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Low staffing in the maternity ward: Keep calm and call the surgeon☆

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ABSTRACT

This paper examines how workload affects the provision of care in a large but understudied segment of the healthcare sector – maternity wards. I use detailed patient-level administrative data on childbirth, and exploit quasi-random assignment of unscheduled patients to different staffing ratios. I find that the probability of C-section increases at a decreasing rate with workload. I show that this result is not attributable to patients' differential sorting across staffing levels. Instead, I find evidence that C-sections are used to alleviate midwives' workload -they are faster than vaginal births and performed by physicians. I also exploit patient's civil status to determine whether the effect varies with patient's bargaining power -single women are on average more likely to be alone in the delivery room. Consistent with induced demand, only single patients are more likely to receive a C-section when admitted at high workload levels.

1. Introduction

Over the last decades health care systems in developed countries have been under constant pressure to reduce costs, despite facing an increasing demand for health care services. In order to avoid a trade-off between cutting down on costs and a negative impact on patient's health outcomes, experts currently point towards the reduction of waste as the best way to go (Berwick and Hackbarth, 2012). Among the several sources of waste, two widely cited ones are: (i) failures of care delivery -the lack of adoption of known best practices-, and (ii) overtreatment -the carrying out of treatments that cannot possibly improve patients' health. These two sources of waste are particularly salient in maternity ward settings.

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The presence of midwives -as opposed to physicians- in assisting birth speaks to the first point. Even though there is consensus about the crucial role of midwives in guaranteeing access to quality services and better health outcomes for both mother and child (Bender et al., 2014), the WHO has already expressed concern about a worldwide "shortage of midwives" (Büscher et al., 2009).[1]

Meanwhile, cesarean sections (C-sections) are the most commonly performed operating room procedures in the US (McDermott et al., 2017) and rank highly among greatly overused interventions. While the international healthcare community considers an ideal rate of C-sections to be between 10–15% (World Health Organization, 1985), country average rates in Europe vary from as low as 15.6% in The Netherlands to as high as 36.8% in Italy (OECD data 2012). This large variation in C-section rates has lead governments and clinicians to express their concern about its possible overuse and potential negative impact on patients health (World Health Organization, 2015). Indeed, C-sections not only cost more than vaginal deliveries, but they also imply higher risks for both the mother and the infant (Deneux-Tharaux et al., 2006; Gregory et al., 2012; Curtin et al., 2015; Costa-Ramón et al., 2018) and, according to a growing medical literature, are associated to lower long-term outcomes of children's health.[2] In addition, because vaginal delivery after a C-section (VBAC) is very unlikely, one C-section sets a path dependency for more C-sections in future births.[3] There is also evidence that women who follow a C-section are more likely to have less children (Norberg and Pantano, 2016) -something that is particularly alarming in developed countries with already low fertility rates- and to develop postnatal depression (Tonei, 2019).

In light of these concerns, a natural question is whether a situation of low midwifery staffing can result in more unnecessary C-sections being performed. There are two ways in which high midwives' workload can lead to a raise in C-sections. First, patients' health may worse with lack of midwives care to a point where a C-section is clinically recommended. Second, physicians may decide to change to surgery to reduce midwives' workload. C-sections take less time than vaginal births since there is no need to wait for the appropriate dilation of the cervix. Furthermore, C-sections are less intensive in midwives' time and more intensive in physicians' time.[4]

To identify the causal effect of workload on the probability of getting a C-section, I exploit a simple natural experiment that varies the level of workload each patient is exposed to in an arguably random manner. This is the case for all unscheduled patients, those that follow the natural course of birth and only go to the hospital once labor has already started and/or their water has broken. Because their precise day and time of admission to the hospital is unknown, the unit's workload level upon being admitted is orthogonal to the patient's demographic and health characteristics (and to their ex-ante probability of delivering by C-section). In addition, my measure of workload varies with both the number of patients who arrived before and the number of midwives on duty in the delivery room, two variables that are unknown to the incoming patient. I provide evidence that the time of admission is uniformly distributed across hours of the day and days of the week only for these unscheduled patients. Moreover, I show that workload is not correlated with commonly known predictors of C-sections like birth-weight, gender, being a first-time mother, age, and ER visits during pregnancy.

The data for this paper comes from a census of births from a large academic medical center in Italy for the period 2011–2014. Three features of this data set make it well suited for tackling the issue at hand. First, Italian birth certificates have precise information on delivery method, allowing the identification of patients attempting a vaginal delivery and those who have a scheduled C-section.[5] This information is crucial to exclude scheduled patients from the analysis sample since their time of admission to the hospital has been arranged in advance with the physician. Second, using patient's ID, each certificate was linked with time stamps containing the exact time of admission and discharge. I use this information to compute the actual number of patients waiting in the delivery room at each point in time. Finally, this is complemented with data on the number of midwives scheduled for duty by month, day of the week and shift. This allows me to adjust demand by supply-side factors. My measure of workload is then calculated as the ratio between the observed number of unscheduled patients waiting to give birth at the time the indexed patient is admitted and the number of midwives scheduled to be in the delivery room.

The analysis is divided in two parts. First, I show that there is a non-linear relationship between midwives' workload and delivery method: the probability of C-section increases at a decreasing rate with workload. More precisely, I find that changing a patient's observed workload at admission from the 10th (RPM=1.25) to the 90th (RPM=3.5) percentile would raise her chances of getting a C-section by 2.5 percentage points (a 24% raise with respect to the mean). Put differently,

[1] This has also been mentioned by midwifery colleges. In a 2015 report, The Royal College of Midwives estimates that the UK "... needs 2600 more midwives to be able to cope with the number of births the country is experiencing... ". The Federal Association of Midwives of Spain (FAME) has as main objective to address the shortage of midwives in the health care system. The president of the Italian Midwifery Association recently stated that "... there is a shortage of midwives. Too few to guaranty the proper level of care that other European Countries have".

[2] Infants born by C-section are not exposed to the maternal bacteria of the birth canal and as a consequence have different intestinal bacteria, which can affect their immune system and other important processes. For a meta-analysis of this literature see (Blustein and Liu, 2015). There is also an emerging economic literature looking at the causal link between C-sections and children's health. They find that babies born by C-section are more likely to visit the ED for a respiratory-related problem within their first year of life (Card et al., 2018; 2019) and more likely to be hospitalized for asthma syndromes up to their adolescence (Jachetta, 2015; Costa-Ramón et al., 2020) with respect to babies born vaginally.

[3] VBAC rate is only 8.3% in the US, and 12% in Italy.

[4] Although recovery time is longer after a C-section relative to a vaginal birth, post-birth care is administered by another staff-team outside the delivery room in the post-natal unit.

[5] Although this seems like indispensable and straight forward information, publicly available vital statistics in the US lacked any information on 'trial of labor' until 2004, making it impossible to separate scheduled from unscheduled patients before that date.

if all patients were to observe a maximum workload level of 1.25 patients-per midwife, about 14 percent of unscheduled C-sections would be avoided. I also find that other measures of treatment intensity are not affected by workload. Similarly, after controlling for method of delivery, maternal and infant morbidity are invariant with workload levels.

The second part of the analysis looks at whether physician induced demand (PID) plays a role in this differential treatment between patients admitted during high and low staffing. Within the agency discrimination framework, physicians are more likely to practice an unnecessary surgery on patients with lower bargaining power. I tests for the presence of agency using patient's civil status, that is, comparing single and married patients. Single patients are -on average- more likely to be alone in the delivery room, reducing the physician's cost of inducing a C-section. Indeed, the probability of delivering by C-section between these two groups is virtually the same for low-workload levels whereas single patients observe a rise in the probability of C-section with a rise in workload.

2. Related literature

This paper contributes to a large literature looking at the effects of workload (measured as patient-to-staff ratios) on patient health outcomes. Most prior studies use exogenous variation in workload stemming from new legislation raising the mandatory minimum staffing ratios (Tong, 2011; Cook et al., 2012; Lin, 2014; Matsudaira, 2014; Chen and Grabowski, 2015). One exception is Evans and Kim (2006), who use variation in the number of admissions in the two days after as an exogenous shock to the effective staff level. These papers find mixed results in terms of the effect of workload on quality of care. My contribution to this literature is twofold. First, previous studies using legislative changes exploit an aggregate, permanent and positive variation in capacity (Harris et al., 2019), while I use *temporary* and *stochastic* changes in the staffing ratios that vary at the *patient* level. Second, I contribute with causal estimates of the effect of workload on health outcomes in a so far understudied segment of the healthcare sector: the maternity ward.

In contrast, there is little empirical work on the effects of workload on the provision of health care (i.e. the channel through which workload may affect health outcomes). There are, however, several recent and concurrent papers tackling this issue using health-care provider administrative data. Harris et al. (2019) look at exogenous changes in nurse capacity in five public clinics in Tennessee and find that providers value sufficient time spent with patients over seeing more patients. Alkalay et al. (2018) use data from eleven primary care clinics in Israel and exploit the absence of colleagues as a source of exogenous variation in physician workload, and find that referrals to specialists and lab tests go down with shorter visits. Neprash (2016) finds that primary care physicians perform fewer procedures and record fewer diagnoses for appointments that start later due to physicians being behind schedule. Finally, Freedman et al. (2021) use unexpected schedule changes as variation in primary care physician's time pressure and find that higher pressure reduces the number of diagnoses recorded and increases both scheduled and unscheduled follow-up care. My paper differs from these papers in three important ways. First, all these papers focus on primary care, an environment where time pressure is among the lowest in health care. Meanwhile, a maternity-ward's demand is mainly driven by unscheduled patients that need assistance within a relatively short span of time.[6] Second, with the exception of Freedman et al. (2021), these papers use shocks to provider availability and time (supply side) while I exploit stochastic variation in patients arrivals driven by nature (demand side). Finally, with the exception of Alkalay et al. (2018), all these papers use data from the US, a context where financial incentives have been shown to significantly affect health-care provision (Clemens and Gottlieb, 2014; Ho and Pakes, 2014).[7] On the contrary, physicians in Italy receive a fix salary, and non-financial incentives may play a bigger role in the supply-driven variation in treatment.[8]

A large related literature studies how physicians may induce a patient's demand against the physician's interpretation of the best interests of the patient (Johnson, 2014).[9] Many of these papers have focused on the maternity ward set-up and the decision of delivery method due to its discretionary nature. One strand of this literature assumes the presence of information asymmetry and exploits variation in a wide range of physicians' incentives to induce. Starting from Gruber and Owings (1996) where they use a fall in physician's salary as a trigger for more C-sections, to other incentives like relative prices between C-sections and vaginal deliveries (Gruber et al., 1999; Alexander et al., 2013; Allin et al., 2015), defensive medicine (Currie and MacLeod, 2008; Dranove and Watanabe, 2010; Bertoli and Grembi, 2019), and physician's scheduling convenience (Lefèvre, 2014).[10] Unlike previous studies, my findings suggest that physicians may have incentives to perform

[6] In a recent and closely related work, Maibom et al. (2021) look at the impact of day-to-day variation in maternity ward crowding on medical procedure use and health outcomes using the universe of births in Denmark. Similarly to this study, they find that maternity wards change the provision of medical procedures in crowded days in ways that alleviate their workload -although they do not observe any change on C-sections- with negligible effects on health. While I only have data for one hospital, my paper contributes with a more precise measure of crowding by using individual -instead of hospital-levels of workload and the number of staff scheduled.

[7] Although this is not exclusive to the US. Brekke et al. (2017) find that physicians in Norway respond to fee changes.

[8] Recent work suggest that non-financial incentives may also be important for the US market. Using survey data linked to fee-for-service Medicare expenditures, Cutler et al. (2019) find that physicians' responsiveness to financial factors play a relatively small role in explaining equilibrium variations in utilization patterns in our context.

[9] However it is worth noticing that changes in health care supply due to changes in private physician incentives may not necessarily have a negative impact on patient welfare. (Jacobson et al., 2017) develop a model where the effect is ambiguous, depending on whether the increase in care provision reflects induced demand for ineffective care or a reduction in prior rationing of effective care.

[10] For an extensive review of the literature on PID in the maternity ward setting see Allin et al. (2015).

medically unnecessary C-sections for reasons other than personal gain.[11] Indeed, if physicians cannot adjust the price nor the quantity, they may resort to lowering the quality of treatment. In the maternity ward setting, a patient's unnecessary C-section can alleviate midwives' workload and allow them to better attend other patients.

Another strand of the literature on PID uses heterogeneity in information asymmetry to explain the variation in C-section levels. Two recent papers compare the treatment received by expert and non-expert patients in the maternity ward set up. Grytten et al. (2011) observe that, in an institutional context with incentives to reduce C-sections, non-expert patients get less C-sections than expert patients. They conclude that a model of statistical discrimination (expert patients are better at communicating with the physician) explains their results better than one of agency discrimination (the physician influences the diagnosis and treatment for non-expert patients). On the contrary, Johnson and Rehavi (2016) find evidence that physicians are more likely to exploit the information asymmetry when it is profitable (agency discrimination). They do so by comparing physician patients with non-physician patients, in settings with and without financial incentives to perform C-sections. My paper differs from them in that I refrain from exploiting variation in information asymmetry. Instead, I use variation in the presence of another person in the delivery room caring for the patient's interest (husband) and raising the physician's cost of inducing an unnecessary treatment.

