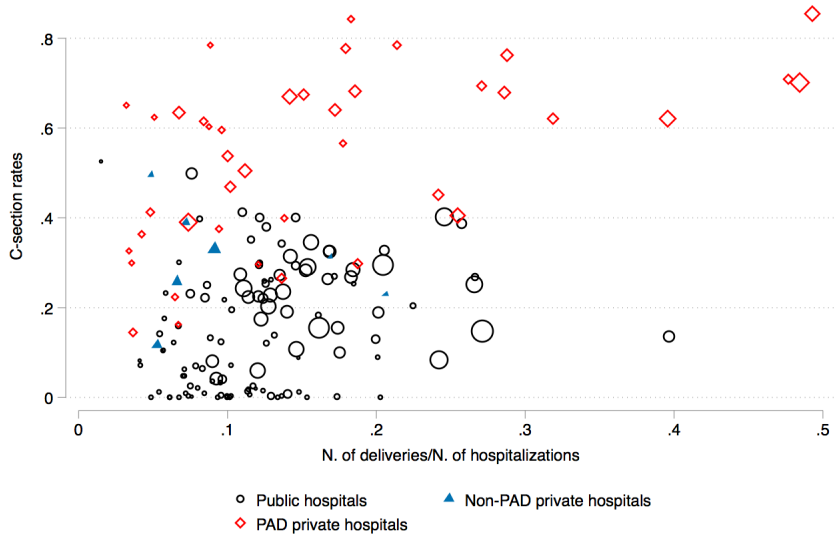


Figure 3: Distribution of hospitals by c-section rates and maternity specialization, 2002

Sample: Hospitals with 100 or more deliveries in 2002.
Note: The size of the circle is proportional to the number of deliveries in the hospital in 2002.

after the policy.[13]

Figure 3 characterizes hospitals in terms of their c-section rates and maternity specialization (measured by the ratio of deliveries over total hospitalizations) in 2002, before the policy change analyzed here. PAD private hospitals (diamonds) have high c-section rates to such extent that there is almost no overlap in terms of c-section rates between these hospitals and public hospitals (circles) and non-PAD-private hospitals (triangles). Moreover, the PAD private hospitals with the highest c-section rates are highly specialized in maternity services. This evidence suggests that PAD private hospitals pursue a business model with a specialization in deliveries financed by public insurance.

Table 1 shows summary statistics of hospital discharge data. They show that

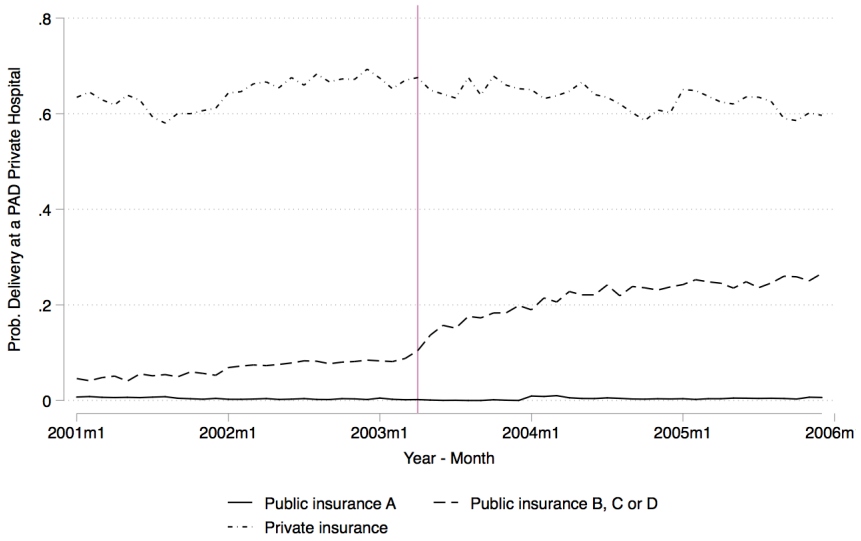
[13]For more details about the characteristics of the different types of hospitals see section A of the Appendix.

28% of all deliveries are c-sections, but the c-section rate is 56% in PAD private hospitals, 30% in non-PAD private hospitals, and 23% in public hospitals. Of all deliveries, 15% occur at PAD private hospitals, 3% at non-PAD private hospitals, and 82% at public hospitals. The distribution of deliveries by the mother's insurance affiliation is 48% for public insurance A, 38% for public insurance B, C, or D, and 14% for private insurance. The average mother's age is 26.8 years.

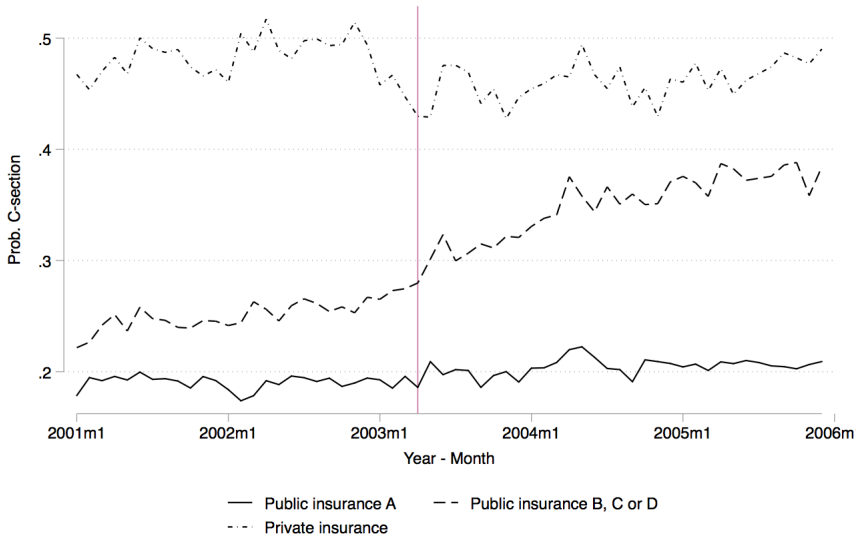
Figures 4a and 4b show the trends in deliveries at PAD private hospitals and c-section rates for women with different types of insurance for 2001–2005. Figure 4b shows that the share of deliveries at PAD hospitals went from 8% in 2002 to 27% in 2005 for women with public insurance B, C or D, while remaining stable for the other groups. Figure 4b shows that c-section rates correlated closely with the type of insurance: 20–25% for women with public insurance A A, 35% for women with public insurance B, C, and D, and 50% for women with private insurance. More relevant for our work, after the policy change, c-section rates increased for eligible groups (public insurance B, C, or D) but remained fairly constant for non-eligible groups (public insurance A and private insurance).

2.3 Empirical Strategy

We estimate the impact of the policy on the probability of a c-section using a DID strategy that exploits the 2003 decrease in the copayment for PAD delivery. We use the affiliation to public insurance groups B, C, or D as the treatment variable, restricting our sample to singleton births only.



(a) Delivery at a PAD private hospital



(b) C-section rates

Figure 4: Trends in delivery at PAD private hospitals and c-section rates by type of insurance

Our estimating equation is

$$\begin{aligned} Y_{it} &= \beta_0 + \beta_1 \, Public\,Insurance\,B, C\,or\,D_{it} \times Post_t \\ &\quad + \beta_2 \, Public\,Insurance\,B, C\,or\,D_{it} \\ &\quad + \beta_3 \, Public\,Insurance\,A_{it} + \mu_t + \delta_c + \lambda_a + \epsilon_{it} \end{aligned} \tag{1}$$

where Y_{it} is the outcome variable (a dummy for cesarean delivery) for delivery i in month-year t, $Public\,Insurance\,B, C\,or\,D_{it}$ is a dummy for delivery by a woman affiliated to public insurance group B, C, or D, $Public\,Insurance\,A_{it}$ is a dummy for delivery by a woman affiliated to public insurance group A, and $Post_t$ is a dummy that equals one after April 2003.[14] Moreover, μ_t is a month-year fixed effect, δ_c is a mother's county of residence fixed effect, λ_a is a mother's age fixed effect, and ϵ_{it} includes unobservables that affect the outcome variable. In our estimating equation, β_1 captures the causal effect of interest.

To justify the common trends assumption we tested the presence of parallel trends in the pre-treatment period. With that purpose, we estimated the following econometric model:

$$\begin{aligned} Y_{it} &= \beta_0 + \textstyle\sum_{\tau=1}^{T} \beta_{1,\tau} \, Public\,Insurance\,B, C\,or\,D_{it} \times \mathbb{1}(t = \tau) \\ &\quad + \beta_2 \, Public\ \ Insurance\,B, C\,or\,D_{it} \\ &\quad + \beta_3 \, Public\,Insurance\,A_{it} + \mu_t + \delta_c + \lambda_a + \epsilon_{it} \end{aligned} \tag{2}$$

where each $\beta_{1,\tau}$ is the coefficient of the interaction between a quarterly dummy and

[14] The norm that decreased the copayment for PAD delivery was approved on February 11th, 2003, but it came into force on April 2nd, 2003.

the treatment dummy, taking the 4th quarter of 2002 as the baseline. The blue line in Figure 5 shows the time-varying coefficients from equation (2). Although most of the pre-treatment impacts are non-significant, we reject the null that all pre-treatment coefficients are zero. This failure to reject the null hypothesis is likely related to an anticipatory effect (discussed below) and some significant (but small in magnitude) impact in the first quarters of 2001. We check the robustness of our results to pre-existent trends by including a linear trend in the treatment group and other robustness checks in Section 2.5.

