Do Abortion Bans Affect Reproductive and Infant Health? Evidence from Texas's 2021 Ban and its Impact on Health Disparities

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Abstract

In June 2022, the U.S. Supreme Court's *Dobbs v. Jackson* decision overturned *Roe v. Wade*, triggering a wave of abortion bans across the country. However, prior to *Dobbs v. Jackson*, Texas's Senate Bill 8 (SB 8) took effect in 2021, banning abortions after six weeks of pregnancy. This earlier law provides a pre-*Dobbs* case study to assess the impact of abortion bans on reproductive health. This paper examines the causal impacts of Texas' abortion ban on reproductive and infant health outcomes, including birth weight and mortality, with a focus on racial and ethnic disparities. Using a unique dataset of county-level and individual-level data, this study finds that the ban led to a 5 percent increase in very low birth weight incidence and a 6 percent rise in infant mortality rates, disproportionately affecting Black non-Hispanic infants, who experienced a nearly fourfold increase in mortality rates relative to white non-Hispanic infants. Additionally, geographic disparities emerged, with counties farther from states with less restrictive abortion policies experiencing more severe outcomes. To explain these disparities, the paper constructs an expanded abortion decision tree to measure unmet reproductive health needs, revealing how groups adjusted fertility choices post-ban. Results indicate a 4 percent increase in fertility and a 40 percent decline in abortion rates after the ban, with Black non-Hispanic women and those in counties far from non-restrictive states facing the largest increases in fertility and unmet needs. The ban also led to shorter interpregnancy intervals (the time between pregnancies), a factor associated with adverse maternal and infant health outcomes. Furthermore, both unintended and intended births exhibited higher rates of infant health complications, indicating spillover effects on the broader reproductive health system. These findings underscore that abortion bans not only significantly impact reproductive health but also amplify pre-existing health disparities, with the most profound consequences for marginalized populations.

Keywords: Reproductive Health, Abortion, Fertility, Infant Health, Abortion Ban, Texas

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1 Introduction

In June 2022, the United States Supreme Court ruled in *Dobbs v. Jackson* that Mississippi's 15-week abortion ban was constitutional, overturning *Roe v. Wade*, as well as an entire generation of cases that have consistently upheld the right to an abortion. This decision led to an immediate wave of abortion bans across the country as "trigger laws" banning abortion in many states went into effect, while other states quickly passed new laws heavily restricting abortion access (Nash and Cross 2021). As of May 2024 nearly two dozen states have enacted laws banning abortion outright or at an early point in pregnancy such as 15-weeks or less (Cole 2023).

However, an earlier decision foreshadowed the Court's ruling. In *Whole Woman's Health v. Jackson*, the Supreme Court refused to rule that Texas's 6-week abortion ban was unconstitutional, allowing the law to go into effect on September 1, 2021. Senate Bill 8 (SB 8) banned abortion in most circumstances after approximately 6 weeks of pregnancy.[1] Like many abortion restrictions, SB 8 took a complicated route through the legal system. It was signed into law by the governor of Texas on May 19, 2021. Known as the Texas Heartbeat Act, section 171.204 of this law mandated that "a physician may not knowingly perform or induce an abortion on a pregnant woman if the physician detected a fetal heartbeat for the unborn child" (*Texas Heartbeat Act* 2021, p. 4). This is typically around 6 weeks of pregnancy, which is before many people know they are pregnant (Planned Parenthood 2024; Center for Reproductive Rights 2021). Further, the law established that any person who "performs or induces an abortion" after the limit, or who "knowingly engages in conduct that aids or abets the performance or inducement of an abortion" is liable to a private civil action by any person, including damages of not less than $10,000 (*Texas Heartbeat Act* 2021, p. 7).[2]

1. While the Texas ban set an earlier gestational limit than the Mississippi ban which was under consideration in *Dobbs*, the state of Mississippi explicitly asked the Court to overturn *Roe v. Wade* as part of their case.

2. Though the legal text of the law uses the term "fetal heartbeat," this is not a medically accurate term according to the American College of Obstetricians and Gynecologists (ACOG), as the chambers of the

Texas's early ban on abortions offers a unique case study for assessing the impact of abortion bans on reproductive health outcomes, providing critical insights into the post-*Dobbs* landscape. While early research has focused on changes in abortion, contraception, and fertility rates following *Dobbs*, there remains a significant gap in understanding the broader, downstream effects of such bans (Maddow-Zimet and Gibson 2024; Kavanaugh and Friedrich-Karnik 2024; Dench, Pineda-Torres, and Myers 2023). Moreover, despite extensive evidence that racial and ethnic disparities are pervasive in reproductive health, few studies have examined whether—and to what extent—abortion bans exacerbate these inequities. Understanding how these laws differentially affect racial and ethnic groups is critical, as marginalized populations may face compounded barriers to healthcare access and reproductive autonomy in the wake of restrictive abortion policies.