3. Clinical and institutional setting

3.1. Choice of delivery method

Maternity wards receive two types of patients: scheduled and unscheduled. The former includes patients admitted for an elective C-section and those who will be induced.[12] For patients following an elective C-sections the date of delivery is set in advance, and there is no possibility for changing delivery method (unless the mother goes into labor before). These pregnancies typically present some health condition that constitute a risk for the mother and/or the baby if delivered vaginally. Similarly, induced patients already know in advance the date they will be induced but, although they will attempt a vaginal delivery, the physician may still decide to change delivery method on the way if considered necessary.

The remaining patients, those attempting to follow the natural course of labor and vaginal delivery, are the main focus of this study. For these patients the process starts with frequent contractions and/or because they believe their water has broken (spontaneous onset of labor). Once the mother arrives to the hospital she is evaluated and if in active labor, she is admitted into the labor and delivery room and assigned a gynecologist and a midwife. If everything goes as planned and the patient is able to have a vaginal delivery, the midwife will be the one helping her through out the whole process.[13] Nevertheless, during labor there are several medical conditions that can emerge and complicate a vaginal birth, putting in danger the health of the infant and/or the mother. Under these circumstances, the midwife and gynecologist may decide to recommend to have a C-section instead. More importantly, the presence of some of these medical conditions depends heavily on the subjective opinion of the physician.[14] This gray area -or asymmetry of information- on when a C-section is necessary gives the medical team more room to recommend surgery to the patient, even when not medically needed.

3.2. Mechanisms

There are, at least, two ways in which high midwives' workload can lead to a raise in C-sections. One possibility is that, during high workload, the midwives' time dedicated to each patient is lower and the quality of care inappropriate, eventually resulting in the need for C-section. Under this scenario, shifting delivery method can be optimal for the patient.

Alternatively, a raise in C-sections with workload can be a consequence of physician induced demand (PID). When the demand for midwives increases (more unscheduled births), holding everything else constant, the team may find it optimal to shift patients from midwives to physicians by changing delivery method. Since a C-section takes less time than a vaginal birth -no need to wait for the appropriate dilation of the cervix-, midwives' workload would be reduced. Unlike in the previous case, under PID the patient receiving an unnecessary C-section is not getting optimal treatment.

3.3. Childbirth in Italian public hospitals

The maternity unit analyzed in this paper is part of one large teaching hospital in Italy. The staff working in the delivery room are paid a fixed salary, meaning they have no personal financial incentive to recommend any particular treatment. On the other hand, hospitals are reimbursed depending on a DRG (Diagnosed-related group) tariff system, which in general gives a higher reward for a C-section than for a vaginal delivery.[15]

[11] One exception is Johnson et al. (2016), where the authors find that physicians are 25% more likely to perform a C-section on patients with whom they have a pre-existing clinical relationship and argue this is due to physician's greater disutility from own-patients' difficult labors.

[12] Most inducements are performed on pregnancies that have past their due date and still haven't started labor.

[13] This is in stark contrast to the standard Obstetrician-led maternity care in the United States where physicians are in charge of all births, including uncomplicated vaginal deliveries.

[14] Two of these more 'subjective' conditions are dystocia (abnormally slow labor) and fetal distress.

[15] For a deeper discussion on the Italian Health System see Francese et al. (2014).

Table 1
Summary statistics.

	All		Married		Single		
	Mean	SD	Mean	SD	Mean	SD	Diff.
Mother characteristics							
(mean) age	32.5	5.6	32.8	5.3	32.1	6.0	−0.75***
% university degree	30.9	46.2	34.0	47.4	26.9	44.4	−7.05***
% middle school	77.3	41.9	78.2	41.3	76.1	42.7	−2.14*
% married	56.6	49.6	100.0	0.0	0.0	0.0	−100.00
% first-time mothers	42.1	49.4	37.1	48.3	48.5	50.0	11.42***
Pregnancy characteristics							
(mean) weeks of gestation	39.0	2.2	38.9	2.2	39.0	2.3	0.04
% preterm (<37 wofg)	6.0	23.8	5.7	23.2	6.5	24.6	0.73
% with at-least 1 ER visit	12.6	33.2	12.5	33.1	12.8	33.4	0.25
Infant characteristics							
% male	51.6	50.0	52.1	50.0	51.1	50.0	−0.99
(mean) weight in grams	3,265.6	533.6	3,276.9	526.5	3,250.8	542.6	−26.11
% low birthweight (< 2500gr)	5.1	21.9	4.9	21.6	5.3	22.3	0.34
% high birthweight (> 4000gr)	5.0	21.9	5.2	22.2	4.8	21.5	−0.34
Travel (±)							
Distance in km	11.7	9.6	11.8	9.7	11.5	9.4	−0.34
Travel time in minutes	19.6	9.5	19.8	9.6	19.5	9.2	−0.32
Outcomes							
% vaginal births	89.6	30.5	90.8	28.9	88.1	32.4	−2.69***
% unscheduled C-sections	10.4	30.5	9.2	28.9	11.9	32.4	2.69***
% operative births	8.8	28.3	8.2	27.5	9.6	29.4	1.34
% transfered to neonatal ICU	7.2	25.9	6.2	24.1	8.6	28.0	2.37***
% lack of skin-to-skin contact	18.0	38.4	16.8	37.4	19.5	39.6	2.74**
% non-exclusive breastfeeding	32.2	46.7	30.3	46.0	34.7	47.6	4.46**
% Apgar score<9	4.7	21.2	4.1	19.9	5.5	22.8	1.34*
% with severe hemorrhage	11.3	31.7	10.2	30.2	12.9	33.5	2.72**
(mean) length of stay in hours	74.3	30.1	74.2	29.5	74.4	31.0	0.21
Observations	6142		3477		2665		6142

Notes: Table contains variables used in the empirical analysis for the main estimation sample for the period 2011–2014. Notably, the sample is limited to singleton mothers who went into labor before giving birth (i.e. attempt a vaginal delivery) without inducement. The last column reports differences in means between married and single patients and whether they are statistically significantly different from zero at standard levels. The category single includes all non-married patients, including single, divorced, separated and widowed.
± Information regarding travel distance and time were obtained from google maps and is only available for patients residing in one of the 42 “commune” (districts) in the province of Florence plus the commune of Prato and Pistoia -covering 87% of my sample.

In Appendix Appendix B, Fig. B.7 uses hospital-level data for Italy in 2017 to show that the rate of C-section is negatively (positively) correlated with the percent of births assisted by a midwife (gynecologist). Table B.9 shows that estimates of a linear regression are statistically significant. Although no causal interpretation can be drawn, this provides evidence of variation in both C-section rates and the use of different health-worker types between Italian hospitals.

4. Empirical methodology

4.1. A natural experiment

An ideal experiment to test for an effect of workload on patients' delivery method would imply assigning parturient women randomly between two different hospital types: a first one with already a large number of patients and a second type, identical to the first, but with few patients and hence ready to focus entirely on the coming patient. This is not possible to implement in practice for obvious reasons.

This paper focuses on patients who attempt to have a vaginal delivery, and uses plausibly exogenous variability in the number of patients and midwives present at admission to causally identify the impact of workload on delivery method. For the majority of births, the time of arrival is unknown to the hospital beforehand. In the same way, the capacity utilization of the maternity ward in a given point in time is unknown to the patients until they reach the hospital. For these patients, their pre-admission probability of developing a complication and delivering by C-section is orthogonal to the level of crowding at the hospital.

The study sample includes all births that, up to the point of arriving to the hospital, followed the “natural” course of pregnancy and labor. This means leaving out all scheduled deliveries where the physician decided, together with the patient,

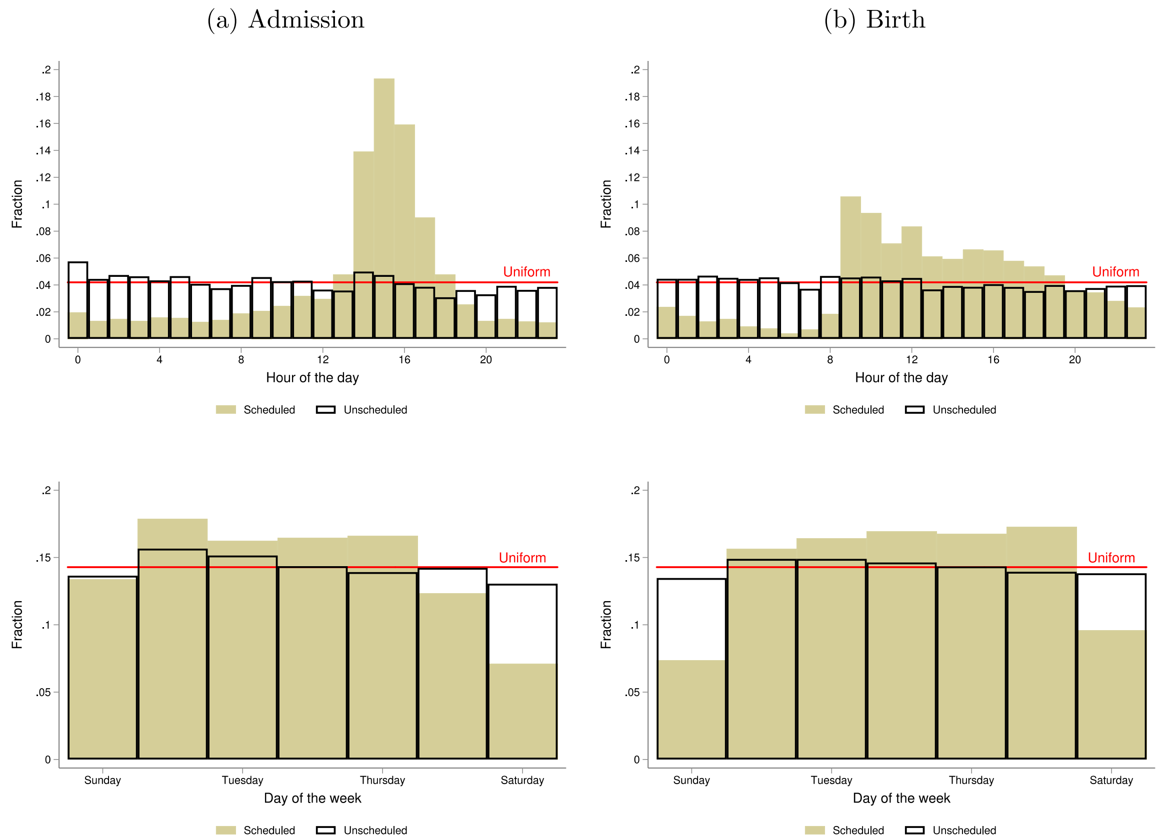

Fig. 1. Distribution of admissions and births. *Notes:* Scheduled patients include elective C-sections and patients who were induced into labor. Unscheduled patients are those who started labor and attempt a vaginal delivery.

the date when the birth should take place. This type of patients are those who had an elective C-section or who were pharmaceutically induced to start labor.[16]

The left column of Fig. 1 shows the distribution of admissions by hour of the day and day of the week. The right column does the same for births. Both scheduled and unscheduled patients distributions are plotted separately for comparison. Admissions of scheduled patients are concentrated in the afternoon, while births start at 9 a.m. and become less and less frequent as the day goes by. Instead, both admissions and births for unscheduled patients are very close to a uniform distribution within a day, albeit with a slightly higher frequency around midnight and a lower frequency in the evening. This is in accordance with previous studies in the medical literature which find evidence of a significant circadian frequency in both the onset of labor and birth of "natural" deliveries, with a peak frequency around midnight and a lowest point in the afternoon (Charles, 1953; Kaiser and Halberg, 1962; Glattre and Bjerkedal, 1983). Although these differences in observations across the time of the day are small, I will include fixed effects for shifts (or hour) of admission to address potential selection effects.

Similarly, when looking at the distribution by days of the week, unscheduled patients are randomly distributed while scheduled patients are less common to be admitted on Saturdays, and less likely to have surgery on Sundays and Saturdays. In Appendix A, I repeat the exercise disaggregating scheduled patients in scheduled C-sections and induced deliveries. Results are qualitatively the same, with both categories showing non-uniform distributions across days and hours.

4.2. Data

Previous studies looking at newborns' health typically use anonymous birth certificates which are publicly available for many countries and for long periods of time. However, these data sets commonly lack information on key variables needed for a rigorous study of staffing levels, namely, the exact date and time of admission of patients (demand side) and the number of staff available (supply side) in each delivery unit.

[16] For more evidence supporting the criteria for selecting the working sample see Appendix A.

The clinical setting for this study is the maternity ward of a large public university hospital in Tuscany (Italy) during the years 2011–2014. With a 31% average C-section rate, this hospital is very close to the national Italian rate of 33% among public hospitals in 2012.[17] The primary databases used are two: (i) birth certificates (Certificato di assistenza al parto); and (ii) hospital admissions (Scheda di Dimissione Ospedaliera). Birth certificates constitute a census of all births that took place in the hospital in this period. They contain information on mother characteristics (e.g. community of residence, education, civil status, age, previous deliveries, etc.), pregnancy characteristics (e.g. weeks of gestation, controls, assisted reproduction, etc.) and birth characteristics (e.g. time of birth, type of labor, attendant, place, weight of the baby etc.). The administrative hospital admission data provides information on the time of admission and time of discharge for each patient. Using unique mother-pregnancy identifiers, both databases can be linked.

