

DISCUSSION PAPER SERIES

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ISSN: 2365-9793

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ABSTRACT

Do Empty Beds Cause Cesarean Deliveries?*

We examine how the number of beds available in a maternity ward affects the likelihood of cesarean delivery and maternal health. Our analysis is based on administrative data from Austria. We exploit idiosyncratic daily variation in the occupancy of maternity hospital beds. We find that empty beds increase the probability of cesarean delivery, hospitalization, and readmission. A one standard deviation decrease in maternity bed occupancy increases the probability of cesarean delivery by 4.0% and subsequent hospitalization by 5.8%. Expectant mothers may benefit from a crowded hospital, even at unfavorable patient-staff ratios, because it may lead to less harmful overtreatment.

JEL Classification: I12, J13, J11, J22, J21

Keywords: capacity, hospital crowding, supplier-induced demand, cesarean delivery, cesarean section, overtreatment, maternal health

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* For helpful discussions and comments we would like to thank Ana Costa-Ramón, Tobin Hanspal, Simon Reif and participants at the 2023 Annual Meeting of the Standing Committee for Health Economics of the Verein für Socialpolitik at the University of Wuppertal. The usual disclaimer applies.

1 Introduction

Modern health care systems must be able to provide a full range of services at all times while maintaining quality standards. Therefore, responsible capacity planning must take into account certain peaks in patient load. Systems must be able to handle predictable peaks, such as flu season, as well as unpredictable events, such as pandemics. As a result, a certain amount of medical resources are free in normal times. This raises the important question of whether (and to what extent) the supply of these “additional” resources affects health care utilization in normal times. Depending on the health care setting, the “additional” resources can lead to overtreatment of patients (Dulleck and Kerschbamer, 2006).

In this paper, we address this issue in the context of hospital capacity. Specifically, we test whether the number of beds available in a maternity ward has an effect on the type of delivery. The case of childbirth is interesting and useful for three reasons. First, childbirth is one of the most common reasons for hospitalization. Second, there are two main types of deliveries that have different effects on the length of hospital stay. The most common type of delivery is vaginal, which requires a short hospital stay. In contrast, a cesarean delivery (CD) requires surgical incisions in the mother’s abdomen and uterus and results in a comparatively longer hospital stay. A CD delivery can be planned in advance if there is a medical reason for it, or it can be unplanned and occur during labor if certain problems arise.¹ In the latter case, physicians have some discretion and can change the mode of delivery on short notice. Economic considerations may play a role, and physicians may overtreat and choose a CD to increase the number of occupied hospital beds. This is usually financially advantageous for the hospital, but in many cases also for the physician. CDs are a particularly important context for studying the effect of capacity on utilization. In most high-income countries, CD rates have increased over time and are now well above the recommended rate.²

Third, it is usually difficult to obtain exogenous variation in capacity.³ The case of maternity wards is different. The vast majority of admissions are pre-registered, leaving little room for selection. However, there is some uncertainty about the exact date of

¹There is a clear consensus that CD improves maternal and infant health outcomes when medically indicated. Guidelines (see, for instance NICE, 2023) recommend CD for breech births (Jensen and Wüst, 2015; Mühlrad, 2022), complications of labor such as fetal distress, cord prolapse, placenta praevia, and other complications, and pre-existing conditions (e.g., certain cases of HIV infection).

²Across OECD countries, 28 percent of all live births in 2017 were delivered by CD (OECD, 2019). In contrast, the recommended CD rate is only between 10 and 15 percent (World Health Organization, 2015). The upward trend in CD rates is unlikely to be explained by changes in the incidence of medical indications. Possible complementary explanations include older women experiencing first-time motherhood, increased *in-vitro* fertilization (OECD, 2013), malpractice liability concerns (Currie and MacLeod, 2008), reductions in CD risk, physician and patient convenience in scheduling (OECD, 2013; Brown III, 1996), and changes in patient preferences (Sachs et al., 1999).

³For example, regional differences in the availability of medical resources should generally not be considered exogenous, as this is an equilibrium outcome determined jointly by supply and demand.

admission. This leads to idiosyncratic daily variations in bed occupancy in a given maternity unit. Unlike regional variation in capacity, this variation within maternity units is unlikely to be correlated with patient characteristics. This allows us to identify the causal effect of bed occupancy on medical procedure use and subsequent maternal health within a simple fixed effects approach.

Our empirical approach is made possible by access to high quality administrative data. Most importantly, we have access to Austrian hospital records, which contain detailed information on the universe of inpatient births between 2002 and 2018. To obtain idiosyncratic variation in capacity, we rely on hospital-specific month fixed effects. Thus, we isolate within-hospital-month variation in bed availability on the day of an expectant mother's admission. This within-hospital-month variation is unlikely to be correlated with unobserved characteristics of the mother.

We find that a one standard deviation increase in the maternity bed occupancy rate reduces the likelihood of a CD by 1.07 percentage points or 3.95 percent. The estimated treatment effect varies little with the inclusion of control variables, such as the share of beds with non-birth admissions. Semi-parametric specifications show that the effect is also fairly constant across the distribution of maternity bed occupancy rates. Thus, our baseline result suggests that physicians are more likely to perform a CD when there are more empty beds in the ward.

This result is robust to several alternative specifications. First, we exclude scheduled CDs because their timing is not idiosyncratic. To exclude them, we rerun our estimates in a sample of weekend and holiday births. Hospitals do not schedule CDs on these days. In this reduced sample, we obtain virtually the same estimated treatment effect. Second, we rerun our estimates in a sample of maternity wards with a very low proportion of non-birth admissions. In this sample, our treatment variable (i.e., the maternity bed occupancy rate) is very close to the overall bed occupancy rate. The latter includes, for example, operations for breast cancer, which are mostly scheduled. Again, we observe very similar treatment effects.

To better understand the mechanism behind our treatment effect, it would be useful to know the extent to which hospital management adjusts staffing in response to low or high maternity bed occupancy rates. While we only observe fixed positions and not actual staffing in our main data, we have access to the actual rosters of the largest maternity unit in Austria. These data provide us with daily information on the actual number of doctors (by type) and nurses on duty for the years 2013 to 2019. Based on a simple regression model, we see that hospital management does not adjust the number of doctors on duty to the actual occupancy rate of maternity beds. For nurses, there is a small pro-cyclical adjustment. Assuming that this practice of staff planning also applies to other maternity units in Austria, we derive a more informative interpretation of our main result. The effect that a lower maternity bed occupancy rate leads to more CDs can be interpreted

by holding hospital staff (almost) constant.

Not only is a CD more costly than a vaginal birth, but it can also have negative health consequences.⁴ Our data allow us to observe hospital readmissions. We use this outcome to test whether adjusting the mode of delivery to the current bed occupancy rate has a detrimental effect on subsequent maternal health. As a sanity check, we first show that a lower maternity bed occupancy rate increases the length of hospital stay (due to an increased likelihood of CD). We find that a one standard deviation decrease in the maternity bed occupancy rate increases the length of hospital stay by 0.2 days, or 7.98 percent. To assess the impact on maternal health, we use the probability of readmission. We find that a one standard deviation decrease in the maternity bed occupancy rate increases the probability of readmission by 0.24 percentage points or 5.84 percent, which is economically significant.

This result seems somewhat counterintuitive at first glance, as we see a negative effect of less hospital crowding on maternal health. As such, this finding is also at odds with most of the literature on hospital crowding, which examines a broad range of admissions. However, it is explained by the specific effect of hospital crowding in maternity units on procedure choice. In maternity units, less hospital crowding leads to more CDs. Since these CDs have more postpartum complications, we find lower readmission rates for women admitted to a more crowded maternity unit.

Considering that hospital management rarely adjusts medical staff to short-term fluctuations in (maternity) bed occupancy, we can even conclude that maternal health outcomes are better when women are admitted to overcrowded hospitals, despite the unfavorable patient-staff ratio. Notably, there are other potential (long-term) costs of non-medically indicated CDs that we cannot study in our setting.⁵ Thus, we should interpret the negative effect of overcapacity (or less hospital crowding) on short-term maternal health as a lower bound of the true total cost.

Our results contribute to the literature examining the relationship between capacity, procedure choice, and subsequent health outcomes. While there is an established medical literature on the topic of “hospital crowding,” to date there are only a handful of papers that use a design-based approach to establish causality.⁶ Almost all of these papers focus

⁴In OECD countries, the average cost of a CD is twice or more the cost of a vaginal birth (Koechlin et al., 2010).

⁵Recent design-based work has shown negative effects of non-medically indicated CD on child health (Costa-Ramón et al., 2022), maternal mental health (Tonei, 2019), and subsequent maternal fertility (Halla et al., 2020).

⁶Broadly speaking, studies in the medical literature compare the outcomes of patients treated during periods of high demand relative to supply. Notably, there is no established definition or measurement of this “crowding”. Studies use both demand-side and supply-side variables (such as the number of admissions, staff-patient ratios, or bed occupancy). One strand of this literature examines permanent changes in health care systems due to legislative changes, while another strand focuses on more sudden shocks. In terms of results, neither strand finds consensus on the health effects of overcrowding. A likely explanation for the variation in findings is the lack of causal identification. The medical literature consists almost entirely of observational studies, which typically rely on differences between regions or hospitals.

on births or neonatal health. This may be explained by the advantageous setting of maternity units, where most admissions are pre-registered, leaving little room for selection, but have some uncertainty in the admission date.⁷ Freedman (2016) exploits within-hospital-month variation in US neonatal intensive care units (NICU) capacity to identify the effect of NICU beds on utilization. He finds increased NICU utilization among newborns with higher birth weights, for whom the decision to admit is more likely to be discretionary. Marks and Choi (2019) examine whether hospital spending affects infant health in California. They use crowding (proxied by the number of births) as an instrumental variable (henceforth IV) for spending. They find that when hospitals are forced to reduce neonatal spending (due to crowding), there is no negative effect on neonatal health.

Most closely related to our paper, are two recent studies using Scandinavian data. Maibom et al. (2021) use within-maternity ward-year variation in Danish data to examine the capacity on delivery type, and mother’s and infant’s health. They find no impact of crowding on the likelihood of a CD, but small negative effects on child and maternal health. A common finding of all these design-based paper is that less “crowding” has no or positive effects on patients’ health. The only exception, besides our paper, is Benses (2022) who uses an IV approach in Norwegian maternity unit data. He finds that children born to mothers admitted on more “crowded” days have fewer medical interventions (with no effect on CDs) but better APGAR scores. This is consistent with our study, which is among the first to show that patients may benefit from more “crowding” (i.e., less capacity) because there is less harmful overtreatment in this scenario. In contrast to previous studies, we can even provide evidence that this holds true for unfavorable patient-to-staff ratios.⁸

Our results also speak to the literature on supplier-induced demand, when physicians shift the demand of patients according to their own self-interest (McGuire, 2000). In the context of CDs, there is evidence for the effect of financial and non-financial incentives. For instance, Gruber and Owings (1996) show that gynaecologists compensated their income shock due to declining fertility by substituting vaginal delivery with the highly reimbursed CDs. Other studies provide evidence for the impact of reimbursement differentials (Gruber

For a review, see Hoot and Aronsky (2008).

⁷Exceptions are, for example, Hoe (2022) and Evans and Kim (2006). The former use idiosyncratic variation in British emergency admissions. The authors show that a one standard deviation increase in admissions increases the readmission rate by about 4 percent. Using a census of hospital discharges in California, Evans and Kim (2006) estimate the impact of Friday and Saturday admission shocks on hospitalized patients admitted on Thursdays. The authors find some evidence that large admission shocks on Friday and Saturday tend to reduce the length of stay and increase the likelihood of subsequent readmission for Thursday patients. The reported coefficients are very small, and the effects on mortality rates remain insignificant.

⁸Facchini (2022) identified a case where a more crowded maternity ward leads to more CDs. He has access to data from one large Italian hospital, which allows him to examine the impact of day-to-day variations in the ratio of midwives to patients. He finds that the likelihood of CDs increases (at a decreasing rate) with their workload. He concludes that CDs are used to alleviate midwives’ workload, as they are faster than vaginal births and performed by physicians.

et al., 1999; Grant, 2009; Foo et al., 2017; Pilvara and Yousefi, 2021). There is also evidence on the impact of and non-financial incentives. Brown III (1996) showed first that the likelihood of unplanned CD is not distributed uniformly over weekdays or daytime. He analysed data from US military hospitals, where obstetricians did not earn extra income for performing a CD. He finds a sharp increase in unplanned CDs on Fridays (between 3 pm and 9 pm), and explains this by obstetricians' demand for leisure on weekends.⁹ Finally, there is evidence that information asymmetry between patients and physicians is important. Johnson and Rehavi (2016) show that physician-mothers are 7.5 percent less likely to have a CD. The authors conclude that physician-mothers are able to achieve at least as good (or even better) health outcomes with less intensive treatment.

The remainder of this paper is organized as follows. Section 2 discusses our research design. Section 3 presents the main estimation results and several sensitivity checks. Section 4 presents supplementary evidence from duty rosters. Section 5 presents the results of occupancy rates on subsequent readmissions. Section 6 tests for several dimensions of treatment effect heterogeneity. Section 7 concludes this paper.

2 Research design

In this section, we first discuss the institutional background. Then, we introduce our data sources, define our estimation sample, and provide descriptive statistics. Next, we present our econometric estimation strategy, and discuss our identifying assumptions.