This paper addresses this critical gap by investigating the causal impact of an abortion ban on infant and reproductive health, focusing on how these effects differ across racial and ethnic groups. Using a unique dataset that combines county-level and individual-level reproductive health data from diverse sources—including restricted-use vital statistics, archived reports, public records requests, as well as local activist and journalist sources—I find that Texas' abortion ban led to significant increases of 5% in the incidence of infants born with very low birth weight, alongside a 6% rise in the infant mortality rate. These effects are strikingly uneven across racial groups: Black non-Hispanic infant mortality rates increased fourfold compared to white non-Hispanic rates in the aftermath of the ban.

Reproductive Justice scholars argue that marginalized populations–such as pregnant people of color and those with low incomes—are disproportionately affected by abortion restrictions and bans.[3] Building on these insights, this paper seeks to explain the dramatic differences in infant health outcomes after Texas's abortion ban by expanding on the work

heart are not fully formed until a later gestational age. The sound that is detected is instead the ultrasound machine translating the electrical activity of the fetal cardiac tissue into a sound that resembles a heartbeat. For this reason, the ACOG recommends the term "cardiac activity" instead of "fetal heartbeat" (American College of Obstetricians and Gynecologists 2023).

3. I use the gender neutral term pregnant people throughout this paper to be inclusive of those who can get pregnant but who do not identify as women.

of Levine (2007). I outline an expanded abortion decision tree for restrictive reproductive health policy environments, such as those emerging in the post-*Dobbs* era. This framework provides a tool for understanding how abortion bans influence reproductive health outcomes beyond just abortion rates, revealing the heterogeneous effects across different demographic groups. The framework suggests that populations unable to shift their fertility choices—such as those in areas with limited access to out-of-state abortion services—are more likely to experience adverse reproductive health outcomes.

To test these predictions, I estimate the effect of Texas's abortion ban on both abortion and fertility rates using county-level data. The results indicate that abortion rates fell by over 40 percent following SB 8, while fertility rates increased by approximately 4 percent. Notably, the ban had a particularly strong impact on Black non-Hispanic women, who saw a significant rise in fertility, while white non-Hispanic women experienced a more modest increase. Additionally, the findings suggest that the impact of the ban on both fertility and abortion rates was more pronounced in counties farther from states with less restrictive abortion laws

Leveraging the logic of the expanded abortion decision tree, this paper develops an accounting framework to estimate the unmet reproductive health needs faced by different groups after an abortion ban. This index can classify the degree to which people in counties have either a) shifted their sexual or contraceptive choices, b) obtained an abortion by other means, or c) given birth. The results suggest that the unmet reproductive health need is largest in counties with higher proportions of Black non-Hispanic residents, as well as counties which are furthest away from states which did not ban abortion after the *Dobbs* decision.

The two primary downstream reproductive health outcomes I examine are birth weight and infant mortality. Birth weight is an important indicator not just of infant health, but has also been associated with a range of childhood and adult health outcomes. For example, lower respiratory health, physical health, and obesity outcomes have all been shown to be associated with low birth weight, especially very low birth weight (Hack 2006; Overpeck et al. 1989; Kuh et al. 2002). Additionally, low birth weight has been associated with adverse social and economic outcomes, with low birth weight infants being more likely to have lower educational attainment in childhood and adolescence, and worse labor market outcomes in adulthood (Bharadwaj, Lundborg, and Rooth 2018; Chatterji, Kim, and Lahiri 2014). Therefore, understanding the effects of an abortion ban on infant health outcomes is important for understanding the broader effects of the ban, and the potential long-term consequences of the ban on the health and well-being of a group. I also examine the effect of the ban on infant mortality, which is uniquely high in the United States relative to other high-income countries, and has been increasing in recent years as the country has become more restrictive in its reproductive health policy environment (Gunja, Gumas, and Williams II 2023; Associated Press 2023).

In addition to finding that the ban led to increases in infant mortality and very low birth weight—particularly among Black non-Hispanic infants—I also observe that the largest increases in these outcomes occurred in counties furthest from states where abortion remains legal after the *Dobbs* decision. These geographic disparities suggest that the effects of the ban on infant health outcomes are most pronounced in groups experiencing the greatest changes in fertility and abortion rates, reinforcing the causal link between the ban and downstream reproductive health outcomes. These findings not only highlight the uneven impact of the ban but also clarify how different groups are disproportionately affected, depending on their access to abortion services.

To further explore the medical pathways through which abortion bans may affect infant health, I examine the relationship between the ban and short interpregnancy intervals (i.e., less than 18 months between live births), which are associated with a broad range of adverse infant health outcomes (Conde-Agudelo et al. 2012). The analysis shows that the ban increased the likelihood of a birth being preceded by a short interpregnancy interval for both white and Black non-Hispanic mothers, offering another mechanism by which the ban exacerbates negative health outcomes.

Lastly, I explore whether the negative health outcomes following the ban are driven by changes in the demographic composition of those giving birth post-ban. Using machine learning techniques and a combined dataset approach, I predict the likelihood of a birth being unintended, based on maternal and birth characteristics. If unintended births—more likely to have resulted in abortions prior to the ban—are now leading to live births, and if such births are linked to worse infant health outcomes, the ban may be influencing these outcomes through shifts in *who* is giving birth. However, my findings reveal that the ban negatively affects health outcomes for both unintended and intended births. This suggests that abortion bans have broader spillover effects on reproductive health systems, possibly affecting the quality of care or the health of pregnant people and infants more generally.

