Does More Prenatal Care Improve Health Outcomes? Evidence from Paid Sick Leave Mandates *

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Abstract

High rates of maternal and infant mortality rates in the U.S. have generated significant concern amongst policymakers. Prenatal healthcare use can protect mothers and infants against health complications, but the inability to take time off work can be a barrier to care-seeking. I analyse the effects of U.S. state-level sick pay mandates on maternal healthcare utilisation and find that prenatal care use increases by 8%. I then evaluate the effectiveness of prenatal care on health outcomes. I find that more prenatal care has no statistically significant effect on severe and rare outcomes, but reduces postnatal depression diagnoses by 7%.

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1 Introduction

Ensuring a healthy pregnancy can protect mothers against health problems and the risk of mortality, and help give children the best possible start in life. I study one of the factors that can improve mothers' and infants' health outcomes at birth - prenatal care. Prenatal care allows doctors to identify potential issues in advance, prevent pregnancy complications to both the mother and child, and discuss lifestyle behaviours that can affect infant health (e.g. smoking during pregnancy). Mothers are advised to get early, and regular prenatal care (Office on Women's Health, 2023), which has been found to benefit infant and maternal health (Yan, 2017; Geiger et al., 2021). Yet prenatal care utilisation is far from universal in the U.S. 25% of pregnant women did not receive early and adequate prenatal care in 2022, and this figure has increased since 2018 (Healthy People, 2022).

Despite the recommendations, in surveys, mothers cite lack of money and being unable to get time off work as reasons for not seeking routine care during pregnancy (Kitsantas et al., 2012). Quantitative evidence exploring these factors, however, is lacking. In this paper, I explore whether lack of paid time-off work is a barrier to obtaining healthcare in the context of expectant mothers. I ask whether sick pay mandates affect employees' healthcare seeking behaviours, such that they seek healthcare that they may have forgone otherwise.

I focus on this setting because of the state of maternal and infant health in the U.S., which has received attention from policymakers (The White House, 2021; Cohen, 2023; Kaine, 2023) and the medical profession (D'Alton et al., 2013). For both the infant and maternal mortality rates, the U.S. ranks below its OECD counterparts (OECD.Stat, 2018) [1]. Access to maternal health care, and particularly high quality care, has been cited as a factor that could reduce maternal mortality (Wong and Kitsantas, 2020). Infant and maternal mortality outcomes are closely tied so factors that drive increased maternal mortality

[1] This is the case even when accounting for methodology changes in the National Vital Statistics System that affect the estimation of the maternal mortality rate (Joseph et al., 2024).

also contribute to elevated infant mortality. Authors have referenced maternal complications during pregnancy and at birth, and medical care during pregnancy and in the postpartum period as contributors to infant mortality (Warren et al., 2022).

There is much support for the position that prenatal care improves maternal and infant health outcomes. Yet there is a lack of consensus in the quantitative literature. Empirical researchers studying the effectiveness of prenatal care face the challenge that mothers who seek timely and more frequent care are more likely to be healthier and practice health behaviours that are protective of the infant. I provide new causal evidence on this matter, by evaluating the effect of more prenatal care visits on maternal and infant health outcomes. In doing so, I am able to explore how a labour market policy affects downstream health outcomes, which is valuable for understanding the true impact of the policy.

My analysis draws on a new and large medical claims dataset for researchers, Inovalon. These data allow me to look at healthcare use and health outcomes of a sample of over 800,000 births between 2010 and 2019. First, to study whether sick pay mandates affect maternal healthcare use, my analysis takes advantage of the staggered adoption of paid sick leave mandates on employers across U.S. states. I use a difference-in-differences approach to estimate the effects of these mandates on the number of prenatal care events, timely prenatal care use, and emergency department use. Second, to study the importance of prenatal care for maternal and infant health, I use a two-staged least squares strategy, instrumenting prenatal care with access to sick pay. This approach allows me to estimate the causal effect of prenatal care on outcomes such as severe maternal morbidity, stillbirth, preterm birth, and postnatal depression.

I find that the introduction of paid sick leave mandates leads to an increase in prenatal care use amongst commercially insured mothers, and no change in emergency department visits. This suggests that if a pregnant individual has a health scare during their pregnancy that requires rapid medical attention, they attend an emergency room. Yet their non-urgent healthcare use increases when they have access to sick days. The rise in prenatal care use is driven by routine pregnancy supervision visits, and chiefly occurs in the first and second trimester. In the instrumental variables analysis, I find that more prenatal care has no significant effect on severe maternal morbidity or stillbirth, but does reduce postnatal depression diagnoses by 7% relative to the mean. Taken together, we can make the following conclusions based on these findings. First, that lack of paid time off work is a limiting factor for mothers seeking routine healthcare during pregnancy. Second, that receiving more prenatal care does not shift the probability of rare health shocks such as severe maternal morbidity. Nonetheless, reducing postnatal depression could both improve the well-being of these mothers and reduce the risk of postnatal death due to mental health conditions, with knock-on benefits for infants.

My paper contributes to two strands of research. First, the literature evaluating sick pay. Due to the wide availability of sick pay across the developed world, there is an extensive literature evaluating sick pay outside of the U.S. (e.g. Ziebarth and Karlsson (2014, 2010); Johansson and Palme (2005); Henrekson and Persson (2004); Puhani and Sonderhof (2010); Halla et al. (2017); Böckerman et al. (2018)). Yet the universal provision of sick pay in these countries means that the literature focuses on changes in the compensation level rather than the change from employers providing no paid sick leave days to full compensation for workers. In the U.S. setting, Callison and Pesko (2022) document a first stage; the introduction of PSL leads to an increase in sick leave coverage for employees, with women experiencing larger gains. Furthermore, there is take up of the benefit (e.g. Ahn and Yelowitz (2016); Maclean et al. (2020)). Employees use approximately 2 additional sick days per year after the introduction of the policy (Maclean et al., 2020). Other work focuses on presenteeism at work and labour productivity (e.g. Cronin et al. (2022)). There is a nascent literature evaluating health related effects in the U.S. For example, access to paid sick leave results in a reduction of influenza-like infection rates (Pichler and Ziebarth (2017); Pichler et al. (2021)), increases in cancer screening Callison et al. (2023), increases in contraception use (Maclean et al., 2023), and a reduction in emergency department (ED) visits for all causes (Ma et al., 2022). The question of what happens to non-urgent care seeking and other forms of preventive care use remains understudied. Chen et al. (2020) look at health care utilisation, but suffer from pre-trends and have a small sample size. I use a large claims dataset, which allows for more precision in measuring health care use.

Second, I contribute to the literature on the effectiveness of prenatal care. From the papers that use robust causal inference methods, effects are mixed and modest - see Corman et al. (2019) for a review. Authors find some positive effects on smoking and breastfeeding behaviors which protect infants' health (Yan, 2017), and reduced mortality for commercially insured mothers at the age cutoff of 35 (Geiger et al., 2021). Others document null or imprecise effects (Rosenzweig and Schultz, 1983, 1988; Evans and Lien, 2005). Timely initiation of prenatal care has been found to increase the child's birth weight (Corman et al., 2019) [2], decrease smoking in the postpartum period, and increase the probability of attending well-child visits (Reichman et al., 2010). Quality of care is important; Kiser (2024) finds that Perinatal Quality Collaboratives, which develop initiatives to improve prenatal care quality, decrease the incidence of eclampsia (particularly amongst Black mothers). A related set of papers evaluate Medicaid expansions, which led to increases in prenatal care. The expansions are found to decrease infant mortality and low-birth weight (Currie and Gruber (1996a,b); Gray (2001); Sonchak (2015)). Access to another form of leave, paid maternity leave, has also been found to reduce the proportion of low-birth weight births (Stearns, 2015). Overall, the literature lacks consensus and focuses on infant health. This paper provides new evidence on the effectiveness of prenatal care, and in particular, more findings on maternal health.

[2]Birth weight is a standard measure of how healthy an infant is, as low birth weight babies are at greater risk of mortality and health problems in their first year of life and beyond (Behrman and Rosenzweig, 2004).

2 Background

2.1 Paid sick leave

Paid sick leave is a paid absence from work for use when an employee or their family member is sick, injured, or receiving medical attention. There is no federal provision for paid sick leave in the United States. Instead, there is a mosaic of paid sick leave entitlement across the country. Fourteen states (Arizona, California, Colorado, Connecticut, Maryland, Massachusetts, Michigan, New Jersey, New Mexico, New York, Oregon, Rhode Island, Vermont, and Washington State) plus Washington D.C. have paid sick leave laws. Additionally, some cities and counties have enacted their own mandates. 77% of private industry workers have access to paid sick leave (U.S. Bureau of Labour Statistics, 2022). There is, however, substantial variation in access to sick pay. Only 51% of part-time private industry workers have access to paid sick leave, and 53% of workers in leisure and hospitality. These statistics, however, do not only capture workers in states with sick pay mandates. Some organisations choose to offer employees sick pay regardless of whether their state has a mandate or not, but data on the prevalence of this practice is lacking and I cannot observe this information in my data. This means that mothers in states without mandates but who in fact do have sick pay access through their employer will be treated as control mothers in my analysis. Thus my control group is composed of a mix of mothers with and without access to sick pay. This may lead my estimates of the effect of state PSL mandates on prenatal care to be underestimates of the effect of *any* PSL mandate on prenatal care. Furthermore, in states without mandated PSL, there may have been increases in employer provided PSL over time, but we can rule out this concern if we do not observe pre-trends in the event studies.

Paid sick leave mandates are similar across states, with some variation in features. Typically, all employees or employees at large businesses (with at least 50 employees) in the state are covered. Some states have a weekly hours requirement. Employees accrue sick leave hours based on number of hours worked, up to a cap of 40 hours in any year. Detailed information on existing paid sick leave laws are available in Supplemental Appendix Section A.

During the time period I study, several cities and counties also enacted paid sick leave mandates. For example, San Francisco enacted its first mandate in 2007. In this paper, I study the effects of state-level paid sick leave mandates. Mothers in states that never introduce a mandate but contain cities that introduce a mandate will be in the control group in my analysis. Again, in this way, my estimates of the effect of state PSL mandates on prenatal care could be underestimates of the effect of *any* PSL mandate on prenatal care.

Employees do have access to other provisions to take time off work, if needed, but none of these are obvious substitutes for paid sick leave. All employees who have worked at least 1,250 hours over the previous year at a company with more than 50 employees are eligible for 12 weeks of unpaid sick leave for specific medical situations affecting themselves or their family members under the Family and Medical Leave Act. This is distinct from paid sick leave in that the leave is not remunerated, and was introduced in 1993, far in advance of the time period that I study in this paper. Second, nine states and Washington D.C. offer paid family and medical leave policies, which are targeted at new parents, employees recovering from a long-term illness, and employees who need to care for a family member with a serious illness. These policies differ from paid sick leave in their provision for time off for long-term, serious illness rather than short-term sickness, injury, or medical treatment. No states simultaneously introduce paid sick leave and paid family and medical leave. Finally, many employees have access to paid time off, which is often used for a vacation or holiday, but may also be used for health related occurrences. Given that the average number of vacation days after one year is only 11 days (U.S. Bureau of Labour Statistics, 2022), employees are likely to try and save these days for vacation or urgent events that arise.

2.2 Prenatal care

Prenatal care involves visits to a health care provider, often an obstetrician-gynaecologist or a general practitioner, for preventative medical care during pregnancy. The goals of prenatal care are to promote the health of the mother and infant, identify and reduce the risk of pregnancy complications, and reduce the infant's chance of complications. The visits often include physical exams, weight checks, blood tests, and ultrasounds (NIH, 2024). The American College of Obstetricians and Gynecologists (ACOG) advise that mothers attend 12 to 14 prenatal care visits throughout their pregnancy (Michel and Fontenot, 2023). The ACOG and Centers for Disease Control and Prevention (CDC) also recommend STI tests, laboratory panels, vaccinations and an ultrasound for mothers (Gourevitch et al., 2022).

"Complicated pregnancies" arise when mothers have pre-existing chronic conditions such as obesity or hypertension, or conditions that develop during pregnancy that pose a risk to the mother and child, such as gestational diabetes. 196 women in every 1,000 experience pregnancy complications, and 16.9 in every 1,000 experience birth complications (Blue Cross Blue Shield, 2022). For complicated pregnancies, mothers will need more intensive prenatal care (Backes et al., 2020), as will mothers with psychosocial risk factors such as a limited support network or intimate partner violence (Peahl and Howell, 2021).

Starting care in the first trimester is particularly important for the mother and her infant as it allows for early identification of conditions that can cause complications, intervention if necessary, and education on healthy behaviours during pregnancy. Early prenatal care has been found to reduce low birthweight of the infant (Frank et al., 1991).

3 Data and sample construction

3.1 Data

My data source is the Inovalon primary source medical claims database [3] (Inovalon, 2019). These data have the advantage of being extensive in the number of patients and coverage across states. Inovalon sources its data from over 150 payers (e.g. insurers) or providers of healthcare and/or administrative services

[3] Harvard University uses Inovalon Insights, LLC as one of its normative benchmarking databases for health care claims.

to adjudicate providers' healthcare claims. The database consists of medical (inpatient and outpatient) claims, prescription drug claims, member and enrolment information, and provider information. I supplement the Inovalon data with the Area Health Resource Files for 2010 to 2019 (U.S. Department of Health & Human Services, 2019) to capture information on county-level socioeconomic, health, and healthcare access characteristics.