2.1 Institutional background

The Austrian health care system is based on a social health insurance system, originally designed as a Bismarckian system. Public health care services are financed by a mix of compulsory health insurance contributions and general tax revenues. The vast majority of the population (99.9 percent) has compulsory health insurance, which is administered by three health insurance funds. Insured persons have free access to all levels of health care without gatekeeping. Health insurance covers both inpatient and outpatient expenses related to illness and childbirth (Bachner et al., 2018). In particular, medical expenses during pregnancy and childbirth are fully covered, regardless of the method of delivery. Expectant mothers are free to choose the hospital where they give birth, although most mothers choose hospitals close to home, especially if they expect a spontaneous delivery. CDs are available in all Austrian hospitals, and planned CDs can be scheduled in any preferred obstetric department. Approximately 98 percent of births take place in hospitals.

Expectant mothers can choose to give birth in private hospitals, and health insurance

⁹A similar pattern is also found in data for California (Spetz et al., 2001), Spain (Costa-Ramón et al., 2018), Austria (Halla et al., 2020), and Finland (Costa-Ramón et al., 2022).

funds cover the costs of childbirth in private hospitals on the same basis as in public hospitals. The difference between the public hospital rate and the private hospital rate is covered either by private supplementary insurance or by out-of-pocket payments. Mothers who have voluntary and private supplementary health insurance or are willing to pay out of pocket can also choose their attending obstetrician and midwife in some hospitals. Unlike some (Anglo-Saxon) health care systems, the vast majority of attending physicians, midwives, and nurses are employed by the hospital of choice.

Due to the working hours of health professionals, the greatest capacity of hospital staff is available during weekdays. Expectant mothers usually register with their preferred hospital in advance, and staffing schedules can be largely coordinated accordingly. Typically, expectant mothers do not have a pre-assigned obstetrician or midwife for delivery. Even if there is a shortage of staff on weekends and holidays, each maternity unit must have a full surgical team available 24 hours a day, seven days a week. This infrastructure ensures that unplanned CD can always be performed. Typically, a team of physicians, midwives, and nurses work closely together in the maternity ward. Uncomplicated births are managed by midwives, and the attending obstetrician is regularly informed of the progress of the birth. If there are complications, the doctors (obstetrician, surgeon, and anesthesiologist) decide if and when a CD will be performed. The operation itself is then performed by the obstetrician or surgeon and the anesthesiologist. Staff usually work in shifts. Therefore, the midwives and obstetricians who take a case on admission to the hospital may not see it through to delivery. Understandably, the surgical team does not have strict shift changes.

2.1.1 Financial incentives for hospitals and physicians

In Austria, hospitals are predominantly reimbursed according to a Diagnosis-Related Group (DRG) payment system (the so-called *LKF system*). The DRG system is a regulatory framework for the standardized grouping of inpatient hospital stays. Each diagnosis group or procedure is assigned a specific point value (DRG points), which represents the average cost of treatment in a group, with one DRG point representing approximately one euro (Geissler et al., 2012). This means that hospitals are paid a fixed amount for each patient based on the DRG points assigned to that patient. The average DRG points for a CD are higher than for a vaginal delivery (4,739 versus 3,037).

Another financial incentive, for both physicians and hospitals, comes from private payments for patients with supplementary health insurance. More than one-third of the population in Austria has such supplementary health insurance.¹⁰ The longer patients stay in hospitals and the more services they receive, the higher these private payments become. Most of these fees go directly to physicians, while hospitals keep between 10 and

¹⁰We do not observe this insurance status in our data.

30 percent. A CD increases the average length of hospital stay by 2.7 days or 68 percent (4.0 for vaginal delivery versus 6.7 bed days for CD).

In addition, due to the high density of hospitals and hospital beds in Austria, small maternity units are at risk of closure or downgrading if they have persistently low occupancy rates. Chief physicians can only be appointed if they supervise at least one other physician and 15 beds. This creates pressure to justify underutilized hospitals, as well as prestige and income pressures for attending physicians.

2.2 Data sources

Our empirical analysis is based on two administrative datasets from Austria. First, we have access to hospital records from the Austrian DRG System. Second, we received detailed work schedules from the largest maternity ward in Austria.

2.2.1 Hospital records

We have access to hospital records for the period between 2002 and 2018. These individual-level data include information on the universe of hospitalizations in public and private hospitals in Austria. These data are extracted from the Austrian DRG system. The advantage of these data is that they provide accurate and high quality information on the medical services used, and we can identify the treating hospital units. The disadvantage of these data is that they contain very little information on the socioeconomic background of the patients.

Our focus is on maternity units. These units are responsible for childbirth and other gynecological services (such as gynecological oncology). We analyze the universe of in-patient births ($n = 1,323,838$) during this period. We have information on basic patient characteristics, diagnoses, and medical procedures. Because our data represent a complete sample of all hospitalizations, we can also calculate variables at the hospital unit level, such as bed occupancy rates. We then consider the effect of these rates on mode of delivery (vaginal versus cesarean). From 2015, we can follow patients over time and observe readmissions as an additional outcome variable.

2.2.2 Duty rosters

We have received data from the biggest maternity ward in Austria located at the *Kepler University Hospital* (KUH) in Linz, Upper Austria.¹¹ The hospital is equipped with approximately 900 beds, and more than 62,000 inpatients are being treated per year. The clinic houses the largest maternity ward in Austria with more than 3,500 births per year. For this maternity ward, we have access to duty rosters of physicians and medical

¹¹The KUH provides basic health care services for the Linz area and top level medical services for the whole province of Upper Austria.

nursing staff including midwives. The data cover the period from 2013 to October 2019, with the exception of 2016. Thus, we can observe on a daily basis how many doctors (by type) and nurses are on duty.

2.3 Estimation sample and descriptive statistics

We start with a sample of all 1,323,838 inpatient births between 2002 and 2018. After deleting inpatient births outside maternity units (30,431) and observations with missing variables (12,084), we end up with an estimation sample of 1,281,323 observations across 90 hospitals.

2.3.1 Main outcome variable

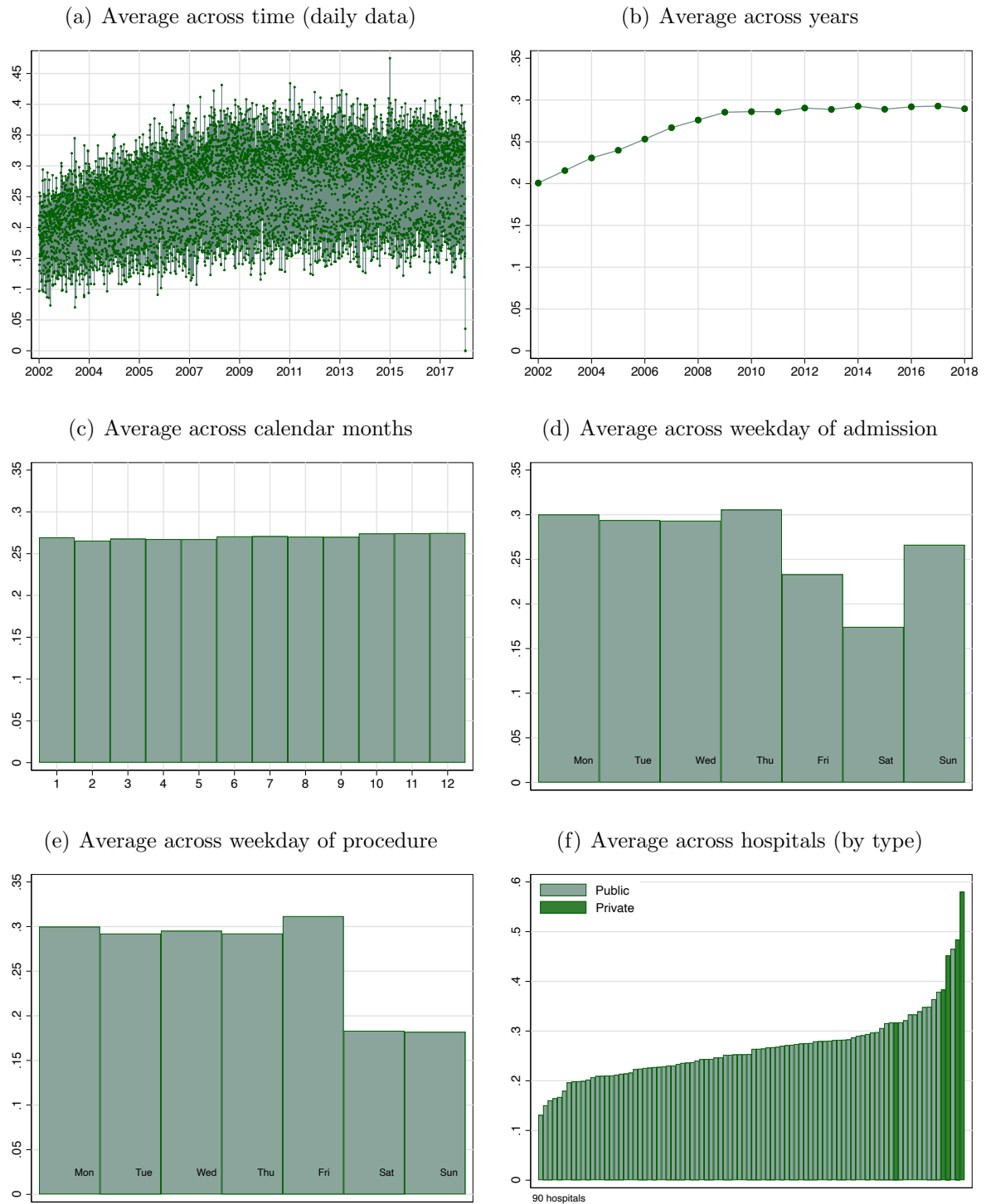
Figure 1 provides descriptive statistics for our outcome variable. On average, about 27.0 percent of all births are CDs. This share has increased over time from 20.1 percent in 2002 to 28.9 percent in 2018 (see panel b). While there is little variation across calendar months (see panel c), we observe the same patterns across weekdays (see panels d and e) as discussed in the literature. First, in terms of day of procedure, there are significantly fewer CDs on Saturdays and Sundays. The most obvious explanation for this is that planned CDs are not scheduled on weekends. Second, there are more CDs on Fridays (as compared to Monday to Thursday). The dominant explanation for this is that there are more non-medically indicated CDs on a Friday than on any other working day, as obstetricians prefer to finish their shift on time. There is also considerable variation between the 90 hospitals, with private hospitals at the top of the distribution (see panel f). Finally, there is significant daily variation in CD rates over time (see panel a).

2.3.2 Treatment variable

Maternity units are responsible for childbirth and other gynaecological services. Childbirth is the most common cause of admission (33.6 percent) in these hospital units.¹² In terms of bed occupancy, childbirth is even more dominant. In our estimation sample, about 74 percent of all occupied hospital beds, are occupied by women admitted for delivery (see Appendix Figure A.1 for detailed statistics). As can be seen, the share of maternity beds has increased from 60 percent in 2003 to 80 percent in 2017, most likely due to unit specialization. For the purpose of our analysis, it is important to distinguish between admissions for births and admissions for other reasons. The majority of births (with the exception of planned CDs, see Section 3.3.1) are unplanned, while the majority of non-birth admissions are planned. This means that maternity bed occupancy rate is less predictable and idiosyncratic on a day-to-day basis. For this reason, we define

¹²This is followed by non-inflammatory disorders of the female genital tract (ICD N8, 16.4 percent) and malignant neoplasm of the breast (ICD C5, 16.4 percent). See Appendix Table A.1.