Notice in Figure 5 that the impacts of the program start in the first quarter of 2003, which is in the quarter immediately previous to the policy. This anticipation effect is related with a drop in the c-section rates of PAD private hospitals during the months previous to the policy (see Figure A.3 in the Appendix), and therefore with the drop in the rates for women with private insurance (see Figure 4b above). One rationale for this anticipation is that the temporary drop in c-section rates is related to increases in capacity ahead of the expansion triggered by the policy. The relationship between hospital utilization and the c-section rates is further explored in Section 3.[15]

As a robustness check for the dynamic impact of reform, we estimate an alternative specification that intends to correct for pre-existing linear trends, which takes

[15]Recall that the policy was implemented in April 2003 but the norm was issued in February.

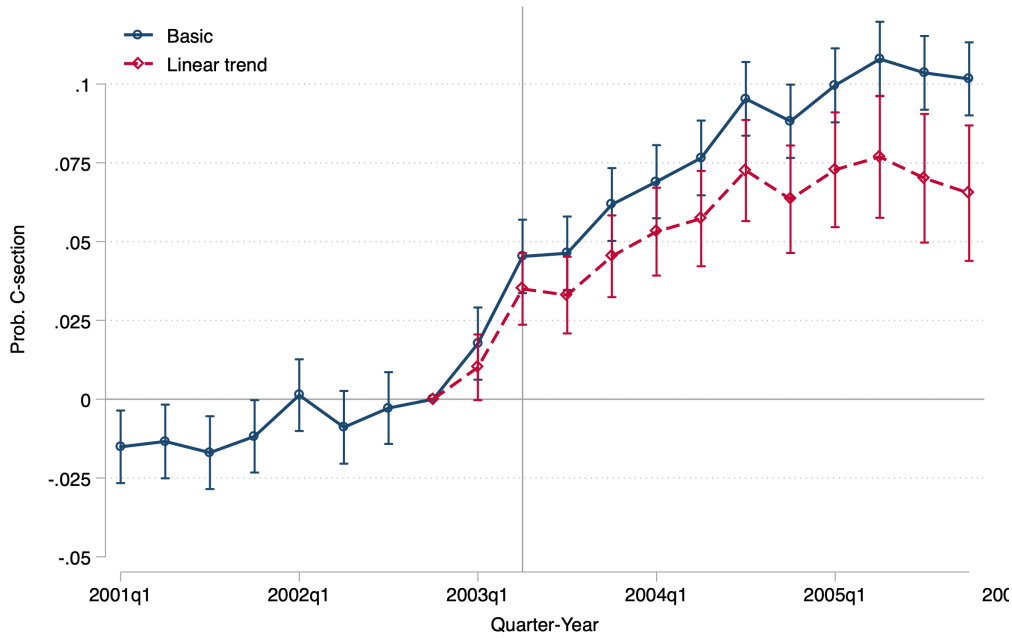


Figure 5: Time-varying effects of the program on the probability of a c-section

the form:

$$
\begin{aligned}
Y_{it} \quad = \quad & \beta_0 + \textstyle\sum_{\tau \geq \underline{T}}^{T} \beta_{1,\tau}\, Public\, Insurance\, B, C\, or\, D_{it} \times \mathbb{1}(t = \tau) \\
& + \beta_2\, Public\, Insurance\, B, C\, or\, D_{it} + \beta_3\, Public\, Insurance\, A \\
& + \beta_4\, Public\, Insurance\, B, C\, or\, D_{it} \times t + \mu_t + \delta_c + \lambda_a + \epsilon_{it}
\end{aligned} \tag{3}
$$

where $\underline{T}$ corresponds to the start of the post-reform period equation (3). Therefore, this specification keeps the period-treatment interactions only for the post-policy period while estimating a linear trend in time interacted with the treatment variable in the pre-period.[16] The post-policy treatment coefficients, shown in a red

[16]We do not include interactions for the pre-period to avoid multicollinearity with the linear trend.

dashed line, are therefore estimated relative to a counterfactual that the observed pre-trend had continued after the policy. As it is apparent, most of the impact of the policy remains even when we control for this linear trend.

2.4 Results

Table 2 presents the estimates of equation (1) for the probability of delivery at a PAD private hospital (columns (1) to (3)) and the probability of a c-section (columns (4) to (6)). Columns (1) and (4) report the estimates for the basic model, columns (2) and (5) include age-year and county-year interactions, and columns (3) and (6) add linear trends in the treatment group (public insurance B, C, and D) and in public insurance A.

Our estimates indicate that, as a consequence of the policy, the probability of delivery at a PAD private hospital increased between 7 (when we include linear trends on the treatment group) and 15 percentage points, and the probability of a c-section increased between 3.1 and 8.7 percentage points. In terms of the sample means (for the treatment group in the pre-treatment period), this implies an increase between 104% and 224% for the probability of delivery at a PAD private hospital and between 13% and 35% for the probability of a c-section. The specification with linear trends in columns (3) and (6) should be interpreted as a lower bound because the linear trend could also capture part of the effect of the policy.

Our interpretation of the previous results is that they are driven by supply-side incentives unrelated to direct price incentives. However, part of these effects can be related to an interaction of supply incentives with patients' preferences. For example, a plausible story is that women with public health insurance have

a marked preference for a c-section that is "satisfied" by private hospitals but not by public hospitals. However, the available evidence does not seem to support this claim (for example, see McCourt et al., 2007).[17] Angeja et al. (2006), using a survey of pregnant women in Santiago, Chile, find that 77.8% of respondents preferred vaginal delivery, and only 9.4% preferred cesarean delivery. The results are similar for women interviewed in public hospitals (c-section rate of 22%) and private hospitals (c-section rate of 60%).

2.5 Robustness checks

In this section, we present robustness checks to our identifying assumptions. For space reasons, we show results for the probability of c-section only. In Section B of the Appendix, we show the same exercises for the probability of delivery at a private hospital.

In addition to the common trends assumption, discussed above, our identification strategy relies on the following assumptions: no contemporaneous confounding policy changes, and no compositional changes in the treated and comparison groups.

The first identifying assumption is that there are no contemporaneous confounding policy changes. We are particularly concerned with two policies: (i) a change in the regulatory framework for private insurance companies which restricts their discretion to change premiums, and (ii) a new policy called AUGE/GES that grants better coverage for individuals with certain health conditions, including preterm birth. Regarding the first policy, the change in the regulatory framework for private

[17] McCourt et al. (2007) reviews the research literature on consumer preferences for elective cesarean section since 2000, and find that a very small number of women request a c-section, ranging from 0.3 to 14%.

insurance companies was approved in May of 2005 but put into effect the following year. Regarding the second policy, AUGE/GES was approved in 2004 but put into effect from July 2005 onwards. We restrict our sample to the period 2001-2005, so it would not affect our results.

In addition, we run a robustness exercise that restricts the sample to a time window around the policy. Columns (1) to (3) of Table 3 show the impact on the probability of a c-section for a time window of 12, 6, and 3 months around the policy. The results imply that, if we restrict the time window to 3 months around the policy, the probability of a c-section increases 2.8 percentage points (against 8.6 with the full-sample). This result implies an increase of 10% in the probability of a c-section following the policy change.

The second identifying assumption is no compositional changes between treated and comparison groups. Given that the treatment condition depends on insurance affiliation, a concern is the possibility of women switching from private to public insurance because of the policy.

As a first robustness check for the second assumption, in column (4) of Table 3 we show the results of equation (1) if we restrict the comparison group to women with public insurance A, and column (5) if we add women with private insurance to the treatment group. The rationale behind this exercise is that the policy should not affect the composition of public insurance A, so dropping women with private insurance (column (4)) or including women with private insurance with those in public insurance B, C, or D (column (5)) should be robust to these concerns.

The results in column (4) with only women with public insurance A as the comparison group are similar to the main model. The result in column (5) shows

that, if we considered women with private insurance as part of the treatment group, the policy would increase the probability of a c-section by 4.6 percentage points, a 16% increase in terms of the sample mean. This effect is smaller than the main model but still significant.