The aforementioned data on patients is complemented with information on the level of staff scheduled to be present in the delivery room each month, day of the week and shift combination. Note that this is not the effective level of staff present at each point in time but the staffing rule of the delivery unit. Anecdotal evidence suggests that deviations from planned levels are rare, even because the hospital calls in someone else when an employee misses a shift.

There were approximately 11,359 singleton births at this hospital between 2011 and 2014. After excluding all scheduled patients the sample goes down to 6,479 births. Finally, after dropping observations with missing time of admission, maternal age, education, birth order, weight and prenatal visits, and patients arriving the first and last 15 days in the sample, the number of observations in the working sample is 6,142. The models described below are fitted to this sample.[18] Table 1 summarizes the variables used in the analysis.

4.3. An exogenous measure of midwives' workload

A good measure of workload contains information on both the number of patients and hospital's staff. For the maternity ward setting I use the ratio of patients to midwives (RPM) in the delivery room.[19] The richness of the data in hand allows me to construct a very precise measure of the number of parturient women in the maternity ward at any point in time and to differentiate between those waiting to give birth and those in postpartum.

There are yet two decisions to be taken regarding the moment at which this ratio is calculated and the type of patients to include in the numerator. On the former, because the median patient stays 7 hours in the delivery room between admission and birth, it is not obvious at what time to measure the level of staffing. The two most straightforward options are at the time of admission and at the time of birth. The last one has the advantage of measuring staff when needed the most, meaning, when the mother needs help to give birth. The problem with this option is that, given that physicians can rush a delivery (e.g. by doing a C-section), the level of staffing at time of birth can be endogenously determined. On the other hand, even though the level of staffing at time of admission can be relatively less relevant, it is indeed an exogenous shock. For these reasons I will use the ratio of patients to midwives calculated at the time of admission of each patient.

On the second issue, it is important to decide which patients are included in this measure of demand. The first option would be to include all patients (regardless of whether they are scheduled or induced). Nevertheless, since the main outcome of interest is the probability of C-section, counting elective C-sections in the measure of staffing would make it biased. To see this, note that when there are more elective C-sections there are also more gynecologists ready to perform them. Incorporating elective C-sections in the numerator would not only include a demand side but also a change in the supply of physicians who can perform C-sections. For this reason, I include in the numerator all patients but those already scheduled to give birth by C-section.[20] Also note that these are the type of patients that shift the demand of midwives' service but not that of physicians' services -who take care of complicated deliveries that use instruments or surgery.

Then, the workload observed by a patient admitted at time t is defined as

$$\text{RPM}_t = \frac{\text{Patients}_t}{\text{Midwives}_t} \tag{1}$$

where the numerator is the number of patients waiting to attempt a vaginal birth, and the denominator is the number of midwives scheduled to be present in the delivery room. The lower panel of Fig. 2 shows the distribution of the RPM. The ratio is unimodal and slightly skewed to the right. On average, there are 2.3 patients for every midwife in the delivery room. Table 2 shows the mean number of midwives, gynecologists, patients in the delivery room and RPM by day of the week and

[17] Hospital and national statistics were obtained from Osservatorio di Epidemiologia dell'Agenzia Regionale di Sanitá (ARS) della Toscana (2014) and Ministero della Salut (2012) respectively.

[18] Results are virtually the same when including plural births in the sample.

[19] One drawback of this measure is that it constraints the coefficient of interest due to the simultaneous variations in numerator and denominator. The fact that my preferred model specification uses fixed effects by shift and day-of-the-week means that all the variation used for the estimation comes solely from fluctuations in the numerator, alleviating this issue. Furthermore, alternative models using fluctuations in the number of patients -instead of the RPM- as treatment finds the same results (see Table B.14).

[20] Note that this is not the same sample as the study sample because it also includes induced deliveries. Those are not at risk of contaminating the measure because they will still attempt a vaginal delivery, and need a midwife to help them.

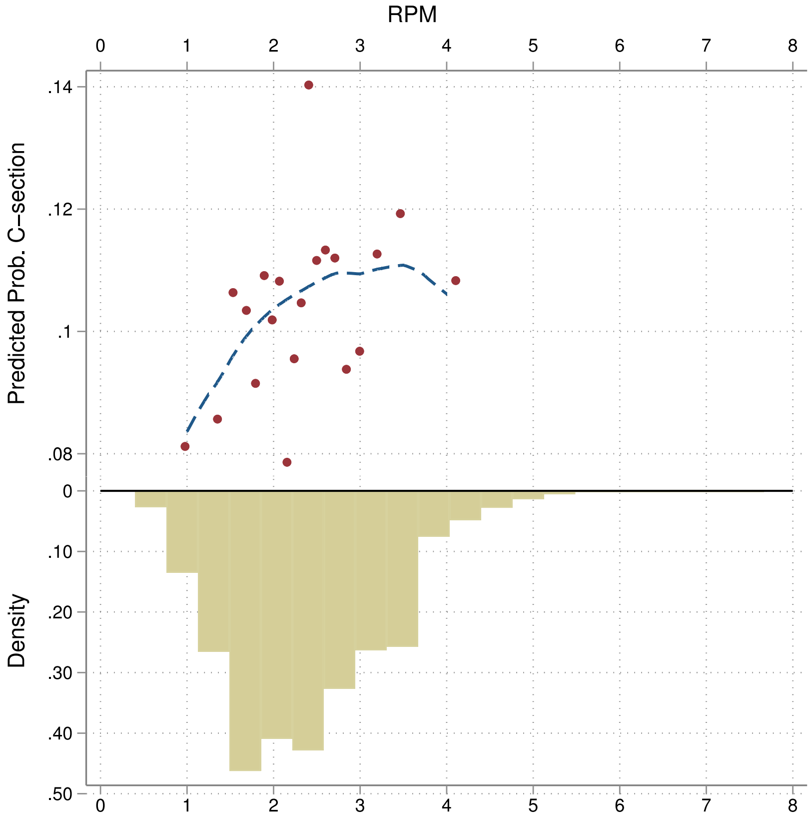

Fig. 2. Density and effect of staffing on probability of C-section. *Notes:* In the upper panel, the dashed line shows the fitted values of a local linear regression using a triangular kernel and a bandwidth of 1.5 RPM, shown over the subset of observations from 1 (5% percentile) to 4 (95% percentile) RPM on the x-axis. The dots are the mean probability of C-section as a function of RPM (controlling for mother and pregnancy variables and time fixed effects mentioned in Section 4.4) using a binned scatter plot with 20 equally sized bins (using "binscatter" in Stata (Stepner, 2013)). The lower panel shows the density distribution of the RPM.

Table 2
Descriptive statistics for the RPM.

	Midwives		Gynecologists		Patients		RPM	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Weekdays								
Morning (7am-1pm)	5	0	3	0	8	2.6	1.6	.53
Afternoon (1pm-7pm)	4	0	3	0	8.4	2.9	2.1	.72
Night (7pm-7am)	3	0	1	0	8.1	2.7	2.7	.89
Saturdays								
Morning (7am-1pm)	4	0	1	0	8.2	2.6	2.1	.64
Afternoon (1pm-7pm)	4	0	1	0	8.2	2.4	2	.61
Night (7pm-7am)	3	0	1	0	7.9	2.6	2.6	.87
Sundays and holidays								
Morning (7am-1pm)	3	0	1	0	7.8	2.7	2.6	.91
Afternoon (1pm-7pm)	3	0	1	0	7.8	2.8	2.6	.92
Night (7pm-7am)	3	0	1	0	7.6	2.6	2.5	.87

Notes: Based on the maternity's staff schedule and birth certificates from the main sample for the period 2011–2014.

shift of admission.[21] The number of midwives is higher during the morning shift (5), and lower at nights and Sundays (3). On the other hand, the average number of patients is virtually the same across days of the week and shifts.[22]

[21] The scheduled number of personnel is constant across months and years in the sample.

[22] Figure B.9 shows the average number of patients and RPM at admission in time (by hour of the day, day of the week, and month of the year). There is no discernible pattern of either measure in time, except for a higher number of patients in the month of August.

4.4. Econometric specification

The first part of the analysis estimates OLS regressions of a binary indicator for C-section on the treatment variable along with demographic and clinical controls. A simple reduced-form linear probability model of the following type is used:

$$y_{it} = \alpha + \beta \mathrm{RPM}_t + \theta \mathrm{X}_i + \gamma \mathrm{G}_t + \theta_t + \epsilon_{it} \tag{2}$$

where y_i is a dummy variable indicating whether birth i had an unscheduled C-section, and RPM_t is the ratio of patients-to-midwives observed at admission time t -constructed as described in Section 4.3. X_i contains individual-level control variables of mother and pregnancy characteristics.[23] To control for supply side changes in physicians' availability, G_t is the number of gynecologists scheduled to be in the delivery room at the time of admission. To control for seasonal and secular variation in outcomes, I include additive fixed effects for shift, day of the week, month, and year of admission (θ_t). Since most supply side changes in the maternity ward take place between shifts and days of the week, I perform robustness checks using fixed effects for day-of-the-week times shift, and using hour of admission fixed effects. Results are virtually the same. β is the coefficient of interest. As discussed above, if patients are more likely to receive a C-section when the RPM is high, then we expect β to be positive.

The second part of the analysis looks at whether physician induced demand (PID) is a possible mechanism through which workload affects the choice of delivery method. When resources are constrained physicians may see optimal to shift some patients to the operative theater to give birth by C-section. This would reduce midwives' workload by reducing the number of patients waiting in the delivery room. Because patients are heterogeneous, physicians will find it easier to offer this treatment to some patients than others. I use patient's civil status as a proxy for bargaining power. For a single woman in Tuscany, the odds of being alone in the delivery room are 1.25 times larger than the odds for a married woman (Osservatorio di Epidemiologia dell'Agenzia Regionale di Sanitá (ARS) della Toscana, 2013). In those cases, the physician only needs to convince one person about the change in procedure -not to mention the patient is in labor and in a lot of pain, which makes it harder to analyze the pros and cons of each alternative. A large medical literature finds that continuous companionship during labor improves women birth experience in several dimensions, including, a reduction in the probability of having a C-section (Bohren et al., 2017).[24]

To test whether the effect of workload varies by civil status, I estimate the following regression:

$$y_{it} = \alpha + \beta_1 \mathrm{RPM}_t + \beta_2 \mathrm{RPM}_t \times \mathrm{Married}_i + \beta_3 \mathrm{Married}_i + \theta \mathrm{X}_i + \gamma \mathrm{G}_t + \theta_t + \epsilon_{it} \tag{3}$$

where $\mathrm{Married}_i$ is an indicator for whether the patient is married or single. The category single includes all non-married patients, including single, divorced, separated and widowed.[25] The remaining variables are defined as in Eq. (2). I expect married patients to be less affected by workload, hence, a negative β_2.

5. Results

5.1. Provider response to workload

The upper panel in Fig. 2 provides the most direct illustration of the effect of workload on the probability of having a C-section, and depicts the essence of the research designed used in the paper. It shows results from two non-parametric ways of summarizing this bivariate relationship. First, the dots are 20 equally sized bins plotting the mean of the y-variable (probability of C-section) against the mean of the x-variable (RPM). Second, the dashed line are the fitted values of a local linear regression. We can observe a positive effect of workload on the probability of C-section, although the effect gets smaller the higher the workload -and may even become negative for very high levels of workload. This is probably due to the limited capacity of the maternity ward to perform more C-sections (in terms of physicians, operative theater, etc.). Arrieta and García Prado (2016) show that capacity constrains limit the amount of unplanned C-sections a hospital can perform in a specific shift-day.

In light of this fact, I test both for a linear and non-linear (quadratic) relationship in the regressions below. Table 3 shows the results of estimating Eq. (2) using a linear -Panel (A)- or quadratic -Panel (B)- form of RPM as treatment. Column one includes fixed effects for year, month and day-of-the-week of admission, controls for number of gynecologists scheduled and the mother and pregnancy controls mentioned in Section 4.4. Columns two, three and four alternate different fixed effects for shift of admission, hour of admission, or a combination of shift times day-of-the-week of admission, respectively. Standard errors are clustered at the date of admission level in all specifications.

[23] These include: mother's age, a dummy for whether she finished tertiary education, a dummy for whether she is married (all other categories are zero, including single, divorced, separated, widows and patients with missing data), a dummy for whether this is her first pregnancy, a dummy for whether the infant is a male, a dummy for whether is a pre-term birth (below 37 weeks of gestation), a dummy for whether the baby is born with low weight (less than 2500 g), a dummy for whether the baby is born with high weight (more than 4000 g), a dummy for whether the mother had at least one emergency check up during pregnancy and a flag dummy for patients without civil status information.

[24] In fact, based on that work, the World Health Organization (WHO) guidelines recommend a companion of the woman's choice during labor and childbirth to improve health outcomes (World Health Organization, 2018).

[25] Results are virtually the same if I keep only married and single patients and exclude the rest from the analysis.

Table 3
Effect of workload on the probability of C-section.