Figure 1: Descriptive statistics on cesarean delivery rates

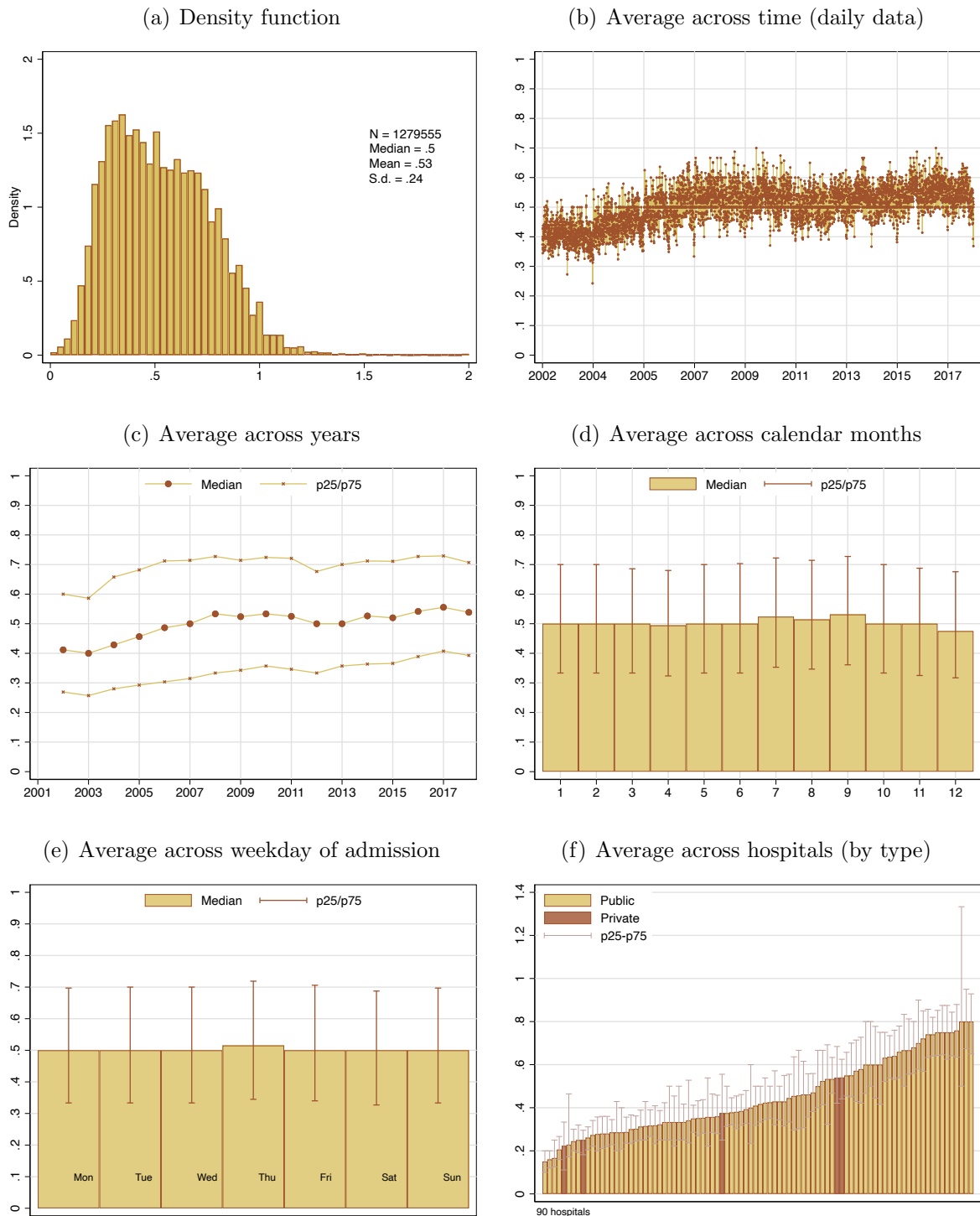


Notes: Cesarean delivery rates are the number of births delivered by cesarean divided by the total number of live births. The number of underlying observations is 1,281,323.

our main treatment variable as the share of all beds occupied by women admitted for childbirth:

$$\frac{\text{Number of beds occupied by women admitted for childbirth}}{\text{Number of beds available in the unit}}, \quad (1)$$

Figure 2: Descriptive statistics on maternity bed occupancy rate



Notes: The variable of interest is defined as the number of women admitted to the maternity unit for childbirth divided by the total number of beds in the unit (i.e., the maternity bed occupancy rate). The number of underlying observations is 1,281,323, except in panel (a) where 1,768 observations with maternity bed occupancy rate values greater than 2 are excluded. The standard deviation in the full sample is 0.29. Descriptive statistics on the share of all occupied hospital beds occupied by women admitted to the maternity ward for delivery are shown in Appendix Figure A.1. Descriptive statistics on the overall bed occupancy rate (i.e., defined as the proportion of all beds occupied by patients with any diagnosis) are shown in Appendix Figure A.2.

and refer to it as the maternity bed occupancy rate. In contrast, the overall bed occupancy rate has a nominator which is the number of all beds occupied regardless of the reason for admission. This variable should not be treated as exogenous. Given the dominance of childbirth, the correlation between the two occupancy rates is quite high and amounts to 0.8.¹³

Figure 2 provides descriptive statistics for the maternity bed occupancy rate. The average maternity bed occupancy rate is around 50 percent (see panel a). Most importantly, it varies considerably from day to day (see panel b). While there is a slight increase over time (see panel c), there is no variation across calendar months (see panel d) or across weekdays (see panel e). Finally, there is considerable variation between the 90 hospitals (see panel f). Appendix Figure A.2 provides descriptive statistics for total bed occupancy rate. We see broadly similar patterns, with the exception of greater variation between weekdays. The comparatively lower overall occupancy at weekends suggests that overall occupancy is comparatively more predictable (and less idiosyncratic) than maternity bed occupancy.

2.4 Estimation approaches

To examine the effect of maternity bed occupancy rate (denoted as maternity bed occ_{ihymw}) on the likelihood of cesarean delivery (CD_{ihymw}) of mother i , we start with a simple linear probability model,

$$\text{CD}_{ihymw} = \alpha + \tau \cdot \text{maternity bed occ}_{ihymw} + \phi_h + \psi_y + \xi_m + \gamma_w + \epsilon_{ihymw}, \quad (2)$$

where we control for hospital (ϕ_h), year (ψ_y , $y = 2002, \dots, 2018$), calendar month (ξ_m , $m = \text{Jan}, \dots, \text{Dec}$), and week-day (γ_w) fixed effects. This approach follows Freedman (2016). The week-day fixed effects are a series of binary indicators for a leisure day (i.e., Saturday, Sunday and any public holiday), for a pre-leisure day (i.e., Friday or any working day before a public holiday), and for each other weekday (i.e., Monday, Tuesday, Thursday), which is neither a leisure nor a pre-leisure day. The basegroup are Wednesdays, which are neither a leisure nor a pre-leisure day.

In further specifications, we replace the hospital and year fixed effects with “hospital \times year”, “hospital \times quarter” or even “hospital \times month” fixed effects. For each specification of fixed effects, we vary the set of further covariates and stepwise include controls for mother’s age, and the plan positions for medical personnel. The latter comprises the regular number of doctors, midwives and nurses (in each case measured per available

¹³In Section 3.3.2, we demonstrate the innocuousness of non-birth bed occupancy for the identification of our treatment effects. In an alternative estimation approach, we use the overall bed occupancy rate as an endogenous treatment variable, which we instrument with the maternity bed occupancy rate (see Appendix Section B). This analysis provides equivalent conclusions.

beds). We can anticipate that the included control variables will have no relevant effect on our estimated treatment effects.

We also use a semi-parametric specification of the maternity bed occupancy rate,

$$\text{CD}_{ihymw} = \alpha + \sum_{p=1}^8 \tau^p \cdot \text{maternity bed occ}_{ihymw}^p + \phi_h + \psi_y + \xi_m + \gamma_w + \epsilon_{ihymw}, \quad (3)$$

where we use binary indicators for the p -th percentile in the maternity bed occupancy rate distribution. The advantage of this specification is that there is no need to impose an explicit functional form between the maternity bed occupancy rate and the probability of cesarean delivery. In equation (2), we impose a linear functional form. Again, we enrich our estimation models with more detailed fixed effects and further covariates.

In all estimation approaches, we calculate clustered standard errors by hospital \times year.

2.5 Identifying assumptions

In our estimations, we rely in the most detailed specification on hospital-specific month fixed effects. These allow us to exploit within-hospital variation in maternity bed availability. We thus flexibly control for factors correlated with maternal preferences, hospital-specific treatment style, cyclical trends in mode of delivery, and hospital-specific cyclical trends.

The identifying assumption underlying our empirical approach is that unobserved within-hospital-month variation in patient characteristics is uncorrelated with within-hospital-month variation in maternity bed occupancy. Put differently, if the types of patients admitted to a hospital change systematically when there are shocks to the number of empty maternity beds, then our empirical strategy fails.

There are two facts that support our identification assumption. First, expectant mothers choose their hospital in advance. Only in very rare cases are women transferred to another hospital during labor. Second, the exact date and time of delivery is unknown. According to the clinical literature, pregnant women are routinely assigned a due date of approximately 280 days after the onset of their last menstrual period. However, only 4 percent of women deliver exactly on the 280th day, and only 70 percent deliver within 10 days of their predicted due date, even when determined by ultrasound (Mongelli et al., 1996). Thus, even if hospitals know the expected due dates of their future patients, the number of births admitted per day is difficult to predict and is likely to vary idiosyncratically.

3 Main estimation results

3.1 Linear specification

Table 1 presents the results of our estimates of the effect of maternity bed occupancy rate on the probability of CD, based on the linear specification. The specifications in panels A through D differ by the covariates included. The covariates are listed/indicated below the coefficient of primary interest. The specifications in columns (1) to (4) differ by type of included fixed effects (FE). In column (1), we control in for hospital and year FE. In column (2), we use instead “hospital \times year” FE. In column (3), we change to “hospital \times quarter” FE, and in column (4) to “hospital \times month” FE. In all specifications, we find a statistically negative effect of the maternity bed occupancy rate on the probability of CD.

The inclusion of covariates (see across panels) has virtually no effect on the estimated effect size. In panel A, we control only for calendar month FE, weekday FE, and those FE indicated in the header of the column. In panel B, we add maternal age FE. Although this variable is an important determinant of CD, its inclusion has virtually no effect on our estimated treatment effect size. This shows that maternal age (conditional on our FEs) is not correlated with the maternity bed occupancy rate. Unfortunately, we do not have other socioeconomic characteristics in our data set, but we are confident that there is no correlation between maternal characteristics and our treatment variable. Consistent with our expectations, we find that higher age is associated with a higher likelihood of CD. Compared to the youngest mothers (under 14), mothers in the 30 to 34 age group have an increased likelihood of about six percentage points. For mothers in the 40 to 44 age group, this gap increases to about 17 percentage points.

In panel C, we add controls for planned medical staff positions. These comprise the regular number of physicians, midwives, and nurses per available bed on a yearly basis. Only one covariate is consistently statistically significant. We find that a one standard deviation increase in the regular number of doctors per available bed (which is equivalent to 0.094) is associated with an increase in the probability of a CD of about 2.13 percentage points.¹⁴ The inclusion of these additional control variables has no effect on the estimated magnitude of the treatment effect of interest. We interpret this irrelevance as evidence supporting the assumption that our treatment variable is conditionally exogenous. Finally, in panel D we control for the non-birth bed occupancy rate. Although this variable cannot be assumed to be exogenous and should not itself be interpreted, it is reassuring to see that its inclusion has virtually no effect on our estimated treatment effect size.

The more detailed FE specifications we use (see across columns), the higher is the estimated effect size. Our preferred specification is the one with lean covariates and

¹⁴In section 4, we present evidence based on the actual number of doctors on duty.

Table 1: The impact of maternity bed occupancy rate on the likelihood of CD

	(1) Hospital & year FE	(2) Hospital×year FE	(3) Hospital×quarter FE	(4) Hospital×month FE
<i>Panel A</i>				
Occupancy	-0.012*** (0.004)	-0.020*** (0.006)	-0.028*** (0.007)	-0.038*** (0.010)
Calendar month FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
<i>Panel B</i>				
Occupancy	-0.012*** (0.004)	-0.019*** (0.006)	-0.026*** (0.007)	-0.037*** (0.010)
Calendar month FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Mother's age	Yes	Yes	Yes	Yes
<i>Panel C</i>				
Occupancy	-0.012*** (0.004)	-0.024*** (0.007)	-0.028*** (0.009)	-0.037*** (0.011)
Docs per used bed	0.038* (0.020)	0.166** (0.069)	0.221** (0.095)	0.238** (0.109)
Nurses per used bed	-0.006 (0.009)	0.006 (0.021)	0.009 (0.021)	0.014 (0.022)
Midwives per used bed	-0.014 (0.009)	-0.031 (0.022)	-0.036 (0.022)	-0.035 (0.023)
Calendar month FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Mother's age	Yes	Yes	Yes	Yes
<i>Panel D</i>				
Occupancy	-0.011*** (0.003)	-0.022*** (0.006)	-0.026*** (0.007)	-0.035*** (0.009)
Docs per used bed	0.026 (0.019)	0.143** (0.066)	0.193** (0.093)	0.205* (0.107)
Nurses per used bed	-0.007 (0.009)	0.015 (0.020)	0.020 (0.020)	0.027 (0.020)
Midwives per used bed	-0.011 (0.009)	-0.022 (0.021)	-0.026 (0.021)	-0.024 (0.021)
Occupancy ^{NB}	0.030*** (0.008)	0.035*** (0.010)	0.044*** (0.009)	0.052*** (0.009)
Calendar month FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Mother's age	Yes	Yes	Yes	Yes
Number of observations	1,281,323	1,281,323	1,281,323	1,281,323
Mean of outcome	0.27	0.27	0.27	0.27

Notes: This table summarizes the regression results of the effect of maternity bed occupancy rate on the probability of cesarean delivery (CD). The basic regression model is shown in equation (2). The specifications in panels A through panel D differ by the covariates included. These covariates are listed/indicated below the coefficient of primary interest. Calendar month FE are a series of binary indicators for January to December. Weekday FE are a series of binary indicators for a leisure day (i.e., Saturday, Sunday and any public holiday), for a pre-leisure day (i.e., Friday or any working day before a public holiday), and for each other weekday (i.e., Monday, Tuesday, Thursday) that is neither a leisure nor a pre-leisure day. The base group is Wednesdays, which are neither a leisure nor a pre-leisure day. Mother's age FE are a series of binary indicators for the following age groups: ≤ 14 (base group), 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, ≥ 50 . The variable $Occupancy^{NB}$ captures the proportion of beds occupied by patients other than expectant mothers. The specifications in columns (1) to (4) differ by the type of FE included. In column (1), we control for hospital and year FE. In column (2), we use "hospital \times year" FE instead. In column (3), we switch to "hospital \times quarter" FE. In column (4) we use "hospital \times month" FE. Clustered standard errors by hospital \times year are reported in parentheses below the coefficients. Asterisks indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

“hospital \times month” FE (see column 4 in panel B). Based on this specification, we find that a one standard deviation increase in the maternity bed occupancy rate reduces the probability of a CD by 1.07 percentage points, or 3.95 percent. This is an economically non-negligible effect size. For comparison, this effect is one third of the effect of a one-standard-deviation-increase in the maternal age, which is a major indication for CD.¹⁵

3.2 Semi-parametric specification

Table 2 summarizes results based on the semi-parametric specification (see equation 3) for varying fixed effects. Here we use our preferred lean covariate specification. We see that the probability of CD increases across the entire distribution of maternity bed occupancy rates. The changes between the binary indicators for the different percentiles show fairly constant changes, suggesting that our simple linear specification from above captures the empirical relationship fairly well. As in the case of the linear specification, we find that more detailed FE specifications (see across columns) lead to larger estimated effect sizes. Appendix Figure A.5 summarizes estimation results of the semi-parametric specification for all combinations of fixed effects and covariates. We see that in each case, the inclusion of covariates has virtually no impact.