This paper is the first to integrate comprehensive data on abortion, fertility, health, and mortality to evaluate the broad impacts of a statewide abortion ban on reproductive health outcomes. It provides the most thorough perspective in the current literature on how restrictive abortion policies contribute to health disparities, particularly for marginalized populations. The rest of this paper is organized as follows. Section 2 reviews the literature on the causal effect of abortion access in the United States, as well as the literature on reproductive health disparities more broadly. Section 3 introduces the expanded abortion decision tree, and how it can be useful for describing the possible ways in which abortion bans may affect reproductive health outcomes. The empirical strategy used in the analysis is discussed in section 4, and the data is described in section 5. Section 6 presents the results on the effect of the abortion ban on abortion and birth rates, section 7 reports the results for the county-specific unmet reproductive health needs, and section 8 presents the results on infant health outcomes. Section 9 describes the approach for building a model to predict unintended fertility and reports its results. Lastly, section 10 summarizes and concludes.

2 Relevant Literature

This paper contributes to several strands of the reproductive health literature. The first is the new literature on the causal effect of abortion restrictions in the United States. An earlier literature examined the effect of abortion liberalization in the United States, with state-level reforms followed by national liberalization with *Roe v. Wade*.[4] The new wave of literature turned to examine the effect of abortion restrictions—which with the establishment of the "undue burden" precedent in *Casey v. Planned Parenthood*, gradually increased in number, especially through the 2010s. This work, studying policies such as Targeted Regulation of Abortion Providers (TRAP) laws, parental consent laws, and mandatory waiting periods, generally focused on abortion rates and fertility (Fischer, Royer, and White 2018; Myers 2021; Lindo et al. 2020; Lindo and Pineda-Torres 2021; Venator and Fletcher 2021; Austin and Harper 2019; Caraher 2023). This literature generally finds that abortion restrictions led to moderate decreases in abortion rates, and small increases in fertility rates. Additional work in this literature has also examined the effect of these restrictions on contraception use, as well as downstream effects such as education and labor market outcomes (Pennington and Venator 2023; Jones and Pineda-Torres 2024; Bahn et al. 2020).

The second strand of literature this paper fits into is the broader literature on disparities in reproductive health outcomes both between and within countries. The United States has the highest maternal mortality rate in the developed world, and is one of the few countries in the world where this rate has increased over the past few decades (World Health Organization 2023). Reproductive health outcomes are also highly disparate, with Black pregnant people experiencing especially high rates of maternal mortality (Hoyert 2023). Infant mortality rates are also extraordinarily high in the United States relative to other high-income

4. This earlier literature generally focused on decreases in fertility after the liberalization of abortion laws, and how changes in fertility translated into changes in educational and labor market outcomes such as female labor supply (Angrist and Evans 2000; Kalist 2004; Oreffice 2007). This literature also compared cohorts of children born before and after legalization, and generally found that children born after legalization were less likely to be born in poverty, be a single parent, or live on welfare (Gruber, Levine, and Staiger 1999; Ananat et al. 2009)

countries, and have also been increasing in recent years (Gunja, Gumas, and Williams II 2023; Associated Press 2023). These rates are similarly racialized, with recent work showing that even within income groups, Black infants are more likely to die than white infants (Kennedy-Moulton et al. 2022). The United States is also one of the few countries in the world that has over this same period become *more* restrictive in its reproductive health policy environment, in stark contrast to Europe and Latin America where countries have gradually liberalized their abortion laws (Fine, Mayall, and Sepúlveda 2017). A number of studies have examined the intersection of increasing abortion restrictions and reproductive health disparities. Descriptive studies have found that states which enacted abortion restrictions have worse maternal and infant health outcomes (Pabayo et al. 2020; Declercq et al. 2022; Stevenson, Root, and Menken 2022). There is more limited causal evidence on the effect of abortion restrictions on maternal and infant health outcomes, though Gardner (2022) finds TRAP laws led to increased rates of hypertensive disorders of pregnancy. This paper contributes to this literature by studying the effect of an abortion ban rather than more moderate restrictions, which as a much larger shock may have more substantial or qualitatively different effects on reproductive health outcomes relative to abortion restrictions like TRAP laws.

Lastly, this paper fits into the emerging literature on the effect of outright abortion bans rather than more moderate restrictions. This literature has started to emerge very recently in light of the *Dobbs* decision. A number of other studies have used Texas's early ban on abortion as a case study on some aspect of reproductive health. Andersen et al. (2023) find reduced travel to Texas abortion clinics and increases in mobility to abortion clinics outside Texas in legal states, and Aiken et al. (2022) find increases in the use of telehealth abortion services after the enactment of Texas's ban. Using state health department data, elevated infant mortality rates in Texas after SB 8 were first reported by Chapman (2023). Gemmill et al. (2024) uses a synthetic control method and provisional state-level counts and finds an increase in infant deaths in Texas of about 13 percent relative to other states. Turning towards states which adopted abortion bans after the *Dobbs* decision, Aiken et al. (2024) find increased use of telehealth abortion services after *Dobbs*, suggesting that pregnant people are seeking out alternative methods of abortion, and Ellison, Brown-Podgorski, and Morgan (2024) find increases in permanent contraception after the decision. Using post-*Dobbs* policy changes after the Supreme Court ruling, Dench, Pineda-Torres, and Myers (2023) find increases in fertility rates after the decision. This paper contributes to this literature by jointly examining both ''first-stage" outcomes of an abortion ban such as abortion and fertility rates, and by tracing how the effect of these bans are carried over for different groups to other reproductive health outcomes, empathizing within-state differences in the effect of Texas's ban. In addition to furthering the understanding into how effects of these bans may differ, this paper also further reifies the causal link between these outcomes by establishing that downstream reproductive health outcomes are felt most acutely in those groups which experienced the largest changes in fertility or abortion rates after the ban, such as Black infants, or those in counties far from states with less restrictive abortion laws.