A second robustness check to further address the possible endogeneity of insurance affiliation is to instrument this variable. Specifically, we use $Share\,Group\,B, C\,or\,D_{ac}$, the share of deliveries by women with public insurance B, C or D by county and age in the 2002 period, as an instrument for mother's insurance affiliation. In terms of equation (1), we instrument $Public\,Insurance\,B, C\,or\,D_{it}$ and its interaction with $Post_t$ using $Share\,Group\,B, C\,or\,D_{ac}$ and its interaction $Post_t$, respectively. Therefore, our reduced form equation is

$$\begin{aligned} Y_{it} \quad = \quad & \beta_0 + \beta_1\, Share\,Group\,B, C\,or\,D_{ac} \times Post_t \\ & + \beta_2\, Share\,Group\,B, C\,or\,D_{ac} + \mu_t + \delta_c + \lambda_a + \epsilon_{it}. \end{aligned} \tag{4}$$

Given that these instruments are only a function of the mother's county of residence and age, the exogeneity condition is satisfied if those variables do not change as a consequence of the policy. This seems plausible because: (i) policy eligibility has no relationship to these variables, and (ii) neither fertility nor birth timing is likely to be affected by a policy that increases options for delivery. The relevance condition is satisfied because the mother's county of residence and age are good predictors of being in groups B, C, or D, a condition that we test using the first stage.

Table 4 shows the estimates of the IV strategy, using the share of deliveries by women with public insurance B, C, and D by county and age in 2002 as an

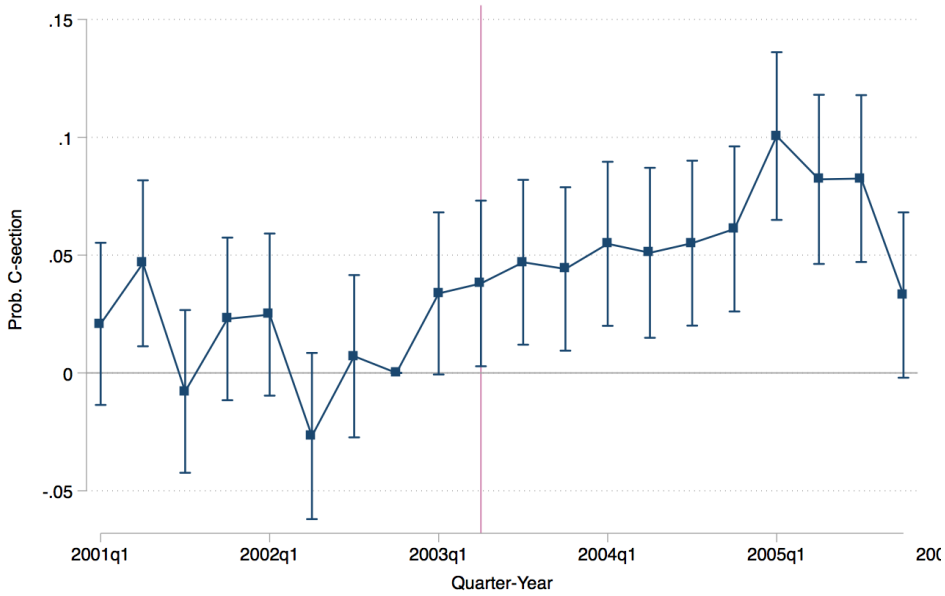


Figure 6: Time-varying effects of the program (Reduced form using the share of deliveries of women with public insurance B, C, and D by county and age in 2002)

instrument for individual insurance affiliation at the time of delivery. Columns (1) and (2) of Table 4) show the OLS and IV estimates for our preferred specification which includes mother's age-year fixed effects, and column (3) and (4) show the first stage estimates. The first stage estimates for our two endogenous variables show that the relevance condition is satisfied. The IV results in column (2) indicate that the probability of a c-section increased by 9.3 percentage points, similarly to our OLS result in column (1).

To provide further evidence of the exogeneity of the instrument, Figure 6 shows the reduced form estimates of a dynamic version of the equation (4) for the probability of a c-section. We observe that the coefficients fluctuate around zero before and increase after the implementation of the policy. The timing of the impacts gives additional support to the validity of the instrument, as it is unlikely that it affects

the outcome directly and not only through the policy.

In Section C of the Appendix, we show additional robustness checks and placebo regressions. Specifically, we first show that our results are robust to a placebo experiment assuming that the policy took place one year earlier (April 2002). We also show that the policy has no impact on mother characteristics, which supports our assumptions regarding compositional changes. Finally, in Section D of the Appendix, we use birth data and the specification in equation (4) to show that the policy caused a decrease in birth weight and gestational age, which is consistent with the increase in c-sections.

3 A model of maternity services

In this section, we propose a *demand-smoothing mechanism* that could explain why profit-maximizing hospitals have higher c-section rates when price incentives are absent. To understand this mechanism, we develop a model of hospital decisions about the mode of delivery without price incentives. We use this model to understand the main trade-off between margins and quantity behind the decision about the mode of delivery.

Although this demand-smoothing mechanism is theoretically plausible, there is a question of whether it is quantitively relevant. To answer this question, we calibrate an extended version of the model and run counterfactual experiments. Specifically, we quantify the effect of limiting the c-section rate of private hospitals on their profits and capacity utilization. In addition, we use the model to analyze the correlation between changes in capacity utilization and changes in c-section rates during the

pre-post policy period.

3.1 Main assumptions

An infinite lived, profit-maximizing hospital chooses the mode of delivery for women requiring maternity services. The hospital is a price-taker and has a capacity of K, i.e. it can make at most K deliveries in a period. In each period t, the hospital faces a demand for maternity services of N women, with $\underline{N} \leq N \leq K$.[18] We define $n = \frac{N}{K}$ and, to simplify notation, normalize K to one. [19] Consequently, all variables should be interpreted in terms of K.

We assume that women requiring maternity services: (i) do not have any medical indication regarding the mode of delivery, (ii) are indifferent about having a vaginal or cesarean delivery, and (iii) are willing to pay a single price $p > 0$ regardless of the mode of delivery.

We also assume that performing a c-section is more costly for the hospital. Specifically, we assume that the cost of a vaginal delivery is c, with $0 < c < p$, and the cost of a c-section is $c\,(1 + y)$, with $0 < y < \overline{y}$.

The problem of the hospital each period t is to allocate $\alpha_t\, n$ cases to vaginal deliveries and $(1 - \alpha_t)n$ to c-sections, to maximize the discounted expected value of future profits.

The timing of the model is represented in Figure 7. At the beginning of period t, the hospital chooses α_t. Cesarean deliveries can be scheduled and we assume that

[18] N can be interpreted as the number of women who get prenatal care from doctors or midwives working at the hospital.

[19] In the basic model that we will present below, the hospital's profit function is linear in K and the solution of the problem is independent of K. In the extended model that we calibrate with the data, the solution depends on K.

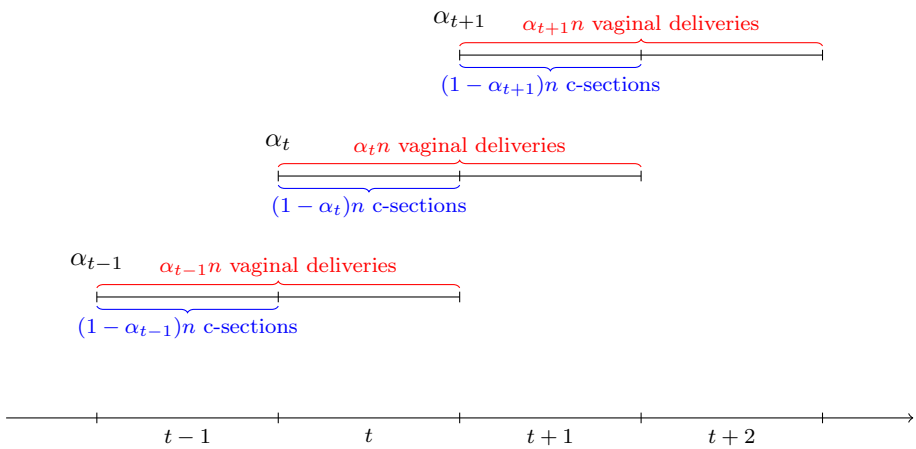


Figure 7: Timing of the model

the hospital performs the $(1-\alpha_t)n$ c-sections in period t.[20]Vaginal deliveries, on the other hand, cannot be scheduled so the actual period of delivery is uncertain.[21] We assume that a vaginal delivery allocated in t can occur in t (*early-term* births) or $t+1$ (*full-term* births).

We assume that the hospital knows α_{t-1} when choosing α_t but it does not have information about the realization of vaginal deliveries in $t-1$.[22]

The number of vaginal deliveries that the hospital performs in period t, Y_t, consists of: (i) women with full-term births from the $\alpha_{t-1}n$ cases allocated to vaginal delivery in $t-1$, and (ii) women with early-term births from the $\alpha_t n$ cases allocated in t. We assume that Y_t is a continuous random variable drawn from a distribution with density $f(y_t; \alpha_{t-1}, \alpha_t, n)$, such that its expectation $E(Y_t; \alpha_{t-1}, \alpha_t, n)$ and variance

[20]This is a mild assumption because, with a constant demand for maternity services, i.e. constant n, the hospital has no incentives to schedule any of the $(1-\alpha_t)n$ c-sections in $t+1$.

[21]Even though hospitals can schedule inductions that do end up in vaginal births, we make this assumption in relative terms with c-sections.

[22]Underlying this assumption is the presence of a lag between enrollment and deliveries so that a hospital has limited information about deliveries (allocated in $t-1$) when it makes an allocation decision at t.