3.3 Additional identification checks

Our basic identification strategy has two components. First, since the vast majority of births are unplanned, the exact maternity bed occupancy rate should be exogenous. Second, we control for hospital-specific month fixed effects and exploit only within-hospital variation in the maternity bed occupancy rate, which should not be correlated with (unobserved) patient characteristics. Below, we perform two identification checks that vary our identifying assumptions. First, we exclude planned CDs. Second, we use sub-samples in which the occupancy rate of maternity beds is, for structural reasons, very close to the overall occupancy rate of beds.

3.3.1 Excluding planned CDs

While we cannot accurately identify planned CDs in our data at the individual level, we can exclude these through a simple sample restriction.¹⁶ We take advantage of the fact that Austrian hospitals schedule planned CDs on working days (i.e., from Monday to Friday) only, and re-run our estimates in the sample of Saturday, Sundays and public

¹⁵A one-standard-deviation-increase in maternal age (i.e, by 5.53 years) increases the probability of a CD by 3.88 percentage points, or 13.24 percent.

¹⁶It is well known that mothers sometimes request a CD that is not medically indicated, and physicians often comply and schedule a planned CD. In this case, physicians essentially have to fake a reason for the CD. They could either fake a condition that justifies a planned CD, or they could categorize it ex-post as an unplanned CD. This creates a measurement error in the planned versus unplanned variable.

Table 2: The impact of maternity bed occupancy rate on the likelihood of CD, semi-parametric specification

	(1) Hospital & year FE	(2) Hospital×year FE	(3) Hospital×quarter FE	(4) Hospital×month FE
10th: Base group				
20th	-0.003 (0.002)	-0.004* (0.002)	-0.005** (0.002)	-0.006*** (0.002)
30th	-0.006*** (0.003)	-0.007*** (0.002)	-0.009*** (0.003)	-0.013*** (0.003)
40th	-0.005* (0.003)	-0.007** (0.003)	-0.009*** (0.003)	-0.015*** (0.003)
50th	-0.010*** (0.003)	-0.013*** (0.003)	-0.016*** (0.003)	-0.023*** (0.003)
60th	-0.013*** (0.003)	-0.016*** (0.004)	-0.019*** (0.004)	-0.028*** (0.004)
70th	-0.017*** (0.004)	-0.021*** (0.004)	-0.025*** (0.004)	-0.034*** (0.005)
80th	-0.017*** (0.004)	-0.023*** (0.004)	-0.027*** (0.005)	-0.037*** (0.005)
90th	-0.017*** (0.004)	-0.026*** (0.005)	-0.031*** (0.005)	-0.043*** (0.005)
Calendar month FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Mother's age	Yes	Yes	Yes	Yes
Number of observations	1,281,323	1,281,323	1,281,323	1,281,323
Mean of outcome	0.27	0.27	0.27	0.27

Notes: This table summarizes the regression results of the effect of maternity bed occupancy rate on the probability of cesarean delivery (CD). The basic regression model is shown in equation (3). These covariates are indicated below the coefficient of primary interest. Calendar month FE are a series of binary indicators for January to December. Weekday FE are a series of binary indicators for a leisure day (i.e., Saturday, Sunday and any public holiday), for a pre-leisure day (i.e., Friday or any working day before a public holiday), and for each other weekday (i.e., Monday, Tuesday, Thursday) that is neither a leisure nor a pre-leisure day. The base group is Wednesdays, which are neither a leisure nor a pre-leisure day. Mother's age FE are a series of binary indicators for the following age groups: ≤ 14 (base group), 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, ≥ 50 . The specifications in columns (1) to (4) differ by the type of FE included. In column (1), we control for hospital and year FE. In column (2), we use "hospital \times year" FE instead. In column (3), we switch to "hospital \times quarter" FE. In column (4) we use "hospital \times month" FE. Clustered standard errors by hospital \times year are reported in parentheses below the coefficients. Asterisks indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: The impact of bed occupancy rate on the likelihood of CD, excluding planned CDs

	All days	Working days	Non-working days
Occupancy	−0.037*** (0.010)	−0.038*** (0.011)	−0.036*** (0.009)
Hospital×month FE	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes
Weekday FE	Yes	No	No
Mother’s age	Yes	Yes	Yes
Number of Obs.	1,281,323	933,910	347,413
Mean of Outcome	0.27	0.29	0.23

Notes: This table summarizes the regression results of the effect of maternity bed occupancy rate on the probability of cesarean delivery (CD). The basic regression model is shown in equation (2). The covariates are indicated below the coefficient of primary interest. Calendar month FE are a series of binary indicators for January to December. Weekday FE are a series of binary indicators for a leisure day (i.e., Saturday, Sunday and any public holiday), for a pre-leisure day (i.e., Friday or any working day before a public holiday), and for each other weekday (i.e., Monday, Tuesday, Thursday) that is neither a leisure nor a pre-leisure day. The base group is Wednesdays, which are neither a leisure nor a pre-leisure day. Mother’s age FE are a series of binary indicators for the following age groups: ≤ 14 (base group), 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, ≥ 50 . Clustered standard errors by hospital \times year are reported in parentheses below the coefficients. Asterisks indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

holidays. For comparison, we also repeat our estimation in the inverse sample.¹⁷ As can be seen in Table 3, the estimated treatment effects in the two samples differ only slightly. The same holds true for the semi-parametric specification (see Appendix Table A.3). We conclude that planned CDs are not a concern in our baseline specification.

3.3.2 Non-maternity bed occupancy

In our baseline specification, we deliberately defined our treatment variable as the maternity bed occupancy rate, ignoring other bed occupancy. We have already shown that i.) the maternity bed occupancy rate and the *overall* bed occupancy rate are highly correlated, and ii.) that controlling for non-birth bed occupancy has virtually no effect on the estimated treatment effect.

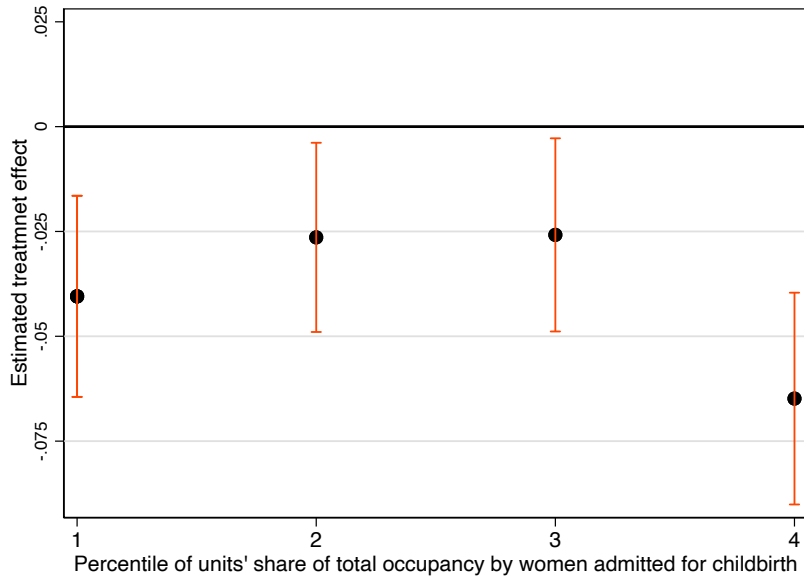
We now repeat our analysis in subsamples of maternity units with persistently different levels of non-birth bed occupancy. There are maternity units which have consistently a higher share of all occupied hospital beds occupied by women admitted for childbirth (see panel f of Appendix Figure A.1). We divide our sample into four subsamples defined by the quartiles of the latter distribution. Then we re-run our estimations in these four equal-sized sub-samples. Figure 3 summarizes the estimation results. Across all four subsamples, we find comparable estimated treatment effects. This provides additional evidence that maternity unit’s non-birth bed occupancy has virtually no effect in our

¹⁷As expected, the CD rate is significantly lower in the Saturday, Sunday and holiday sample compared to the weekday sample (0.23 versus 0.29).

estimation approach.¹⁸

In an alternative estimation approach, we use the *overall* bed occupancy rate as an endogenous treatment variable and instrument it with the maternity bed occupancy rate. The logic is that the overall bed occupancy rate is endogenous due to scheduled non-birth admissions, and the instrumental variable (hereafter IV) approach allows us to focus on the exogenous part due to birth admissions. This analysis leads to equivalent conclusions (see Appendix Section B).

Figure 3: The impact of maternity bed occupancy rate on the likelihood of cesarean delivery by maternity units’ share of occupancy by women admitted for childbirth



Notes: This figure summarizes regression results of the effect of maternity bed occupancy rate on the probability of cesarean delivery in four different sub-samples. These sub-samples are defined as the quartiles in the maternity unit’s distribution of the share of overall occupancy by women admitted for childbirth. Each regression is based on an equivalent estimation specification as the estimate summarized in Column (4) of panel B of Table 1. Orange bars represent 95 percent confidence intervals.

4 Supplementary evidence from duty rosters

To better understand the mechanism behind our treatment effect, we use our data from duty rosters. In particular, we test whether hospital management adjusts staffing in response to low or high maternity bed occupancy rates. In doing so, we regress the daily maternity bed occupancy rate on the number of doctors and nurses on duty. As in our main estimation model (see equation 2), we control for year, calendar month, and

¹⁸Alternatively, we define the distribution of the share of overall occupancy by women admitted for childbirth based on hospital×month observations and split the sample based on the resulting distribution. This approach also captures contemporaneous fluctuations and focuses less on structural differences. Again, we observe very comparable treatment effects across these subsamples.

Table 4: The impact of maternity bed occupancy rate on the number of medical staff on duty

	Number of docs	Number of obstetricians	Number of surgeons	Number of nurses
Occupancy rate	0.261 (0.189) [0.010]	0.151 (0.162) [0.006]	0.116 (0.099) [0.016]	10.997*** (1.691) [0.048]
Year FE	Yes	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Number of Obs.	2,129	2,129	2,129	2,129
Mean of Outcome	8.40	7.02	1.76	103.34
R-squared	0.92	0.92	0.68	0.93

Notes: These regressions are based on daily duty roster data from the biggest maternity ward in Austria. It covers the years 2013 through 2019 (with the exception of 2016). Standard errors in parenthesis below with *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Beta coefficients in brackets below.

weekday fixed effects. The estimation results are summarized in Table 4. It turns out that hospital management does not adjust the number of doctors on duty to the actual occupancy rate of maternity beds (see column 1). The estimated coefficient is statistically and economically insignificant. This is also the case for obstetricians (see column 2) and surgeons (see column 3) separately. This suggests that the maternity unit is sticking to its fixed roster of doctors. For nurses, there is a small pro-cyclical adjustment (see column 4). A one standard deviation increase in the maternity bed occupancy rate is associated with a 0.05 standard deviation increase in the number of nurses on duty. This effect is highly statistically significant but economically small.

Assuming that this practice of planning staffing levels applies to other maternity units in Austria, we can refine our conclusions from above. We conclude that the effect that a lower maternity bed occupancy rate leads to more CDs can be interpreted by holding hospital staff (almost) constant. This finding is also important for the interpretation of results for subsequent maternal health presented in the next section.

5 The impact of bed occupancy rate on readmission

A CD is not only more expensive than a vaginal birth, it may also have negative health consequences. An important step in our analysis is therefore to examine whether women, who end up having a CD because of low maternity bed occupancy rates, also have worse health outcomes. We use readmissions to assess subsequent maternal health.

First, as a sanity check, we regress the length of the initial hospital stay on the maternity bed occupancy rate.¹⁹ Recovery from a CD typically takes longer than it

¹⁹Descriptive statistics for the length of the initial hospital stay are provided in Appendix Figures A.3.

would from a vaginal birth. Descriptively, we see that mothers who deliver by CD have an additional 2.72 days in hospital (4.01 days versus 6.73 days). We use the same regression setup as in the case of CDs (see equation 2) and regress the length of the initial hospital stay (measured in days) on the maternity bed occupancy rate. Note that in this case we cannot easily apply a causal interpretation. There could be an reverse causal effect of maternity bed occupancy on length of stay. Hospitals may send patients home earlier when hospital beds are scarce.

The estimation results are summarized in Table A.2. We find a negative association between maternity bed occupancy and length of initial hospital stay. This is consistent with an explanation in which a higher maternity bed occupancy rate reduces the likelihood of CD and, in turn, shortens hospital stay. It is also consistent with patients being sent home early due to bed shortages. Based on our preferred specification (see column 4 in panel B), a one standard deviation decrease in the maternity bed occupancy rate is associated with a 0.20 days (or 4.29 percent) shorter length of hospital.