3.2 Sample construction

My sample is made up of commercially insured females aged 18 to 51 who gave birth between 2010 and 2019 inclusive, sometimes more than once, resulting in a sample of mother-births. Mothers must have continuous medical coverage 6 months prior to the estimated date of their last menstrual period. I define a delivery using the Kuklina method for identifying obstetric deliveries (Kuklina et al., 2008) [4]. I focus on commercially insured mothers as these individuals are the group most likely to be employed. For the most part, individuals with commercial insurance receive health insurance through their employer. Some individuals may receive commercial insurance through the employer of a family member, and some individuals may choose to purchase commercial insurance privately. I do not observe the insurance source of a mother, so I cannot see if the mother has employer sponsored insurance or whether she is covered by her spouse's insurance.

I need to identify the mother's state to assess whether a mother has been affected by a paid sick leave policy. I approximate the mother's state by identifying the mother's location in 2022. I then exclude mothers where the mother state location does not match the delivery provider state location in 2022. I use this approach as a limitation of the Inovalon data is the inability to see the geographic location of a medical event on the claim in the year of

[4] The Kuklina method involves using additional International Classification of Diseases (ICD) codes, beyond the maternal outcome of delivery code Z37.0, to identify obstetric deliveries. These additional codes include the "normal delivery" ICD code, diagnosis-related group delivery codes for caesarean and vaginal deliveries, and ICD procedure codes for delivery related procedures. Deliveries are excluded if they involve an abortion or abnormal pregnancy outcome, such as an ectopic pregnancy.

the birth. I can only see the provider's location and the mother's location at a fixed point in time, in 2022. [5]

Further, I exclude mothers whose estimated birth location is Washington D.C., where paid sick leave was introduced in 2008, before my first year of data. Mothers in Colorado, New Mexico and New York remain "untreated" in my sample, as these states enacted paid sick leave laws after 2019. I also exclude mothers for whom I cannot calculate age. I set out the sample size at each stage of these exclusions in Supplemental Appendix Section B. I also provide counts of mother-births by state in Supplemental Appendix Table G1.

3.3 Descriptive statistics

Table 1 gives the descriptive statistics of my mother-birth sample. The mean and median age of mothers giving birth is 31. The median age of mothers in the U.S. is 30 (United States Census Bureau, 2022). As is often the case with claims data, the data is incomplete on ethnicity of the mother so I cannot comment on the representativeness of the sample with regard to race or ethnicity. The majority of mothers (78%) are on a PPO medical insurance plan.

[5] Note that this does not mean that the mother and provider must remain in the Inovalon data until 2022. The provider need not still be practicing in 2022, either.

Table 1. Descriptive statistics for mother-birth sample

	Mean/%	Std. Dev.
Age at delivery	30.93	5.43
Black	0.03	0.17
White	0.13	0.34
Hispanic	0.03	0.16
Asian	0.01	0.09
Other race/ethnicity	0.06	0.23
Unknown race/ethnicity	0.75	0.43
Elixhauser	0.26	0.55
Any EPO	0.02	0.15
Any HMO	0.18	0.38
Any PPO	0.78	0.42
Any POS	0.05	0.22

Notes: N=809,313. This table shows summary statistics of the mother-birth sample. Sample defined as births between 2010 and 2020 to mothers aged 18-51 with continuous commercial medical insurance coverage 6 months prior to the last menstrual period. “Elixhauser” is the Elixhauser comorbidity index of the mother at birth. “Any EPO” is whether the patient had any Exclusive Provider Organization plan type during the period in which the birth occurred. “Any HMO” is whether the patient had any Health Maintenance Organization plan type. “Any PPO” is whether the patient had any Preferred Provider Organization plan type. “Any POS” is whether the patient had any Point of Service plan type.

3.4 Variables

To analyse the effect of PSL on prenatal care, my main outcome is the number of prenatal care events that a mother has. I define prenatal care events using ICD-10, Current Procedural Terminology (CPT), and Healthcare Common Procedure Codes (HCPC) used in Gourevitch et al. (2022) and Sinaiko (2025). Please see Supplemental Appendix Section C for these codes. Identifying the full picture of a mother’s prenatal care can be difficult in healthcare claims data, as prenatal care is often included as part of the global fee for a delivery [6]. Thus we may not see all of the prenatal care interactions that took place in the data if there is no billing for these individual prenatal care interactions. I use two approaches to check that I have a suitable measure of prenatal care events in this paper. First, I include ICD-10, CPT, and HCPC codes that denote services that occur during prenatal care visits. Although we may be unable

[6] A global delivery fee is a single fee that covers the charges for labour and delivery, routine prenatal care, and postpartum care provided by a single physician or physician group. It does not cover all visits and services during a pregnancy.

to see all prenatal visits in the data, prenatal services such as genetic testing and ultrasounds are more likely to be billed separately and not included in the global delivery fee. Second, I carve out office visits from both the prenatal services and prenatal visits outcomes. Specifically, I carve out Evaluation and Management (E&M) claims. These E&M claims are more likely to be included in the global delivery fee, rather than being billed separately and visible in the claims data. However, there is variation in their inclusion across insurers and plans which I cannot identify in these data. My primary definition of prenatal care includes prenatal services, and excludes E&M visits. For robustness, I show the results using alternative definitions. I then break down this aggregate measure and look at the different types of prenatal care and how they change with the introduction of paid sick leave. The disaggregated categories of prenatal care consist of: ultrasounds, pregnancy supervision visits, genetic tests, foetal tests, pregnancy tests, lab tests, and E&M visits. Pregnancy supervision visit refers to regular outpatient visits during the pregnancy, for supervision of the pregnancy, antenatal screening, and risk assessment. E&M claims refer to visits and services that involve evaluating and managing patient health. Further, given the importance of prenatal care initiation in the first trimester in increasing birth weight (Frank et al., 1991), I use two related outcomes in my analysis. First, an indicator for first prenatal care visit in the first trimester, and second, the delay in days from the first trimester before the first prenatal care visit.

To analyse the effect of prenatal care on maternal and infant health, my main outcomes are severe maternal morbidity, stillbirth, preterm birth, and postnatal depression [7]. These conditions are identified using ICD-10 and CPT codes, which can be found in Supplemental Appendix Section D. Severe maternal morbidity is an index of various negative outcomes during labour and delivery that have significant implications for the mother's health (The American College of Obstetricians and Gynecologists (2016)). For analysis, I construct a binary variable that takes the value one if the mother has a diagnosis of any

[7] Unfortunately, I am unable to observe mortality and link mothers to infants in these data. This means that I cannot study outcomes such as low-birth weight or NICU admission.

of twenty one indicators defined by the Centers for Disease Control and Prevention (CDC, 2023). To give some examples, these indicators include: acute myocardial infarction, cardiac arrest, eclampsia, and hysterectomy. Postnatal depression is an indicator variable equal to one if the mother has a diagnosis of depression or anxiety at some point between delivery and six weeks postpartum. The stillbirth and pre-term indicators equate to one if the mother has an associated billing code at delivery, or up to 6 weeks before or after pregnancy. Preterm birth puts the infant at increased risk of mortality and a host of health and development problems (Butler et al., 2007). A mother is defined as having an induction if they have an associated billing code at delivery or up to one week postpartum.

4 Empirical strategy

4.1 Paid sick leave and maternal care utilisation

An ideal experiment to evaluate the effects of paid sick leave on maternal care utilisation would randomly assign mothers paid sick leave access to one group of mothers. Without such a random experiment, I evaluate the effects of access to paid sick leave using a difference-in-differences (DiD) approach that exploits variation in the introduction of paid sick leave mandates across time and states.

There have been numerous advances in the staggered difference-in-differences literature in recent years that address concerns with the two-way fixed effects (TWFE) method. In particular, when using a DiD model to evaluate the staggered introduction of a policy, the DiD coefficient estimate is a weighted average, which may represent a biased average treatment effect if there is effect heterogeneity across states and time. To overcome this problem, I use the estimator put forth in Callaway and Sant'Anna (2021). I select this estimation procedure as it allows for heterogeneity in treatment effects when the average treatment effect varies across time periods and states. This may be the case if over time, workers are more likely to take paid sick leave days when available to them, due to changing attitudes or a more supportive environment.

4.1.1 Specification

The empirical model for a DiD approach is given by:

$$PC_{ist} = \alpha + \beta \cdot D_{st} + \kappa \cdot X_{ist} + \gamma_t + \delta_s + \varepsilon_{ist} \tag{1}$$

where mother i gives birth in state s in year t. The time fixed effect is γ_t and δ_s is the state fixed effect. PC denotes a prenatal care outcome. For example, the number of prenatal care events, prenatal care initiation in the first trimester, or delay in prenatal care initiation. D_{st} equals 1 if there is a paid sick leave mandate in state s in year t. D_{st} is the DiD variable of interest. The coefficient β captures the causal effect of mandated sick pay on my various y outcomes. Controls X_{ist} are age, and, at the county level, percent with high-school degree, and a rural-urban indicator.

We also wish to examine event studies to assess pre-trends. Further, there may be effect heterogeneity over time. As employees have to accrue sick pay hours over time, we could see a delay in the effects of the policy. The two-way fixed effects event study model is denoted by:

$$PC_{ist} = \alpha + \sum_{k=-7, k\neq 1}^{5} \beta_k \cdot D_{sk} + \kappa \cdot X_{ist} + \gamma_t + \delta_s + \varepsilon_{ist} \tag{2}$$

I estimate the βs in these two equations using the estimator of Callaway and Sant'Anna (2021). The authors' approach involves estimating disaggregated state-time average treatment effects for each time period. I use the doubly robust estimation method. We can then aggregate these state-time effects into an event study plot showing the average effects across different lengths of exposure to a sick pay mandate.

I truncate the event study plots and ATT estimates (dropping observations) to seven years before and five years after the sick pay mandate date, to ensure that the results are not simply for one state for that lead or lag. I specify the reference year to be $t = -1$. I cluster standard errors at the state level. I set the control group to be "never treated" mothers, but my results are robust to including the "not yet treated" mothers (see Section 6).

4.1.2 Identification

The critical assumption required for DiD estimation is the parallel trends assumption: the treatment and control states have parallel trends in outcomes absent treatment. Seeing these counterfactual outcomes is not possible, but event study plots allow me to assess pre-treatment trends. If we see that the DiD coefficients in the pre-treatment time periods are not statistically different from zero, then we cannot reject the hypothesis that access to paid sick leave had no effect on prenatal care before the mandate was introduced.

Roth (2024) points out that we may observe a kink in event studies produced using Callaway and Sant'Anna (2021) as the pre-treatment coefficients are estimated differently to the post-treatment coefficients. Specifically, the pre-treatment coefficients are "short differences" that compare neighbouring time periods, and the post-treatment coefficients are "long differences" that compare the current time period with the period before treatment. If there is a simple linear time trend, say, then the event study estimated using Callaway and Sant'Anna (2021) can produce a jump in the coefficients from $t = 1$ onwards. Callaway and Sant'Anna (2021) provide an estimator option that plots "long differences" both before and after treatment, which I use for all event studies in this paper.

4.2 Prenatal care and health outcomes

A naive OLS approach involving regressing maternal or infant outcomes directly on the number of prenatal care events would likely suffer from statistical endogeneity. One source of such endogeneity is reverse causality. Maternal health status may affect the number of prenatal care events if mothers who are at high risk of experiencing problems at birth also receive more prenatal care. A second source is omitted variables. Although I attempt to control for socioeconomic characteristics through county-level indicators such as rural or urban status and median household income, I cannot observe patient level characteristics such as income that could affect prenatal care and maternal health. An ideal experiment would involve randomly assigning mothers a specific number of prenatal care events. In absence of this, to overcome statistical endogeneity, I use a two-stage least squares (2SLS) strategy. I instrument the number of prenatal care events with the presence of a paid sick leave mandate in a state-year.

4.2.1 Specification

The model is given by:

$$H_{ist} = \zeta + \mu \cdot PC_{ist} + \eta \cdot X_{ist} + \epsilon_{ist} \tag{3}$$

$$PC_{ist} = \alpha + \beta \cdot D_{ist} + \kappa \cdot X_{ist} + \gamma_t + \delta_s + \varepsilon_{ist} \tag{4}$$

H denotes an infant or maternal health outcome, and the other variables are as above. I supplement the 2SLS analysis with additional controls that are relevant for analysing maternal and infant health. Specifically, X_{ist} consists of age, the individual's Elixhauser comorbidity index, and, at the county level, percent with high-school degree, a rural or urban indicator, median household income, infant mortality rate, OB-GYN per capita. Aside from this, the first stage, given by Equation 4, is the same as Equation 1.

4.2.2 Identification

For identification of β as the local average treatment effect of receiving prenatal care, the 2SLS approach relies on several assumptions. The key identifying assumptions are relevance and the exclusion restriction.