$Var(Y_t; \alpha_{t-1}, \alpha_t, n)$ are increasing in α_{t-1}, α_t and n. [23]

In period t, after the hospital allocates a capacity of $(1-\alpha_t)n$ to c-sections, the remaining capacity for vaginal deliveries is:

$$k^v(\alpha_t, n) = 1 - (1-\alpha_t)n.$$

Due to the uncertainty in the timing of vaginal deliveries and the limited capacity of the hospital, there are situations where the hospital is capacity constrained and must refer some women to another hospital. Therefore, the actual number of vaginal deliveries at t is given by:

$$q^v\left(Y_t, \alpha_t, n\right) = \min\{Y_t, k^v(\alpha_t, n)\}.$$

We assume that referrals are costly for the hospital in terms of reputation and includes an additional cost equal to θ times the number of referrals. The number of referrals at t are given by:

$$q^r\left(Y_{t,}\alpha_t, n\right) = \max\{0, Y_t - k^v(\alpha_t, n)\}.$$

Given the previous assumptions, the hospital's profit function at t can be written as

$$\pi(Y_t, \alpha_t; n) = (p-c)q^v\left(Y_t, \alpha_t, n\right) + (p - c(1+y))[(1-\alpha_t)\,n] - \theta\, q^r\left(Y_{t,}\alpha_t, n\right),$$

[23] These assumptions are meant to capture that expectation and variance of vaginal deliveries must be increasing in the number of women allocated to vaginal deliveries in t and $t-1$, $\alpha_t n$ and $\alpha_{t-1} n$ respectively.

where the first term is the hospital's profit from performing vaginal deliveries, the second term is the profit from c-sections, and the third term is the cost of referrals.

Hospital's problem

The hospital chooses the share of vaginal deliveries $\{\alpha_t\}_{t=1}^{\infty}$ to maximize the expected present value of future profits

$$\max_{\{\alpha_t\}_{t=1}^{\infty}} E\left[\sum_{t=1}^{\infty} \delta^t \pi(Y_t, \alpha_t; n) | I_t\right],$$

where $0 \leq \delta \leq 1$ is the discount factor, and I_t is the information available at t.

Given the recursive nature of the problem, we can solve an equivalent problem using the Bellman equation

$$V(\alpha_{t-1}) = \max_{0 \leq \alpha_t \leq 1} E\left[\pi(Y_t, \alpha_t; n) | \alpha_{t-1}\right] + \delta V(\alpha_t),$$

where the expected profit is

$$\begin{aligned} E\left[\pi(Y_t, \alpha_t; n) | \alpha_{t-1}\right] =& (p-c) E\left[q^v(Y_t, \alpha_t; n) | \alpha_{t-1}\right] + (p - c(1+y))[(1-\alpha_t)\, n] \\ & - \theta\, E\left[q^r(Y_t, \alpha_t; n) | \alpha_{t-1}\right]. \end{aligned}$$

3.2 Basic model

To obtain an analytical solution and understand the main mechanism in the model, first, we assume that Y_t follows a uniform distribution between 0 and $(\alpha_{t-1} + \alpha_t)n$:

$Y_t \sim \mathrm{U}(0, (\alpha_{t-1} + \alpha_t)n)$.[24] [25] Under this distributional assumption, the expected profit is:[26]

$$
\begin{aligned}
E\left[\pi(Y_t, \alpha_t; n) | \alpha_{t-1}\right] = (p-c)&\left\{k^v(\alpha_t, n)\left(1 - \frac{k^v(\alpha_t, n)}{2(\alpha_{t-1}+\alpha_t)n}\right)\right\} \\
&+ (p - c(1+y))\left[(1-\alpha_t)n\right] \\
&- \theta\left[\frac{\left[(\alpha_{t-1}+\alpha_t)n - k^v(\alpha_t, n)\right]^2}{2(\alpha_{t-1}+\alpha_t)n}\right].
\end{aligned}
$$

Steady-state equilibrium

We solve the steady-state equilibrium with a constant α^*. In the steady-state equilibrium, the first-order condition for optimality is

$$
\begin{aligned}
&(p-c)\left[n - \frac{k^v(\alpha^*, n)}{2\alpha^*}\left(1 - \frac{(1+\delta)k^v(\alpha^*, n)}{4\alpha^* n}\right)\right] - (p - c(1+y))n \\
&- \theta\left[\frac{k^v(\alpha^*, n)}{2\alpha^*}\left(1 - \frac{(1+\delta)k^v(\alpha^*, n)}{4\alpha^* n}\right) - \frac{(1-\delta)n}{2}\right] = 0. \qquad (5)
\end{aligned}
$$

The first term in equation (5) is the increase in profits (due to an increase in α_t) from performing more vaginal deliveries in t and $t+1$; the second term indicates the foregone profits due to a decrease in c-sections, and the third term is the increase

[24] Under $Y_t \sim \mathrm{U}(0, (\alpha_{t-1}+\alpha_t)n)$, we have that $E(Y_t) = \frac{(\alpha_{t-1}+\alpha_t)}{2}n$ and $Var(Y_t) = \frac{(\alpha_{t-1}+\alpha_t)^2}{12}n^2$. The expectation is consistent with each vaginal delivery having a probability of $\frac{1}{2}$ of being full-term and taking the expectation over the sum of vaginal deliveries allocated in t and $t+1$.

[25] In section 3.3 we will use a more flexible distribution to calibrate the model with the data and to run counterfactual experiments.

[26] This is the expected profit function when vaginal deliveries are capacity constrained, i.e. $k^v(\alpha_t, n) \leq (\alpha_{t-1} + \alpha_t)n$. This is the relevant case because it is never optimal for the hospital to choose α_t such as there is excess capacity for vaginal deliveries. If that is the case, the hospital can substitute c-sections for vaginal deliveries one-to-one, without doing any referrals, increasing its profits.

in reputational costs (with the expression in brackets being positive for a δ high enough).

To understand the main mechanism in this model, suppose that $\theta = 0$ and $\delta = 1$ and rewrite the first-order condition as

$$(p-c)\left[n - \frac{k^{v*}(\alpha^*, n)}{2\alpha^*}\left(1 - \frac{k^v(\alpha^*, n)}{2\alpha^* n}\right)\right] = (p - c(1+y))n. \tag{6}$$

This equation provides the basic intuition of the mechanism. In the margin, an increase in α_t increases the number of vaginal deliveries (term between brackets in the left-hand side) by less that it decreases c-sections (equals to n in the right-hand side), so the total number of deliveries decreases (*a negative quantity effect*). However, the net effect on profits can be positive because vaginal deliveries have higher margins (*a positive price effect*). Both effects cancel each other out in equilibrium. [27]

The solution of the steady state α^* is

$$\alpha^* = \begin{cases} \frac{1-n}{n} z(p, c, y, \theta, \delta) & \text{if } n \geq \underline{n}(p, c, y, \theta), \\ 1 & \text{if } n < \underline{n}(p, c, y, \theta), \end{cases}$$

where $z(p, c, y, \theta, \delta) = \frac{2\sqrt{(p-c+\theta)(p-c-2cy(1+\delta)+\delta^2\theta)}-(1-\delta)(p-c+\delta)}{(3-\delta)(p-c)+(3\delta-1)\theta-8cy}$ and $\underline{n}(p, c, y, \theta) = 1/(1+z(p, c, y, \theta, \delta))$.[28]

[27] Moreover, the marginal increase in vaginal deliveries is decreasing in α^*: there are decreasing returns to scale of increasing α_t.

[28] In the basic model, we have $\overline{y} = \frac{(3-\delta)(p-c)+(3\delta-1)\theta}{8c}$. If we assume $\delta = 1$ and $\theta = 0$ then

Comparative statics

It is straightforward to show that the share of vaginal deliveries in steady state, α^* is decreasing in the demand, n, the price of deliveries, p, and the cost of referrals, θ. Moreover, α^* is increasing in the cost of vaginal deliveries, c, and in the cost premium of c-sections, y.

The interpretation of why α^* decreases with the demand for maternity services n comes again from the first-order condition in equation (6). Mathematically, the ratio between the marginal increase in vaginal deliveries, $\left[\frac{k_v(\alpha^*,n)}{2\alpha^*}\left(1-\frac{(1+\delta)k_v(\alpha^*,n)}{4\alpha^* n}\right)\right]$ and the marginal decrease in c-sections, n, is decreasing in n. In other words, when n increases the hospital must sacrifice more c-sections if it wants to perform an additional vaginal delivery. This is mainly driven by the positive relation between and n and the variance of vaginal deliveries. [29]

Figure 8 illustrates that α^* is decreasing in n for $p = 1$, $c = 0.7$, $y = 0.15$, $\theta = 0.5$, and $\delta = 1$.

3.3 Calibration

We extend the basic model to replicate some features in the data and run counterfactual experiments. The main difference between this extended model and the basic model is that now the optimal policy of a given hospital i will depend on its

$y \leq \frac{1}{4}\frac{(p-c)}{c}$, that is the additional cost of a c-section should be less than 25% of the margin for vaginal deliveries.