Between 2015 and 2018, 4.2 percent of all women admitted for childbirth were readmitted within 6 months to a maternity unit (which includes the department of obstetrics and gynecology).²⁰ The maternal readmission rate is higher for women who delivered by CD (3.8 percent versus 4.9 percent). To test whether lower maternity bed occupancy affects readmission, we use the same estimation approach as for CDs (see equation 2), and regress the binary readmission variable on the maternity bed occupancy rate. The estimation results are summarized in Table 5. Again, we find that the inclusion of additional covariates has little impact, while the use of more detailed fixed effects leads to larger estimated effect sizes in absolute terms. Based on our preferred specification, we find that a one standard deviation decrease in the maternity bed occupancy rate increases the likelihood of readmission by 0.24 percentage points. Given an average readmission rate of 5.84 percent, this is an economically significant effect of low occupancy rates on maternal health.²¹

The negative effect of less hospital crowding on maternal health seems counterintuitive at first glance. The finding is at odds with most of the literature on hospital crowding, which examines a broad range of admissions. However, it is explained by the specific effect of hospital crowding in maternity units on procedure choice. In maternity units, less hospital crowding leads to more CDs. Given that these CDs have more postpartum complications, we find lower readmission rates for women admitted to a more crowded maternity unit. Since these CDs lead to more readmissions, this could be considered

²⁰Descriptive statistics for readmissions are provided in Appendix Figure A.4.

²¹Estimates based on the semi-parametric specification for these two additional outcomes are summarized in Appendix Figures A.6 and A.7. As in the case of CD, we see that the changes between the binary indicators for the different percentiles show fairly constant changes, suggesting that our simple linear specification from above captures the empirical relationship fairly well. The inclusion of covariates has virtually no effect. In the case of hospitalization, more detailed fixed effects lead to larger estimated effect sizes in absolute terms. This is less pronounced for readmission.

harmful overtreatment. We conclude that expectant mothers may benefit from a crowded hospital, even with an unfavorable patient-staff ratio (see Section 4) — because it leads to less harmful overtreatment.

6 Heterogenous treatment effects

In a final step, we check for several dimensions of potential treatment effect heterogeneity.²² First, we split our sample by maternal age. The results are shown in the panels on the left side of Figure 4. Maternity bed occupancy has a statistically significant negative effect on the odds of CD across the maternal age distribution (see panel a). The estimated effect sizes are very similar across all age groups. In contrast, for the outcome length of hospital stay, we see clear heterogeneity in the treatment effect (see panel c). The effect increases with maternal age. This suggests that while the probability of a CD decreases uniformly with age, additional CDs result in comparatively longer hospital stays for “older” mothers. This can be explained by a longer recovery time after surgery for “older” patients. The effects on readmission by age are less clear (see panel e). While we find negative effects of more “crowded” hospitals except for the youngest group of mothers, the effects are statistically significant only for mothers in the 25-29 age group. This may be related to the reduced sample size for the readmission outcome.

Second, we split our sample by hospitals’ CD rates. The results are shown in the panels on the right side of Figure 4. We find statistically significant treatment effects for CDs across the distribution of hospital CD rates. For hospitals with the highest CD rates (i.e., those in the fourth quartile), we see slightly higher treatment effects (see panel b). This pattern is reinforced by the results for length of stay (see panel d). With respect to readmissions, we do not find a very clear pattern. The estimated effect size is more or less constant from the first to the fourth quartile and only significant in the third quartile. The lack of statistical significance may be due to the reduced sample size.

7 Summary and policy implications

The effect of the availability of medical resources on their rate of utilization and health outcomes is hard to identify. This paper examines this question in the context of maternity units and procedure choice. This is an important and interesting setting because of recent increases in cesarean delivery rates. To identify the effect of available maternity beds on the likelihood of a CD and hospital readmission, we estimate the effect of the number of empty beds available in the maternity unit on the day of mother’s admission. The number of admitted births is hard to predict and idiosyncratic. In our estimations, we

²²We do not have socioeconomic information on the mothers.

Table 5: The impact of the maternity bed occupancy rate on the likelihood of readmission

	(1) Hospital FE	(2) Hospital×year FE	(3) Hospital×quarter FE	(4) Hospital×month FE
<i>Panel A</i>				
Occupancy	-0.008*** (0.003)	-0.010*** (0.003)	-0.011*** (0.003)	-0.011*** (0.003)
Calendar month FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
<i>Panel B</i>				
Occupancy	-0.009*** (0.003)	-0.010*** (0.003)	-0.011*** (0.003)	-0.011*** (0.003)
Calendar month FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Mother's age	Yes	Yes	Yes	Yes
<i>Panel C</i>				
Occupancy	-0.008*** (0.003)	-0.009*** (0.003)	-0.010*** (0.003)	-0.009*** (0.003)
Docs per used bed	-0.015 (0.017)	0.098 (0.068)	0.120 (0.073)	0.123 (0.074)
Nurses per used bed	0.000 (0.004)	-0.002 (0.007)	-0.000 (0.007)	-0.001 (0.007)
Midwives per used bed	0.007* (0.004)	0.003 (0.006)	0.002 (0.007)	0.002 (0.008)
Calendar month FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Mother's age	Yes	Yes	Yes	Yes
<i>Panel D</i>				
Occupancy	-0.008*** (0.003)	-0.009*** (0.003)	-0.009*** (0.003)	-0.009*** (0.003)
Docs per used bed	-0.015 (0.017)	0.097 (0.067)	0.118 (0.072)	0.121* (0.073)
Nurses per used bed	-0.000 (0.004)	-0.002 (0.007)	-0.000 (0.007)	-0.001 (0.007)
Midwives per used bed	0.007 (0.004)	0.003 (0.006)	0.002 (0.007)	0.002 (0.007)
Occupancy ^{NB}	0.002 (0.003)	0.000 (0.005)	0.003 (0.005)	0.002 (0.005)
Calendar month FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Mother's age	Yes	Yes	Yes	Yes
Number of observations	329,025	329,025	329,025	329,025
Mean of Outcome	0.04	0.04	0.04	0.04

Notes: This table summarizes the regression results of the effect of maternity bed occupancy rate on the likelihood of readmission. The basic regression model is shown in equation (2). The specifications in panels A through panel D differ by the covariates included. These covariates are listed/indicated below the coefficient of primary interest. Calendar month FE are a series of binary indicators for January to December. Weekday FE are a series of binary indicators for a leisure day (i.e., Saturday, Sunday and any public holiday), for a pre-leisure day (i.e., Friday or any working day before a public holiday), and for each other weekday (i.e., Monday, Tuesday, Thursday) that is neither a leisure nor a pre-leisure day. The base group is Wednesdays, which are neither a leisure nor a pre-leisure day. Mother's age FE are a series of binary indicators for the following age groups: ≤ 14 (base group), 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, ≥ 50 . The variable $Occupancy^{NB}$ captures the proportion of beds occupied by patients other than expectant mothers. The specifications in columns (1) to (4) differ by the type of FE included. In column (1), we control for hospital and year FE. In column (2), we use "hospital \times year" FE instead. In column (3), we switch to "hospital \times quarter" FE. In column (4) we use "hospital \times month" FE. Clustered standard errors by hospital \times year are reported in parentheses below the coefficients. Asterisks indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

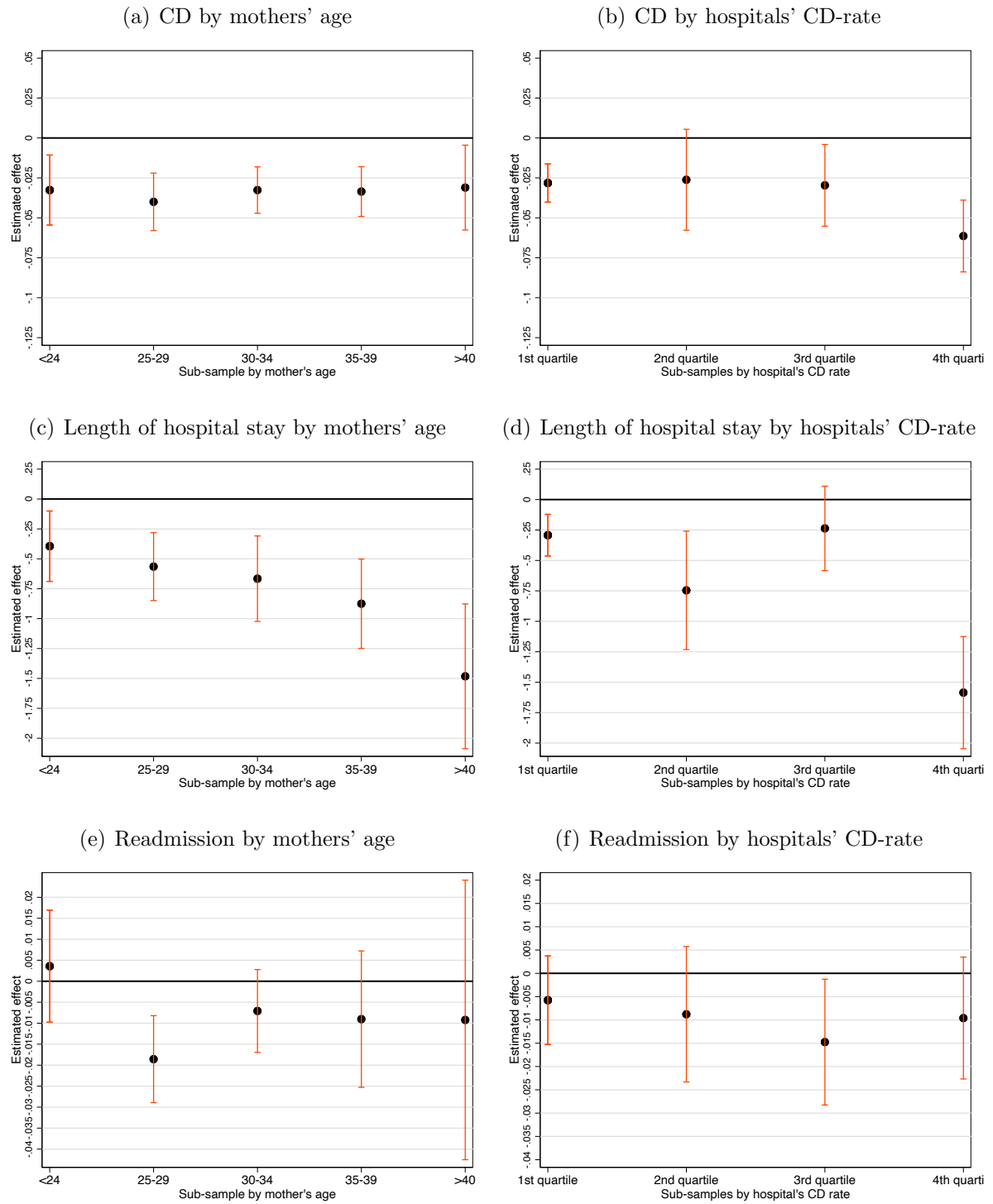
rely on hospital-specific monthly fixed effects, which enable us to exploit within hospital-month variation in maternity beds availability. We therefore flexibly control for factors correlated with the mother’s preferences, hospital specific treatment style, the cyclical and trends in delivery type, and the cyclical and trends specific to each hospital.

We find that a one standard deviation increase in the maternity bed occupancy rate reduces the likelihood of a CD by 1.14 percentage points or 4.12 percent. The estimated treatment effect varies little with the inclusion of control variables, such as the share of beds with non-birth admissions. Semi-parametric specifications show that the effect is also fairly constant across the distribution of maternity bed occupancy rates. Our finding suggests that physicians are more likely to perform a CD when there are more empty beds in the ward. This is of financial benefit to the hospital and, in many cases, to the attending obstetrician as well.

A CD is not only more costly than a vaginal birth, but it can also have negative health consequences. We find that a one standard deviation decrease in the maternity bed occupancy rate increases the length of hospital stay by 0.20 days or 4.29 percent and the likelihood of readmission by 0.24 percentage points or 5.84 percent. The negative effect of less hospital crowding on maternal health seems counterintuitive at first, and also contradicts most of the literature on hospital crowding. However, it is explained by the specific effect of hospital crowding in maternity units on procedure choice. In maternity wards, less crowding leads to more CDs which increase the length of stay. Given that these CDs have more postpartum complications, we find lower readmission rates for women admitted to a more crowded maternity unit. We conclude that expectant mothers may benefit from a crowded hospital, even with an unfavorable patient-staff ratio—because it may lead to less harmful overtreatment. While additional care and specialized medical technologies improve child outcomes in many cases (see, e.g., Bharadwaj et al., 2013; Daysal et al., 2015; Jensen and Wüst, 2015), institutional settings must achieve an optimal level of treatment intensity (Almond and Doyle, 2011).

While these findings are interesting in the context of maternity units, they may apply to any type of care where there is a choice of procedure that is related to hospital stay or other dimensions of reimbursement in which utilization rates vary. In the context of a medical technology with high fixed costs, physicians and hospitals face incentives to use this technology rather than leave it unused.