Relevance is satisfied if we have a strong first stage. In the Results Section 5, Table 2, I show evidence of this. For the 2SLS analysis, I use a simple TWFE approach for the first stage as estimation via TWFE does not violate the assumptions of IV. TWFE estimation of the first stage satisfies relevance, as shown in Appendix Table A5. I report both the Cragg-Donald F statistic (Cragg and Donald, 1993) and effective F-statistic of Olea and Pflueger (2013). Given that I only have one endogenous regressor, this statistic is the F-statistic to test the hypothesis that the instrument does not enter the first stage regression (Stock and Yogo, 2005). The F statistic is 4.20, lower than what is considered a strong instrument. I am, however, operating in the just identified IV scenario. Angrist and Kolesár (2024) state that the median bias of the just identified IV is minimised and halved if the first stage t statistic, t_1, (and thus the coefficient estimate) is greater than zero. This theoretical results relies on the assumption that the population first stage is positive, which is a relevant assumption in my setting. I posit that the availability of paid sick leave leads to an increase in prenatal care use. I find that the estimated first stage has a positive coefficient, the expected sign. In my case, $t_1 = 2.05$, and so I proceed with the IV analysis. Further, in the case of a single instrument and single endogenous regressor, Anderson-Rubin confidence intervals are efficient and of the correct size even in the case of weak instruments (Andrews et al., 2019). I report the p-value of the Anderson-Rubin test of $H_0 : \beta = \beta_0$, as well as the 95% confidence intervals, in Section 5.2 Tables 4 and 5.

Exclusion is satisfied if paid sick leave impacts health outcomes only through prenatal care, and not through other channels. I cannot directly test this assumption, but I discuss exclusion in relation to my results in Section 6. Estimation of the first stage via TWFE does not violate exclusion. The sources of bias that arise from using TWFE, such as the presence of heterogenous treatment effects or delayed effects of a policy, are not correlated with the error term in the second stage equation.

In addition to these assumptions, my instrument must address conditional independence. In this setting, this requires that PSL mandates are uncorrelated with maternal and infant health outcomes, conditional on state-year fixed effects and controls. In this institutional context, that the conditional independence assumption holds is convincing. It seems reasonable to assume that the month the mandate is introduced in any state is random and uncorrelated with maternal and infant health outcomes at birth.

If there are heterogenous treatment effects of prenatal care on maternal and infant health, we also require monotonicity to hold to interpret the instrumental variables estimates as LATE. Monotonicity in this setting demands that PSL mandates must weakly increase prenatal care use for all mothers, or weakly decrease use for all. It seems implausible that the mandates will have opposing effects on mothers, and I expect them to weakly increase prenatal care use. In Appendix Table A4, I provide an assessment of the monotonicity assumption that tests whether the instrument, presence of a sick pay mandate, and the number of prenatal care events are positively correlated for any group of mothers. I break the sample down into groups of above and below median for various maternal characteristics and repeat the first stage analysis for the subsamples. This analysis shows that both mothers below and above the median age in the sample seek weakly more prenatal care after the introduction of mandates. The sample finding is replicated for mothers residing in above and below median counties in terms of the infant mortality rate, OB-GYNs per capita, and metro and non-metro status. In addition, in Appendix Figure B7, I plot the cumulative distribution functions (CDF) of the number of prenatal care events for treated and untreated, or not yet treated, mothers. The CDFs do not cross, which shows stochastic dominance; the number of prenatal care events for mothers that have access to PSL is stochastically larger than that for mothers who do not have access to PSL. Further, a Kolmogorov-Smirnov test confirms stochastic dominance. I test the null hypothesis that the number of prenatal care events for post-treatment mothers comes from the same distribution as the number of events for pre-treatment mothers, against the alternative hypothesis that the former stochastically dominates the second. The null hypothesis is rejected with $p < 0.001$. I then run a second Kolmogorov-Smirnov test where the null is the same, but the alternative hypothesis is that distribution of the number of prenatal care events for pre-treatment mothers lies above the same distribution for post-treatment mothers. The null hypothesis is not rejected with $p = 0$. These tests give additional reassurance that the monotonicity assumption is reasonable.

Finally, the Stable Unit Treatment Value Assumption must hold. The potential outcome for one unit must be unaffected by the assignment of treatment to the other units. In my setting, for example, this means that mothers in Massachusetts having access to PSL does not affect New Hampshire mothers' use of prenatal care. Mothers in New Hampshire do not have access to PSL, unlike mothers in Massachusetts. This is reasonable to assume.

With the instrumental variables approach set out here, the local average treatment effect will be the causal effect among commercially insured mothers who sought more prenatal care after their state introduced PSL, weighted by the change in the number of visits.

5 Results

5.1 Effects of paid sick leave on healthcare utilisation during pregnancy

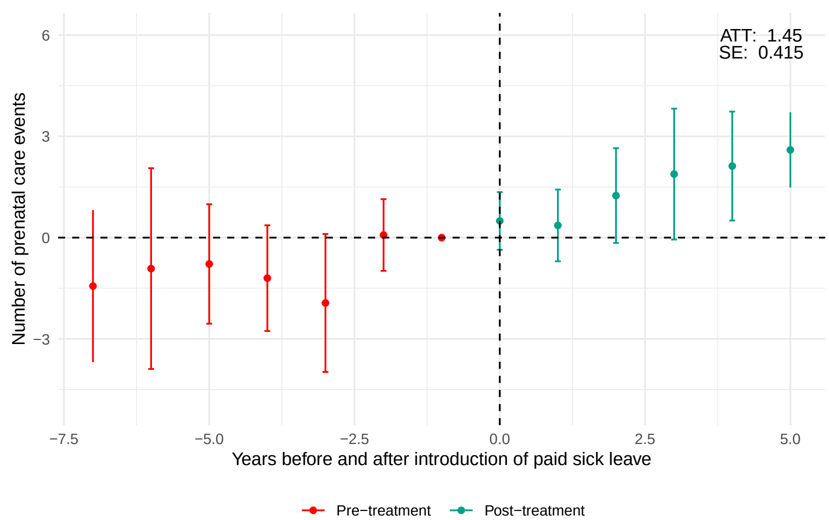
There is an increase in the number of prenatal care events following the introduction of a paid sick leave mandate, as shown in Figure 1. The aggregated effects across the post-treatment period are shown in Table 2. There is an increase in the number of prenatal care events by 1.5 events, an 8% increase relative to the mean of 17.5. 99% of mothers in my sample get some prenatal care.

The increase in prenatal care events appears to be driven by prenatal supervision visits (see Figure 2 and Table 3). There is an increase by 1.1 visits, a 17% increase relative to the mean of 6.7. There is little to no change in ultrasounds, pregnancy tests, foetal tests, genetic tests, and other lab tests (see Table 3 and Supplemental Appendix Figures H1-H6).

To put these figures in context, as mentioned above, the ACOG recommends 12 to 14 prenatal office visits for a term pregnancy (Michel and Fontenot, 2023). Pregnancy supervision visits are more comparable to the office visits specified in the the ACOG guidelines (recall that my main outcome includes not only visits to an OB-GYN, but pregnancy tests, ultrasounds, and the other forms of testing described in the data section).

We see that there is a delayed uptake of prenatal care following the introduction of the mandates, and that the effect increases over time. The delayed effect may be due to time for accrual of paid sick leave. Employees accrue one hour of paid sick leave for every 30 to 52 hours, depending on the state of employment. Further, most states did not implement mandates in January of the relevant year. There may also be hesitancy to use paid sick leave until it has become normalised in a workplace, which could also explain the increased effect with time.

Figure 1. The effect of paid sick leave on prenatal care



Notes: N = 809,313. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of prenatal care events. See Appendix for codes used to define prenatal care events. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Table 2. Effects of paid sick leave on prenatal care

	Dependent variable:			
	Num. Prenatal Care	Any Prenatal Care	First Trimester Care	Prenatal Care Delay
PSL Mandate	1.448 *** (0.415)	0.002 (0.002)	0.011 (0.012)	-1.261 (1.354)
Mean	17.52	0.99	0.86	8.94

*p<0.05; **p<0.01; ***p<0.001

Notes: N = 809,313. This table shows the effects of paid sick leave access on prenatal care use. Treatment effects defined as the aggregate of the state-time average treatment effects estimated using Callaway and Sant'Anna (2021). "First trimester care" is whether the mother had any prenatal care during her first trimester. "Prenatal care delay" is the number of days until the first prenatal care event counted from the end of the first trimester. This variable equals zero if the mother had any prenatal care during her first trimester. See Appendix for codes used to define prenatal care events. "Post treatment" defined as last menstrual period occurring after the sick pay mandate was introduced in their state. All models include the following controls: age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. Model includes state and year fixed effects. Standard errors, clustered at the state level, in parentheses.

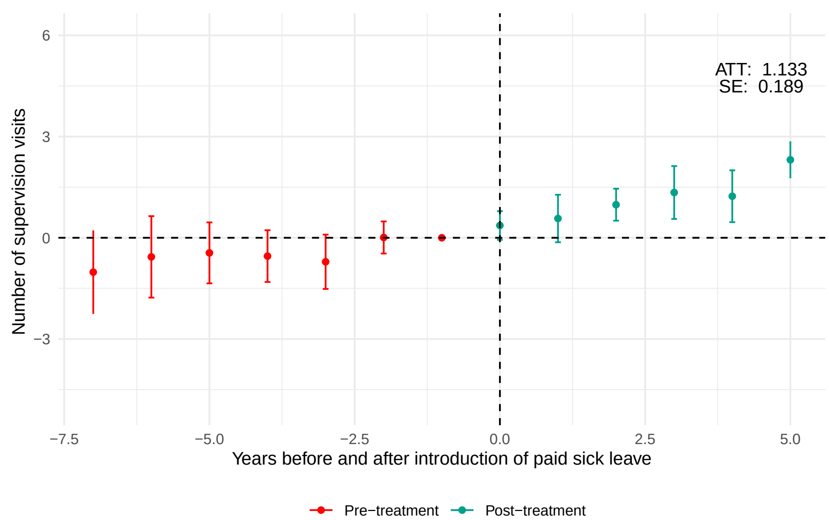
Table 3. Effects of paid sick leave on prenatal care, by type

	Dependent variable:						
	Lab Tests	Preg. Tests	Foetal Tests	Gen. Tests	Supervision Visits	US	E&M
PSL Mandate	-0.237 * (0.117)	0.024 (0.082)	0.207 (0.119)	0.157 *** (0.049)	1.133 *** (0.189)	0.165 (0.118)	-0.377 * (0.161)
Mean	2.08	1.48	2.10	0.83	6.74	4.29	0.81

*p<0.05; **p<0.01; ***p<0.001

Notes: N = 809,313. This table shows the effects of paid sick leave access on different types of prenatal care use. Treatment effects defined as the aggregate of the state-time average treatment effects estimated using Callaway and Sant'Anna (2021). See Appendix for codes used to define each prenatal care type. "Gen. Tests" is genetic tests. "US" is ultrasounds. "E&M" is evaluation and management visits. "Post treatment" defined as last menstrual period occurring after the sick pay mandate was introduced in their state. All models include the following controls: age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. All models include state and year fixed effects. Standard errors, clustered at the state level, in parentheses.

Figure 2. The effect of paid sick leave on prenatal supervision visits



Notes: N = 809,313. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of pregnancy supervision visits. See Appendix for codes used to define pregnancy supervision visits. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

We see no significant effects on prenatal care initiation and delay, as shown in Table 2 and the event studies in Appendix Figures B1 and B2. Although there are no significant effects, the signs of the effects are in the direction we would expect. A positive effect on first trimester care indicates a greater likelihood of starting prenatal care in the first trimester. A negative sign on prenatal care delay suggests a reduction in the delay to the first prenatal care visit. Note that a high proportion, 85%, of mother-births in our sample start prenatal care in their first trimester. These mothers may already be aware that they should visit their OB/GYN when they find out that they are pregnant.

In addition to timely prenatal care initiation, a higher cadence of prenatal care visits early on in the pregnancy increases the likelihood of identifying any pre-existing conditions or pregnancy complications. I break down number of prenatal care events by trimester and find that the increase in events occurs in the first and second trimester (see Table A1 and Supplemental Appendix Figures H7 and H8). There is no significant increase in prenatal care episodes in the third trimester as shown in Supplemental Appendix Figure H9.

I do not find any significant changes in emergency department use, as shown in Table A2 and Appendix Figures B3 and B4. This suggests that mothers with and without access to paid sick leave seek urgent care if a problem arises that demands it.

Combined, these results suggest that the introduction of sick pay affects the use of prenatal care on the intensive margin. Sick pay allows this group of mothers to take paid time off to seek additional prenatal care. Prenatal care use is not significantly affected on the extensive margin; essentially all mothers in my sample have at least one prenatal care event. The increase in the number of prenatal care events is driven by pregnancy supervision visits: regular outpatient prenatal care visits. Paid sick leave access does not significantly affect the timeliness of prenatal care. Finally, no statistically significant effects on emergency department use support the hypothesis that mothers seek urgent care when it is needed, regardless of access to sick pay.

5.2 Effects of prenatal care on maternal and infant health

Table 4 shows both the OLS and IV estimates of the effect of more prenatal care on severe maternal morbidity, postnatal depression, stillbirth, and preterm birth. The IV analysis shows that more prenatal care leads to a significant reduction in the likelihood of a postnatal depression diagnosis, by 7% relative to the mean of 9%. The OLS estimate for postnatal depression is of an opposite sign, positive, and significant. This suggests that endogeneity is a problem with OLS. One potential explanation is that mothers who seek more prenatal care are doing so because they are experiencing mental health symptoms and so the probability of diagnosis is higher.