[29] Specifically, when we increase n we have, on the one hand, an increase of both the mean of the distribution of vaginal deliveries and the capacity allocated to vaginal deliveries by the same magnitude (recall that $k_v(\alpha_t, n) = 1 - (1 - \alpha_t)n$). However, increasing n also raises the variance of the distribution therefore, the mean of vaginal deliveries performed increase by less than the increase in the mean of the distribution of vaginal deliveries.

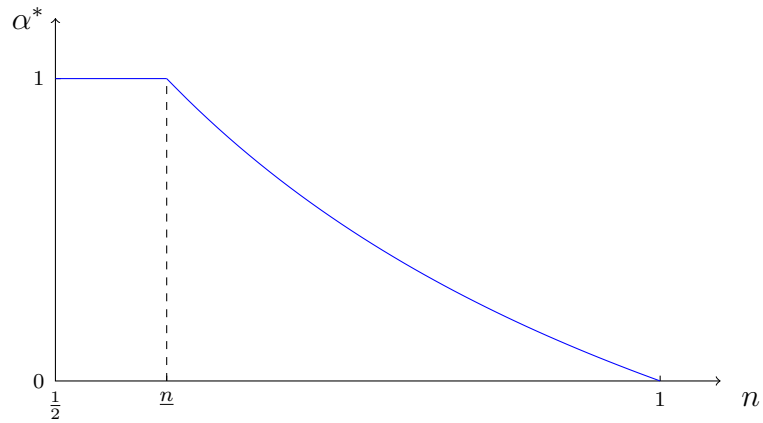


Figure 8: Equilibrium α

capacity, K_i.[30] We calibrate the model using data on private hospitals for the period 2006–2007. For details on the extended model and the calibration see Section E in the Appendix.

Table 5 shows the c-section rate, capacity utilization, and standard deviation of vaginal deliveries for the data and the model. The model replicates the moments that σ and θ are trying to match in the data: the average c-section rate and capacity utilization. Remarkably, the model also predicts a standard deviation (SD) of vaginal deliveries (a moment not used in the calibration) that is similar to that observed in the data.[31]

Figure 9 shows the fit of the model with the cross-section of hospitals: Panel (A) for c-section rates and Panel (B) for capacity utilization. In general, the model captures the correlations between these variables and hospital capacity. In the case of the c-section rate, the model predicts more dispersion than what we observe in the data, which is not surprising given that this is a very stylized model with only

[30] We also use a more flexible functional form for the distribution of vaginal deliveries.

[31] As shown in the Appendix, the model does also a good job predicting the cross-sectional distribution of SD of vaginal deliveries.

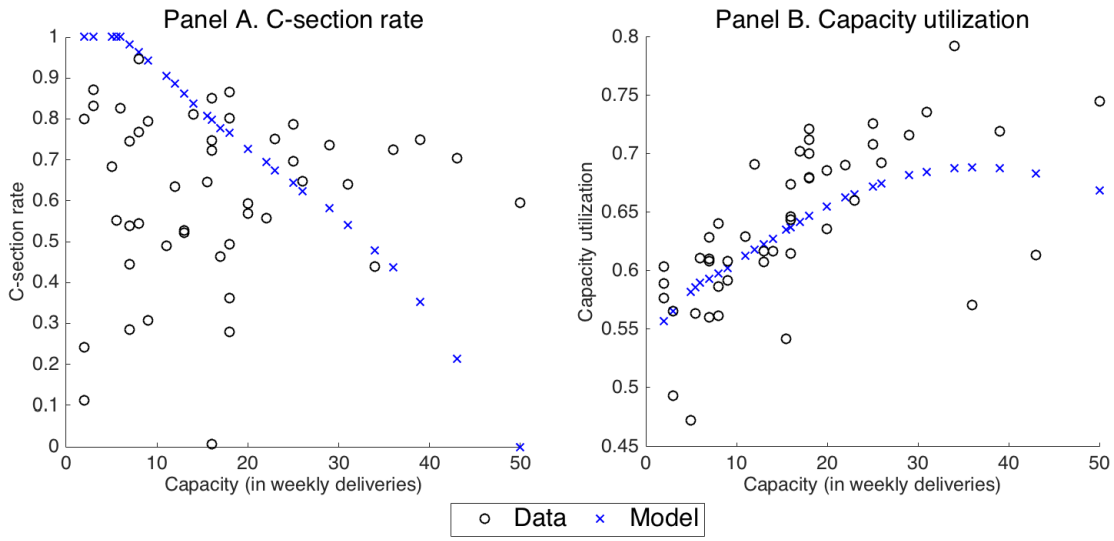


Figure 9: Model fit

Notes: The graph reports c-section rates and capacity utilization for PAD private hospitals. For each hospital, a black circle is the mean c-section rate or capacity utilization in 2006–2007 and a blue cross is the prediction of the same variable from the model. Hospital capacity is the 90 percentile of weekly births in the period 2006–2007.

one source of uncertainty. The negative relationship between c-section rates and hospital capacity in Panel (A) of Figure 9 suggests that small hospitals are more vulnerable to fluctuations in deliveries than the large hospitals and thus are more likely to use c-sections to avoid referrals.

3.4 Counterfactual experiments

We use the calibrated model to quantify the opportunity cost of hospitals when they reduce their c-section rates. To do so, we run two counterfactual experiments. In both experiments, we assume that each hospital is forced to choose the allocation of deliveries to have a c-section rate of .26, which is the average c-section rate for public hospitals in 2006–2007. Table 6 shows summary statistics for both experiments. Panels (A) through (D) of Figure 10 show the c-section rate, capacity utilization,

number of referrals, and profits, respectively, for each hospital in the baseline and the counterfactuals experiments.

In Experiment 1, we assume that each hospital must reduce its c-section rate but keeping the demand fixed, which, in other words, means that hospitals accept the same number of cases as in our baseline scenario.

As shown in Table 6, the limit in the c-section rates forces hospitals to decrease their capacity utilization from 65% to 62%. Given that hospitals increase the share of vaginal deliveries while receiving the same number of cases, they increase their ratio of referrals to capacity from 2% to 5%. Therefore, it is more likely that hospitals have to refer elsewhere part of the vaginal deliveries they have previously committed to attend if a large number of them happen to occur at the same time. Given the moderate decrease in capacity utilization, the 14% drop in profits is mainly explained by the reputational costs due to the sharp increase in referrals. Notice in Panel (C) and (D) of Figure 10 that the increase in referrals and their negative effects on profits are concentrated in smaller hospitals (those with a capacity below 25 deliveries per week).

In Experiment 1 we have assumed that hospitals keep accepting the same number of patients as in our baseline scenario despite incurring high costs in the form of lost reputation. It seems more realistic to assume that hospitals prefer to accept fewer cases beforehand to avoid this reputation cost. Therefore, in Experiment 2, on top to the same limit to c-section rates than in Experiment 1 (0.26), we set an upper bound to the ratio of referrals to capacity of 2% and adjust the demand for maternity services n for each hospital accordingly (see Panel (C) of Figure 10).[32]

[32]In the baseline scenario, the maximum rejection rate was 1.75% so the 2% is not restrictive for the baseline model.