Figure 4: Treatment effects on all outcomes by mother’s age and hospital’s CD rate



Notes: This figure summarizes regression results of the effect of maternity bed occupancy rate on all three outcomes (i.e., probability of cesarean delivery, duration of hospital stay, and readmission). The left panels show estimates by mothers’ age (see panels a, c, and e). Five sub-samples are defined by mother’s age at admission. The number of observations for the first two outcomes in each sub-sample are as follows: < 24: 244,674, 25-29: 394,877, 30-34: 398,369, 35-39: 199,267, > 40: 44,136. The number of observation for the outcome readmission is lower, since we do not observe readmissions before 2015. The right panels show estimates by hospitals’ CD-rate (see panels b, d, and f). Four sub-samples are defined as the quartiles in the CD rate distribution across hospitals (see panel f in Figure 1). Each regression is based on an equivalent estimation specification as the estimate summarized in Column (4) of panel B of Table 1. Orange bars represent 95 percent confidence intervals.

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Web appendix

This web appendix provides additional material discussed in the unpublished manuscript “Do Empty Beds Cause Cesarean Deliveries?” by Florian Bachner, Martin Halla, and Gerald J. Pruckner.

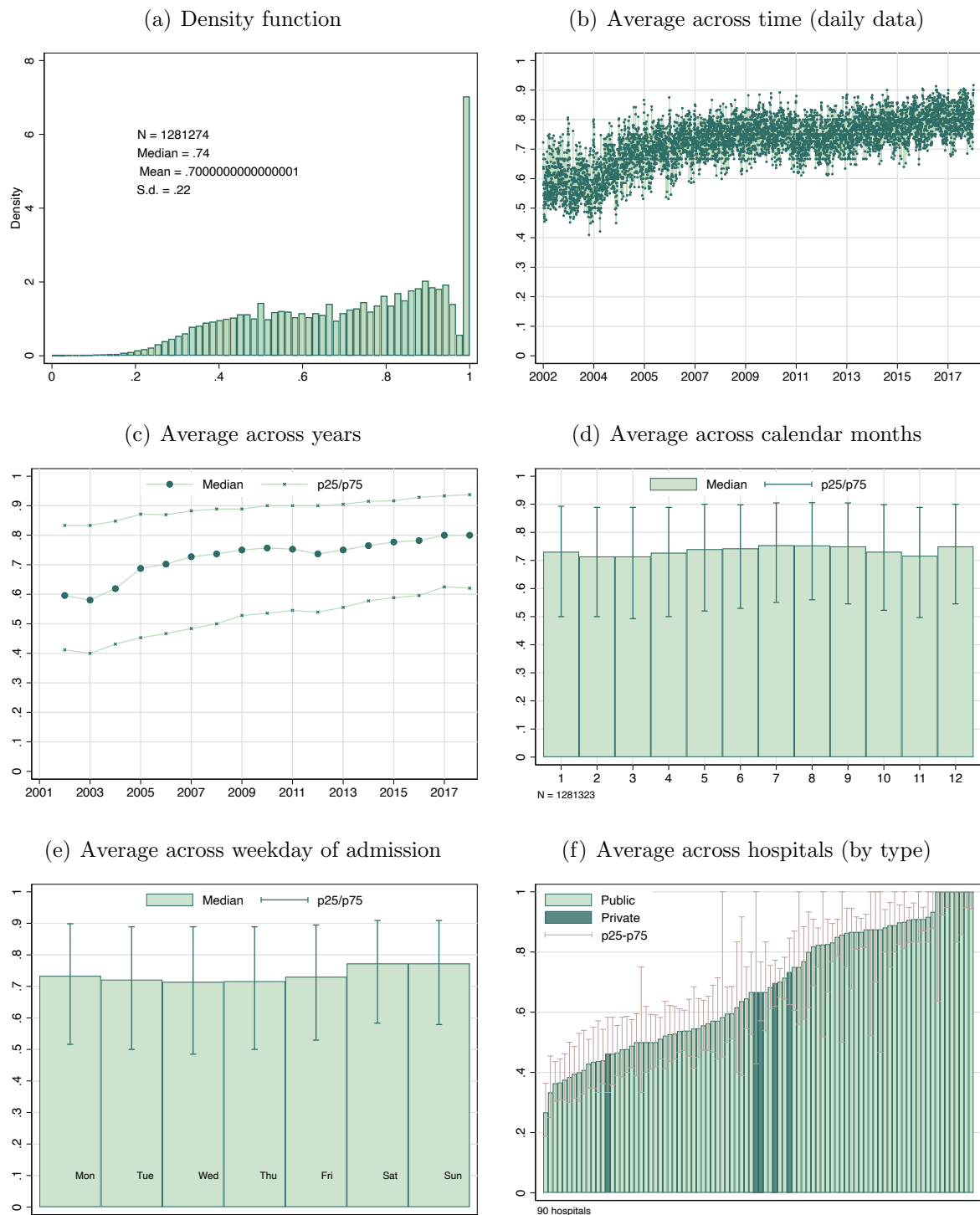
A Additional figures and tables

Table A.1: Top-10 non-delivery diagnosis groups in Austrian maternity units, by different ICD-10 digits groups

ICD-10 diagnosis group	Abs. no.	Rel. share	Cum. share
<i>1-digit diagnosis groups</i>			
N - Diseases of the genitourinary system	866,448	0.472	0.472
C - Malignant neoplasms	449,444	0.245	0.717
D - Other neoplasms (in situ, benign, other)	214,290	0.117	0.834
R - Symptoms, signs and abnormal clinical and laboratory ...	77,559	0.042	0.876
Z - Factors influencing health status and contact with ...	58,586	0.032	0.908
A - Certain infectious and parasitic diseases	28,809	0.016	0.924
P - Certain conditions originating in the perinatal period	24,246	0.013	0.937
K - Diseases of the digestive system	20,375	0.011	0.948
T - Injuries involving multiple body regions	16,627	0.009	0.957
<i>2-digits diagnosis groups</i>			
N8 - Noninflammatory disorders of female genital tract	420,607	0.164	0.164
C5 - Malignant neoplasm of breast	420,471	0.164	0.328
N9 - Other noninflammatory disorders of vulva and perineum	282,219	0.110	0.438
O0 - Pregnancy with abortive outcome	214,737	0.084	0.522
O2 - Other abnormal products of conception	192,925	0.075	0.598
D2 - Benign neoplasm of soft tissue of (retro)peritoneum	144,004	0.056	0.654
O4 - Polyhydramnios	117,537	0.046	0.700
N7 - Salpingitis and oophoritis	73,057	0.029	0.728
O3 - Multiple gestation	72,427	0.028	0.756
N3 - Zystitis	64,540	0.025	0.782
<i>3-digits diagnosis groups</i>			
C50 - Malignant neoplasm of breast	190,308	0.074	0.074
N92 - Excessive, frequent and irregular menstruation	141,448	0.055	0.128
C56 - Malignant neoplasm of uterus, part unspecified	127,758	0.049	0.178
O02 - Other abnormal products of conception	115,231	0.045	0.223
D25 - Leiomyoma of uterus	97,217	0.038	0.260
N84 - Polyp of female genital tract	95,162	0.037	0.297
N83 - Noninflammatory disorders of ovary, fallopian tube	89,789	0.035	0.332
O47 - Medical abortion	89,628	0.035	0.367
N81 - Female genital prolapse	62,273	0.024	0.391
N87 - Dysplasia of cervix uteri	61,941	0.024	0.415

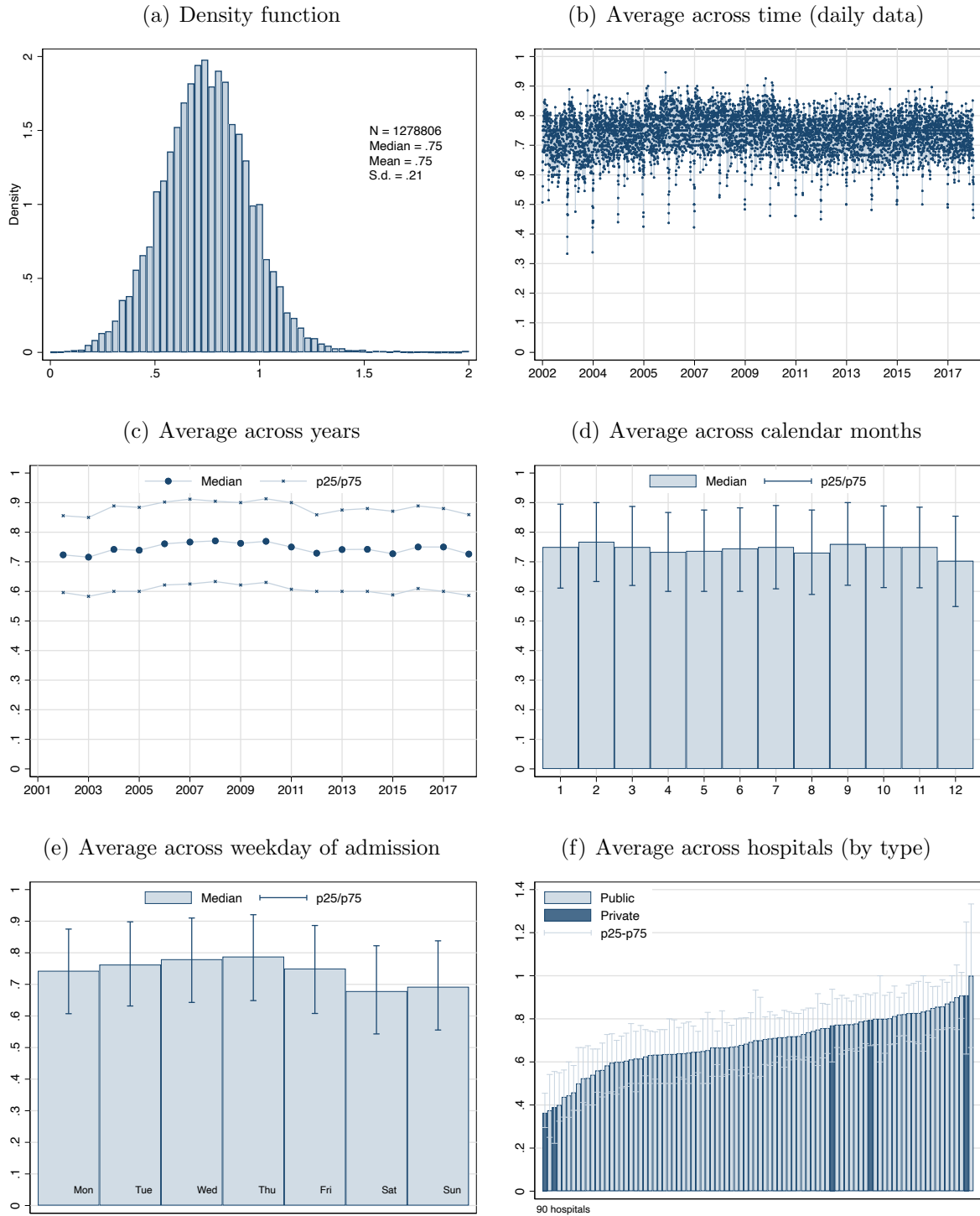
Notes: These figures refer to all patients admitted to a maternity unit in Austria in the period between 2002 and 2018 with a diagnosis other than “O80-O84 Delivery”. The figures are extracted from the Austrian DRG system (the so-called *LKF-System*).

Figure A.1: Descriptive statistics on the share of maternity beds



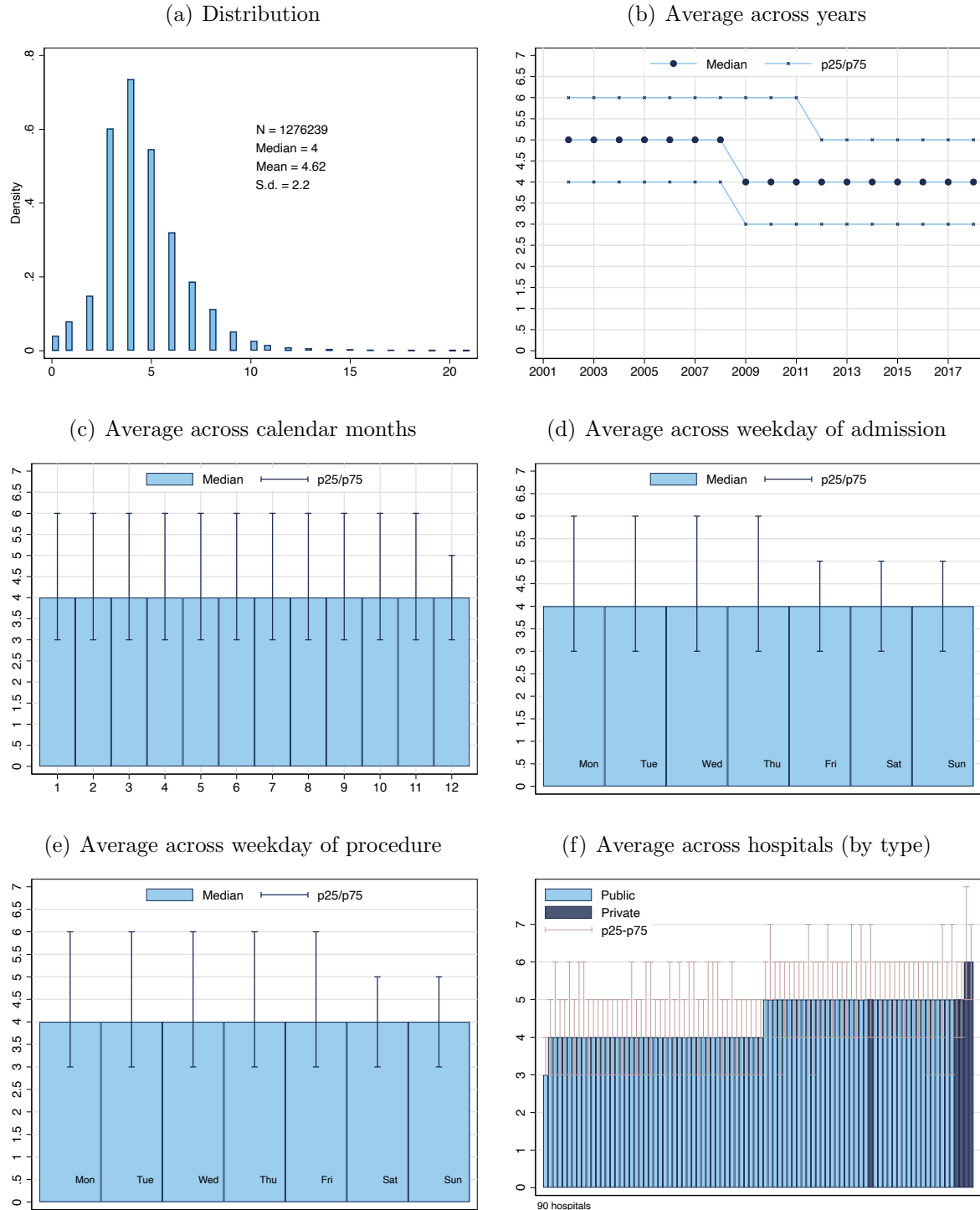
Notes: The variable of interest is defined as the share of all occupied hospital beds occupied by women admitted to the maternity ward for delivery. The number of underlying observations is 1,281,274.