	(1)	(2)	(3)	(4)
Panel (A)				
RPM	0.011**	0.009*	0.009*	0.008
	(0.005)	(0.005)	(0.005)	(0.005)
Panel (B)				
RPM	0.041**	0.036**	0.037**	0.033**
	(0.016)	(0.017)	(0.017)	(0.017)
RPM x RPM	−0.005**	−0.005*	−0.005*	−0.005*
	(0.003)	(0.003)	(0.003)	(0.003)
Observations	6138	6138	6138	6138
Fixed Effects		Shift	Hour	DoWxShift

Notes: All models contain fixed effects for year, month and day of the week of admission, controls for number of gynecologists scheduled and mother and pregnancy controls as mentioned in Section 4.4. Standard errors, clustered by date of admission, are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

In Panel (A), column one suggests that there is a positive and statistically significant effect of workload on the probability of C-section. A one unit increase in the RPM raises the probability of C-section by 1.1 percentage points (or an 11% with respect to the mean). However, once we include more controls for time of admission, the effect gets slightly smaller and statistically insignificant. A similar pattern emerges when looking at Panel (B), although estimates are statistically significant through out the different specifications. In line with the non-parametric results in Fig. 2, a quadratic relationship seems to better fit the data.[26] Using results from the most demanding specification -column four-, changing a patient's observed workload at admission from the 10th (RPM=1.25) to the 90th (RPM=3.5) percentile would raise her chances of getting a C-section by 2.5 percentage points (a 24% raise with respect to the mean). The size of the effect is comparable with previous studies looking at all C-sections and changes in monetary compensation. Johnson et al. (2016) find that physicians are 25% more likely to perform a C-section on patients with whom they have a pre-existing clinical relationship and argue this is due to physician's greater disutility from own-patients' difficult labors. Similarly, Allin et al. (2015) find that doubling the compensation for a C-section relative to a vaginal delivery increases the likelihood that a physician opts for the former by just more than five percentage points, all else equal.

The stability of the coefficient across columns (models) speaks to the robustness of the estimates and the exogeneity of my treatment measure. The key assumption to interpret this estimates as causal is that the residual variation in workload is uncorrelated with unobservable characteristics that also impact the probability of having a C-section. While this assumption is inherently untestable, Table B.11 presents an informal assessment of the credibility of the design. Each column presents a series of estimations for regressions of maternal and birth characteristics on my treatment, the RPM at the time of admission of the patient. To identify the effect of workload, we need that predetermined characteristics are uncorrelated with workload -once controls are included. As Table B.11 shows, most estimates for both linear and quadratic forms of workload are not statistically significant. One exception is the gender of the newborn. These coefficients suggest that, as workload increases, the probability of admitting a male newborn decrease at a decreasing rate. However, this cannot explain the increase in C-sections with workload since male newborns are more likely to be delivered by C-sections than female ones, so we would expect the opposite sign of the coefficients. In general, given the small differences, these estimates lend credibility to the identifying assumption that, conditional on the set of fixed effects and controls, the model identifies the impact of workload on outcomes.

I provide further evidence on this using a placebo test. Figure 3 shows estimated coefficients from a single regression including the RPM at different points in times in 24 hours lapses, from three days before to three days after a patient's admission. As expected, only treatment at the time of admission is statistically significant. Importantly, although the RPM is correlated in time, I can still identify the effect at time of admission when including measures of RPM at other times.

Table 4 provides further evidence that the effect is not the result of initial differential patient conditions along the workload distribution. Each pair of columns uses a sample of births admitted in one specific shifts. Since during weekdays there are three gynecologists scheduled for the delivery room in the morning and afternoon shift and only one for the night shift, I expect the effect of workload on C-section to happen only on patients admitted during the day. Indeed, this is what I find. The estimates are not only not-statistically significant for the night sample, but they are one seventh of the size of the effect during the afternoon shift. Interestingly, although the effects are similar in size for the morning and afternoon shifts, they are only statistically significant for the latter. This may have to do with the fact that most scheduled C-sections take place during the morning shift, hence the likelihood of having idle physicians are higher in the afternoon.

[26] This is confirmed when comparing the Akaike information criterion (AIC) across different parametric models (Table B.12). A similar pattern emerges when including plural births in either the sample, the staffing measure (RPM), or both (Table B.13). Finally, results are very similar when using number of patients -instead of RPM- as treatment (Table B.14).

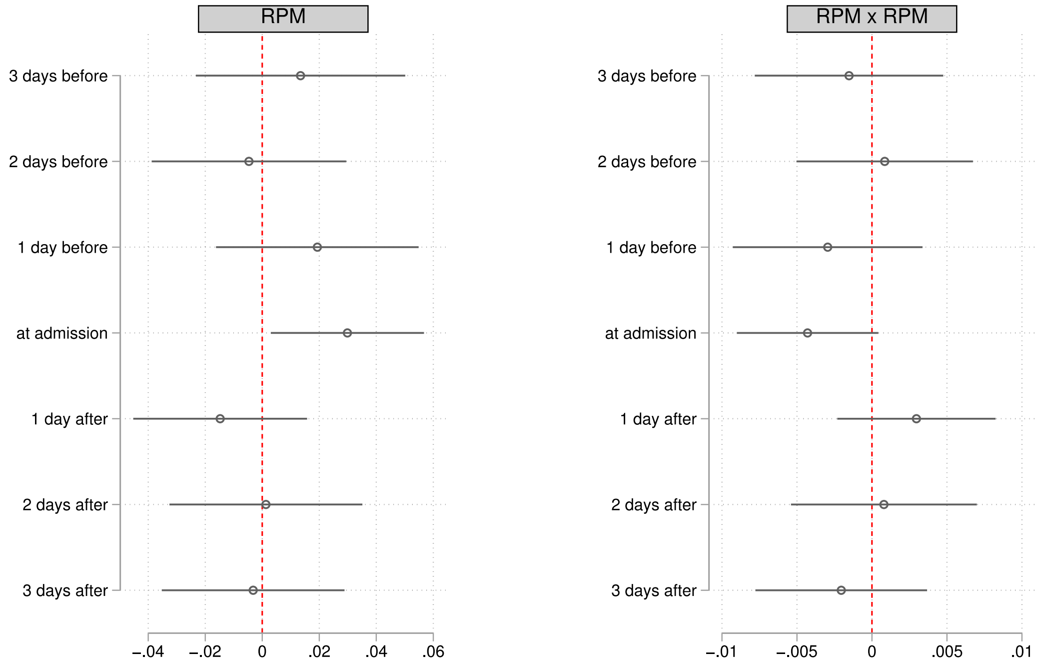

Fig. 3. The effect of treatment at different points in time. *Notes:* The figure represents the coefficients and 90% CI from a regression of the probability of C-section on the RPM measured at seven different points in times and in 24 hours lapses, from three days before to three days after the time of admission. The regression includes all the controls mentioned in Section 4.4. Standard errors are clustered by week of admission.

Table 4
Effect of workload by shift of admission.

	Morning		Afternoon		Night	
	(1)	(2)	(3)	(4)	(5)	(6)
RPM	0.009	0.129	0.028**	0.106**	0.003	0.012
	(0.017)	(0.085)	(0.014)	(0.043)	(0.007)	(0.025)
RPM × RPM		−0.035		−0.017**		−0.001
		(0.023)		(0.008)		(0.004)
Observations	1086	1086	1122	1122	2285	2285

Notes: The sample is limited to weekdays since the same shifts have different staffing scheduled on weekends. All models contain the controls mentioned in Section 4.4. Standard errors, clustered by date of admission, are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

This is inline with previous work that shows that the availability of medical resources may positively affect their rate of utilization (Freedman, 2016).[27]

One potential concern is that patients who arrive too early in the labor process are asked to return later to avoid a long wait. This can be a confounding factor if the likelihood of not admitting these patients varies with workload -less likely to admit them if ward is full. Unfortunately, the data lacks information on hospital arrivals that were not admitted. However, I perform two additional exercises to see if this occurs. First, I look at whether workload is correlated with distance or travel time. Assuming that the maternity ward is less likely to send back patients who live further away, we should observe a positive correlation between workload and distance. Instead, Table B.15 shows that neither the linear nor the quadratic form of workload seem to be correlated with either travel variable. Second, I perform a robustness check adding these controls to my main model. Table B.16 shows that estimates are virtually the same. Furthermore, if selective admission based on midwives' workload was driving the results, then the effects should be present independently from physician availability. However, we have already seen in Table 4 that this is not the case. Finally, even if the ward sends back patients who arrive too early when workload is high, this would create a downward bias and my results would be a lower bound of the true effect -we would expect the patient to come back with equal or worse health, and chances are the ward has the same or lower workload.[28]

[27] One important assumption for this exercise to be valid is that there is no selection of patients across time of the day. Table B.17 shows that observable characteristics are balanced across shifts. However, it could still be the case that unobservable characteristics differ by shift. The included fixed effects by hour, shift, or shift times day-of-the-week should take care of these differences.

Table 5
Ancillary procedures.

	Operative birth		Episiotomy		Any analgesic		Missing analgesic	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RPM	0.005	0.006	0.008	0.008	−0.016	−0.006	0.043	0.040
	(0.020)	(0.021)	(0.023)	(0.024)	(0.032)	(0.032)	(0.027)	(0.028)
RPM x RPM	−0.000	−0.000	−0.001	−0.000	0.001	−0.000	−0.006	−0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)	(0.005)
Observations	6138	6138	6137	6137	3084	3084	6138	6138
Mean dep.	0.088	0.088	0.186	0.186	0.269	0.269	0.497	0.497
DoWxShift FE		Yes		Yes		Yes		Yes

Notes: All models contain the controls mentioned in Section 4.4. Standard errors, clustered by date of admission, are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Finally, is possible that patients who get these 'extra' C-sections have a preference for this delivery method, and this -unobserved- preference is somehow correlated with workload. Grytten et al. (2013) find that immigrant-mothers' mode of delivery in Norway is affected by the rate of C-section in their home country -a proxy for preferences-, with a stronger effect for scheduled C-sections. However, because here I focus exclusively on unscheduled C-sections, my estimates are obtained from a sample of patients who have already revealed a preference for vaginal delivery by attempting a natural birth. Given these conditions, the effect is more likely to be the result of decisions taken in the delivery room regarding when to stop labor and change treatment rather than from maternal preferences for C-sections.

5.2. Additional treatment margins

The evidence above suggests that workload shifts delivery method from vaginal birth to C-section. However, workload can affect other treatment decisions in childbirth. Two such decisions are performing an operative vaginal birth and/or an episiotomy.[29] A higher likelihood in these procedures has been linked to scarce or absent midwifery care and the presence of obstetricians or physicians instead (Hatem et al., 2008). If a lack of midwife care is negatively affecting patients' health, we would expect both these treatment decisions to go up with workload. Finally, a third margin is the use of anesthesia. The use of analgesics can be considered a more discretionary decision which is intensive in midwives' and anesthetist's time. Under time pressure, physicians may decide to reduce the use of this input.

Table 5 presents estimates of Eq. (2) using indicators for operative birth, episiotomy, any analgesic (including epidural), and whether there is no information regarding analgesic provision as dependent variables, and a quadratic form of workload.[30] This last one is included because about half the observations have missing data on analgesic. The absence of any statistically significant effect on having an operative birth and an episiotomy puts into question whether the raise in C-section is due to the worsening of patients health at high workload levels. Regarding the provision of analgesics and whether this information is missing, the coefficients are not statistically significant.

5.3. Maternal and infant morbidity

The estimates above demonstrate that patients arriving during high workload levels receive more C-sections than patients admitted at a low RPM. However, one may be also interested in the consequences of high workload on maternal and infant health. In order to test this, I re-estimate Eq. (2) using indicators for maternal and infant morbidity as dependent variables and a quadratic form of workload.[31]

In the economics literature the most commonly studied health outcomes for births are weight-at-birth, fetal mortality and maternal mortality. However, both maternal and fetal deaths are extremely rare events in Italy: 4 per 100,000 births and 2.7 per 1,000 births, respectively. In the case of weight-at-birth, because treatment here is defined at the moment of admission to the hospital, it is considered a pre-defined outcome (not affected by treatment). Nevertheless, the restricted-use version of the birth certificates in hand contains other measures of morbidity. The analysis below include those maternal and infant conditions that occur in at least 1% of births. For mothers, I only have information post-partum hemorrhage and post-birth length of stay. A higher probability of hemorrhage can be a result of low quality of care. Similarly, a longer recovery and hospital stay can be a sign of worse health conditions after birth.

For infants, I observe whether mother and child achieved skin-to-skin contact, whether the newborn was exclusively breastfeed, whether the newborn had an APGAR score below 9, and whether the newborn was transferred to a neonatal

[28] A similar concern is if the hospital redirect patients to another hospital when workload is high. However, anecdotal evidence from the ward's staff suggest that, although it has happened, patients are rarely referred to another hospital.

[29] Operative vaginal delivery refers to a delivery in which the physician uses forceps or a vacuum device to assist the mother in transitioning the fetus to extra-uterine life. An episiotomy is a surgical cut performed at the opening of the vagina during childbirth to help a difficult delivery.

[30] Results using a linear form of workload are reported in Table B.18.

[31] Tables B.20 and B.19 report estimates using a linear form of workload.

Table 6
Maternal health.