3 The Expanded Abortion Decision Tree

The abortion decision tree is a tool for understanding the ways in which abortion restrictions may affect fertility outcomes, as well as have possible spillovers on other reproductive health, social, and economic outcomes. The tree represents the possible decisions that a person able to get pregnant would have to navigate before getting an abortion or giving birth. Levine (2007) outlines an abortion decision tree comprised of 5 nodes: contraception, pregnancy, non-pregnancy, abortion and birth. I expand upon this decision tree in order to highlight the institutional features of the abortion decision tree in a restrictive reproductive health regime, such as the one in many states after the *Dobbs* decision.

The expanded abortion tree is shown in figure 1. An abortion ban like SB 8—or the many other laws which create restrictive reproductive health regimes—may have an effect on each level of the tree. The top nodes of the tree broadly reflect decisions made prior to the point of pregnancy. First is the decision to engage in sexual activity which may result in a pregnancy. An abortion ban, increasing the risk of a birth, may lead some people to change their behavior and engage in less heterosexual intercourse which leads to pregnancy. This may be reflected in decreased sexual activity overall, or more specifically penile-vaginal sex. Using data from the Reproductive Health Impact Study, Kavanaugh and Friedrich-Karnik (2024) find that after the *Dobbs* decision there was a decrease in penile-vaginal sex, although this may be a continuation of a trend (Ueda et al. 2020).

After sexual activity, the second node in the tree is contraception intensity, ranging from no contraception to highly effective contraception. Levine (2007) describes a model where contraception intensity adjusts to the cost of an abortion or birth, whichever is lowest. Since more effective methods of contraception such as Long Acting Reversible Contraceptives (LARCs) like Intrauterine Devices (IUDs) may have a higher upfront cost due to the need for a procedure to insert and later remove the device, someone may choose a less effective method of contraception that is less costly and more convenient (e.g., condoms) in an environment with liberal abortion laws (Pennington and Venator 2023). However, an increase in the cost of an abortion increases the relative cost of an unintended pregnancy, which may lead to an increase in contraception intensity. There is evidence that these changes in contraception intensity can be substantial. After Wisconsin announced an abortion restriction in 2015, as well as after the 2016 presidential election, Pennington and Venator (2023) find that there was a substantial increase in the use of LARCs in response to the increased uncertainty in the reproductive health policy regime. Similarly, Ellison, Brown-Podgorski, and Morgan (2024) find large increases in permanent contraception after the *Dobbs* decision, especially increases in tubal ligation.

The choice of contraception determines the relative probability of pregnancy.[5] If a preg-

5. Emergency contraception is another option for preventing pregnancy after unprotected sex or if a contraceptive method fails. Emergency contraception is only effective within three to five days after sex, and can thus be considered a lower-intensity and less effective form of contraception in the abortion decision tree. Further, while about about a quarter of pregnant people have used emergency contraception at some

nancy occurs, the pregnant person faces the next level of the decision tree, and must decide whether to continue the pregnancy or to have an abortion, unless the pregnancy ends in a miscarriage or stillbirth.[6] If the person decides to obtain an abortion, they face two options to end the pregnancy. Firstly, they can go to a clinic, hospital, or physician's office in their home state to obtain a medication abortion or a surgical abortion. I define these as a ''recorded" abortion because for many states, these abortions are reported to the state health department, and it is possible to obtain data on the number of these abortions performed in a given year. Alternatively, they can seek an abortion in a way that is less likely to be recorded in official state health department data. A primary way to do this is to travel to another state to obtain an abortion, which define as a travel abortion.[7] Another way is that that they can self-manage their abortion. This practice involves obtaining an abortion without the direct supervision of a healthcare provider. This often involves purchasing abortion pills online through organizations such as Aid Access, which works with legitimate abortion providers to prescribe abortion pills and send them in the mail. It is also possible to buy abortion pills through a less reputable websites (Murtagh et al. 2018). In rare cases, pregnant people might try to end their pregnancy using dangerous and life-threatening methods, like inserting a sharp object, harmful substance, or toxic chemicals into the vagina, or causing injury to their abdomen (Harris and Grossman 2020).[8]

point in their life, only a very small number use it regularly (Guttmacher Institute 2021; Daniels and Abma 2020).

6. Another possibility is that the mother dies during her pregnancy. This can be considered a separate node in the tree, or added to the miscarriage node.