Figure A.2: Descriptive statistics on the overall bed occupancy rate



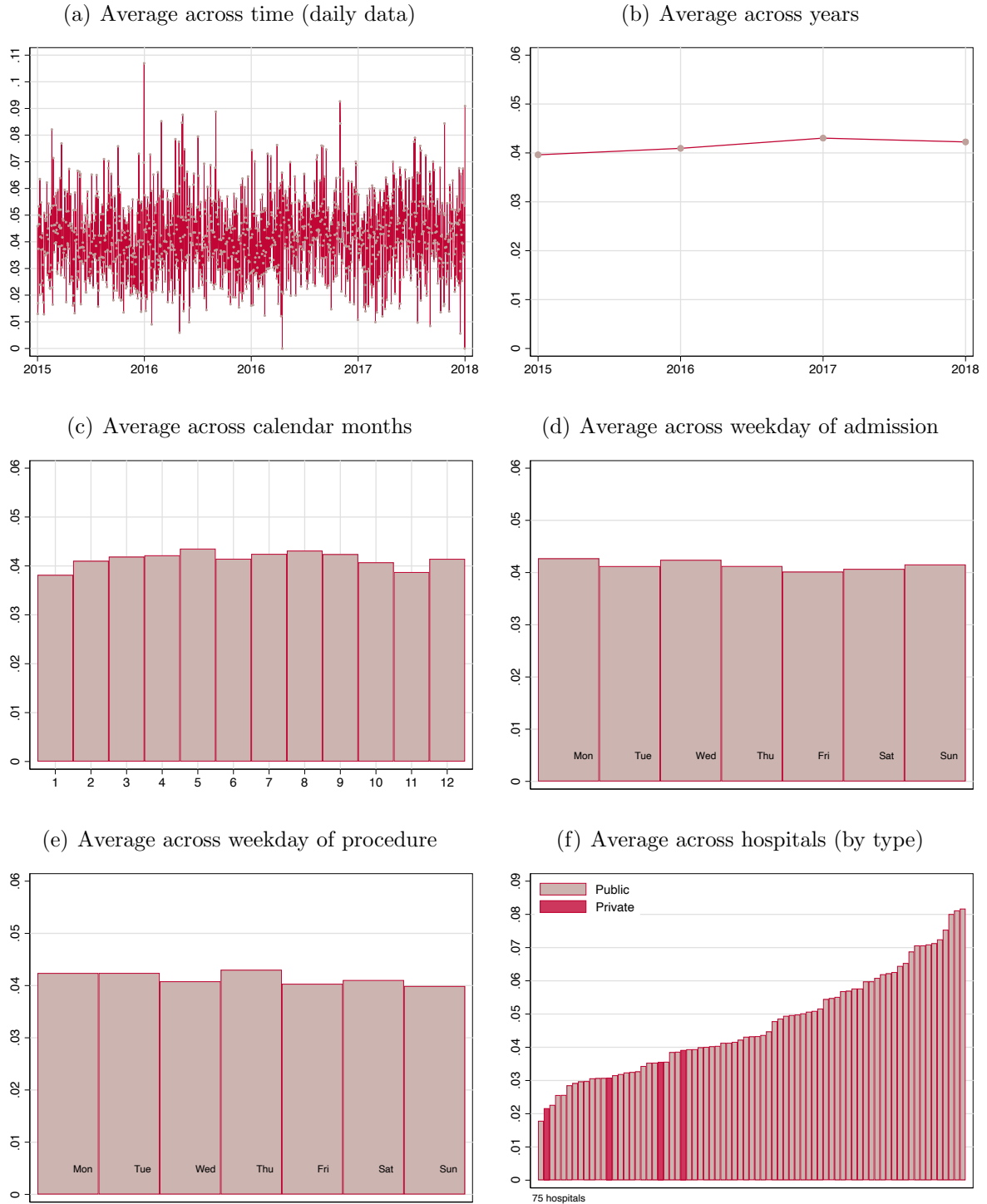
Notes: The overall bed occupancy rate is defined as the proportion of all beds occupied by patients with any diagnosis. The number of underlying observations is 1,281,323. Except in panel (a), where 2,517 observations with overall bed occupancy rate values greater than 2 are excluded.

Figure A.3: Descriptive statistics on the length of hospital stay



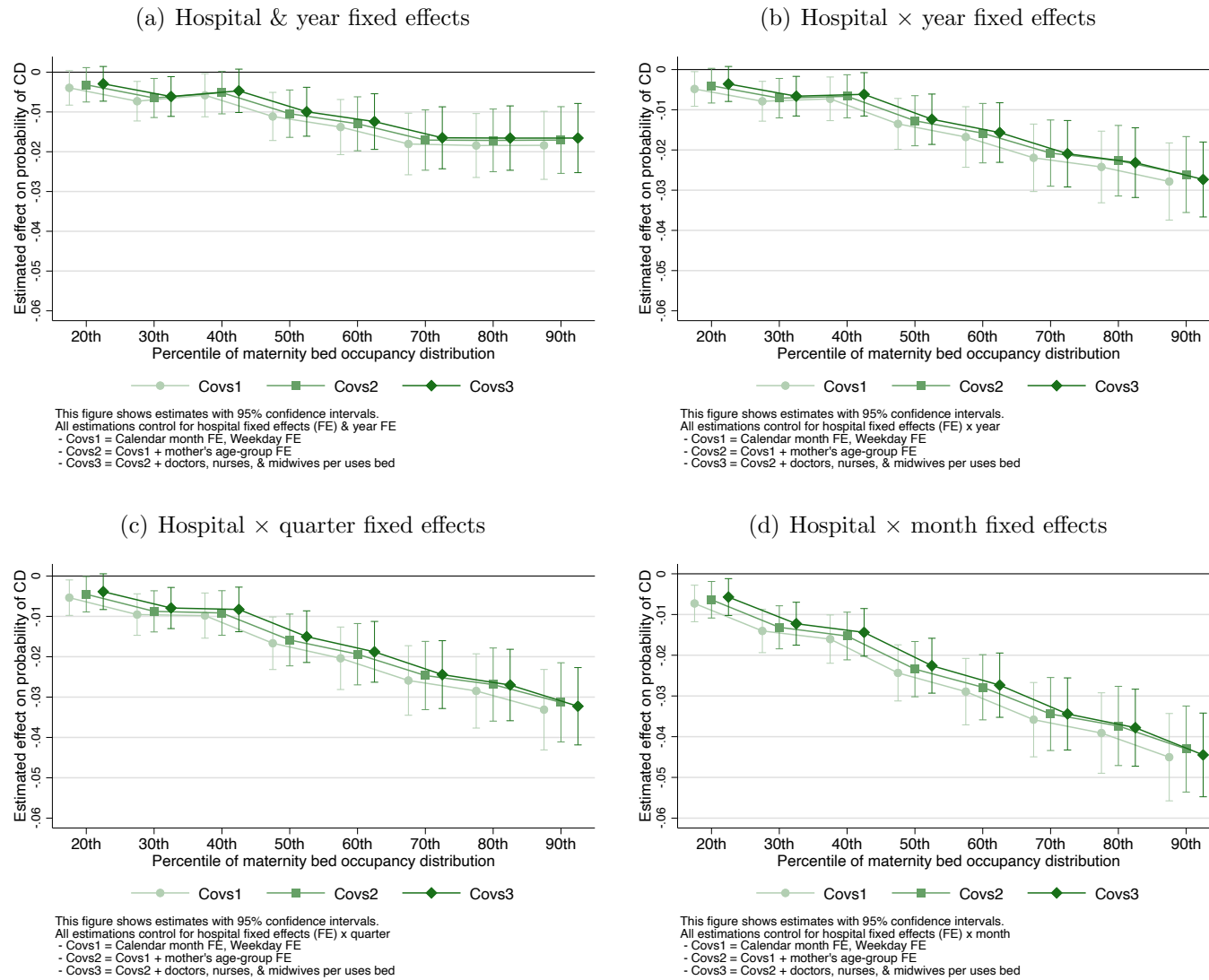
Notes: The number of underlying observations is 1,281,323, except in panel (a), where 5,084 observations with hospital stays longer than 21 days are excluded.

Figure A.4: Descriptive statistics on readmissions



Notes: Readmission is defined as an admission to an obstetric department within 6 months of delivery. We can observe readmissions from 2015 onwards. The number of observations is 329,059.

Figure A.5: The impact of maternity bed occupancy rate on the likelihood of CD; summary of different semi-parametric specifications



A.7

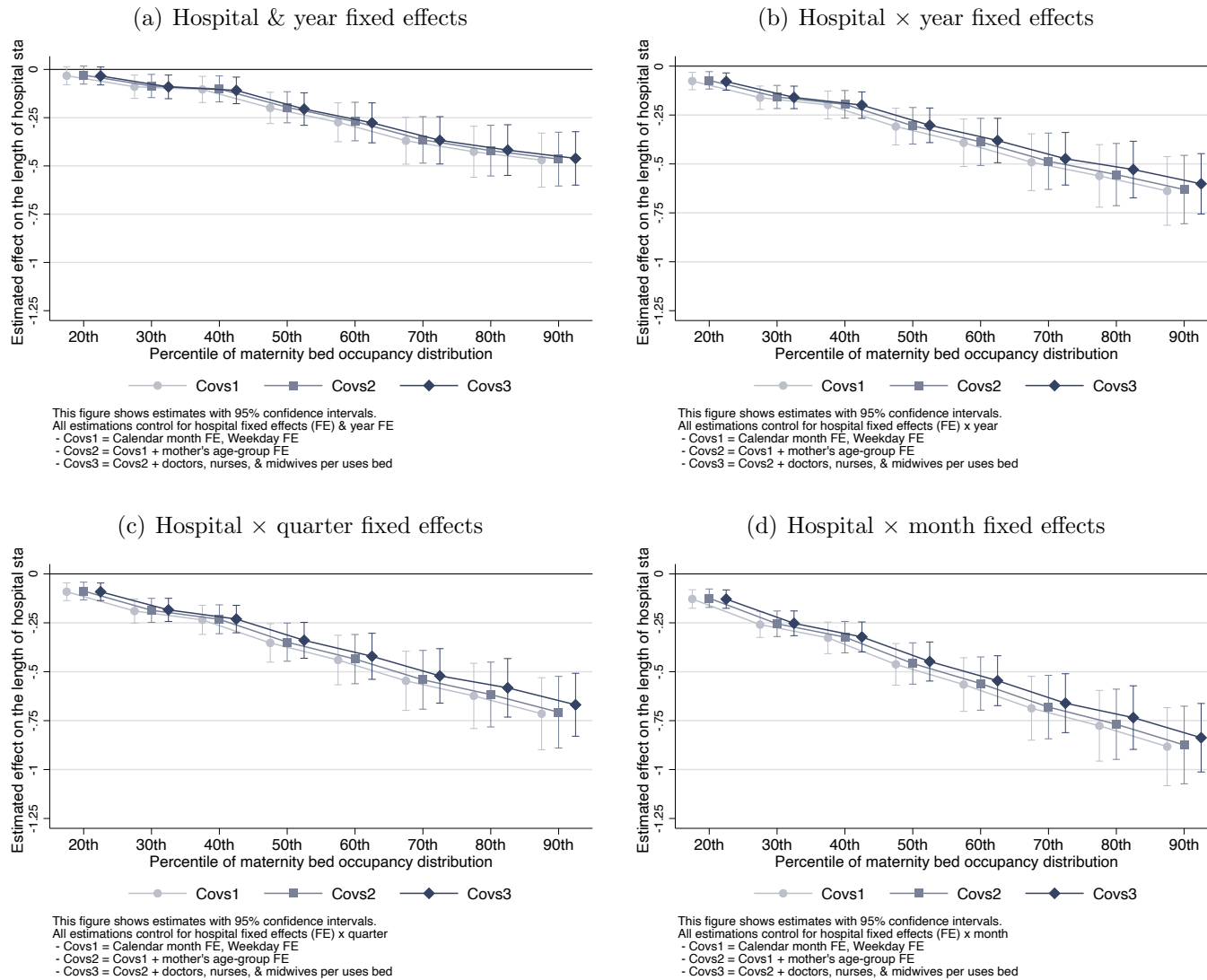
Notes: This figure summarizes the regression results of the effect of maternity bed occupancy rate on the likelihood of cesarean delivery (CD). The basic regression model is shown in equation (3). The specifications in panels (a) to (d) differ by type of included fixed effects (FE). These are indicated in the header. In each panel, we summarize three specifications with varying covariates. These covariates are listed on the bottom of each panel. The bars show 95 percent confidence intervals based on clustered standard errors by hospital \times year.