	Post-partum hemorrhage		(log) Length of stay	
	(1)	(2)	(3)	(4)
RPM	0.041**	0.009	−0.023	−0.029
	(0.017)	(0.007)	(0.021)	(0.020)
RPM x RPM	−0.006**	−0.001	0.005	0.005
	(0.003)	(0.001)	(0.004)	(0.004)
C-section		0.945***		0.230***
		(0.008)		(0.012)
Observations	6138	6138	5934	5934
Mean dep.	0.113	0.113	4.250	4.250

Notes: Post-partum hemorrhage is defined as loosing more than 1000 ml of blood. Length of stay is measured from birth to discharge. All models contain the controls mentioned in Section 4.4 and Day-of-the-Week of admission times shift fixed effects. Standard errors, clustered by date of admission, are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 7
Infant health.

	No skin-to-skin contact		Non-exclusive breastfeeding		Apgar score<9		Neonatal ICU	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RPM	0.024	0.013	−0.008	−0.015	0.011	0.009	−0.012	−0.013
	(0.024)	(0.023)	(0.033)	(0.032)	(0.012)	(0.012)	(0.013)	(0.013)
RPM x RPM	−0.003	−0.001	0.003	0.004	−0.001	−0.001	0.002	0.002
	(0.004)	(0.004)	(0.006)	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)
C-section		0.306***		0.185***		0.047***		0.045***
		(0.021)		(0.023)		(0.011)		(0.011)
Observations	5412	5412	4797	4797	6138	6138	6127	6127
Mean dep.	0.180	0.180	0.322	0.322	0.047	0.047	0.072	0.072

Notes: All models contain the controls mentioned in Section 4.4 and Day-of-the-Week of admission times shift fixed effects. Standard errors, clustered by date of admission, are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

intensive care unit (NICU).[32] A higher probability of needing NICU or a low Apgar score can be signals of low care quality. Similarly, if human resources are scarce, midwives may decide to skip some steps of the service considered important but not essential. For example, they may decide that helping the newly mother achieve skin-to-skin contact with her newborn is not as important as helping another woman in labor to deliver. The same reasoning applies for not giving exclusive breastfeeding.[33]

Table 6 reports estimates of the effect of workload on each of the two maternal morbidity outcomes. To try and disentangle the effect of workload on morbidity independently of delivery method, I include regressions with and without conditioning for having a C-section. I find a positive effect of workload on the probability of having a post-partum hemorrhage, although this effect is entirely driven by the higher likelihood of delivering by C-section. Surprisingly, I find no effect of workload on length of stay.

Table 7 displays estimates of the effect of workload on each of the four infant outcomes. The coefficients are not statistically significant for all infant health outcomes. However, these results should be taken with caution given that some estimates are quite imprecise due the small sample size and the rarity of some of these conditions. In addition, there may be other conditions that are affected by workload but unobserved in the data at hand.

5.4. Physician induced demand?

The estimates above strongly suggest that higher workload leads to more C-sections, while there is no change on other medical treatment options nor health outcomes for the patients -if anything, there is a raise in post-partum hemorrhage due to the extra C-sections. In this part of the paper I provide suggestive evidence that physician induced demand can explain

[32] The Apgar score is a method used to quickly summarize the health of newborn children. The Apgar scale is determined by evaluating the newborn baby on five simple criteria on a scale from zero to two, then summing up the five values thus obtained. The resulting Apgar score ranges from zero to 10.

[33] While it is clear why a higher probability of going to NICU or having a low APGAR score are not desirable, there are also compelling arguments regarding the importance of the remaining set of outcomes. In a systematic review, Ip et al. (2007) find that breastfeeding is associated with both decreased risk for many early-life diseases and conditions as well as with health benefits to women. Similarly, using an instrumental variable estimator, Fitzsimons and Vera-Hernández (2015) find large effects of breastfeeding on children's cognitive development. Meanwhile, skin-to-skin contact has been shown to increase the probability and length of exclusive breastfeeding (Moore et al., 2007), as well as substantially reducing neonatal mortality among preterm babies in hospitals (Lawn et al., 2010).

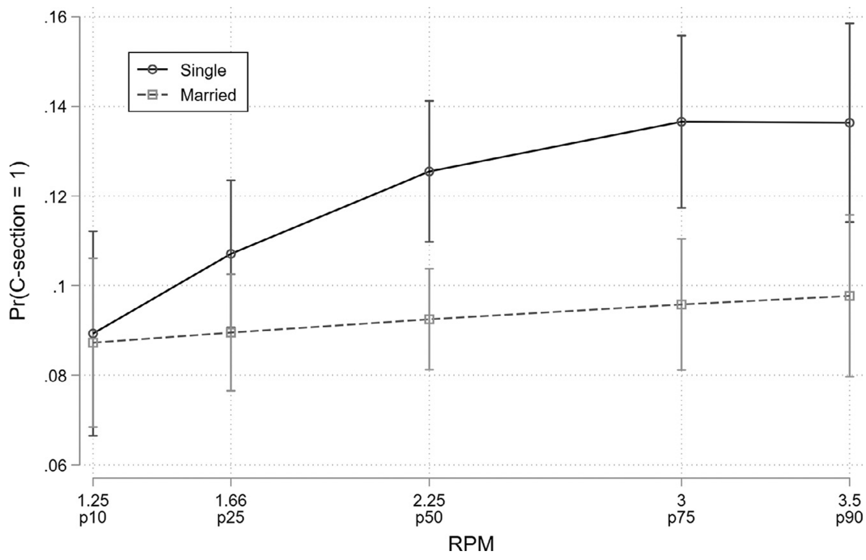

Fig. 4. Average marginal effect of workload on probability of C-section. *Notes:* The figure reports the average marginal effect of workload on the probability of C-section at 10th, 25th, 50th, 75th and 90th percentiles of workload. The model contains the controls mentioned in Section 4.4 and Day-of-the-Week of admission times shift fixed effects. Brackets show the 95% confidence intervals with standard errors clustered by date of admission.

this effect. Under this scenario, physicians will find it easier to induce patients with a lower bargaining power. As discussed above, I expect non-married patients to be more affected by workload levels because they are more likely to be alone in the delivery room.

The key assumption in this exercise is that the level of care and treatment needed by married and single mothers are equally affected by workload. One potential concern is that single mothers may have a lower health than married mothers, and that this difference gets exacerbated during high workload times. Then physicians may decide to send single mothers to the operative theater because of health conditions and not due to PID. Table 1 reports average observable characteristics for married and single mothers and their differences. As expected, married mothers tend to be older, more likely to have a tertiary degree, and less likely to be first-time mothers. Although the first one is a factor that can raise the need for C-section, the other two have the opposite effect. Furthermore, all pregnancy and infant pre-treatment health characteristics are balanced across the two groups. Similarly, there is no statistically significant difference between the two groups in hour or day-of-the-week of admission (see Table B.10 and Fig. B.8 in the Appendix.).

Figure 4 reports the average marginal effects obtained for each group from estimating Eq. (3). As expected, single mothers observed an increasing probability of C-section for higher workload levels, while married mothers observed almost no association between the two variables.[34] For example, while both single and married patients observe a similar rate of C-section when observing workload at the 10th percentile (8.86% and 8.60% respectively), single patients are 42% more likely to have a C-section than married patients if admitted when workload is at the 90th percentile.

Table 8 displays the estimated coefficients in column one, as well as repeated estimations where I restrict the sample to specific groups based on some pre-treatment characteristic. Column two restricts the sample to healthy pregnancies (not preterm nor low weight at birth), young patients (mother below 34 years old), patients with at least one prior birth, and patients with a tertiary degree. Importantly, in all models, the coefficient on the linear and squared RPM and the coefficients on their interactions with the married indicator are statistically significant, close in magnitude and of opposite sign.

Of course, I cannot totally rule out that married and single patients' health are not differently affected by workload in ways beyond the observed characteristics. However, the evidence provided above strongly suggest that this is a potential channel while the role of other factors like health differences seem to play a smaller part. Table B.21 provides further evidence in support of PID by extending the analysis to other patient characteristics that can be associated with bargaining power (higher education and past-birth experience). The second column shows that mothers without a university degree show a stronger gradient with workload, although the difference between the two groups is not statistically significant —in line with the findings in Johnson and Rehavi (2016). Similarly, column three shows that only first-time mothers observe an increase in the probability of delivering by C-section, while already experienced mother see no change in their delivery method with workload.

[34] Using data from the state of New Jersey (US), Currie and MacLeod (2017) observe that, conditional on C-section risk, single women are more likely to have C-sections, as are African-American and Hispanic women, less educated women, older mothers, and mothers of first born children. They do not comment on what might be behind this gap in probabilities by demographic groups, and do not separate low and high workload levels.

Table 8
Effect of workload by civil status.

	(1) All	(2) Only healthy	(3) Only young	(4) Only not first-time	(5) Only with university
RPM	0.080***	0.085***	0.076**	0.067*	0.091*
	(0.027)	(0.028)	(0.031)	(0.035)	(0.049)
RPM x RPM	−0.013***	−0.014***	−0.011*	−0.009	−0.017**
	(0.005)	(0.005)	(0.006)	(0.006)	(0.008)
Married	0.072*	0.068	0.080	0.081	0.172**
	(0.043)	(0.044)	(0.051)	(0.058)	(0.077)
RPM x Married	−0.076**	−0.075**	−0.087**	−0.077*	−0.128**
	(0.034)	(0.034)	(0.041)	(0.045)	(0.058)
RPM x RPM x Married	0.013**	0.012**	0.015**	0.012	0.021**
	(0.006)	(0.006)	(0.008)	(0.008)	(0.010)
Observations	6138	5674	3706	3559	1900
Mean dep.	0.104	0.098	0.088	0.092	0.097

Notes: All models contain the controls mentioned in Section 4.4. 'Only healthy' includes patients with a non-preterm non-low-weight birth. 'Only young' includes only patients below 34 years old. 'Only not firs-time' includes only patients who have had a previous birth. 'Only with university' includes only patients with a tertiary degree. Standard errors, clustered by date of admission, are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

6. Discussion and conclusion

This paper presents a novel approach to understand whether variations in workload affect the quality of care. My identification strategy relies on exploiting plausibly exogenous variation in the ratio of patients-to-midwives (RPM) at the time of admission among unscheduled patients who attempt a vaginal delivery.

I find that patients admitted during high workload have a higher likelihood of getting a C-section. More precisely, changing a patient's observed workload at admission from the 10th (RPM=1.25) to the 90th (RPM=3.5) percentile would raise her chances of getting a C-section by 2.5 percentage points (a 24% raise with respect to the mean). In my sample of unscheduled births, this increase is the same effect as raising mother's age by five years. Other risk factors have a larger effect. For example, newborns with a low weight-at-birth observe a 10.4 percentage points higher probability of C-section than other patients.

This change in delivery method can be explained by a worsening of patients health condition due to lower midwife care, or by physician induced demand. I provide suggestive evidence of the presence of the latter. I find that, while single and married women have the same probability of C-section when workload is low, the likelihood increases with workload for single women only. I interpret this within an agency discrimination model, where single women are more likely to be alone in the delivery room and are easier to induce. Importantly, I fail to find an effect on other measures of treatment intensity or maternal and infant health. While the results taken together are strongly suggestive of PID as the primary driver, I cannot rule out that the true cause is some other unobserved dimension on which married and other patients differ.

My estimates imply that, if all patients were to observe a maximum workload level of 1.25 patients-per-midwife (10th percentile) approximately 14 percent of unscheduled C-sections would be avoided. This suggests that eliminating midwife shortages in maternity wards would have a very significant effect on the already high levels of C-sections seen in developed countries (Italy included). Considering only the difference in costs between a vaginal and C-section delivery, these "extra C-sections" cost about € 40,530 per year for the hospital under analysis.[35] Although this is not enough to hire the necessary number of midwives to assure an RPM below the 10th percentile, other costs beyond the hospital's financial burden should be considered (e.g. patients satisfaction, short and long-term effects of C-sections on mothers and infant's health). An alternative policy is to concentrate maternity wards in fewer but bigger units and benefit from economies of scale and smooth demand. The larger the population a hospital serves, the lower the coefficient of variation of demand, and hence the higher the occupancy rate (Long and Feldstein, 1967).[36]

[35] Back of the envelope calculations suggest that there are about 198 "extra" C-sections in the 4 years sample due to workload. According to the prices on acute interventions published by the Italian Ministry of Health, a vaginal delivery without complication is rated at € 1272, while a C-section costs € 2092. Hence the difference (€ 820 times the number of extra C-sections (198) divided by the number of years (4) gives € 40,530.

[36] In recent work, (Facchini, 2021) show that physicians performing C-sections can suffer from human capital depreciation when they do not perform surgery frequently, which can be alleviated with a higher occupancy rate. Furthermore, de Elejalde and Giolito (2021) provide evidence that private hospitals in Chile raise their occupancy rate using scheduled C-sections as a demand-smoothing mechanism to increase revenue by increasing the number of deliveries while holding hospital capacity constant.

It is important to remember that this study has been carried out using data from a public hospital in a midwifery-led maternity care setting where health workers have no economic incentives that could influence treatment. Caution must be used in extrapolating these findings to other environments where maternity care is organized differently. Furthermore, although not directly tested here, it is possible that some patients, most likely those with weaker health before admission, are better off with an emergency C-section than going through a vaginal birth with scarce midwives' help. This remains an open question for future research.

Declaration of Competing Interest

None.