7. The primary context in this paper for which travel abortions are relevant is when a person travels to another state to obtain an abortion when the procedure is banned in their home state, such as traveling from Texas across the state border to New Mexico. However, travel abortions occur in other contexts where there are nearby jurisdictions with different degrees of legal abortion access. For example, before Ireland legalized abortion through a referendum in 2018, many Irish women would travel to the mainland United Kingdom to obtain an abortion. In 2014 alone, over 3,700 women gave Irish addresses to English and Welsh abortion providers, compared to just 26 abortions performed in Ireland (United Kingdom Department of Health 2015; Ireland Department of Health 2015).

8. Self-terminating a pregnancy using sharp instruments, blunt trauma, heat, or toxic chemicals was more common prior to passage of *Roe v. Wade* in the 1970s. Farin, Hoehn-Velasco, and Pesko (2021) finds substantial reductions in non-white maternal mortality after the legalization of abortion, partly due to the reduction in life-threatening self-managed abortions.

An abortion ban can dramatically affect the choice of abortion method, and in the case of a total ban, completely eliminate the ability to get a recorded abortion except in a very limited set of circumstances. This leaves traveling to an unrestricted state or self-managing an abortion as the only options. There is evidence that both of these options have increased after an abortion ban. Andersen et al. (2023) use mobility data and find that after the enactment of SB 8, there was substantial increase in movement from Texas to abortion clinics in nearby states. Aiken et al. (2022) find that after SB 8, there was a sustained increase in the use of Aid Access Telehealth abortion services. It is important to note that self-managing an abortion can be dangerous legally as well, especially with the increased criminalization of abortion seekers and providers that is often tied to abortion ban legislation. Using court records and media reports from 2000-2020, Huss, Diaz-Tello, and Samari (2023) found that at least 61 people had been investigated or arrested for alleged self-managed abortion, or for helping someone else self-manage an abortion.

Overall, there is evidence that abortion restrictions can affect all nodes of the abortion tree, from sexual activity to the choice of abortion method. This has implications for how an abortion ban may affect not only fertility outcomes, but also other reproductive health outcomes such as maternal and infant health. If pregnant people are able to shift their choices along the decision tree after an abortion ban, for example by increasing contraception intensity or having less penile-vaginal sex, then the effect of the ban on births may be relatively small. This in turn could result in little to no worsening in infant or maternal health outcomes, and perhaps even small improvements if pregnant people are able to shift their choices in a way that reduces the risk of adverse outcomes. On the other hand, if pregnant people are unable to shift their behavior, then the effect of the ban on births may be substantial, and the inability to obtain an abortion may result in worse health outcomes for pregnant people and infants.

Critically, the ability to shift choices along the abortion decision tree after an abortion ban may be heterogeneous by group, with some groups being able to more easily shift behavior than others. For example, an abortion ban may result in little to no increase in births for pregnant people who are able to travel to another state for an abortion or who have health insurance to pay for a LARC. For these women, while they may have lost substantial access to abortion, they may be able to offset this loss by obtaining an abortion through other means or by changing their contraceptive behavior. For those who have less access to resources, an abortion ban may result in a substantial increase in births, since they are unable to shift their behavior from a recorded abortion to choices at the top or bottom of the decision tree. Existing evidence suggests there are substantially different effects of abortion restrictions for different groups, especially those facing inequalities in health outcomes more generally, such as minority communities or those with lower incomes. For example, Caraher (2023) finds that counties with higher proportions of Black or Hispanic residents experienced larger decreases in abortion rates after a TRAP law or mandatory waiting period law was enforced.

This ability—or lack thereof—for pregnant people to shift their behavior along the abortion decision tree after an abortion ban is important for understanding the causal relationship between a restrictive reproductive health regime and reproductive health outcomes, and how groups may be affected by these bans differently. In order to estimate how an abortion ban may alter outcomes along the abortion decision tree, in the remainder of this section I develop a summary statistic which measures how much a group is able to shift their fertility choices after an abortion ban.

The abortion decision tree can be represented in an accounting framework.[9] Births can be represented as a linear function of pregnancies, abortions, and miscarriages:

$$B = P(C, S) - (A_r + A_t + A_s + M) \tag{1}$$

where B is the number of births, P is the number of pregnancies which is a function of

9. The National Center for Health Statistics uses a similar ''tree'' framework to estimate total pregnancies (Rossen et al. 2023).

contraception intensity C and sexual activity S, A_r is the number of recorded abortions, A_s is the number of self-managed abortions, A_t is the number of abortions by traveling outside the legal jurisdiction, and M is the number of miscarriages. Changes in births after an abortion ban, ΔB, can then be decomposed into changes in the other components of the fertility tree:

$$\Delta B = \Delta P(C, S) - \Delta A_r - \Delta A_t - \Delta A_s - \Delta M. \tag{2}$$

Rearranging the terms,

$$\Delta B + \Delta A_r = \Delta P(C, S) - \Delta A_t - \Delta A_s - \Delta M. \tag{3}$$