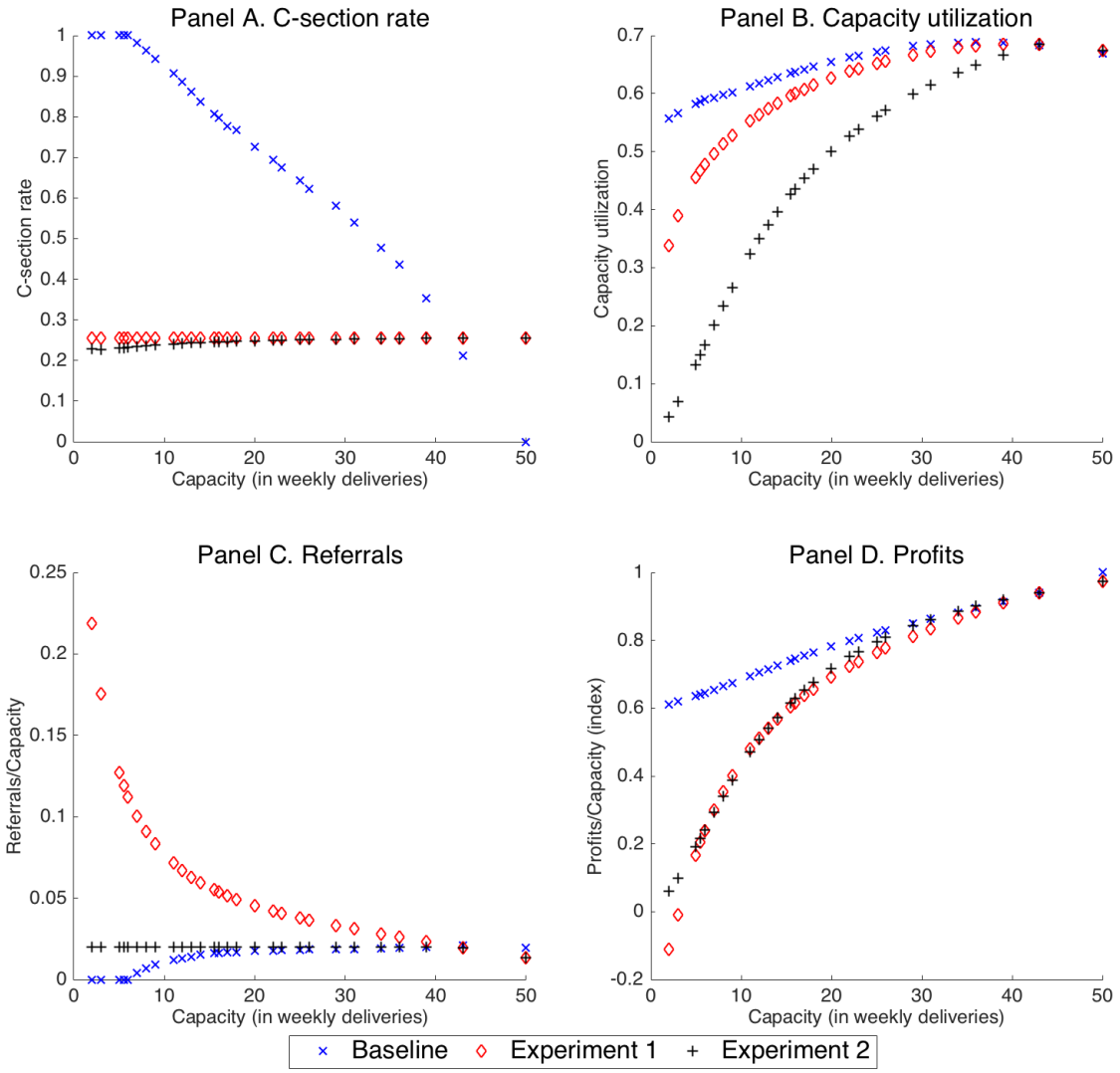


Figure 10: Counterfactual experiments

Notes: The graph reports c-section rates (A), capacity utilization (B), referrals (C) and profits (D) for PAD private hospitals for the baseline and two counterfactual experiments.

Experiment 1 sets a c-section rate of 0.26 (the mean c-section rate for public and non-PAD private hospitals) for each hospital. Experiment 2 sets a c-section rate of 0.26 and an upper bound on the ratio of referrals over capacity of 0.02 for each hospital.

Hospital capacity is the 90 percentile of weekly births in the period 2006–2007.

As shown in Table 6, in Experiment 2, profits decrease by 12% (versus 14% in Experiment 1), but the limit in referrals implies that hospitals reduce their capacity utilization by 24% (5% in Experiment 1). Therefore, unlike the previous experiment, here the lower profits are explained by the decrease in capacity utilization rather than by reputational costs. Panels (B) and (D) of Figure 10 show that, as it was the case in Experiment 1, the drop in capacity utilization and profits occurs mainly in smaller hospitals.

3.5 Policy analysis

The main prediction of our basic model is that c-section rates are increasing in hospitals' capacity utilization. In this section, we use data on hospital utilization rates before and after the policy, and our calibrated model, to study if the demand-smoothing mechanism can explain, at least in part, the observed behavior in the c-section rates of PAD hospitals.

As shown in Table 7, average capacity utilization in private PAD hospitals increased from 65% in 2001–2002 (before the policy) to 67% in 2006-2007 (after the policy). An important feature of this period is that, at the hospital level, this change in capacity utilization is positively correlated with changes in c-section rates. Figure 11, which displays changes in capacity utilization (in the horizontal axis) and changes in c-section rates (in the vertical axis), clearly shows that hospitals that increased their capacity utilization tend to increase their c-section rates and vice versa.

We use the calibrated model to study the relationship between utilization and c-section rates. To do so, we choose hospital demand for each hospital to match ca-

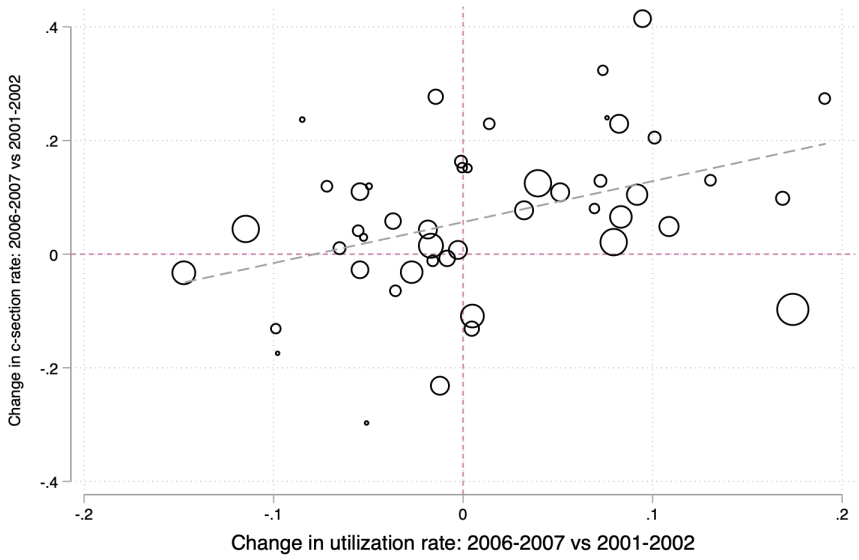


Figure 11: Changes in c-section rates vs changes in utilization rates

Notes: The graph reports changes in c-section rates and capacity utilization between 2001–2002 (before) and 2006–2007 (after) for PAD private hospitals.

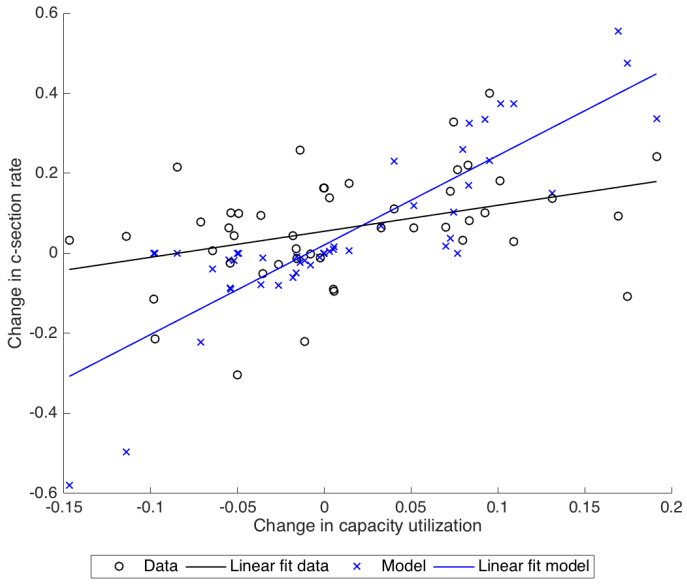


Figure 12: Policy simulation

Notes: The graph reports changes in c-section rates and capacity utilization between 2001–2002 (before) and 2006–2007 (after) for PAD private hospitals. For each hospital, a black circle refers to the data and a blue cross is the prediction from the model.

pacity utilization in 2001–2002 (before the policy) and 2006–2007 (after the policy). Keeping each hospital capacity fixed at the 2006–2007 level, we solve the c-section rate for each hospital before and after. Table 7 shows that the model predicts an increase of 6 percentage points in the c-section rate, slightly over-predicting the change observed in the data (5 percentage points). More importantly, the model also replicates the positive correlation between changes in capacity utilization and c-section rate across hospitals. Figure 12 compares the model with the data: black circles represent actual data and blue crosses represent the model simulation. The linear fits show that these changes are positively correlated in the data and the model, even though this correlation is higher in the model.

This simulation provides further evidence that the demand-smoothing incentive for cesarean deliveries can explain, at least, part of the effects of the policy.

4 Expected demand and scheduling of deliveries

The model of the previous section shows that a profit-maximizing hospital can use a high c-section rate to neutralize the random component of vaginal deliveries. Here we will provide evidence that private hospitals use c-sections to accommodate deliveries when demand fluctuates from week to week. Therefore, our hypothesis is that high c-section rate hospitals smooth out demand over time by moving deliveries between high and low demand weeks.

If our hypothesis is correct, the actual date of birth of a baby should change as a function of the expected demand for deliveries in a given hospital. That is, hospitals may manipulate the date of birth for babies conceived at week w if they

expect a higher than normal number of deliveries at their due date (week $w + 40$). In this section, we show evidence that an early-term birth is more likely to occur if a delivery was originally due in a high-demand week for the hospital.

4.1 Data and empirical strategy

We use birth certificates data from DEIS for the period 2002–2016[33], which contains the name of the hospital, birth date and gestational age (and therefore the week of conception). The data also include information on weight and size at birth, whether it is a singleton birth or not, and mother's characteristics (age, county of residence, marital status, number of children, educational level and labor force participation). Table 8 reports summary statistics for birth data.