Appendix A. The working sample and scheduled patients

The working sample used in the main paper is restricted to only those unscheduled patients who attempt to have a vaginal delivery after going through labor, and leaves out scheduled patients. Scheduled patients can be further divided in two groups: (i) elective C-sections, and (ii) pharmacologically-induced patients. This appendix shows evidence of how the latter group's transition through the maternity ward resembles more that of elective C-section rather than the one of unscheduled patients, and hence should not be included in the working sample.

One important caveat of the data is that one cannot disentangle scheduled from unscheduled patients among those who were pharmacologically induced. However, anecdotal evidence from the ward's staff suggest that most of them are scheduled (e.g. overdue pregnancy). Furthermore, a descriptive analysis of the data seems to corroborate that. Figures A.5 and A.6 present the distribution of patients across hours and days as performed in section 1.3.1 of the main paper except that now scheduled patients are further divided between elective C-sections and induced. Starting from Fig. A.5, it shows that there is a pick in admissions for both elective C-sections and induced patients during the afternoon shift, and then again a pick in time of birth (although the pick is later in the day for induced patients relative to the elective C-sections). Nevertheless, the picks are less pronounced for induced patients, suggesting that some of them may be arriving at random hours of the day like unscheduled patients do.

Even though the distribution by hours of induced patients seem to follow that of elective C-sections, their distribution by day of the week instead is closer to that of unscheduled patients. Even though admissions are slightly lower during weekends, births are evenly distributed across all days of the week. This is probably due to the fact that, as long as everything goes well, these patients are taken care of by midwives (not physicians).

The evidence provided in this appendix supports the idea of excluding both elective C-sections and pharmacologically induced patients from the working sample, but to include the latter group in the treatment variable given that they are primordially seen by midwives.

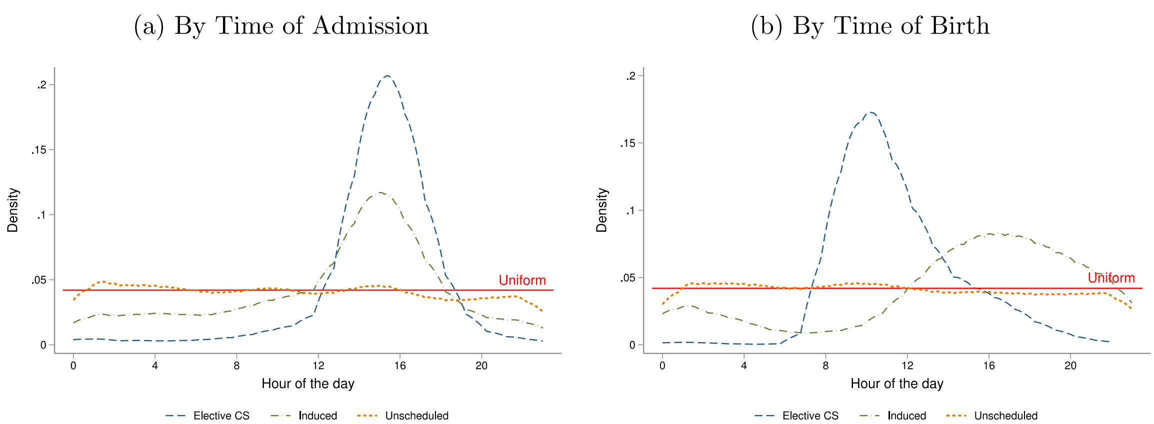

Fig. A.1. Distribution of admissions and births by hour. *Notes:* The figure reports the distribution of patients across hour of admission (left) and hour of birth (right) by type of delivery..

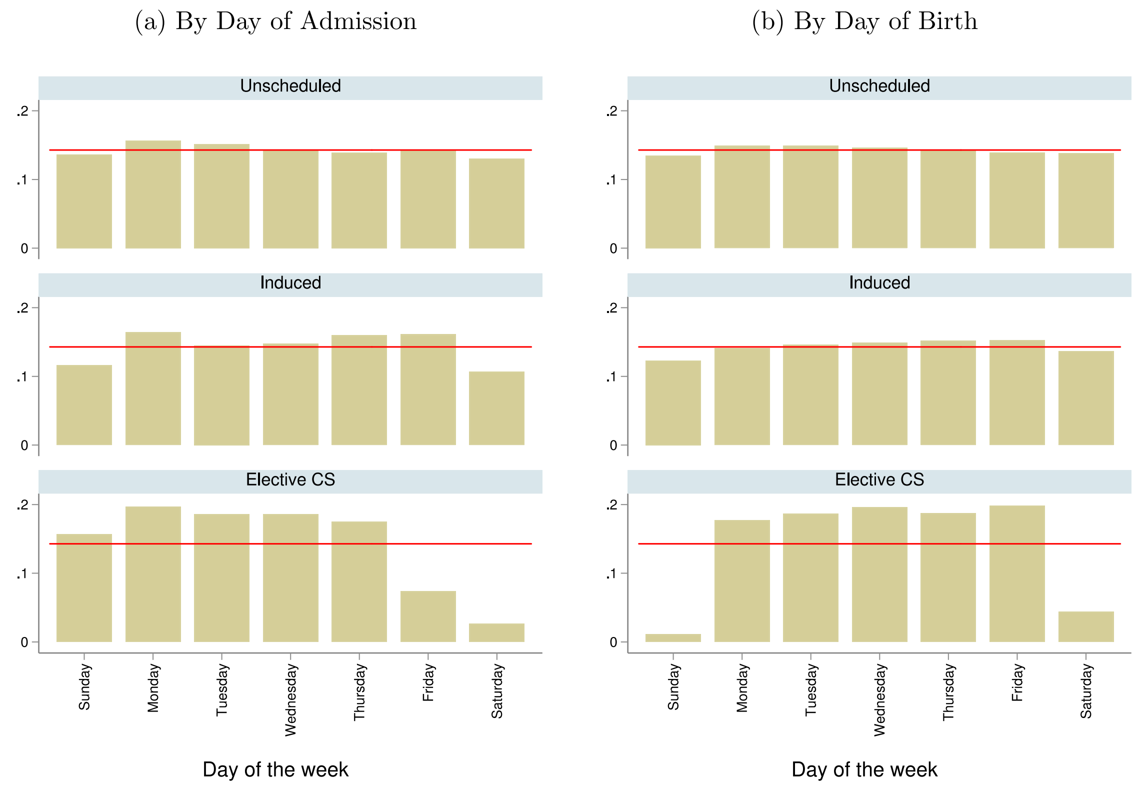

Fig. A.2. Frequency of admissions and births by day. *Notes:* The figure reports the distribution of patients across day of admission (left panel) and day of birth (right panel) by type of delivery. .

Appendix B. Other Graphs and Tables

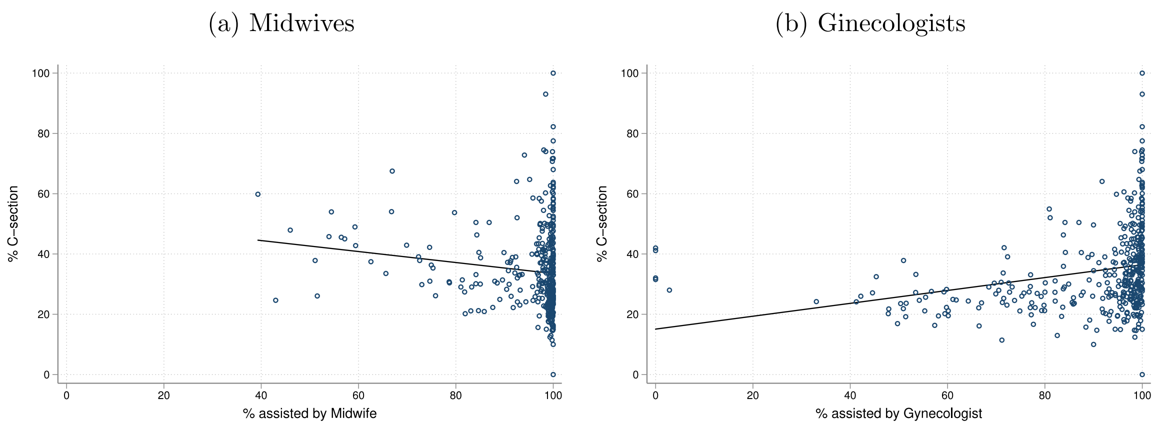

Fig. B.1. Correlation between C-section rates and the presence of different health-workers. *Notes:* Data from the Italian General Directorate of Health Prevention (Ministry of Health) based on birth certificates from 2017. The sample includes 394 maternity wards in Italy out of 433 (39 units have no information on the staff present at birth). Each dot corresponds to a hospital. The solid line in each panel plots the fitted values from a regression of the C-section rate on the percent of births assisted by each health-worker.

Table B.1
The correlation between rate of C-section and the presence of different types of health-workers.

	(1) Midwives	(2) Gynecologists
% births assisted by...	−0.159***	0.210***
	(0.002)	(0.001)
Mean dep.	33.437	33.437

Notes: The dependent variable is the rate of C-sections by hospital (×100). The sample includes all hospitals with a maternity ward in Italy in 2017. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B.2
Summary statistics - Admission times.

	All		Married		Single		
	Mean	SD	Mean	SD	Mean	SD	Diff.
Day of admission							
Sunday	13.5	34.2	13.2	33.8	13.9	34.6	0.75
Monday	15.5	36.2	15.2	35.9	15.9	36.6	0.73
Tuesday	15.2	35.9	15.8	36.5	14.3	35.0	−1.52
Wednesday	14.5	35.2	14.2	34.9	14.8	35.5	0.58
Thursday	13.9	34.6	13.6	34.3	14.1	34.9	0.51
Friday	14.3	35.0	14.4	35.1	14.1	34.8	−0.27
Saturday	13.2	33.9	13.6	34.3	12.8	33.4	−0.78
Hour of admission							
1	5.8	23.5	6.2	24.1	5.4	22.5	−0.85
2	4.5	20.8	4.4	20.6	4.7	21.1	0.26
3	4.6	20.9	4.7	21.1	4.5	20.7	−0.22
4	4.7	21.2	4.9	21.7	4.4	20.6	−0.52
5	4.4	20.5	4.3	20.4	4.5	20.7	0.16
6	4.6	21.0	4.5	20.8	4.8	21.3	0.22
7	4.1	19.9	3.9	19.3	4.5	20.7	0.58
8	3.5	18.4	3.5	18.3	3.6	18.5	0.08
9	3.9	19.5	4.0	19.5	3.9	19.4	−0.07
10	4.8	21.3	4.4	20.6	5.2	22.2	0.75
11	4.3	20.3	4.5	20.6	4.1	19.9	−0.33
13	3.7	18.8	3.7	18.9	3.6	18.7	−0.07
14	3.5	18.5	3.5	18.4	3.6	18.5	0.06
15	4.8	21.5	4.9	21.7	4.7	21.1	−0.26
16	4.9	21.6	5.0	21.8	4.8	21.3	−0.24
18	3.7	19.0	3.5	18.5	4.0	19.6	0.48
19	2.9	16.9	2.9	16.8	3.0	17.1	0.10
20	3.6	18.7	3.7	19.0	3.5	18.4	−0.25
21	3.3	17.8	3.1	17.3	3.6	18.5	0.49
22	4.1	19.8	4.0	19.5	4.2	20.1	0.23
23	3.6	18.6	3.9	19.3	3.3	17.8	−0.59
24	3.9	19.5	3.9	19.3	4.1	19.7	0.20
Observations	6142		3477		2665		6142

Notes: The sample is limited to singleton mothers who went into labor before giving birth (i.e. attempt a vaginal delivery) without inducement. The last column reports differences in means between married and single patients and whether they are statistically significantly different from zero at standard levels. The category single includes all non-married patients, including single, divorced, separated and widowed.

Table B.3
The effect of workload (RPM) on pre-determined characteristics.