A surprising finding is that more prenatal care leads to more preterm births, based on the IV estimates. An increased probability of preterm birth is a "worse" outcome as it is associated with poor health later on for infants. In contrast, the negative OLS estimate suggests that more prenatal care is associated with fewer instances of preterm birth. Preterm birth can occur due to induced labour (World Health Organisation, 2023). In column 2 of Table 5, I look at induction, to see whether the increase in preterm births is matched by an increase in inductions. It is, although the Anderson-Rubin confidence interval does not allow us to rule out a null effect. One interpretation could be that more prenatal care visits allows for increased identification of problems where using induced labour is a preferred or necessary approach. Doctors may be inducing these births for the health of the mother and child, and the increased inductions could be linked to the increase in preterm births.

The IV estimates reveal no statistically significant effects on severe maternal morbidity or stillbirth. The confidence intervals do not allow us to rule out either positive or negative effects. In contrast, for these variables, the OLS estimates are significant. The imprecision of the IV estimates means that we cannot draw conclusions on whether the IV and OLS estimates differ. Table 5 also shows that I find no statistically significant effect on caesareans, including scheduled caesareans, in the IV analysis.

Table 4. Effects of prenatal care on maternal and infant health

	SMM		Depression		Stillbirth		Preterm	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Prenatal	0.04***	0.02	0.11***	-0.63*	-0.01***	-0.02	-0.02**	0.47**
Care	(0.00)	(0.13)	(0.01)	(0.27)	(0.00)	(0.07)	(0.00)	(0.17)
Mean (%)	2.00	2.00	9.00	9.00	1.00	1.00	1.00	1.00
R^2	0.015	0.016	0.068	0.013	0.000	0.001	0.009	-0.085
AR p-val		0.86		0.01		0.81		0.01
AR CI		(-0.003, ∞)		(-∞, -0.002)		(-∞, 0.001)		(0.002, ∞)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: N= 649,242. This table shows the estimated effects of the number of prenatal care events on maternal and infant health outcomes. Coefficient estimates multiplied by 100. “Prenatal care” is the number of prenatal care events. “SMM” is severe maternal morbidity. “Depression” is postnatal depression or anxiety. See Appendix for codes used to define prenatal care events and the health outcomes. All models include the following controls: age at delivery, percent of county with a high school degree, a rural-urban measure of the county, median household income in the county, the infant mortality rate in the county, the number of OB-GYNs per capita in the county, and the Elixhauser comorbidity index at birth. All models include state and year fixed effects. “AR p-val” is the p-value of the Anderson-Rubin test. “AR CI” is the 95% Anderson-Rubin confidence interval. Standard errors, clustered at the state level, in parentheses.

Table 5. Effects of prenatal care on delivery procedures

	Induction		Caesarean		Scheduled Caesarean	
	OLS	IV	OLS	IV	OLS	IV
Prenatal Care	-0.06***	1.93*	0.42***	-0.37	0.16***	-0.48
	(0.01)	(0.80)	(0.00)	(0.35)	(0.00)	(0.43)
Mean (percent)	4.00	4.00	26.00	26.00	8.00	8.00
R2	0.026	-0.767	0.037	0.008	0.014	-0.027
AR p-val		0.05		0.27		0.34
AR CI		(-0.001, ∞)		(-∞, 0.006)		(-0.026, 0.032)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: N= 649,242. This table shows the estimated effects of the number of prenatal care events on delivery procedures. Coefficient estimates multiplied by 100. “Prenatal care” is the number of prenatal care events. See Appendix for codes used to define prenatal care events and the procedures. All models include the following controls: age at delivery, percent of county with a high school degree, a rural-urban measure of the county, median household income in the county, the infant mortality rate in the county, the number of OB-GYNs per capita in the county, and the Elixhauser comorbidity index at birth. All models include state and year fixed effects. “AR p-val” is the p-value of the Anderson-Rubin test. “AR CI” is the 95% Anderson-Rubin confidence interval. Standard errors, clustered at the state level, in parentheses.

The reduced form effect estimates of PSL on maternal health outcomes are displayed in Appendix Table A6, and the event study estimates are shown in Supplemental Appendix Figures H10-H13. These show insignificant estimates, but the coefficient on postnatal depression is negative and of similar magnitude to the IV estimate.

6 Robustness

The result that paid sick leave mandates increase the number of prenatal care events is robust to alternative definitions of prenatal care, as shown in Appendix Table A3. The event studies of prenatal care including office visits and with the alternative Gourevitch et al. (2022) definition can be found in Appendix Figures B5 and B6. The first column in Appendix Table A3 shows the main prenatal care definition used in this paper. Columns two to four show alternative definitions of prenatal care. The alternative prenatal care definition includes fewer prenatal services (e.g. lab tests, foetal tests, ultrasounds) which is why the mean number of events is lower. As shown in Table 3, paid sick leave access has small to no effects on these services.

For the main analysis of PSL on prenatal care use, the control group consists of "never treated" mothers. These are units that never received treatment, i.e. mothers who delivered in states that never received paid sick leave mandates. As another test for robustness, I repeat the analysis with the control containing "not yet treated" mothers in addition to those that are "never treated". The event study for the number of prenatal care events looks very similar and the aggregated treatment effect is also consistent, as shown in Supplemental Appendix Figure H14.

The instrumental variables' exclusion restriction requires that access to paid sick leave affects health outcomes only through the channel of prenatal care. My main findings are that more prenatal care reduces the probability of a postnatal depression diagnosis, and increases the likelihood of a preterm and induced birth. For the exclusion restriction to hold in this context, mothers taking more paid sick leave experience a reduction in postnatal depression through the increased prenatal care, and not through another channel. Similarly, they see an increase in preterm births and induction through the increased prenatal care, and not via another causal pathway. For preterm births and induction, there is no obvious such channel. For postnatal depression, one may be concerned that access to PSL in and of itself could improve mental health and reduce stress. The PSL days themselves could be mental health improving beyond the prenatal care visits, and the knowledge that paid time off is available to the mother may provide comfort that eases anxiety. Further, having PSL days may also allow mothers to use other forms of paid time off, such as holiday/vacation time for leisure when they may have reserved these days previously. To assess the merit of this concern, I test whether the introduction of PSL mandates affects mental health diagnoses amongst non-mothers. In Appendix Figure B8, I show that the probability of a mental health diagnosis in this comparison sample does not change with the introduction of paid sick leave. I describe the sample construction process in Supplemental Appendix E. This analysis suggests that the direct channel of mental health reduction through access to PSL is of limited concern.

Additionally, one may worry that PSL was introduced in the same year as other policies or initiatives that could affect prenatal care use. I check and verify that state family and medical leave policies were not introduced at the same time as PSL. The perinatal care quality initiatives (PQC) that are studied in Kiser (2024) are also relevant potential confounders [8]. Washington is the only state that introduces the PQC in the same year as PSL. Supplemental Appendix Figure H15 shows that dropping Washington from the analysis does not materially affect the estimated treatment effects. A few policy changes targeting Medicaid insured mothers occurred during my study period (e.g. Medicaid expansions, Presumptive Eligibility for Pregnant Women), but my sample is commercially insured. Commercially insured mothers are also unlikely to be affected by WIC expansions.

[8] Kiser (2024) sets out the years of PQC implementation in her paper, and the FMLA effective dates can be found here: https://bipartisanpolicy.org/download/?file=/wp-content/uploads/2025/02/2025-Feb.-Features-of-PFL-programs.pdf.

I repeat the instrumental variables analysis with an alternative instrument: years since the paid sick leave mandate was introduced in the mother's state. This variable is zero for mother-births that occur prior to the introduction of a paid sick leave mandate, and for mothers that reside in states that do not have a paid sick leave mandate in the time period I study. The motivation behind using this instrument comes from the lagged uptick in prenatal care events after the introduction of a mandate, evident in Figure 1. The F statistic on the first stage of this instrument is also low, (see Supplemental Appendix Table G2), but this remains a just-identified model as discussed in Section 4. The results of this robustness analysis can be found in Supplemental Appendix Tables G3 and G4. The IV estimates are in the same direction as those presented in the main IV analysis in Table 4.

As I do not condition on continuous enrolment past birth, we may worry that there is attrition in the sample after birth and that this attrition is a contributing factor to the decline in postpartum depression diagnoses. Across the whole sample, the attrition rate is low, at 8.1%. In Supplemental Appendix Table G5 I show the attrition rates by state. Any one individual state does not have an attrition rate higher than 1.1%. This analysis suggests that attrition is not a substantial concern.

The event study depicting the effect of PSL access on prenatal care shows a delayed effect that grows over time. In Section 5 I note that this could be explained by the need to accumulate PSL days or mandate implementation mid way through the year. Another factor could be the composition of states across my study period. Four states (WA, MD, RI, NJ) implemented PSL in 2018, and so outcomes for mothers residing in these states are only measured for one year post implementation. The $t = 1$ estimate that is close to zero could be driven by one of these states. I run a leave one state out analysis (see Supplemental Appendix Figures H15-H18) with these four states to show that the delayed treatment effects are not sensitive to any of these states individually.

7 Conclusion

This paper examines whether sick pay access affects mothers' use of healthcare during pregnancy, with a focus on prenatal care. This setting is important given the higher rates of maternal and infant mortality rates in the U.S. relative to OECD comparators (OECD.Stat, 2018), and as medical care use during pregnancy is cited as a contributing factor (Kamal et al., 2019; Wong and Kitsantas, 2020).

I find a significant increase in the number of prenatal care events following the introduction of a state level sick pay mandate. Overall, there is an 8% increase relative to the mean of 17.5 events in the post treatment period. This increase is predominantly driven by an increase in pregnancy supervision visits. I find a 17% increase in supervision visits relative to the mean of 6.74. Recall that there will be some mothers in states without mandates that have sick pay access through their employer or city. Thus the effect of any PSL mandate on prenatal care use may in fact be higher than the estimates presented here. I find no significant effects on prenatal care initiation, which may be the case if these mothers are aware of the medical recommendations to start prenatal care in the first trimester and prioritise attending a timely first visit. I find no statistically significant change in mothers' emergency department use, suggesting that mothers seek medical care when urgent health shocks arise.

I then ask whether the increase in prenatal care use translates to improved maternal and infant health outcomes. I find that more prenatal care reduces postnatal depression diagnoses by 7% relative to the mean. To put this figure into context, we can look to prior work evaluating other policies and mechanisms that have been found to impact mental health. Baicker et al. (2013) find that Medicaid coverage decreased the rate of depression by 30% amongst the Oregon Health Experiment enrollees in the first two years. Lindahl (2005) studies positive income shocks from lottery winnings in Sweden, and finds that a 10% increase in income leads to a reduction in poor mental health symptoms by 7 percentage points, a 13% reduction relative to the mean. Schmidt et al.

(2023) find that an $1,000 increase in a cash and food benefits decreases severe psychological distress by 8.4% of the mean. The estimated effects on severe maternal morbidity, stillbirth, and caesareans are too imprecise to rule out effects in either direction.

In this sample, receiving more prenatal care does not affect rare health events such as severe maternal morbidity. Yet this sample consists of commercially insured mothers, a group likely to be employed and in employment where they have had health insurance for a protracted period before and throughout their pregnancy.

Given the evidence on substantial income inequalities in maternal and infant health in the U.S. (Kennedy-Moulton et al., 2022), research on these questions in the setting of low-income mothers is important. This is a limitation of my analysis. Low-income mothers are most likely underrepresented in this commercially insured sample and I am unable to look at heterogenous treatment effects by income in these data. Future research that focuses on low-income women would be a valuable contribution.

Nonetheless, if more prenatal care does reduce maternal stress and depression in commercially insured mothers, this could have a meaningful impact on postnatal mortality. Half of maternal deaths occur in the postnatal period (Centers for Disease Control and Prevention, 2022), and it is estimated that 11% of maternal deaths are related to mental health conditions (Trost et al., 2021). Furthermore, the impact of anxiety and depression on mothers is likely to extend past the postpartum period and have spillover effects on other aspects of their lives. For example, productivity in the workplace, upon return. As a result, the effects that I find may represent a lower bound of the potential direct and indirect effects.

Based on these findings, we can conclude that paid sick leave policies are a potential policy lever to address the maternal health crisis by helping protect mothers against depression and anxiety in the postpartum period. More research is needed on the effectiveness of prenatal care for low-income mothers in the U.S. setting if we are to better understand how to address high rates of maternal and infant deaths.

A Appendix Tables

Appendix Table A1. Effects of paid sick leave on prenatal care, by trimester

	Dependent variable:		
	Num. Prenatal Care, 1st Tri.	Num. Prenatal Care, 2nd Tri.	Num. Prenatal Care, 3rd Tri.
PSL Mandate	0.563 *** (0.083)	0.651 *** (0.118)	0.234 (0.261)
Mean	4.43	4.92	8.17

*p<0.05; **p<0.01; ***p<0.001

Notes: N = 809,313. This table shows the effects of paid sick leave access on prenatal care, by trimester. Treatment effects defined as the aggregate of the state-time average treatment effects estimated using Callaway and Sant'Anna (2021). See Appendix for codes used to define prenatal care events. "Post treatment" defined as last menstrual period occurring after the sick pay mandate was introduced in their state. All models include the following controls: age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. All models include state and year fixed effects. Standard errors, clustered at the state level, in parentheses.