Table A.2: The impact of the maternity bed occupancy rate on length of hospital stay

	(1) Hospital & year FE	(2) Hospital×year FE	(3) Hospital×quarter FE	(4) Hospital×month FE
<i>Panel A</i>				
Occupancy	-0.311*** (0.109)	-0.408*** (0.147)	-0.555*** (0.178)	-0.702*** (0.222)
Calendar month FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
<i>Panel B</i>				
Occupancy	-0.309*** (0.109)	-0.404*** (0.146)	-0.550*** (0.178)	-0.696*** (0.221)
Calendar month FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Mother's age	Yes	Yes	Yes	Yes
<i>Panel C</i>				
Occupancy	-0.310*** (0.105)	-0.453*** (0.166)	-0.529*** (0.189)	-0.649*** (0.231)
Docs per used bed	0.619* (0.351)	3.799*** (1.171)	4.465*** (1.556)	4.652*** (1.784)
Nurses per used bed	-0.257* (0.146)	-0.184 (0.476)	-0.121 (0.482)	-0.057 (0.493)
Midwives per used bed	0.129 (0.194)	0.636 (0.547)	0.622 (0.578)	0.648 (0.591)
Calendar month FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Mother's age	Yes	Yes	Yes	Yes
<i>Panel D</i>				
Occupancy	-0.272*** (0.084)	-0.421*** (0.129)	-0.484*** (0.148)	-0.596*** (0.184)
Docs per used bed	0.336 (0.343)	3.165*** (1.034)	3.791*** (1.447)	3.904** (1.670)
Nurses per used bed	-0.275* (0.144)	0.061 (0.442)	0.153 (0.441)	0.233 (0.446)
Midwives per used bed	0.193 (0.185)	0.884* (0.495)	0.850 (0.522)	0.889* (0.529)
Occupancy ^{NB}	0.730*** (0.149)	0.982*** (0.177)	1.087*** (0.157)	1.175*** (0.169)
Calendar month FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Mother's age	Yes	Yes	Yes	Yes
Number of observations	1,281,323	1,281,323	1,281,323	1,281,323
Mean of outcome	4.75	4.75	4.75	4.75

Notes: This table summarizes the regression results of the effect of maternity bed occupancy rate on the length of hospital stay. The basic regression model is shown in equation (2). The specifications in panels A through panel D differ by the covariates included. These covariates are listed/indicated below the coefficient of primary interest. Calendar month FE are a series of binary indicators for January to December. Weekday FE are a series of binary indicators for a leisure day (i.e., Saturday, Sunday and any public holiday), for a pre-leisure day (i.e., Friday or any working day before a public holiday), and for each other weekday (i.e., Monday, Tuesday, Thursday) that is neither a leisure nor a pre-leisure day. The base group is Wednesdays, which are neither a leisure nor a pre-leisure day. Mother's age FE are a series of binary indicators for the following age groups: ≤ 14 (base group), 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, ≥ 50 . The variable Occupancy^{NB} captures the proportion of beds occupied by patients other than expectant mothers. The specifications in columns (1) to (4) differ by the type of FE included. In column (1), we control for hospital and year FE. In column (2), we use "hospital \times year" FE instead. In column (3), we switch to "hospital \times quarter" FE. In column (4) we use "hospital \times month" FE. Clustered standard errors by hospital \times year are reported in parentheses below the coefficients. Asterisks indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

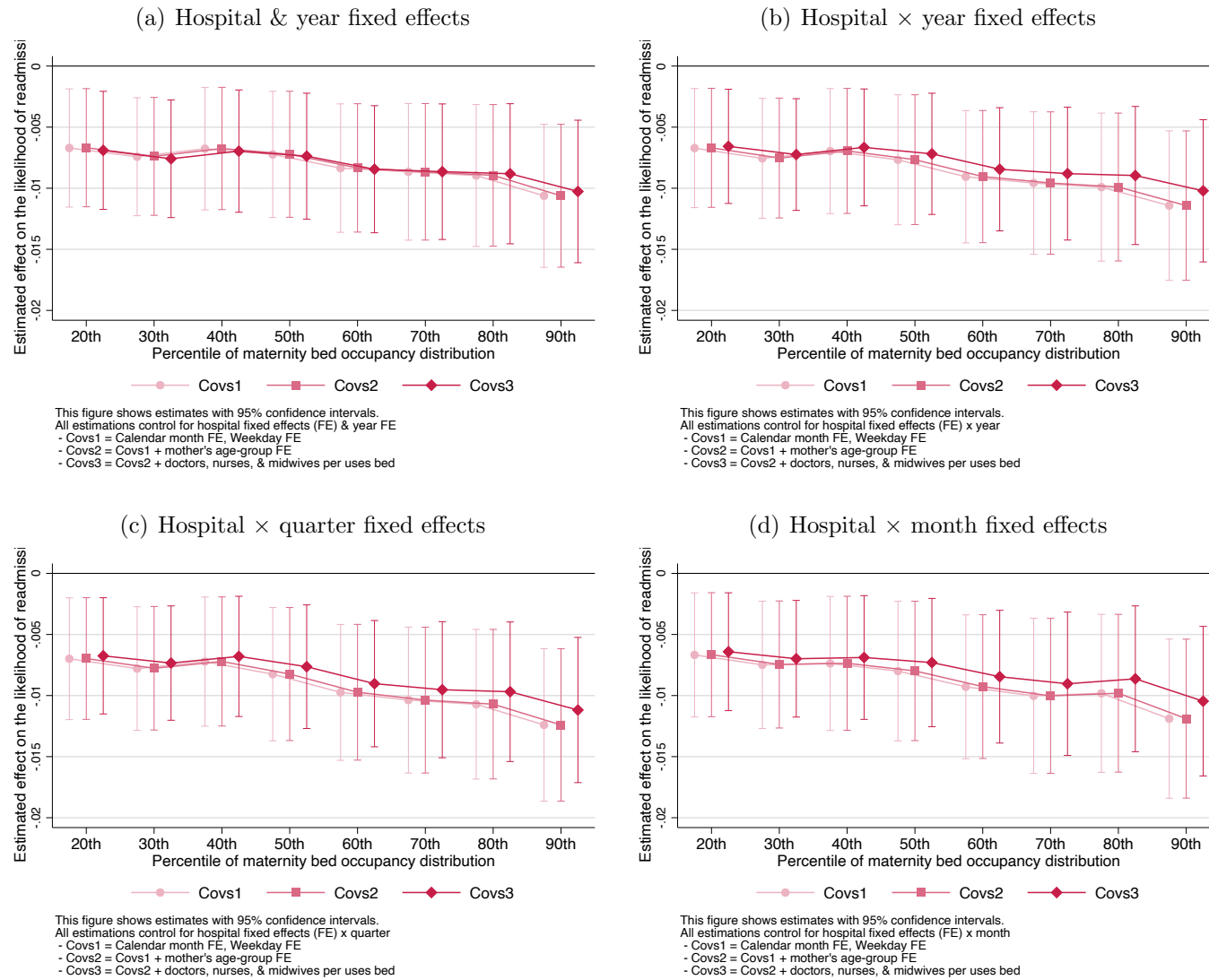
Figure A.6: The impact of maternity bed occupancy rate on the length of hospital stay; summary of different semi-parametric specifications



A.9

Notes: This figure summarizes the regression results of the effect of maternity bed occupancy rate on the length of hospital stay. The basic regression model is shown in equation (3). The specifications in panels (a) to (d) differ by type of included fixed effects (FE). These are indicated in the header. In each panel, we summarize three specifications with varying covariates. These covariates are listed on the bottom of each panel. The bars show 95 percent confidence intervals, based on clustered standard errors by hospital \times year.

Figure A.7: The impact of maternity bed occupancy rate on the likelihood of readmission; summary of different semi-parametric specifications



Notes: This figure summarizes the regression results of the effect of maternity bed occupancy rate on the likelihood of readmission. The basic regression model is shown in equation (3). The specifications in panels (a) to (d) differ by type of included fixed effects (FE). These are indicated in the header. In each panel, we summarize three specifications with varying covariates. These covariates are listed on the bottom of each panel. The bars show 95 percent confidence intervals, based on clustered standard errors by hospital \times year.

Table A.3: The impact of bed occupancy rate on the likelihood of CD, excluding planned CDs; semi-parametric specification

	All days	Working days	Non-working days
10th: Base group			
20th	−0.006*** (0.002)	−0.007*** (0.003)	−0.006* (0.004)
30th	−0.013*** (0.003)	−0.015*** (0.003)	−0.008* (0.004)
40th	−0.015*** (0.003)	−0.018*** (0.003)	−0.012** (0.005)
50th	−0.023*** (0.003)	−0.026*** (0.004)	−0.018*** (0.005)
60th	−0.028*** (0.004)	−0.032*** (0.004)	−0.020*** (0.006)
70th	−0.034*** (0.005)	−0.037*** (0.005)	−0.029*** (0.006)
80th	−0.037*** (0.005)	−0.040*** (0.005)	−0.033*** (0.006)
90th	−0.043*** (0.005)	−0.046*** (0.006)	−0.039*** (0.007)
Hospital×month FE	Yes	Yes	Yes
Calendar month FE	Yes	Yes	Yes
Weekday FE	Yes	No	No
Mother's age	Yes	Yes	Yes
Number of Obs.	1,281,323	933,910	347,413
Mean of Outcome	0.27	0.29	0.23

Notes: This table summarizes the regression results of the effect of maternity bed occupancy rate on the probability of cesarean delivery (CD). The basic regression model is shown in equation (3). The covariates are indicated below the coefficient of primary interest. Calendar month FE are a series of binary indicators for January to December. Weekday FE are a series of binary indicators for a leisure day (i.e., Saturday, Sunday and any public holiday), for a pre-leisure day (i.e., Friday or any working day before a public holiday), and for each other weekday (i.e., Monday, Tuesday, Thursday) that is neither a leisure nor a pre-leisure day. The base group is Wednesdays, which are neither a leisure nor a pre-leisure day. Mother's age FE are a series of binary indicators for the following age groups: ≤ 14 (base group), 15-19, 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, ≥ 50 . Clustered standard errors by hospital \times year are reported in parentheses below the coefficients. Asterisks indicate statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B Instrumental variable approach

In an alternative estimation approach, we use the overall bed occupancy rate as an endogenous treatment variable and instrument it with the maternity bed occupancy rate. The logic is that the overall bed occupancy rate is endogenous due to planable non-birth admission, and the instrumental variable (henceforth IV) approach allows us to focus on the exogenous part due to birth admissions. Therefore, we estimate the following first stage estimation:

$$\text{overall bed occ}_{ihymw} = \beta_1 + \gamma_1 \cdot \text{maternity bed occ}_{ihymw} + \phi_h + \psi_y + \xi_m + \gamma_w + \epsilon_{ihymw}. \quad (4)$$

We find a robust positive effect of maternity bed occupancy rate on overall bed occupancy rate. The γ_1 is about 10, which corresponds with a beta coefficients of 0.18. The F-statistic on the instrument is 12.79. From the first-stage regression, we derive the predicted values overall $\hat{\text{bed occ}}_{ihymw}$, which represent the variation in the the overall bed occupancy rate that is driven by the maternity bed occupancy rate. We use this exogenous variation in the second stage equation to estimated parameter of interest:

$$\text{CD}_{ihymw} = \beta_2 + \gamma_2 \cdot \text{overall } \hat{\text{bed occ}}_{ihymw} + \phi_h + \psi_y + \xi_m + \gamma_w + u_{ihymw}, \quad (5)$$

We obtain a $\hat{\gamma}_2$ of minus 0.0037. In this IV framework, our original equation (3) can be interpreted as the reduced form that relates the (exogenous) IV to the outcome variable. The LATE-estimate γ_2 is essentially a by the first-stage coefficient re-scaled version from the reduced form estimate: $0.037/10 = 0.0037$.

For our IV to be a valid, we must assume (i) that the maternity bed occupancy rate affects the probability of a probability of cesarean delivery only through the channel of overall bed occupancy rate, and (ii) that it is not correlated with any unobserved determinants of cesarean delivery included in the error term u_{ihymw} .

If these conditions hold, then γ_2 provides us with a *local average treatment effect* (LATE) that identifies the causal effect of a higher overall bed occupancy rate, due to a higher maternity bed occupancy rate, on the probability of a cesarean delivery. Thus, an increase in the overall bed occupancy rate by one percentage points increase the probability of a cesarean delivery by 0.37 percentage points.

In our context, we prefer the interpretation of the reduced form estimate. Since we have shown that including the non-birth bed occupancy rate as a control variable (see Panel D of Table 1) has no impact, and that our estimated treatment effects are constant across maternity units with different non-birth bed occupancy rates (see Figure 3), we consider our baseline approach to be reliable.