	Age	With university	With highschool	Married	First-time mother	Weeks of gestation	Emergency visit	Male newborn	Weight at birth
Panel (A)									
RPM	0.034	0.004	0.002	−0.005	0.003	−0.003	−0.003	−0.010	13.227
	(0.096)	(0.008)	(0.007)	(0.007)	(0.008)	(0.040)	(0.005)	(0.009)	(9.694)
Panel (B)									
RPM	0.460	−0.037	0.002	−0.044*	0.020	0.007	0.028	−0.067**	−3.834
	(0.309)	(0.027)	(0.028)	(0.027)	(0.031)	(0.115)	(0.019)	(0.029)	(29.358)
RPM x RPM	−0.077	0.007*	−0.000	0.007	−0.003	−0.002	−0.006*	0.010**	3.096
	(0.051)	(0.004)	(0.005)	(0.005)	(0.006)	(0.019)	(0.003)	(0.005)	(4.954)
N	6142	6142	6142	6142	6142	6140	6142	6142	6142
Mean dep.	32.522	0.309	0.773	0.566	0.421	38.959	0.126	0.516	3265.561

Notes: Each column regresses a different maternal or pregnancy control on a measure of workload. All models contain fixed effects for year, month and day-of-the-week times shift of admission. Panel (A) shows coefficients for regressions using as treatment a linear form of workload. Panel (B) shows coefficients for regressions using as treatment a quadratic form of workload. Standard errors, clustered by date of admission, are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

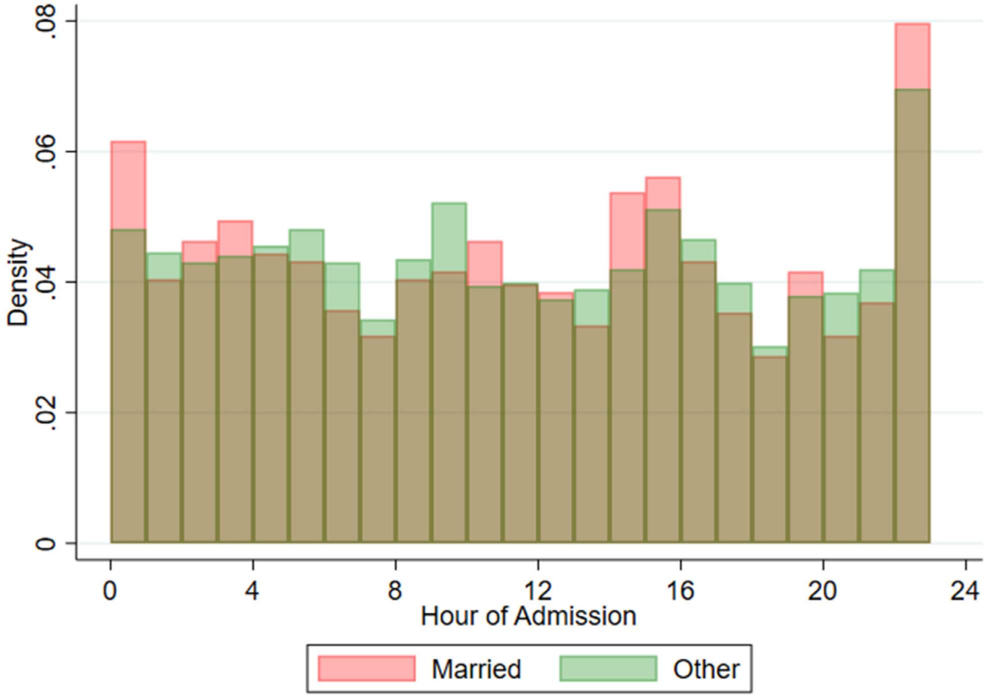

Fig. B.2. Frequency of admissions by civil status across hour of admission. *Notes:* The figure reports the distribution of patients admitted on weekdays across hour of admission by whether they are married or not. Using a two-sample Kolmogorov-Smirnov test I cannot reject the null that the largest differences in the distribution for these two groups are equal to zero (the p-value for the combined test is 0.859).

Table B.4
Model selection.

	(1)	(2)	(3)	(4)
RPM	0.011**	0.041**	0.050	
	(0.005)	(0.016)	(0.040)	
RPM × RPM		−0.005**	−0.009	
		(0.003)	(0.013)	
RPM × RPM × RPM			0.000	
			(0.001)	
20–40th RPM				0.023*
				(0.012)
40–60th RPM				0.021
				(0.014)
60–80th RPM				0.032**
				(0.013)
>80th RPM				0.035**
				(0.015)
Observations	6138	6138	6138	6138
AIC	2641.0	2640.0	2642.0	2643.7

Notes: All models contain the controls mentioned in Section 4.4. Standard errors, clustered by date of admission, are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

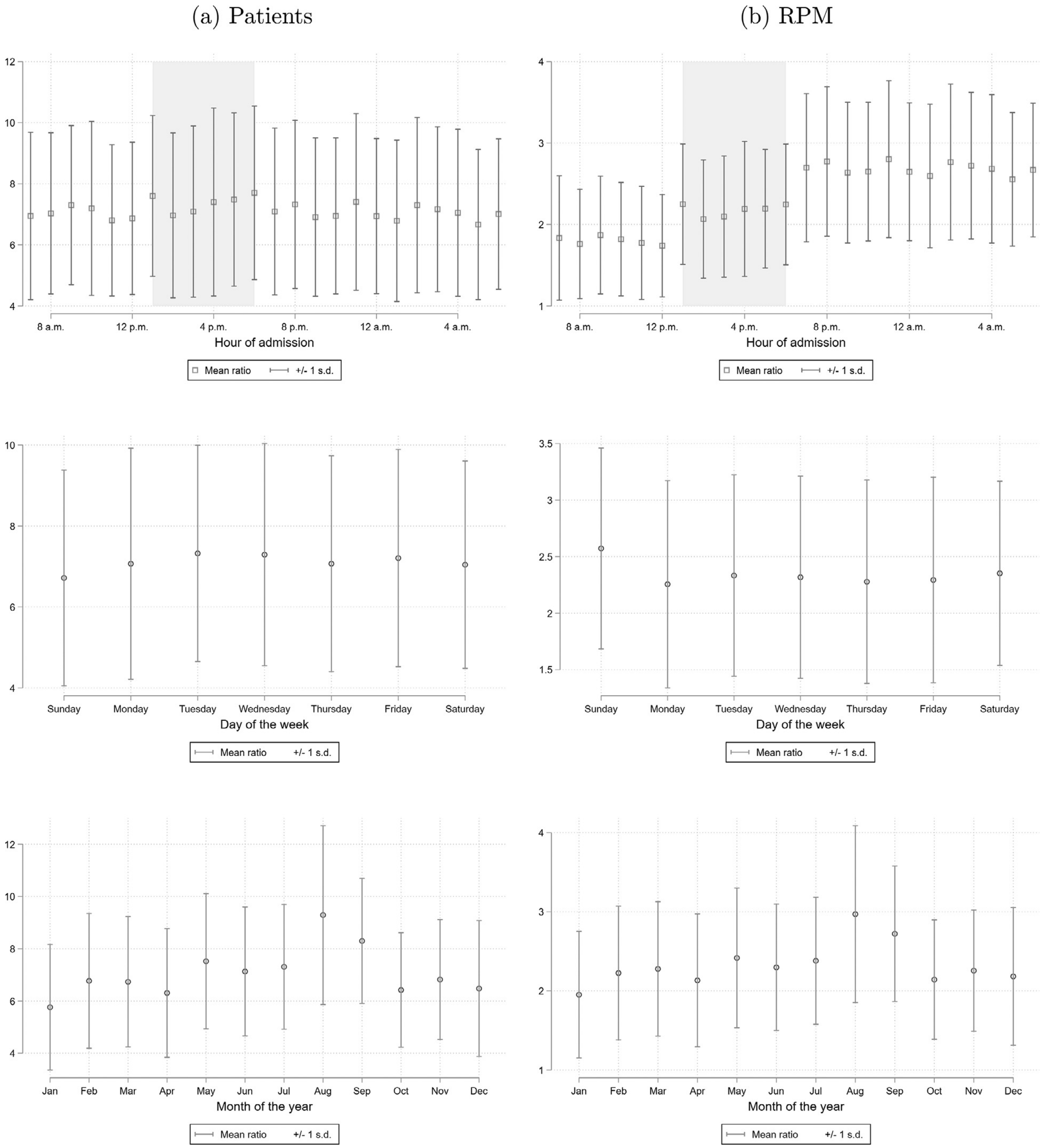

Fig. B.3. Distribution of RPM and patients in time. *Notes:* The figure reports the average and standard deviation of the number of patients (left column) and the RPM (right column) for each hour-of-the-day, day-of-the-week and month-of-the-year. The RPM at time of admission is defined as the number of patients attempting to have vaginal delivery over the number of midwives scheduled to be on duty in the delivery unit. Shaded area in first row marks the afternoon shift. .

Table B.5
Robustness to different samples and staffing measures.

	(1)	(2)	(3)	(4)
Panel (A)				
RPM	0.008	0.007	0.010*	0.009*
	(0.005)	(0.005)	(0.005)	(0.005)
Panel (B)				
RPM	0.033**	0.034**	0.039**	0.039**
	(0.017)	(0.015)	(0.018)	(0.016)
RPM x RPM	−0.005*	−0.005**	−0.005*	−0.005**
	(0.003)	(0.002)	(0.003)	(0.002)
Observations	6138	6138	6317	6317
Sample	Singleton	Singleton	All	All
RPM	Singleton	All	Singleton	All

Notes: All contain the controls mentioned in Section 4.4 and Day-of-Week of admission times shift fixed effects. The first column reports my main estimates. In columns one and two the sample corresponds to only singleton births while columns three and four include plural births. Columns two and four also include plural births in the staffing measure(RPM). Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B6
Effect of patient shocks on the probability of C-section.

	(1)	(2)	(3)	(4)
Panel (A)				
Patients	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Panel (B)				
Patients	0.011**	0.011**	0.012**	0.012**
	(0.005)	(0.005)	(0.005)	(0.005)
Patients x Patients	−0.001*	−0.001*	−0.001*	−0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	6138	6138	6138	6138
Fixed Effects		Shift	Hour	DowXShift

Notes: All models contain fixed effects for year, month and day of the week of admission, controls for number of gynecologists scheduled and mother and pregnancy controls as mentioned in Section 4.4. Standard errors, clustered by date of admission, are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.7
Correlation travel and workload.

	Travel time		Distance	
	(1)	(2)	(3)	(4)
RPM	0.002	−0.330	0.040	−0.297
	(0.180)	(0.616)	(0.180)	(0.606)
RPM × RPM		0.060		0.061
		(0.108)		(0.105)
Observations	5333	5333	5333	5333
Mean dep.	19.7	19.7	11.7	11.7

Notes: Travel time (in minutes) and distance (in kilometers) are obtained from google maps. All models contain the controls mentioned in Section 4.4. Standard errors, clustered by date of admission, are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.8
Robustness to travel time and distance.

	(1)	(2)	(3)	(4)	(5)	(6)
RPM	0.008	0.007	0.007	0.033**	0.035**	0.035*
	(0.005)	(0.005)	(0.005)	(0.017)	(0.018)	(0.018)
RPM × RPM				−0.005*	−0.005*	−0.005*
				(0.003)	(0.003)	(0.003)
Travel time			−0.001			−0.001
			(0.002)			(0.002)
Distance			0.002			0.002
			(0.002)			(0.002)
Observations	6138	5333	5333	6138	5333	5333

Notes: Travel time (in minutes) and distance (in kilometers) are obtained from google maps. Columns one and four show the baseline estimates. Column two, three, five and six keep only observations with information on travel time and distance. Columns three and six add controls for travel time and distance. All models contain the controls mentioned in Section 4.4. Standard errors, clustered by date of admission, are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.9
Balance characteristics by shift.

	Morning (1)		Afternoon (2)		Night (3)		(1)-(3)	(1)-(2)
	Mean	SD	Mean	SD	Mean	SD	Diff.	Diff.
Mother characteristics								
(mean) age	32.5	5.6	32.7	5.5	32.5	5.7	−0.12	0.09
% university degree	31.9	46.6	29.6	45.7	31.1	46.3	2.32	0.76
% married	56.8	49.6	56.2	49.6	56.7	49.6	0.57	0.01
% first-time mothers	41.9	49.4	42.6	49.5	41.9	49.3	−0.70	0.05
Pregnancy characteristics								
% preterm (<37 wofg)	7.0	25.6	6.3	24.2	5.5	22.8	0.77	1.54*
% with at-least 1 ER visit	13.2	33.9	14.0	34.7	11.7	32.1	−0.74	1.55
Infant characteristics								
% male	53.8	49.9	49.2	50.0	51.7	50.0	4.62*	2.07
(mean) weight in grams	3,250.9	561.9	3,248.5	556.7	3,280.5	507.9	2.47	−29.61
% low birthweight (< 2,5kg)	5.4	22.6	6.3	24.2	4.3	20.4	−0.84	1.08
% high birthweight (> 4kg)	4.9	21.7	5.2	22.3	5.0	21.7	−0.30	−0.02
Observations	1496		1488		3158		2984	4654

Notes: Table shows the average characteristics of patients arriving in each staff shift and their differences and whether they are statistically significant.

Table B.10
Ancillary procedures - linear workload.

	Operative birth		Episiotomy		Any analgesic		Missing analgesic	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RPM	0.005	0.005	0.005	0.006	−0.010	−0.006	0.009	0.007
	(0.005)	(0.005)	(0.006)	(0.006)	(0.010)	(0.010)	(0.008)	(0.008)
Observations	6138	6138	6137	6137	3084	3084	6138	6138
Mean dep.	0.088	0.088	0.186	0.186	0.269	0.269	0.497	0.497
DoWxShift FE		Yes		Yes		Yes		Yes

Notes: All models contain the controls mentioned in Section 4.4. Standard errors, clustered by date of admission, are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.11
Infant health - linear workload.

	No skin-to-skin contact		Non-exclusive breastfeeding		Apgar score<9		Neonatal ICU	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RPM	0.010	0.007	0.007	0.005	0.004	0.004	−0.003	−0.003
	(0.007)	(0.006)	(0.009)	(0.009)	(0.003)	(0.003)	(0.004)	(0.004)
C-section		0.306***		0.185***		0.047***		0.045***
		(0.021)		(0.023)		(0.011)		(0.011)
Observations	5412	5412	4797	4797	6138	6138	6127	6127
Mean dep.	0.180	0.180	0.322	0.322	0.047	0.047	0.072	0.072

Notes: All models contain the controls mentioned in Section 4.4. Standard errors, clustered by date of admission, are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.12
Maternal health - linear workload.