Appendix Table A2. Effects of paid sick leave on emergency department use

	Dependent variable:	
	Any ED Visit	Num. ED Visits
PSL Mandate	0.010 (0.030)	0.025 (0.075)
Mean	0.31	0.56

*p<0.05; **p<0.01; ***p<0.001

Notes: N = 809,313. This table shows the effects of paid sick leave access on emergency department use. Treatment effects defined as the aggregate of the state-time average treatment effects estimated using Callaway and Sant'Anna (2021). See Appendix for codes used to define emergency department visits. "Post treatment" defined as last menstrual period occurring after the sick pay mandate was introduced in their state. All models include the following controls: age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. All models include state and year fixed effects. Standard errors, clustered at the state level, in parentheses.

Appendix Table A3. Effects of paid sick leave on alternative definitions of number of prenatal care events

	Dependent variable:			
	(1)	(2)	(3)	(4)
	Num. Prenatal Care	(1) w/ E&M	Alternative Def. of (1)	(3) w/ E&M
PSL Mandate	1.448 ***	1.072 **	1.043 ***	0.664 *
	(0.387)	(0.371)	(0.321)	(0.279)
Mean	17.52	18.33	14.02	14.84

*p<0.05; **p<0.01; ***p<0.001

Notes: N = 809,313. Treatment effects defined as the aggregate of the state-time average treatment effects estimated using Callaway and Sant'Anna (2021). The outcome in column (1) is the main prenatal care definition. The outcome in column (2) includes evaluation and management (E&M) visits. The outcome in column (3) is the alternative definition of prenatal care, and that in column (4) includes E&M visits. See Appendix for codes used to define prenatal care events. "Post treatment" defined as last menstrual period occurring after the sick pay mandate was introduced in their state. All models include the following controls: age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. All models include state and year fixed effects. Standard errors, clustered at the state level, in parentheses.

Appendix Table A4. Assessing monotonicity

	Dependent variable:							
	Number of prenatal care events							
	Age+	Age-	Mort.+	Mort.-	Metro	Non-Metro	OB+	OB-
PSL Mandate	1.45*	0.65	1.93***	0.75	1.25*	1.28*	0.79	1.65**
	(0.70)	(0.46)	(0.33)	(0.69)	(0.63)	(0.64)	(0.58)	(0.64)
N	376,949	272,458	329,242	320,165	645,955	3,452	380,212	269,195

* p < 0.05, ** p < 0.01, *** p < 0.001.

Notes: This table shows the first-stage two-way fixed effects estimates for each sub-sample of patients. See Appendix for codes used to define prenatal care events. "Age+" denotes above median age at delivery. "Age-" denotes below median age at delivery. "Mort.+" denotes above median infant mortality rate in the mother's birth county. "Mort.-" denotes below median infant mortality rate in the mother's birth county. "Metro" denotes mothers residing in metropolitan counties. "Non-Metro" denotes mothers residing in non-metropolitan counties. "OB+" denotes above median OB-GYN per capita in the mother's birth county. "OB-" denotes below median OB-GYN per capita in the mother's birth county. "Post treatment" defined as last menstrual period occurring after the sick pay mandate was introduced in their state. All models include the following controls: age at delivery, percent of county with a high school degree, a rural-urban measure of the county, median household income in the county, the infant mortality rate in the county, the number of OB-GYNs per capita in the county, and the Elixhauser comorbidity index at birth. All models include state and year fixed effects. All models include state and year fixed effects. Standard errors, clustered at the state level, in parentheses.

Appendix Table A5. First stage

	Prenatal Care
Post Treatment	1.25*
	(0.61)
Mean	17.52
F-stat	4.20
Effective F-stat	4.20
N	649,242

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the first stage two-way fixed effects estimates. See Appendix for codes used to define prenatal care events. "Post treatment" defined as last menstrual period occurring after the sick pay mandate was introduced in their state. Controls include age at delivery, percent of county with a high school degree, a rural-urban measure of the county, median household income in the county, the infant mortality rate in the county, the number of OB-GYNs per capita in the county, and the Elixhauser comorbidity index at birth. The model includes state and year fixed effects. "Effective F-stat' is that of Olea and Pflueger (2013). Standard errors, clustered at the state level, in parentheses.

Appendix Table A6. Reduced form

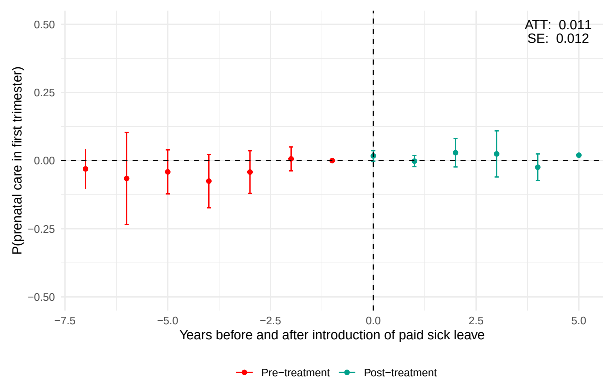
	Dependent variable:			
	SMM	Postnatal Depression	Stillbirth	Preterm
PSL	0.247	-0.482	0.107	0.180
Mandate	(0.292)	(0.679)	(0.117)	(0.151)
Mean(%)	2.08	9.25	0.79	1.36

*p<0.05; **p<0.01; ***p<0.001

Notes: N = 809,313. This table shows reduced form effects estimated using Callaway and Sant'Anna (2021). Coefficients multiplied by 100. "SMM" is severe maternal morbidity. See Appendix for codes used to define the health outcomes. "PSL Mandate" defined as last menstrual period occurring after the sick pay mandate was introduced in their state. All models include the following controls: age at delivery, percent of county with a high school degree, and a rural-urban measure of the county. All models include state and year fixed effects. Standard errors, clustered at the state level, in parentheses.

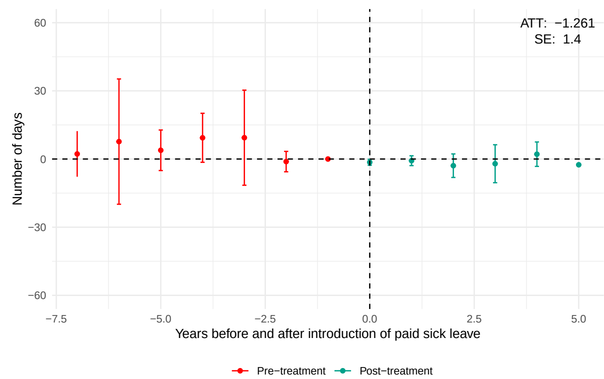
B Appendix Figures

Appendix Figure B1. The effect of paid sick leave on first trimester care



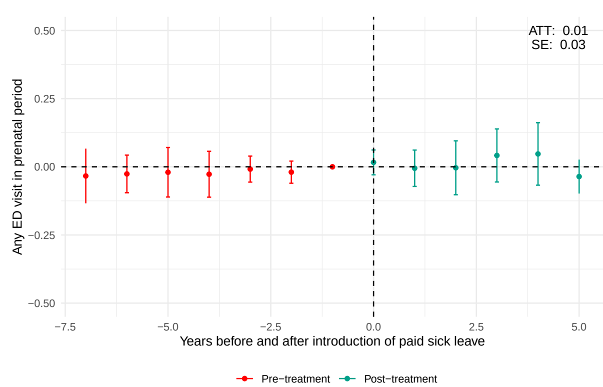
Notes: N = 809,313. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the probability of first trimester care. See Appendix for codes used to define prenatal care events. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure B2. The effect of paid sick leave on prenatal delay



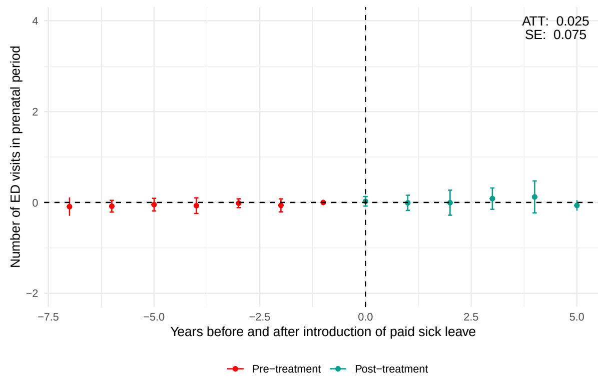
Notes: N = 809,313. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of days following the end of the first trimester until the first prenatal care event. See Appendix for codes used to define prenatal care events. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure B3. The effect of paid sick leave on any emergency department visit



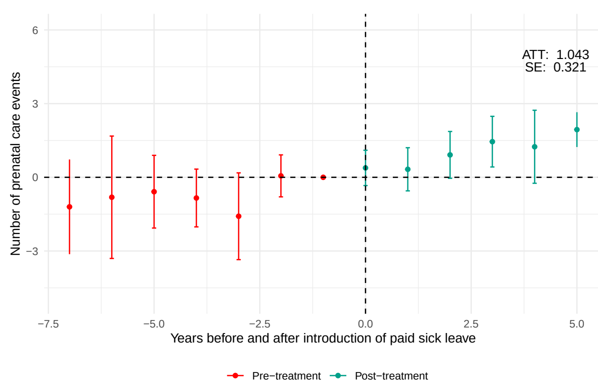
Notes: N = 809,313. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the probability of an emergency department visit. See Appendix for codes used to define emergency department visits. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure B4. The effect of paid sick leave on the number of emergency department visits



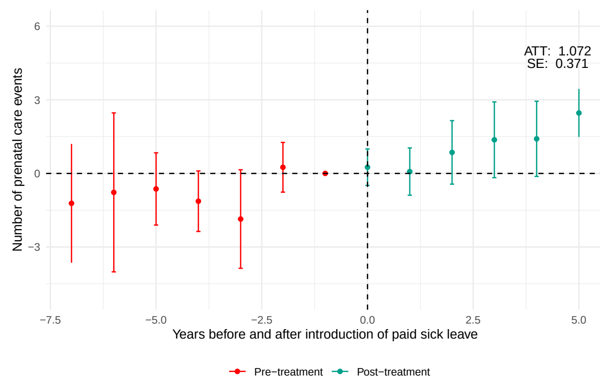
Notes: N = 809,313. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of emergency department visits. See Appendix for codes used to define emergency department visits. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure B5. The effect of paid sick leave on prenatal care (alternative definition)



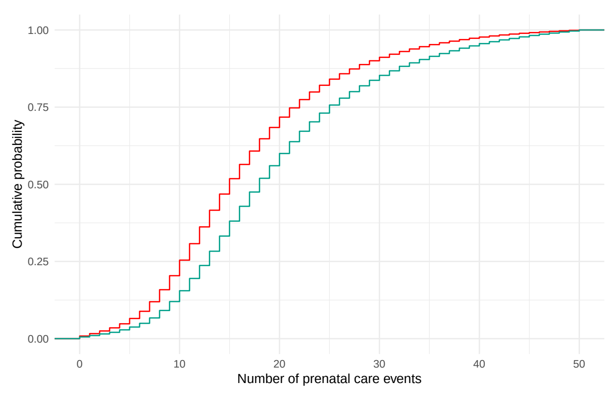
Notes: N = 809,313. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of prenatal care events (alternative definition). See Appendix for codes used to define prenatal care events. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure B6. The effect of paid sick leave on prenatal care (including office visits)



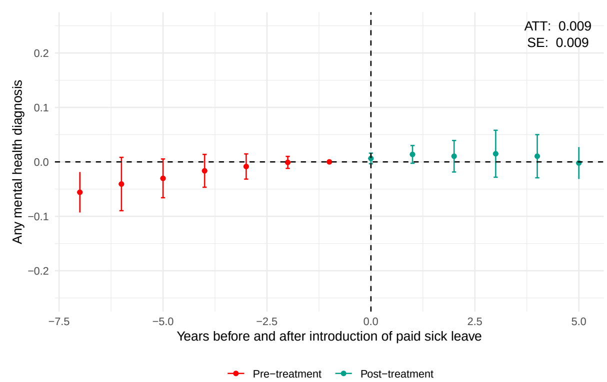
Notes: N = 809,313. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of prenatal care events (including office visits). See Appendix for codes used to define prenatal care events. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure B7. Cumulative distribution of the number of prenatal care events, by treatment status



Notes: N = 649,242. "Pre-treatment" is the CDF for mother-births that occur before the state has introduced a PSL mandate, or for mother-births that occur in states that are never treated. "Post-treatment" is the CDF for mother-births that occur after their state has introduced a PSL mandate. The x-axis is the number of prenatal care events. The y-axis is the cumulative probability. See Appendix for codes used to define prenatal care events.