The left-hand side of the equation, $\Delta B + \Delta A_r$, can be interpreted as the unmet reproductive health needs of a population after an abortion ban. Assuming that $\Delta A_r < 0$ after an abortion ban is enacted, if $\Delta B + \Delta A_r$ is small and close to zero, it indicates that the group is not able to offset the loss of abortion access, and abortions which would have taken place without the ban are resulting in births. If this value is negative and further from zero (i.e., ΔP, ΔA_t, or ΔA_s are relatively large), it indicates that the population is shifting their fertility choices after the abortion ban towards another node along the abortion decision tree, for example by obtaining an abortion through travel, or by reducing the number of pregnancies after the ban through lower penile-vaginal intercourse or increased contraception use. Thus, I define the Reproductive Health Needs Index (RHNI) as the sum of births and recorded abortions after an abortion ban as

$$\text{RHNI} = \Delta B + \Delta A_r. \tag{4}$$

There are several benefits to using a compound measure like the RHNI to estimate the effect of an abortion ban on reproductive health outcomes, rather than just examining one outcome alone. There are many nodes along the abortion decision tree which are difficult to measure or have highly imperfect data, such as sexual activity, miscarriages, and especially self-managed abortions which in some states are illegal by their very nature.[10] One benefit of the RHNI is that it can be estimated using observable data on abortion and fertility rates, which are available in many states, and can therefore shed light onto the changes of the less observable nodes of the tree. Another benefit is that it can be used to compare the effect of an abortion ban on different groups, since abortion and birth data are available at finer geographic levels such as county-level, or even sometimes at the individual-level. This is especially important for understanding how the effects of abortion bans may be concentrated in marginalized populations, such as Black women, impoverished pregnant people, or teenagers, or how the ability of pregnant people to shift their fertility choices after an abortion ban may be determined by other exogenous factors, such as distance to a state with less restrictive abortion laws. Lastly, the RNHI can also be useful for interpreting reproductive health effects of abortion bans. For example, it is plausible that an abortion ban may have the most negative health effects on populations that are least able to shift their fertility choices towards contraception after the ban. Therefore, if the RHNI is very small for a population, it would suggest that the ban might also have negative effects on other reproductive health outcomes, such as infant health. This also lends more confidence to causal estimates of the effect of abortion bans on reproductive health outcomes. One way to estimate the policy ''bite" of an abortion restriction is to first establish its effect on abortion and fertility rates, such as jointly through the RNHI. If the effect of the ban on abortion and fertility rates is large for the same sub-population for which the ban has a large effect on downstream reproductive health outcomes, this provides more confidence to the causal interpretation of the effect of the ban on reproductive health outcomes.

10. While some survey data, such as the National Survey of Family Growth (NSFG) or the Behavioral Risk Factor Surveillance System (BRFSS), can be used to analyze changes in sexual behavior or contraceptive use, these data are often not available at large counts at the state-level, are restricted-use or—as in the case of Texas for the BRFSS—certain states do not participate in the family planning module of the survey.

4 Empirical Strategy

To estimate the effect of Texas's ban on abortion rates, fertility rates, or mortality outcomes, a difference-in-differences model is estimated using annual county-level data:

$$Y_{it} = \sum_{k=-5}^{-2} \beta_k D_{it}^k + \sum_{k=0}^{1} \beta_k D_{it}^k + X_{itc}\Omega + \alpha_i + \tau_t + \epsilon_{it} \tag{5}$$

where Y_{it} is the outcome for county i in time t for Texas, α_i are county fixed effects, τ_t are time fixed effects, X_{it} is a vector of control variables, and ϵ_{it} is the error term. The D_{it}^k are lead and lag terms, with the β_k coefficients representing the effect of the law in the kth period of treatment. Negative values of k represent a check for trends in outcomes before treatment, and positive values of k represent the effect of the law in the post-treatment period. Given the recent enactment of these laws, a 7-year window is used, with the first year of treatment ($t = 0$) being 2021, the year the first ban was enacted. The total ban is then reflected in the second year of treatment ($t = 1$), in 2022. Pooled estimates for the post-treatment period are also estimated.

Several variations of equation 5 are estimated. First, outcomes are estimated without any control variables, then using county-level populations as weights, and county-level economic and population-based control variables. These control variables include county-level unemployment rates, poverty rates, log median household income, labor force participation rates, and Republican vote shares. County-level population shares of teenagers aged 15-19, adults aged 20-24, adults aged 25-34, adults aged 35-44, Black non-Hispanic women of reproductive age, white non-Hispanic women of reproductive, Hispanic women of reproductive age, and total women of reproductive age are also included as control variables, as well as the total number of women of reproductive age in the county. The difference-in-differences estimates exclude counties with fewer than 1000 women of reproductive age in 2020. Additionally, some specifications are estimated using nearest-neighbor matching weights, where the control group is weighted by the inverse of the Mahalanobis distance between the treatment and control group. I report standard errors clustered at the county and state-year level.[11]

To estimate the effect of Texas's 6-week abortion ban on birth weights, I estimate the following regression using individual-level birth certificate data:

$$Y_{bit} = \sum_{k=-5}^{-2} \beta_k D_{bit}^k + \sum_{k=0}^{1} \beta_k D_{bit}^k + X_{bitc}\Omega + \alpha_i + \tau_t + \epsilon_{bit} \tag{6}$$

where Y_{bit} is the outcome for birth b in county i in time t for Texas, α_i are county fixed effects, τ_t are time fixed effects, X_{bit} is a vector of control variables, and ϵ_{bit} is the error term. The D_{bit}^k are lead and lag terms, with the β_k terms representing the effect of treatment and the check for pre-existing trends prior to the enactment of the policy.