To measure expected hospital demand in a week, we add all potential births in a week for a hospital, assuming full-term delivery (at a gestational age of 40 weeks), regardless of the actual date of birth. Then, to identify high and low expected demand weeks, we use the 25th, 50th and 75th percentiles of the distribution of expected demand for a hospital in a given year.

Given our definition of high and low expected demand weeks, we want to know if the probability of an early-term birth (on week 37 or 38) depends on the hospital's expected demand during week 40 of that pregnancy. To do that, we estimate the following equation:

[33]The dataset begins in the 2nd half of 2002 because the hospital name has only been reported consistently since that date.

$$
\begin{aligned}
Y_{i,h,w} \quad = \quad & \beta_0 + \beta_1\, demand_25_50_pctl_{h,w+40} + \beta_2\, demand_50_75_pctl_{h,w+40} \\
& + \beta_3\, demand_75_more_{h,w+40} + \beta_4 X_{i,h,w} + \mu_{h,m} + \delta_c + \lambda_{a,y} + \epsilon_{i,w}
\end{aligned} \tag{7}
$$

where $Y_{i,h,w}$ is a dummy for early-term birth (on week 37 or 38) for baby i, born in hospital h and conceived in week w. Here, $demand_25_50_pctl$, $demand_50_75_pctl$ and $demand_75_more$ are dummies indicating the percentile of expected demand (between the 25th and 50th percentile, between the 50th and 75th percentile, or above the 75th percentile, respectively) in week $w+40$ for hospital h, and $X_{i,h,w}$ includes a singleton birth dummy and the mother's characteristics (number of children, educational level, and marital status), while $\mu_{h,m}$ is a hospital-month interaction, δ_c is a mother's county of residence fixed effect, and $\lambda_{a,y}$ is a mother's age-year interaction.[34]

The β's in equation (7) measure the effect of a high expected demand on the probability of an early-term birth.

Our main source of variation here is the week of conception in a month for a given hospital. Identification relies on the week of conception being "as good as randomly assigned" within a hospital-month of conception cell, which we believe is a credible assumption.[35]

[34]Table F.1 in the Appendix shows similar results using a linear and a quadratic specification, being the results consistent with those from the nonlinear specification.

[35]This specification has the implicit assumption that there are not referrals to other hospitals. However, the results in this section are robust to an alternative specification with the "demand" variable based on the number of births in the county rather than those at a given hospital. See Table F.2 in the Appendix.

4.2 Results

Table 9 shows the effects of expected demand on the probability of an early-term birth for public and non-PAD private hospitals (column (1)), and for PAD private hospitals (column (2)). The impact of high expected demand on early-term birth for public and non-PAD private hospitals is close to zero, but this is not the case for PAD private hospitals. Specifically, we find that if a baby is due on a high expected demand week, the probability of an early-term birth increases by 0.4/0.8 percentage points. In terms of the sample mean, this is around a 1.1/2.2% increase given that 36% of births in our sample occur on week 37 or 38. Therefore, our results point to private hospitals scheduling deliveries as a function of their expected demand. .

Given these results, we may expect that private hospitals with high c-section rates have greater flexibility to use c-sections to accommodate deliveries between high and low-demand weeks. Therefore, in Table 10, we allow for heterogeneous effects for hospitals with different c-section rates, by classifying them in terciles by their average fraction of c-sections. Table 10 shows that we did not find an effect of high expected demand on hospitals with low c-section rates ($\leq$ 25%, column (1)). Therefore, the impact of expected demand appears to be concentrated in hospitals where c-sections represent more than 40% of deliveries. Note that the effect increases with expected demand, as shown in column (3).[36]

[36] Our results are robust to alternative specifications, such linear and quadratic functions on expected deliveries. See Appendix.

5 Discussion and conclusion

In the previous sections, we have analyzed the connection between private hospitals and c-section rates. First, in Section 2 we have shown that a policy change in Chile that increased delivery in private hospitals by reducing the out-of-pocket cost for women with public health insurance produced a sizable increase in c-section rates despite private hospitals receiving the same price for cesarean or vaginal deliveries. Given that the policy studied here implies a flat delivery price, independent of the mode of delivery, it is unlikely that price incentives are the main channel behind the results, as for example in Gruber et al. (1999), or more recently in Allin et al. (2015) and Foo et al. (2017).[37]

The results from our model of Section 3 and the empirical evidence in Section 4 suggest that the demand-smoothing mechanism, i.e. hospitals scheduling c-sections to increase the total number of deliveries, may be one factor behind the higher c-section rate in private hospitals. C-sections allow hospitals to smooth the timing of deliveries in two different dimensions. First, as shown in the model of Section 3, by scheduling deliveries that otherwise may occur at the same time due to the random timing of vaginal births. Second, as shown in Section 4, by rescheduling a delivery when the demand for maternity services fluctuates from week to week.

Even though it seems that the demand-smoothing mechanism is indeed playing a role in explaining c-section rates in private hospitals, we cannot rule out that other mechanisms can be at work (other than a price mechanism).

One explanation for the higher number of c-sections in the private sector is

[37] Gruber and Owings (1996) took a different approach and used changes in fertility rates in the US from 1970 to 1982 to estimate the causal effect of decreased demand on the behavior of obstetricians/gynecologists (performing vaginal or cesarean delivery).

related to *defensive medicine*. Hospitals may react to fears of medical liability by providing suboptimal care, performing either more or fewer procedures than what would be medically necessary. Even though liability pressure has been traditionally linked with a higher c-section rate (see, for example Dubay et al., 1999), some recent evidence show lack of effects (e.g. Frakes, 2012) or even negative effects (see for example Currie and MacLeod, 2008).[38]

Another possible factor is *procedural skill* (see Currie and MacLeod, 2016). It may be the case that physicians at private hospitals are more likely to be surgically skilled than those at public hospitals. However, we still need an explanation for private hospitals being more prone to hiring more surgically skilled doctors. Even though procedural skill may explain why there is a variation in c-section rates across hospitals (even controlling for observed characteristics of the pregnancies), it does not necessarily explain why some type of hospitals (private hospitals) have systematically higher c-section rates than other types (public hospitals).

A third explanation is related to hospital congestion. For example, Facchini (2020), using data from a large public hospital in Italy and (unlike our case) leaving out all scheduled deliveries, finds that c-sections are more likely when there is a high patient/midwife ratio.[39] The main difference between this paper and the literature on hospital congestion is that, while these papers investigate whether hospitals are more likely to perform c-sections when faced with unexpected demand, we are concerned with hospitals systematically using c-sections to program their deliveries.

[38]In a recent paper, Frakes and Gruber (2020) find, using the fact that active-duty patients treated in military facilities cannot sue for negligent care, that liability immunity increases cesarean utilization.

[39]Moreover, Using data on maternity admissions for 30 hospitals in Washington state, Balakrishnan and Soderstrom (2000) only find a correlation between c-sections and "congested" days for pregnancies that were classified as at risk for c-section, but not for the full sample of patients.

Similar to the case of procedural skill, we also believe that the congestion argument is unlikely to explain the permanent differences in c-section rates by type of hospital, like those we have observed in Chile in the last two decades.

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Table 1: Descriptive statistics for hospital discharge data, 2002

Variables	Mean	s.d.
Cesarean section rate	0.28	0.45
in PAD private hospitals	0.56	0.50
in non-PAD private hospitals	0.30	0.46
in public hospitals	0.23	0.42
Delivery at a PAD private hospital	0.15	0.36
Delivery at a non-PAD private hospital	0.03	0.17
Delivery at a public hospital	0.82	0.38
Public insurance A	0.48	0.50
Public insurance B, C or D	0.38	0.49
Private insurance	0.14	0.34
Age	26.8	6.8
Patient's length of stay	3.3	1.9
Observations	850,007	

Source: Departamento de Estadísticas e Información de Salud (DEIS), Ministerio de Salud, Chile.

Table 2: Effect of decreasing copayments on PAD delivery

	Delivery at a PAD hospital			Cesarean section		
	(1)	(2)	(3)	(4)	(5)	(6)
Public Insurance B, C or D	0.150***	0.145***	0.070***	0.087***	0.086***	0.031***
× Post	[0.001]	[0.001]	[0.002]	[0.002]	[0.002]	[0.004]
Age-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	No	Yes	Yes	No	Yes	Yes
Linear trend Public Ins. A	No	No	Yes	No	No	Yes
Linear trend Public Ins. B, C, D	No	No	Yes	No	No	Yes
Mean DV		0.067			0.252	
R-squared	0.431	0.445	0.446	0.114	0.121	0.122
Observations	850,004	849,991	849,991	850,004	849,991	849,991

Note: This table reports DID estimates of the effect of decreasing copayments on PAD delivery on the probability of delivery at a PAD private hospital and the probability of a cesarean delivery. PAD private hospitals are hospitals that participate in the PAD program but are not in the public healthcare system. *Public Insurance's B, C or D* is a dummy for a delivery by a woman with public insurance's B, C or D, and *Post* is a dummy that equals one after April 2003.

All regressions include mother's county of residence and age fixed effects, and month fixed effects.