Appendix Figure B8. The effect of paid sick leave on depression diagnoses (comparison sample)



Notes: N = 27,767,516. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of mental health diagnoses. See Appendix for codes used to define mental health. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

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Supplemental Appendix: Does More Prenatal Care Improve Health Outcomes? Evidence from Paid Sick Leave Mandates

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May 8, 2025

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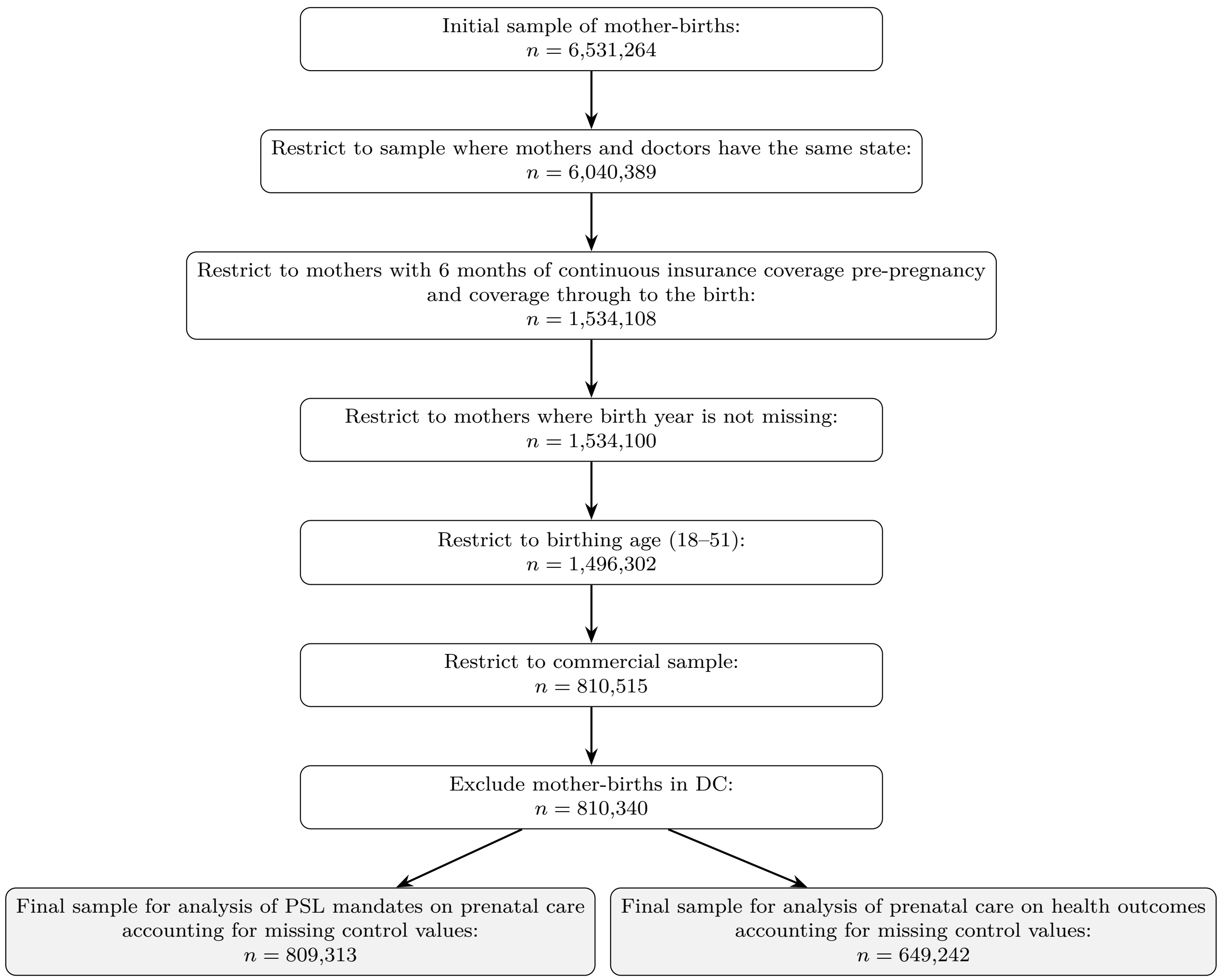
A Overview of Employer Sick Pay Mandates in the U.S.

Region	Law Effective	Content
Washington D.C.	Nov 13, 2008	"Qualified employees"; 1 hour of paid sick leave for every 43 hours, 90 days accrual period; up to 3 to 9 days depending on employer size; own sickness or family; no health care or restaurant employees; extension to 20,000 temporary and tipped employees (retrosp. in Sep 2014)
Connecticut	Jan 1, 2012	Full-time service sector employees at employers with $>$ 49 employees (20% of workforce); 1 hour for every 40 hours; up to 5 days; own sickness or family member, 680 hours accrual period (4 months)
California	July 1, 2015	All employees; 1 hour of paid sick leave for every 30 hours; minimum 24 hours; own sickness or family member; 90 days accrual period
Massachusetts	July 1, 2015	All employees at employers with $>$ 10 employees; 1 hour for every 40 hours; up to 40 hours; own sickness or family member; 90 days accrual period
Oregon	Jan 1, 2016	All employees at employers with $>$ 9 employees; 1 hour every 30 hours; 90 days accrual period; up to 40 hours; own sickness or family member
Vermont	Jan 1, 2017	Employees w/ 18 hours/week & >20 weeks/year at employers with $>$ 5 employees; 1 hour every 52 hours; up to 24 hours in 2017, 40 hours thereafter; own sickness or family member; underage employees and employers in the first year exempt; some state employees & per diem employees in health care or long-term care facility exempt
Arizona	July 1, 2017	All employees; 1 hour for every 30 hours; up to 40 hours at employers with $>$ 14 employees, up to 24 hours <15 employees; own sickness or family member; employers can impose a 90-day accrual period for new employees
Washington	Jan 1, 2018	All employees except those who are exempt from the minimum wage law; 1 hour for every 40 hours; no cap but no more than 40 hours carry over; own sickness or family member; 90-day accrual for new employees
Maryland	Feb 11, 2018	Employees w/ 12 hours/week at employers with $>$ 14 employees (<15 employees 40 hours unpaid); 1 hour for every 30 hours; employers can cap at 64 hours accrual and 40 hours carry over; own sickness or family member, also for parental leave; certain groups exempt (e.g., temp. agency employees)
Rhode Island	July 1, 2018	All employees; 1 hour for every 35 hours; 24 hours in firms $>$ 17 (2018, 2019); 40 hours in firms $>$ 17 (2020+); own sickness or family member; 90-day accrual period
New Jersey	Oct 28, 2018	All employees; 1 hour for every 30 hours up to 40 hours/year; per diem health care employees exempt own sickness or family member; 120-day accrual for new employees; preempts city laws
Michigan	Mar 28, 2019	Employees w/ 25 hours/week employed for 25 weeks at employers with $>$ 49 employees; 1 hour for every 35 hours; government employees, certain railway and air carrier employees exempt; own sickness or family member; 90-day accrual for new employees

Source: Maclean et al. (2020)

B Sample size flow diagram



C Billing codes used to define prenatal care

Outcome	Codes
Prenatal visit procedures	**HCPCS:** H1000, H1001, H1002, H1003, H1004, H1005; **CPT:** 0500F, 0502F, 59425, 59426, 0501F, 0503F, 59420; **ICD-10-CM:** Z36*, Z34*, O09*, Z037; **ICD-9-CM:** V28, V220, V221, V23, V89.
Evaluation and management visits	**CPT:** 99211, 99212, 99213, 99214, 99215, 99201, 99202, 99203, 99204, 99205, 99241, 99242, 99243, 99244, 99245, 99401, 99402, 99403, 99404, 99384, 99385, 99386, 99394, 99395, 99396, 3725F, 3351F, 3352F, 3353F, 3354F, 96150, 96151, 96152, 96156, 96158, 96127, 1220F, 3008F, 3074F, 3075F, 3077F, 3078F, 3079F, 3080F, 2000F, 2001F, 99500; **HCPCS:** G0442, G0443, G0444, G0445, G0446, G0447, G8431, G8432, G8433, G8510, G8511, G9717, H0004, G8419, G8420, G8421, G8422, G8938, G8752, G8753, G8754, G8755.
Foetal testing	**CPT:** 59025, 76818, 76819, 76820, 76821.
Genetic testing	**CPT:** 81200, 81205, 81209, 81220, 81242, 81250, 81251, 81255, 81257, 81260, 81290, 81329, 81330, 81361, 81412, 81443, 81508, 81509, 81510, 81511, 81512, 0124U, 0125U, 0126U, 82105, 82106, 82677, 84163, 86336, 81420, 81422, 81507, 0009M, 0168U, 81228, 81229; **HCPCS:** S3835, S3847, S3848, S3849, S3850, S3851, S3870.
Obstetrical laboratory tests	**CPT:** 80055, 80081, 80050, 86762, 86765, 86901, 86906, 3290F, 3291F, 3293F, 87806, 87534, 87535, 87536, 87537, 87538, 87539, 87390, 87391, 87389, 3292F, 3490F, 3491F, 3492F, 3494F, 3496F, 3497F, 3498F, 3500F, 3502F, 3503F, 86689, 86701, 86702, 86703, 86592, 86593, 3512F, 0065U, 87285, 86781, 86780, 0064U, 80074, 86704, 86705, 86706, 87340, 87341, 87516, 87517, 87110, 87270, 87320, 87810, 86631, 86632, 87490, 87491, 87492, 87590, 87591, 87592, 87850; **HCPCS:** G9228, G0432, G0433, G0435, S3645, G0475, G8869, G9912, G9820; **ICD-10-CM:** Z114; **ICD-9-CM:** V7389.
Pregnancy tests	**CPT:** 81025, 84163, 84703, 84702, 84704, 0167U; **ICD-10-CM:** Z3200, Z3201; **ICD-9-CM:** V7240, V7242.
Ultrasounds	**CPT:** 76805, 76810, 76811, 76812, 76815, 76816, 76817, 76801, 76802, 76813, 76814.

Sources: Gourevitch et al. (2022), Sinaiko (2025)

D Billing codes used for the maternal health outcomes

Outcome	Codes
Severe maternal morbidity	**ICD-9-CMP:** 996*, 990*, 6839, 6849, 6859, 6869, 6879, 689, 683, 684, 685, 686, 687, 311, 9670, 9671, 9672; **ICD-9-CMD:** 410*, 441*, 5845, 5846, 5847, 5848, 5849, 6693*, 5185*, 51881, 51882, 51884, 7991, 6731*, 42741, 42742, 4275, 2866, 2869, 6413*, 6663*, 6426*, 9971, 0463, 34839, 36234, 430*, 431*, 432*, 433*, 434*, 435*, 436*, 437*, 6715*, 6740*, 99702, 4280, 4281, 42820, 42821, 42823, 42830, 42831, 42833, 42840, 42841, 42843, 4289, 5184, 6680*, 6681*, 6682*, 9954, 99586, 038*, 449, 78552, 99591, 99592, 99802, 6702*, 6691*, 78550, 78551, 78559, 9950, 9980, 99800, 99801, 99809, 28242, 28262, 28264, 28269, 28952, 4150, 4151*, 6730*, 6732*, 6733*, 6738*; **ICD-10-CMP:** 5A12012, 5A2204Z, 30230H0, 30230K0, 30230L0, 30230M0, 30230N0, 30230P0, 30230R0, 30230T0, 30230H1, 30230K1, 30230L1, 30230M1, 30230N1, 30230P1, 30230R1, 30230T1, 30233H0, 30233K0, 30233L0, 30233M0, 30233N0, 30233P0, 30233R0, 30233T0, 30233H1, 30233K1, 30233L1, 30233M1, 30233N1, 30233P1, 30233R1, 30233T1, 30240H0, 30240K0, 30240L0, 30240M0, 30240N0, 30240P0, 30240R0, 30240T0, 30240H1, 30240K1, 30240L1, 30240M1, 30240N1, 30240P1, 30240R1, 30240T1, 30243H0, 30243K0, 30243L0, 30243M0, 30243N0, 30243P0, 30243R0, 30243T0, 30243H1, 30243K1, 30243L1, 30243M1, 30243N1, 30243P1, 30243R1, 30243T1, 0UT90ZL, 0UT90ZZ, 0UT97ZL, 0UT97ZZ, 0B110F4, 0B113F4, 0B114F4, 5A1935Z, 5A1945Z, 5A1955Z; **ICD-10-CMD:** I21*, I22*, I71*, I79*, N17*, O904, J80, J951, J952, J953, J9582*, J960*, J962*, J969*, R0603, R092, O88112, O88113, O88119, O8812, O8813, I46*, I490*, D65, D688, D689, O45002, O45003, O45009, O45012, O45013, O45019, O45022, O45023, O45029, O45092, O45093, O45099, O46002, O46003, O46009, O46012, O46013, O46019, O46022, O46023, O46029, O46092, O46093, O46099, O670, O723, O15*, I97120, I97121, I97130, I97131, I97710, I97711, A812, G45*, G46*, G9349, H340*, I60*, I61*, I62*, I6300, I6301*, I631*, I632*, I633*, I634*, I635*, I636, I638*, I639, I65*, I66*, I67*, I68*, O2250, O2252, O2253, I97810, I97811, I97820, I97821, O873, I501, I5020, I5021, I5023, I5030, I5031, I5033, I5040, I5041, I5043, I50810, I50811, I50813, I50814, I5082, I5083, I5084, I5089, I509, J810, O29112, O29113, O29119, O29122, O29123, O29129, O29192, O29193, O29199, O29212, O29213, O29219, O29292, O29293, O29299, O740, O741, O742, O743, O890*, O891, O892, T882XXA, T883XXA, A327, A40*, A41*, I76, O85, O8604, R6520, R6521, T8112XA, T8144XA, O751, R57*, T782XXA, T8110XA, T8111XA, T8119XA, T886XXA, D5700, D5701, D5702, D57211, D57212, D57219, D57411, D57412, D57419, D57811, D57812, D57819, I26*, O88012, O88013, O88019, O8802, O8803, O88212, O88213, O88219, O8822, O8823, O88312, O88313, O88319, O8832, O8833, O88812, O88813, O88819, O8882, O8883, T800XXA
Postnatal depression	**ICD-9-CMD:** 64840, 64841, 64842, 64843, 64844, 29621, 29622, 29623, 29624, 29625, 29626, 29630, 29631, 29632, 29633, 29634, 29635, 29636, 29682, 311, 2962, 29384, 30000, 30001, 30002, 30009, 30010, 308*; **ICD-10-CMD:** F53*, O906, F99, O9934*, F32*, F33*, F41*, F43*
Stillbirth	**ICD-9-CMD:** V271, V273, V274, V276, V277, 6564; **ICD-10-CM:** Z371, Z373, Z374, Z376, Z377, P95, O364
Pre-term	**ICD-9-CMD:** 64421, 7650, 7651, 76521, 76522, 76523, 76524, 76525, 76526, 76527, 76528; **ICD-10-CMD:** O601, P072, P073, O603
Induction	**ICD-9-CMP:** 734, 731, 7301; **ICD-10-CMP:** 3E033VJ, 3E0P7GC, 0U7C7ZZ, 0U7C7DZ
Caesarean	**ICD-9-CMP:** 6697*, 741, 742, 744, 7499; **ICD-10-CMP:** O82, O7582; **CPT:** 59510, 59514, 59515, 59525, 59611, 59620, 59622, 1968, 1969
Scheduled Caesarean	**ICD-9-CMP:** 6697*; **ICD-10-CMP:** 6697*