As seen in the Policy Surveillance Program dataset, states enacted bans of various gestational limits in 2022. In order to estimate a cleaner effect of these laws, only states which do not pass a ban until after 2022 are included in the comparison group.[12] This ensures that the control group is not contaminated by states which pass bans in 2022 after the *Dobbs* decision. Only states which do not have a ban at a gestational limit less than 20 weeks are included as controls.

In addition to the difference-in-differences estimates, I also estimate the effect of the ban on outcomes using the synthetic control method at the state-level following Abadie, Diamond, and Hainmueller (2010) over a 12 year period. To test for statistical significance in the synthetic control estimates, I rank the ratio of the post-treatment Root Mean Squared Prediction Error (RMSPE) to the pre-treatment RMSPE of a placebo intervention for all control states. If the treated state (i.e., Texas) is in the top percentage of the distribution of

11. The standard errors are clustered at county and state-year level in this analysis, even though the treatment is at the state-level. However, inference in difference-in-differences estimates in the case with few treated clusters can misestimate the true standard errors depending on certain factors such as cluster size, so I refrain from clustering at the state-level in the main results. In the appendix, I present the event study estimates clustered at the state-level using the method described in Ferman and Pinto (2019), which allows for valid inference with few treated clusters and corrects for heteroskedasticity based on cluster size. The confidence intervals using the Ferman and Pinto (2019) are generally smaller than using county and state-year clustering, so I report the more conservative confidence intervals in the main text.

12. States which pass a ban in 2023, however, are included as comparisons. These states are North Carolina and Nebraska. States which enact a ban after the estimation window are likely more similar to Texas in their policy regimes, and therefore are important points of comparison.

placebo state RMSPE ratios, then the effect of the ban is considered statistically significant. The synthetic control estimates are slightly larger in magnitude compared to the difference-in-differences estimates, and are reported in the appendix.

In order to estimate the county-specific RHNI, I first estimate the effect of the ban on the abortion rate and fertility rate for each county. I do this by subsetting the data to include only the treated county and all control counties, and then estimating specification in equation 5. I then add the point estimate from each county-specific fertility rate regression to the point estimate from each county-specific abortion rate regression.

5 Data

This paper relies on several sources of data to estimate the effect of Texas's abortion ban on reproductive health outcomes. In addition to policy change variables, it is necessary to construct a dataset which includes county-level information on abortion rates, fertility rates, and other reproductive health outcomes. A major contribution of this paper is to combine these data sets and estimate these outcomes collectively.

5.1 Abortion Policy Data

The overturning of *Roe v. Wade* in the *Dobbs* decision led to a wave of abortion bans in state legislatures across the country. The rollout of these bans in the summer and fall of 2022 was chaotic, with bans being implemented, blocked, and then re-instated all in the span of a few months. In some states, such as Wisconsin, uncertainty about whether or not pre-*Roe* abortion bans would be enforced led clinics to stop providing abortions altogether, despite the legal ambiguity (Lehr and Faust 2023). In other states, such as Utah, local courts blocked total or near-total bans, but allowed bans at gestational limits to go into effect (ACLU of Utah 2023).

In order to identify valid control states for the causal difference-in-differences analysis, it is necessary to account for each state's abortion policy in the months after the *Dobbs* decision. The primary dataset used to track these laws is the Policy Surveillance Program's Post-*Dobbs* State Abortion Restrictions and Protections dataset (Policy Surveillance Program and Advancing New Standards in Reproductive Health Care 2023). While several other organizations such as the Guttmacher Institute and the Center for Reproductive Rights track changes in policy at the state level, the Policy Surveillance Program dataset records the month of enforcement of each law, as well as the gestational limit and the type of law. This allows for the construction of a monthly panel, which can then be more accurately assigned to years in the county-level abortion data. However, given the chaos around the rollout of these laws, I manually verified each policy change using a combination of local news reports or press releases from local branches reproductive health advocacy groups, such as the American Civil Liberties Union (ACLU) or Planned Parenthood. Local sources were used to clarify ambiguities in the Policy Surveillance Program dataset, and to construct a more accurate timeline of policy changes. Appendix A outlines a brief history of each state's abortion policy changes after the *Dobbs* decision, with links to the local sources used to verify each change.

Figure 2 shows the number of states that enforced abortion bans from September 2021 to July 2023. A state-month is assigned an abortion ban based on the policy it had in place on the last day of the month. The dotted line represents the month of enforcement of SB 8 in Texas, which was the first state to enforce a strict gestational limit prior to the Supreme Court's decision. The figure shows that the number of states which enforce abortion bans increases dramatically after the *Dobbs* decision, indicated by the dashed line, which represents the enactment of "trigger" laws in several states—abortion bans which were technically state laws but were unenforceable prior to the *Dobbs* decision. In the months after the *Dobbs* decision, some states made existing bans even more restrictive, with several states reducing their gestational limit from 6-14 weeks to total bans.