Columns (3) and (6) include linear trends in public insurance A and in public insurance B, C or D.

The mean of dependent variable corresponds to the treated in the pre-treatment period.

Robust standard errors reported in brackets.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 3: Effect of decreasing copayments on the probability of a c-section: Robustness

	Different windows			Public insurance A	Private insurance
	± 12 months	±6 months	± 3 months	as control	as treatment
	(1)	(2)	(3)	(4)	(5)
Treatment × Post	0.051***	0.035***	0.028***	0.072***	0.046***
	[0.003]	[0.004]	[0.006]	[0.002]	[0.002]
Mean DV	0.261	0.265	0.271	0.252	0.322
R-squared	0.121	0.121	0.117	0.102	0.120
Observations	343,737	171,378	84,304	733,095	849,991

Notes: This table reports estimates of the effect of decreasing copayments on PAD delivery on the probability of a c-section. PAD private hospitals are hospitals that participate in the PAD program but are not in the public healthcare system. *Public Insurance B, C or D* is a dummy for a delivery by a woman with public insurance B, C or D, and *Post* is a dummy that equals one after April 2003.

All regressions include *Public Insurance A*, *Public Insurance B, C or D*, and mother's age-year, county, and month fixed effects. Column (1) to (3) use different time windows around the policy (12, 6 and 3 months), columns (4) restricts the comparison group only to women with public insurance A, and column (5) uses women with private insurance and public insurance B, C or D as the treatment group.

The mean of dependent variable corresponds to the treated in the pre-treatment period.

Robust standard errors reported in brackets.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 4: IV/2SLS estimates of the effect of decreasing copayments on PAD delivery on the probability of a c-section

	Cesarean section		First stage	
	OLS	IV/2SLS	Treatment	Treatment × Post
	(1)	(2)	(3)	(4)
Public Insurance B, C or D × Post	0.087***	0.093***		
	[0.002]	[0.030]		
Share Public Insurance B, C or D			0.416***	−0.180***
			[0.012]	[0.016]
Share Public Insurance B, C or D × Post			−0.282***	0.401***
			[0.023]	[0.036]
F stat (weak inst.)			617.2	132.3
p-value (weak inst.)			0.000	0.000
Mean DV	0.251			
Observations	843,375	843,375	843,375	843,375

Notes: This table reports IV estimates of the effect of decreasing copayments on PAD delivery on the probability of a c-section. PAD private hospitals are hospitals that participate in the PAD program but are not in the public healthcare system. *Public Insurance B, C or D* is a dummy for a delivery by a woman with public insurance B, C or D, and *Post* is a dummy that equals one after April 2003.

The instruments are *Share Public Insurance B, C or D* and its interactions with *Post*, where *Share Public Insurance B, C or D* is the share of deliveries in 2002 by women with public insurance B, C or D of age a and living in county c.

All regressions include *Public Insurance B, C or D*, and mother's age-year, county-year, and month fixed effects.

The test for weak instruments uses the F statistics and p-values from Sanderson and Windmeijer (2016).

The mean of dependent variable corresponds to the treated in the pre-treatment period.

Robust standard errors for column (1), and standard errors, clustered by mother's county of residence, for column (2) - (4) reported in brackets.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 5: Model fit: Data versus model

	Data	Model
C-section rate	0.63	0.64
Capacity utilization	0.67	0.65
SD(weekly deliveries)	5.95	4.16

Notes: This table reports means weighted by hospital capacity for c-section rates, capacity utilization, and standard deviation of weekly deliveries computed from the data and predicted by the model.

For each hospital, a c-section rate is the ratio between the mean of weekly cesarean deliveries and the mean of weekly deliveries, and capacity utilization is the ratio between the mean of weekly deliveries and hospital capacity. Hospital capacity is the 90 percentile of weekly births in the period 2006–2007.

The data uses sample means and standard deviations for the period 2006–2007.

The model uses expectations and standard deviations for a hospital with the same capacity as the data.

Table 6: Counterfactual experiments

	Baseline	Counterfactual 1		Counterfactual 2	
		Mean	Change (in %)	Mean	Change (in %)
C-section rate	0.64	0.26	−60	0.25	−61
Capacity utilization	0.65	0.62	−5	0.50	−24
SD(weekly deliveries)	4.16	5.42	30	5.37	29
Referrals (over capacity)	0.02	0.05	200	0.02	22
Profits (over capacity)	0.80	0.69	−14	0.71	−12

Notes: This table reports means weighted by hospital capacity for different variables in the base model and two counterfactual experiments.

Experiment 1 sets a c-section rate of 0.26 (the mean c-section rate for public and non-PAD private hospitals) for each hospital. Experiment 2 sets a c-section rate of 0.26 and an upper bound on the ratio of transfers over capacity of 0.02 for each hospital. c-section rate is the ratio between the mean of cesarean deliveries and the mean of total deliveries, capacity utilization is the mean of total deliveries over the hospital capacity, SD(weekly deliveries) is the standard deviation of weekly deliveries, transfers is the ratio between mean transfers and hospital capacity, and profits is the ratio between mean profits and hospital capacity. Hospital capacity is the 90 percentile of weekly births in the period 2006–2007.

Table 7: Policy simulation

	Data			Model		
	Before	After	Change	Before	After	Change
C-section rate	0.57	0.63	0.05	0.64	0.70	0.06
Capacity utilization	0.65	0.67	0.02	0.65	0.67	0.02

Notes: This table reports c-section rates before (period 2001–2002) and after (2006–2007) the policy change.

The policy simulation fix hospital capacity using the capacity in the data in 2006–2007, and set the hospital demand for each hospital to match capacity utilization in 2001–2002 (before) and 2006–2007 (after).

Table 8: Descriptive statistics for birth data, 2002-2016

Variables	Mean	s.d.
Delivery at a PAD private hospital	0.27	0.44
Delivery at a non-PAD private hospital	0.05	0.22
Delivery at a public hospital	0.68	0.47
Gestational age at birth (in weeks)	38.6	1.5
Early-term birth (on week 37 or 38)	0.36	0.48
Preterm	0.07	0.25
Multiple births	0.02	0.13
Mother's age	27.4	6.7
Mother's labor force participation	0.39	0.49
N. of children	1.9	1.0
Observations	$3,442,284$	

Source: Departamento de Estadísticas e Información de Salud (DEIS), Ministerio de Salud, Chile.

Table 9: Effect of expected hospital demand on the probability of early-term birth

	Public and Non-PAD Private Hospitals	PAD Private Hospitals
	(1)	(2)
25th pctl < Demand ≤ 50th pctl	−0.001	0.002
	[0.001]	[0.002]
50th pctl < Demand ≤ 75th pctl	0.001	0.005**
	[0.001]	[0.002]
Demand > 75th pctl	0.000	0.009***
	[0.001]	[0.002]
Mean DV	0.315	0.496
R-squared	0.042	0.076
Observations	2,445,726	895,403

Notes: This table reports OLS estimates of expected hospital demand on early-term birth (gestational age 37 or 38 weeks) for the period 2002–2016. *Demand* is the expected hospital demand in week w of year y for hospital h. 25th pctl < Demand ≤ 50th pctl is a dummy that indicates if that expected demand is in the 25 to 50 percentile of the distribution of expected demand for the hospital h in year y. Similar definitions apply for other dummies.

All regressions control for single birth, sex of the baby, number of children, mother's educational level, and mother's age-year, mother's county of residence, and hospital-month fixed effects.

The mean of dependent variable corresponds to the treated in the pre-treatment period.

Standard errors, clustered by hospital, reported in brackets.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 10: Effect of expected hospital demand on the probability of early-term birth by hospital c-section rate intensity

	C-section rate $\leq 25\%$	C-section rate 25 - 40%	C-section rate $\geq 40\%$
	(1)	(2)	(3)
25th pctl < Demand $\leq$ 50th pctl	−0.000	−0.002	0.001
	[0.002]	[0.002]	[0.002]
50th pctl < Demand $\leq$ 75th pctl	0.002*	−0.001	0.004**
	[0.001]	[0.002]	[0.002]
Demand > 75th pctl	0.001	−0.001	0.008***
	[0.002]	[0.002]	[0.002]
Mean DV	0.304	0.325	0.463
R-squared	0.037	0.040	0.089
Observations	1,138,885	1,095,011	1,107,133

Notes: This table reports OLS estimates of expected hospital demand on early-term birth (gestational age 37 or 38 weeks) for all hospitals in the period 2002–2016. *Demand* is the expected hospital demand in week w of year y for hospital h. 25th pctl < Demand $\leq$ 50th pctl is a dummy that indicates if that expected demand is in the 25 to 50 percentile of the distribution of expected demand for the hospital h in year y. Similar definitions apply for other dummies. C-section rate is the average c-section rate for a hospital in 2002–2016.
All regressions control for single birth, sex of the baby, number of children, mother's educational level, and mother's age-year, mother's county of residence, and hospital-month fixed effects.
The mean of dependent variable corresponds to the treated in the pre-treatment period.
Standard errors, clustered by hospital, reported in brackets.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.