Sources: Geiger et al. (2021), Danilack et al. (2016), Sherman and Ali (2018), CDC (2023)

E Construction of comparison sample to evaluate the effects of PSL mandates on mental health diagnoses

To test whether the introduction of PSL mandates affect the rates of mental health diagnoses directly, I construct a sample of women aged 18 to 51 with commercial insurance that did not have a birth in the period of 2010 to 2019 using the Inovalon data. I restrict the sample to women who have at least 15 months continuous enrolment, to match the continuous enrolment restriction I place on mothers (from 6 months before pregnancy up to birth). I then identify whether these women have a mental health diagnosis using the billing codes set out in Supplemental Appendix Table E. These billing codes match those that define postnatal depression in Supplemental Appendix Table C, with the removal of any codes that refer to the pregnancy or postpartum period. This gives me a panel dataset of individuals with and without a mental health diagnosis in a given state-year (N=7,716,508 individuals, N=27,767,516 individual-years). I then estimate Equation 2 using Callaway and Sant'Anna (2021), as described in Section 4. The outcome variable is an indicator variable for whether the individual has a mental health diagnosis. As before, I cluster standard errors at the state level. I include state and year fixed effects and control for age. I am unable to control for the additional county level variables because I only observe three-digit zipcode for these women whereas for the mother sample, I am able to ascertain birth county using the birth hospital location.

F Billing codes used for comparison sample analysis

Outcome	Codes
Mental health	**ICD-9-CMD:** 29621, 29622, 29623, 29624, 29625, 29626, 29630, 29631, 29632, 29633, 29634, 29635, 29636, 29682, 311, 2962, 29384, 30000, 30001, 30002, 30009, 30010, 308*; **ICD-10-CMD:** F99, F32*, F33*, F41*, F43*

Sources: Sherman and Ali (2018)

G Appendix Tables

Appendix Table G1. Counts of Unique Mother-Births by State

State	N	State	N
AK	416	NC	5924
AL	3032	ND	1334
AR	5330	NE	2983
AZ	5370	NH	1984
CA	54539	NJ	30587
CO	6721	NM	12116
CT	4755	NV	2123
DE	761	NY	35194
FL	23963	OH	72875
GA	16195	OK	15665
HI	309	OR	5908
IA	4329	PA	20098
ID	9541	PR	8
IL	89656	RI	322
IN	25350	SC	4629
KS	3968	SD	1555
KY	18036	TN	6403
LA	5077	TX	108548
MA	3895	UT	4451
MD	2756	VA	23085
ME	1376	VT	251
MI	72528	WA	9289
MN	53036	WI	12858
MO	11653	WV	1301
MS	1930	WY	782
MT	4518		

Note: N=809,313. This table shows the total number of mother-births by state.

Appendix Table G2. First stage (alternative instrument)

	Prenatal Care
Years Since Mandate	0.35
	(0.21)
Mean	17.52
F-stat	2.72
Effective F-stat	2.72
N	649,242

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the first stage two-way fixed effects estimates using the alternative instrument. See Appendix for codes used to define prenatal care events. "Years since mandate" defined as the number of years prior to the last menstrual period that the sick pay mandate has been in place in the mother's state. Controls include age at delivery, percent of county with a high school degree, a rural-urban measure of the county, median household income in the county, the infant mortality rate in the county, the number of OB-GYNs per capita in the county, and the Elixhauser comorbidity index at birth. The model includes state and year fixed effects. "Effective F-stat' is that of Olea and Pflueger (2013). Standard errors, clustered at the state level, in parentheses.

Appendix Table G3. Effects of prenatal care on maternal and infant health (alternative instrument)

	SMM		Depression		Stillbirth		Preterm	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Prenatal Care	0.04***	0.02	0.11***	-1.14+	-0.01***	0.05	-0.02**	0.59+
	(0.00)	(0.13)	(0.01)	(0.58)	(0.00)	(0.06)	(0.00)	(0.32)
Mean (%)	2.00	2.00	9.00	9.00	1.00	1.00	1.00	1.00
R^2	0.02	0.02	0.07	-0.10	0.00	-0.00	0.01	-0.17
AR p-val		0.86		0.01		0.49		0.00
AR CI		$(-\infty, \infty)$		$(-\infty,\infty)$		$(-\infty, \infty)$		$(-\infty, \infty)$

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: N= 649,407. This table shows the estimated effects of the number of prenatal care events on maternal and infant health outcomes using the alternative instrument of years since paid sick leave mandate. Coefficient estimates multiplied by 100. "Prenatal care" is the number of prenatal care events. "SMM" is severe maternal morbidity. "Depression" is postnatal depression or anxiety. See Appendix for codes used to define prenatal care events and the health outcomes. All models include the following controls: age at delivery, percent of county with a high school degree, a rural-urban measure of the county, median household income in the county, the infant mortality rate in the county, the number of OB-GYNs per capita in the county, and the Elixhauser comorbidity index at birth. All models include state and year fixed effects. "AR p-val" is the p-value of the Anderson-Rubin test. "AR CI" is the 95% Anderson-Rubin confidence interval. Standard errors, clustered at the state level, in parentheses.

Appendix Table G4. Effects of prenatal care on delivery procedures (alternative instrument)

	Induction		Caesarean		Scheduled Caesarean	
	OLS	IV	OLS	IV	OLS	IV
Prenatal Care	-0.06***	2.51+	0.42***	-0.59	0.16***	-1.23+
	(0.01)	(1.45)	(0.00)	(0.71)	(0.00)	(0.67)
Mean (%)	4.00	4.00	26.00	26.00	8.00	8.00
R^2	0.03	-1.42	0.04	-0.01	0.01	-0.22
AR p-val		0.02		0.45		0.10
AR CI		(-0.08, ∞)		(-∞, ∞)		(-∞, ∞)

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: N= 649,407. This table shows the estimated effects of the number of prenatal care events on delivery procedures using the alternative instrument of years since paid sick leave mandate. Coefficient estimates multiplied by 100. "Prenatal care" is the number of prenatal care events. See Appendix for codes used to define prenatal care events and procedures. All models include the following controls: age at delivery, percent of county with a high school degree, a rural-urban measure of the county, median household income in the county, the infant mortality rate in the county, the number of OB-GYNs per capita in the county, and the Elixhauser comorbidity index at birth. All models include state and year fixed effects. "AR p-val" is the p-value of the Anderson-Rubin test. "AR CI" is the 95% Anderson-Rubin confidence interval. Standard errors, clustered at the state level, in parentheses.

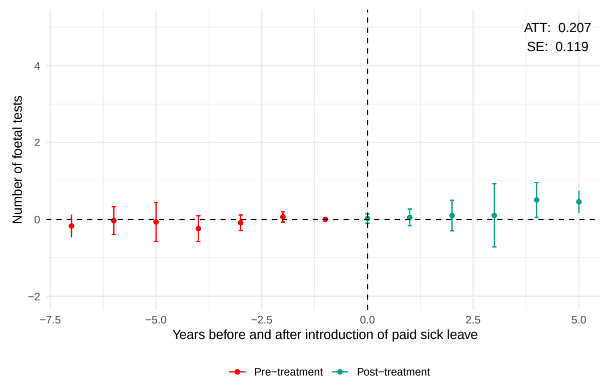
Appendix Table G5. Attrition Rates By State

State	Attrition Rate	State	Attrition Rate
AK	0.0	NC	0.1
AL	0.0	ND	0.0
AR	0.1	NE	0.0
AZ	0.1	NH	0.0
CA	1.0	NJ	0.4
CO	0.1	NM	0.1
CT	0.1	NV	0.1
DE	0.0	NY	0.5
FL	0.6	OH	0.6
GA	0.2	OK	0.1
HI	0.0	OR	0.1
IA	0.0	PA	0.3
ID	0.1	PR	0.0
IL	0.5	RI	0.0
IN	0.2	SC	0.0
KS	0.0	SD	0.0
KY	0.1	TN	0.1
LA	0.0	TX	1.1
MA	0.1	UT	0.1
MD	0.0	VA	0.1
ME	0.0	VT	0.0
MI	0.4	WA	0.1
MN	0.4	WI	0.1
MO	0.1	WV	0.0
MS	0.0	WY	0.0
MT	0.0		

Note: N=809,313. This table shows sample attrition rates by state. Attrition rate defined as the proportion of mothers who do not have a claim in the Inovalon data at or after 6 weeks postpartum relative to all sample mothers.

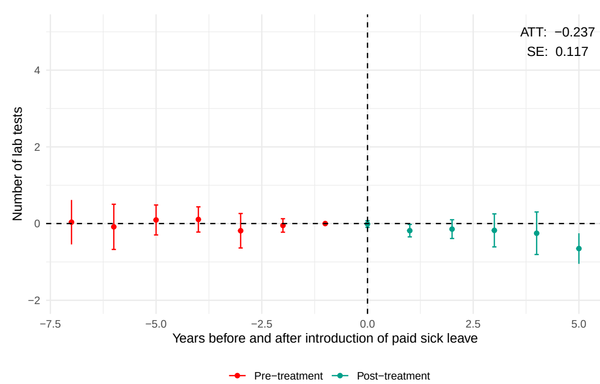
H Appendix Figures

Appendix Figure H1. The effect of paid sick leave on the number of foetal tests



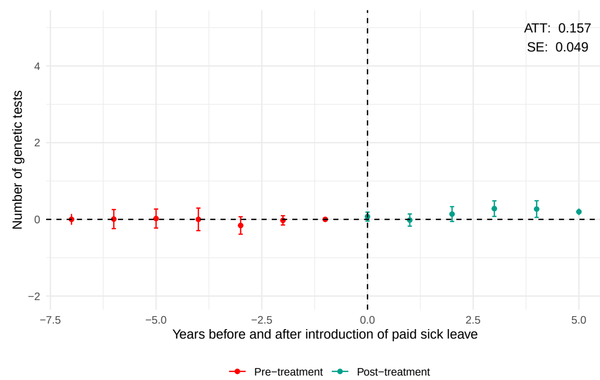
Notes: N = 809,313. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of foetal tests. See Appendix for codes used to define foetal tests. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure H2. The effect of paid sick leave on the number of lab tests



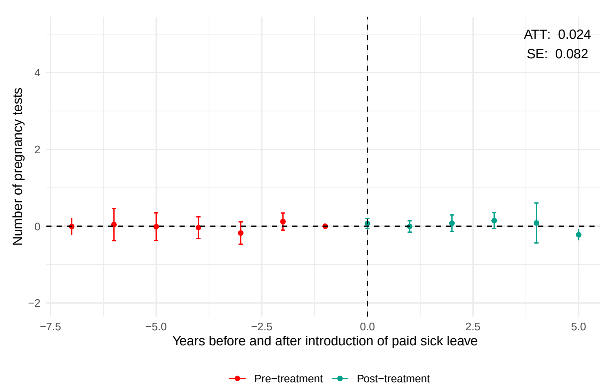
Notes: N = 809,313. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of lab tests. See Appendix for codes used to define lab tests. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure H3. The effect of paid sick leave on the number of genetic tests