	Post-partum hemorrhage		(log) Length of stay	
	(1)	(2)	(3)	(4)
RPM	0.009*	0.002	0.002	0.001
	(0.005)	(0.002)	(0.006)	(0.005)
C-section		0.945***		0.230***
		(0.008)		(0.012)
Observations	6138	6138	5934	5934
Mean dep.	0.113	0.113	4.250	4.250

Notes: All models contain the controls mentioned in Section 4.4. Standard errors, clustered by date of admission, are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B.13
Effect by other mother characteristics.

	Characteristic (**C**)			
	married	with university	not first-time mother	age<35
RPM	0.080***	0.049**	0.064***	0.069**
	(0.027)	(0.019)	(0.025)	(0.027)
RPM x RPM	−0.013***	−0.007*	−0.011**	−0.012***
	(0.005)	(0.003)	(0.004)	(0.004)
RPM x **C**	−0.076**	−0.048	−0.057*	−0.056*
	(0.034)	(0.035)	(0.033)	(0.033)
RPM x RPM x **C**	0.013**	0.006	0.012*	0.012**
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	6138	6138	6138	6138
Mean dep.	0.104	0.104	0.104	0.104

Notes: Each column reports coefficients from a separate regression interacting the treatment with a different mother characteristic (**C**). RPM and RPM x RPM represent the effect when **C** = 0. All models contain mother and pregnancy controls and time fixed effects mentioned in Section 4.4 and Day-of-Week of admission times shift fixed effects. Standard errors, clustered by date of admission, are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

References

Alexander, D., et al., 2013. Does Physician Compensation Impact Procedure Choice and Patient Health? Technical Report.
Alkalay, A., Eizenberg, A., Lahad, A., Shurtz, I., et al., 2018. Physician workload and treatment choice: the case of primary care. Technical Report. CEPR Discussion Papers.
Allin, S., Baker, M., Isabelle, M., Stabile, M., 2015. Physician Incentives and the Rise in C-sections: Evidence from Canada. Technical Report. National Bureau of Economic Research.
Arrieta, A., García Prado, A., 2016. Non-elective c-sections in public hospitals: capacity constraints and doctor incentives. Appl. Econ. 48 (49), 4719–4731.
Bender, P. T. H., Homer, C., Matthews, Z., Nove, A., Sochas, L., Campbell, J., deBernis, L., 2014. The state of the world's midwifery: a universal pathway, a woman's right to health. https://eprints.soton.ac.uk/391219/.
Bertoli, P., Grembi, V., 2019. Malpractice risk and medical treatment selection. J. Public Econ. 174, 22–35.
Berwick, D.M., Hackbarth, A.D., 2012. Eliminating waste in us health care. JAMA 307 (14), 1513–1516.
Blustein, J., Liu, J., 2015. Time to consider the risks of caesarean delivery for long term child health. BMJ 350.
Bohren, M.A., Hofmeyr, G.J., Sakala, C., Fukuzawa, R.K., Cuthbert, A., 2017. Continuous support for women during childbirth. Cochrane Database Syst. Rev. (7).
Brekke, K.R., Holmås, T.H., Monstad, K., Straume, O.R., 2017. Do treatment decisions depend on physicians' financial incentives? J. Public Econ. 155, 74–92.
Büscher, A., Sivertsen, B., White, J., et al., 2009. Nurses and midwives: a force for health. WHO Europe, Copenhagen.
Card, D., Fenizia, A., Silver, D., 2018. The Health Effects of Cesarean Delivery for Low-Risk First Births. Technical Report. National Bureau of Economic Research.
Card, D., Fenizia, A., Silver, D., 2019. The Health Impacts of Hospital Delivery Practices. Technical Report. National Bureau of Economic Research.
Charles, E., 1953. The hour of birth: a study of the distribution of times of onset of labour and of delivery throughout the 24-hour period. Br. J. Preventive Social Med. 7 (2), 43.
Chen, M.M., Grabowski, D.C., 2015. Intended and unintended consequences of minimum staffing standards for nursing homes. Health Econ. 24 (7), 822–839.
Clemens, J., Gottlieb, J.D., 2014. Do physicians' financial incentives affect medical treatment and patient health? Am. Econ. Rev. 104 (4), 1320–1349.
Cook, A., Gaynor, M., Stephens Jr, M., Taylor, L., 2012. The effect of a hospital nurse staffing mandate on patient health outcomes: evidence from California's minimum staffing regulation. J. Health Econ. 31 (2), 340–348.
Costa-Ramón, A., Kortelainen, M., Rodŕıguez-González, A., Sääksvuori, L., 2020. The long-run effects of cesarean sections. J. Hum. Resour. 0719–10334R1.
Costa-Ramón, A.M., Rodríguez-González, A., Serra-Burriel, M., Campillo-Artero, C., 2018. It's about time: cesarean sections and neonatal health. J. Health Econ. 59, 46–59.
Currie, J., MacLeod, W.B., 2008. First do no harm? Tort reform and birth outcomes. Q. J. Econ. 123 (2).
Currie, J., MacLeod, W.B., 2017. Diagnosing expertise: human capital, decision making, and performance among physicians. J. Labor Econ. 35 (1), 1–43.
Curtin, S., Gregory, K., Korst, L., Uddin, S., 2015. Maternal morbidity for vaginal and cesarean deliveries, according to previous cesarean history: new data from the birth certificate, 2013. Natl. Vital Stat. Rep. 64 (4), 1.

Cutler, D., Skinner, J.S., Stern, A.D., Wennberg, D., 2019. Physician beliefs and patient preferences: a new look at regional variation in health care spending. Am. Econ. J. Econ. Policy 11 (1), 192–221.
Deneux-Tharaux, C., Carmona, E., Bouvier-Colle, M.-H., Bréart, G., 2006. Postpartum maternal mortality and cesarean delivery. Obstet. Gynecol. 108 (3, Part 1), 541–548.
Dranove, D., Watanabe, Y., 2010. Influence and deterrence: how obstetricians respond to litigation against themselves and their colleagues. Am. Law Econ. Rev. 12 (1), 69–94.
de Elejalde, R., Giolito, E., 2021. A demand-smoothing incentive for cesarean deliveries. J. Health Econ. 75, 102411.
Evans, W.N., Kim, B., 2006. Patient outcomes when hospitals experience a surge in admissions. J. Health Econ. 25 (2), 365–388.
Facchini, G., 2021. Forgetting-by-not-doing: the case of surgeons and cesarean sections. Health Econ..
Fitzsimons, E., Vera-Hernández, M., 2015. Breastfeeding and Child Development. University College London and Institute for Fiscal Studies, London. (May 2015), http://www.homepages.ucl.ac.uk/-uctpamv/papers/breastfeeding.pdf
Francese, M., Piacenza, M., Romanelli, M., Turati, G., 2014. Understanding inappropriateness in health spending: the role of regional policies and institutions in caesarean deliveries. Reg. Sci. Urban Econ. 49, 262–277.
Freedman, S., 2016. Capacity and utilization in health care: the effect of empty beds on neonatal intensive care admission. Am. Econ. J. Econ. Policy 8 (2), 154–185.
Freedman, S., Golberstein, E., Huang, T.-Y., Satin, D.J., Smith, L.B., 2021. Docs with their eyes on the clock? The effect of time pressures on primary care productivity. J. Health Econ. 77, 102442.
Glattre, E., Bjerkedal, T., 1983. The 24-hour rhythmicity of birth: a populational study. Acta Obstet. Gynecol. Scand. 62 (1), 31–36.
Gregory, K.D., Jackson, S., Korst, L., Fridman, M., 2012. Cesarean versus vaginal delivery: whose risks? Whose benefits? Am. J. Perinatol. 29 (01), 07–18.
Gruber, J., Kim, J., Mayzlin, D., 1999. Physician fees and procedure intensity: the case of cesarean delivery. J. Health Econ. 18 (4), 473–490.
Gruber, J., Owings, M., 1996. Physician financial incentives and cesarean section delivery. Rand J. Econ. 99–123.
Grytten, J., Skau, I., Sørensen, R., 2011. Do expert patients get better treatment than others? Agency discrimination and statistical discrimination in obstetrics. J. Health Econ. 30 (1), 163–180.
Grytten, J., Skau, I., Sørensen, R., 2013. Do mothers decide? The impact of preferences in healthcare. J. Hum. Resour. 48 (1), 142–168.
Harris, M.C., Liu, Y., McCarthy, I., 2019. Capacity Constraints and the Provision of Public Services: The Case of Workers in Public Health Clinics. Technical Report. National Bureau of Economic Research.
Hatem, M., Sandall, J., Devane, D., Soltani, H., Gates, S., 2008. Midwife-led versus other models of care for childbearing women. Cochrane Libr..
Ho, K., Pakes, A., 2014. Physician payment reform and hospital referrals. Am. Econ. Rev. 104 (5), 200–205.
Ip, S., Chung, M., Raman, G., Chew, P., Magula, N., DeVine, D., Trikalinos, T., Lau, J., 2007. Breastfeeding and Maternal and Infant Health Outcomes in Developed Countries. Evidence Report/Technology Assessment no. 153..
Jachetta, C., 2015. Cesarean sections and later child health outcomes. Unpublished.
Jacobson, M.G., Chang, T.Y., Earle, C.C., Newhouse, J.P., 2017. Physician agency and patient survival. J. Econ. Behav. Organ. 134, 27–47.
Johnson, E., Rehavi, M.M., Chan Jr, D.C., Carusi, D., 2016. A Doctor Will See You Now: Physician-Patient Relationships and Clinical Decisions. Technical Report. National Bureau of Economic Research.
Johnson, E.M., 2014. Physician-induced demand. Encycl. Health Econ. 3 (77), 77–83.
Johnson, E.M., Rehavi, M.M., 2016. Physicians treating physicians: information and incentives in childbirth. Am. Econ. J. Econ. Policy 8 (1), 115–141. doi:10.1257/pol.20140160.
Kaiser, I., Halberg, F., 1962. Circadian periodic aspects of birth. Ann. N. Y. Acad. Sci. 98 (4), 1056–1068.
Lawn, J.E., Mwansa-Kambafwile, J., Horta, B.L., Barros, F.C., Cousens, S., 2010. Kangaroo mother care to prevent neonatal deaths due to preterm birth complications. Int. J. Epidemiol. 39 (suppl 1), i144–i154.
Lefèvre, M., 2014. Physician induced demand for c-sections: does the convenience incentive matter? Working Papers 14/08. Health, Econometrics and Data Group (HEDG).
Lin, H., 2014. Revisiting the relationship between nurse staffing and quality of care in nursing homes: an instrumental variables approach. J. Health Econ. 37, 13–24.
Long, M.F., Feldstein, P.J., 1967. Economics of hospital systems: peak loads and regional coordination. Am. Econ. Rev. 57 (2), 119–129.
Maibom, J., Sievertsen, H.H., Simonsen, M., Wüst, M., 2021. Maternity ward crowding, procedure use, and child health. J. Health Econ. 75, 102399.
Matsudaira, J.D., 2014. Government regulation and the quality of healthcare evidence from minimum staffing legislation for nursing homes. J. Hum. Resour. 49 (1), 32–72.
McDermott, K., Freeman, W., Elixhauser, A., 2017. Overview of operating room procedures during inpatient stays in us hospitals, 2014. HCUP Stat. Brief 233, 1–18.
Ministero della Salut, 2012. Certificato di assistenza al parto (CeDAP). Analisi dell'evento nascita - Anno 2012. Technical Report. http://www.salute.gov.it/imgs/C_17_pubblicazioni_2768_allegato.pdf
Moore, E.R., Anderson, G.C., Bergman, N., et al., 2007. Early skin-to-skin contact for mothers and their healthy newborn infants. Cochrane Database Syst. Rev. 3.
Neprash, H.T., 2016. Better Late than Never? Physician Response to Schedule Disruptions. Technical Report. Working paper.
Norberg, K., Pantano, J., 2016. Cesarean sections and subsequent fertility. J. Popul. Econ. 29 (1), 5–37.
Osservatorio di Epidemiologia dell'Agenzia Regionale di Sanitá (ARS) della Toscana, 2013. Nascere in Toscana. Anni 2008–2011. Technical Report. http://www.ars.toscana.it/files/pubblicazioni/Volumi/2013/72_cap_2013.pdf
Osservatorio di Epidemiologia dell'Agenzia Regionale di Sanitá (ARS) della Toscana, 2014. Nascere in Toscana 2012. Technical Report. https://www.ars.toscana.it/files/pubblicazioni/in_cifre/2_Incifre_CAP_web.pdf
Stepner, M., 2013. BINSCATTER: Stata Module to Generate Binned Scatterplots. Statistical Software Components, Boston College Department of Economics. https://ideas.repec.org/c/boc/bocode/s457709.html
Tonei, V., 2019. Mother's mental health after childbirth: does the delivery method matter? J. Health Econ. 63, 182–196.
Tong, P.K., 2011. The effects of california minimum nurse staffing laws on nurse labor and patient mortality in skilled nursing facilities. Health Econ. 20 (7), 802–816.
World Health Organization, 1985. Appropriate technology for birth. Lancet 2, 436–437.
World Health Organization, 2015. WHO Statement on Caesarean Section Rates. Technical Report. http://www.who.int/reproductivehealth/publications/maternal_perinatal_health/cs-statement/en/
World Health Organization, 2018. Who recommendation on companionship during labour and childbirth. https://extranet.who.int/rhl/topics/preconception-pregnancy-childbirth-and-postpartum-care/care-during-childbirth/who-recommendation-companionship-during-labour-and-childbirthl.