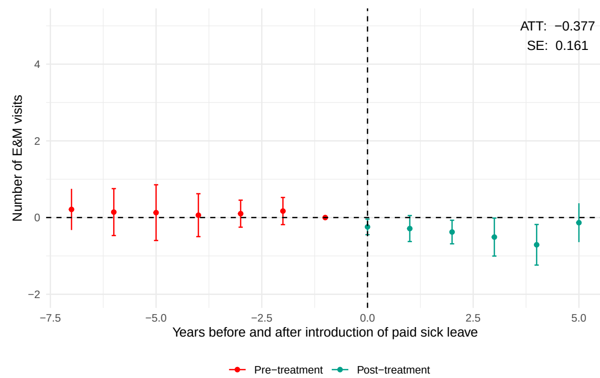
Notes: N = 809,313. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of genetic tests. See Appendix for codes used to define genetic tests. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure H4. The effect of paid sick leave on the number of pregnancy tests



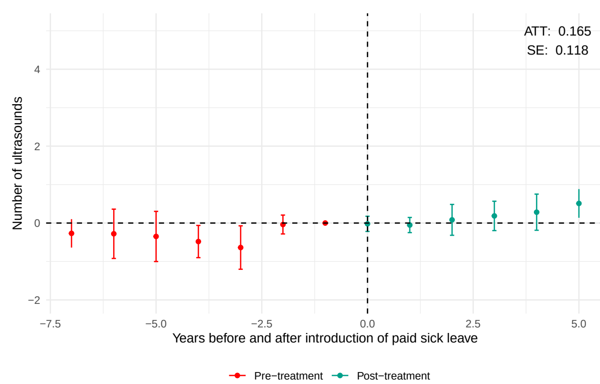
Notes: N = 809,313. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of pregnancy tests. See Appendix for codes used to define pregnancy tests. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure H5. The effect of paid sick leave on the number of E&M visits



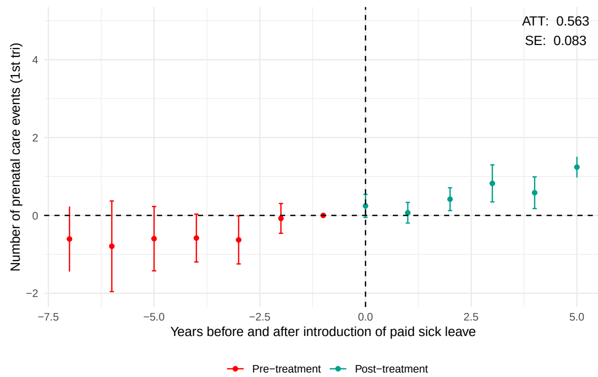
Notes: N = 809,313. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of evaluation and management (E&M) visits. See Appendix for codes used to define E&M visits. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure H6. The effect of paid sick leave on the number of ultrasounds



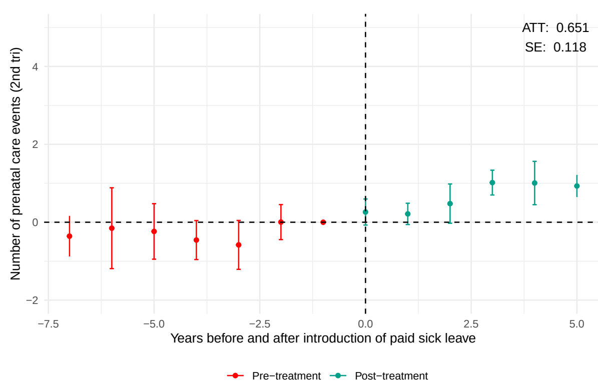
Notes: N = 809,313. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of ultrasounds. See Appendix for codes used to define ultrasounds. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure H7. The effect of paid sick leave on number of prenatal care episodes in the 1st trimester



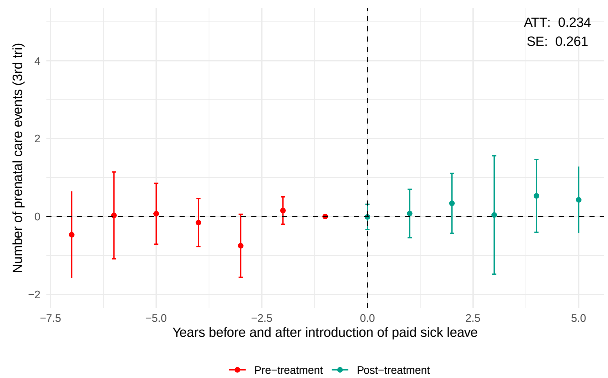
Notes: N = 809,313. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of prenatal care events in the first trimester. See Appendix for codes used to define prenatal care events. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure H8. The effect of paid sick leave on number of prenatal care episodes in the 2nd trimester



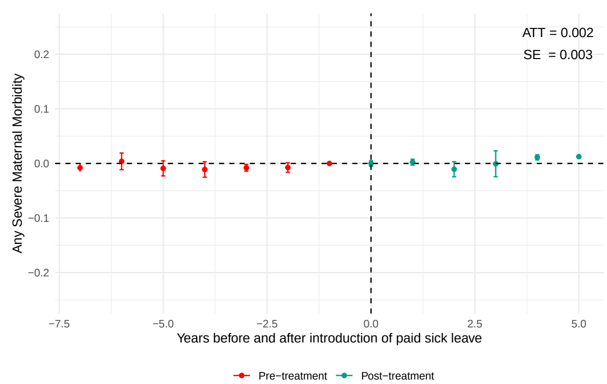
Notes: N = 809,313. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of prenatal care events in the second trimester. See Appendix for codes used to define prenatal care events. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure H9. The effect of paid sick leave on number of prenatal care episodes in the 3rd trimester



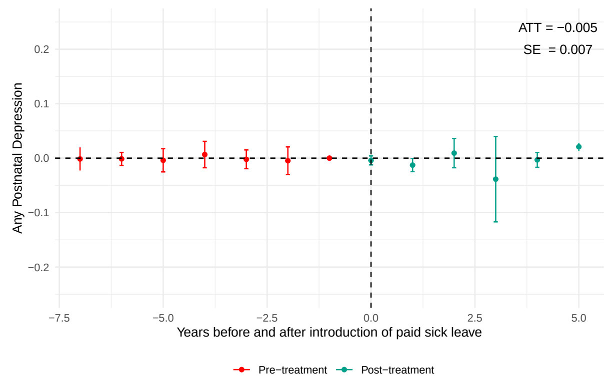
Notes: N = 809,313. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of prenatal care events in the third trimester. See Appendix for codes used to define prenatal care events. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure H10. The effect of paid sick leave on severe maternal morbidity



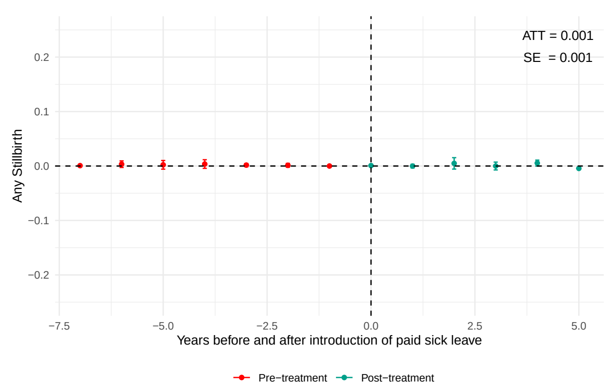
Notes: N = 649,242. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of prenatal care events. See Appendix for codes used to define SMM. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure H11. The effect of paid sick leave on postnatal depression



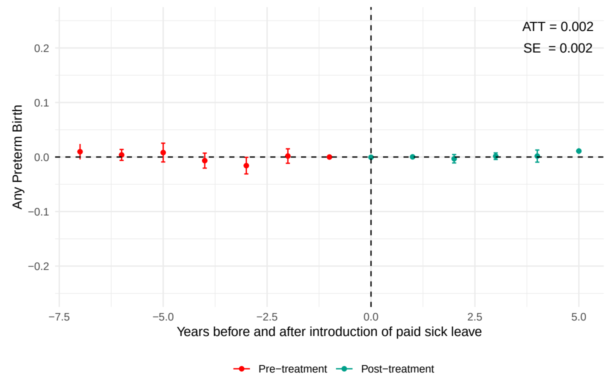
Notes: N = 649,242. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'A nna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of prenatal care events. See Appendix for codes used to define postnatal depression. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure H12. The effect of paid sick leave on severe maternal morbidity



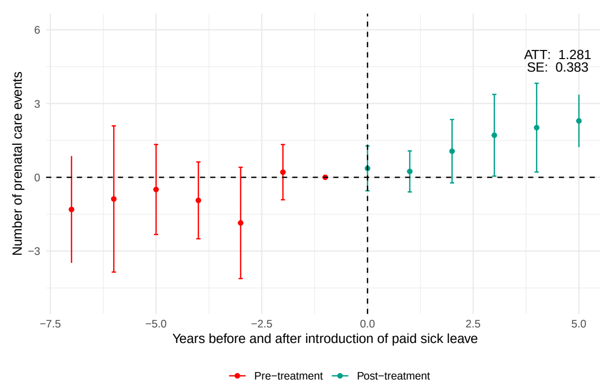
Notes: N = 649,242. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of prenatal care events. See Appendix for codes used to define stillbirth. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure H13. The effect of paid sick leave on preterm birth



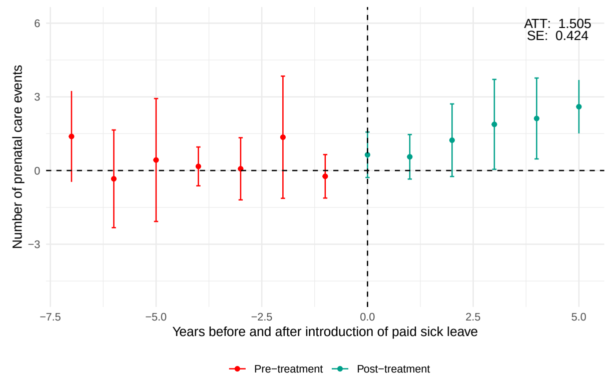
Notes: N = 649,242. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of prenatal care events. See Appendix for codes used to define preterm birth. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure H14. The effect of paid sick leave on prenatal care (alternative control group)



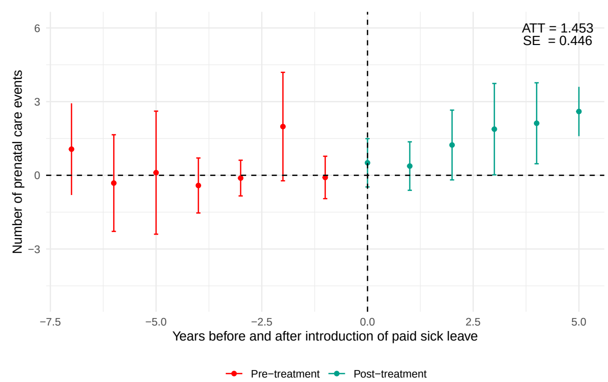
Notes: N = 809,313. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of prenatal care events. See Appendix for codes used to define prenatal care events. This robustness analysis uses an alternative control group of not yet treated mothers in addition to mothers that are never treated. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure H15. The effect of paid sick leave on prenatal care (less WA)



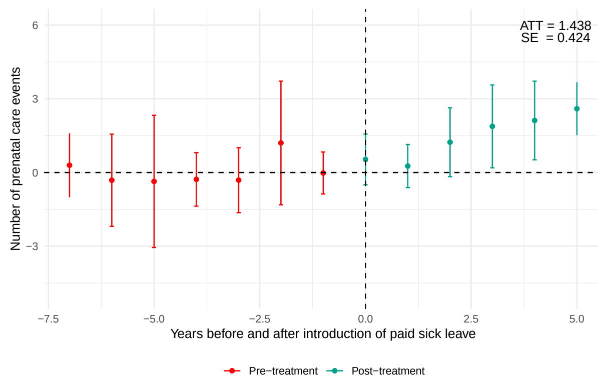
Notes: N = 800,024. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of prenatal care events. The sample drops mother-births in WA. See Appendix for codes used to define prenatal care events. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure H16. The effect of paid sick leave on prenatal care (less MD)



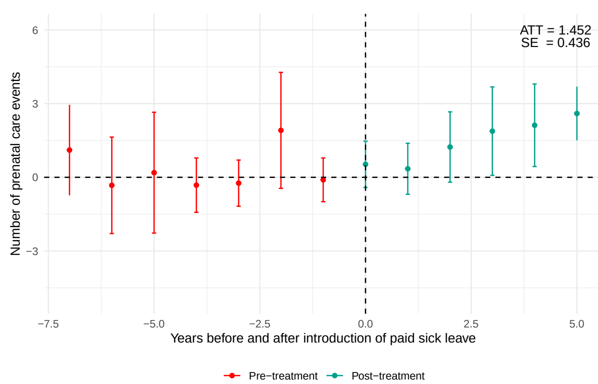
Notes: N = 806,557. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of prenatal care events. The sample drops mother-births in MD. See Appendix for codes used to define prenatal care events. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure H17. The effect of paid sick leave on prenatal care (less NJ)



Notes: N = 778,726. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of prenatal care events. The sample drops mother-births in NJ. See Appendix for codes used to define prenatal care events. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.

Appendix Figure H18. The effect of paid sick leave on prenatal care (less RI)



Notes: N = 808,991. Equation 2 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of paid sick leave. The y-axis is the number of prenatal care events. The sample drops mother-births in RI. See Appendix for codes used to define prenatal care events. Controls for age at delivery, percent of county with a high school degree, and the rural-urban measure of the county. The model includes state and year fixed effects. Standard errors clustered at the state level.