These policy changes are shown geographically in figure 3. Each panel represents, for a given month, which states have enacted bans by gestational limit. July 2022 in the top right panel represents the first month post-*Dobbs*, and the bottom right panel represents December 2022. The states which have enacted bans are concentrated in the South and Midwest, with a few states in the West and Northeast. By the end of the 2022, there were 17 states which had abortion bans in effect. Texas implemented its ban on abortions in two stages across two years, as seen in figures 2 and 3. The first stage was the enactment of SB 8, which banned abortion after 6 weeks of pregnancy. This was enacted in September 2021. The second was a total ban on abortion, enacted as a trigger law immediately after the *Dobbs* decision in June 2022.

Previous literature has shown that distance to abortion services is an important determinant of abortion access, and that increases in distance to abortion services can lead to decreases in abortion rates and increases in fertility (Myers 2024; Lindo et al. 2020). I also use the abortion policy data to estimate the distance of each county in Texas to the nearest county in a state with a less restrictive abortion policy. To calculate this distance, I select the states around Texas to which pregnant people are most likely to travel to obtain an abortion, omitting states which enacted a law banning abortion at gestational limits of less than 20 weeks in 2022 after the *Dobbs* decision. I then compute the distance from the geographic center of each county in Texas to the geographic center of every county in states which did not pass a ban in 2022 using the Vincenty Ellipsoid formula, and then find the minimum value across these distances for each county in Texas. Figure 4 shows the distance of each county in Texas to the nearest state which did not pass a ban in 2022 after the *Dobbs* decision. Counties in the southeast of the state are furthest away from a county with legal abortion, since the states east of Texas all passed bans in 2022, while states to the North and West of Texas did not.

5.2 Abortion Rate Data

County-level abortion rates are estimated using an updated version of the county-level abortion data from Caraher (2023). This data reports the number of abortion by county of residence for about 30 states, and is available from the late 1990s to 2021 or 2022. This dataset is constructed from a number of state-specific sources, including archived vital statistics reports, state health department databases, state abortion reports, as well as direct public records request.

Critically, abortion counts are reported by county of residence rather than county of occurrence. This is important as many people travel within a state to obtain an abortion, and therefore county of occurrence data can severely misestimate the number of abortions of county residents. This is especially the case in a state like Texas, where a large number of clinics closed after the enactment of abortion restrictions such as Targeted Regulation of Abortion Providers (TRAP) laws in the 2010s (Grossman et al. 2014).

States have various reporting requirements with regard to abortion. Many states do not report abortion data at all, such as California. Other states report abortion only by county of occurrence, or larger aggregates. Importantly, over half the states make abortion data available at the county level, and there is no clear relationship in the reporting of abortion data and the political climate of the state, which is essential for a difference-in-differences analysis. While some states have data-sharing agreements with other states implying that a person who travels to another state for an abortion may have their abortion reported to their home state, these agreements are not universal and it is unclear how complete these agreements are. Appendix table B1 shows the availability of county-year abortion data by state.

In the aftermath of the *Dobbs* decision, there may be changes in the reporting of abortion data. For example, Georgia has stopped reporting county-level abortion data as of November 2023. Additionally, there may be changes in the data-sharing agreements between states, as liberal states which border restrictive states may be less willing to share information about cross-state abortions.

Abortion rates are calculated as the number of abortions per county of residence divided by the number of women of reproductive age (15-44) in the county (in thousands). Population data are from the Census Bureau County Intercensal estimates (U.S. Census Bureau 2021, 2023a). Certain states report abortion counts with suppressed values for counties with small counts. In these cases, I drop these county-year observations from the analysis.

Figure 5 shows the abortion rates for Texas and other states from 2010 to 2022. As can be seen, Texas initially had a higher abortion rate than the rest of the country, but this rate dropped substantially after the enactment of a TRAP law in 2013, and then again after the enactment of SB 8 in 2021 and the total ban in 2022. The rest of the county experienced a more gradual decline in the abortion rate over this decade, with a moderate increase in 2021 and 2022. This recent increase in the national abortion rate, despite the *Dobbs* decision, has been observed in other abortion data sets as well, such as the Guttmacher Institute's data (Maddow-Zimet and Gibson 2024).[13]

5.3 Birth Certificate Data

The birth data comes from the National Center for Health Statistics (NCHS). These data are restricted-use, and are only available to researchers who have completed the NCHS Research Data Center Data Use Agreement (DUA). Specifically, these are all-county natality files, which include all birth certificates issued in the United States in a given year. Total births are computed as the total number of birth certificates in a given county-year. Counties refer to the mother's county of residence. Birth counts are aggregated to the county-year level. The fertility rate is calculated as the total number of births in a county-year divided by the total number of women age 15-44 (in thousands) in a given year. Population data are from the Census Bureau County Intercensal estimates. To calculate race and ethnic group-

13. Appendix figure C1 shows the average abortion rates from 2016–2020 by county of residence in Texas. Prior to the enactment of the ban, abortion rates are higher in East Texas and near the Capital region in central Texas, and are lowest in the upper Rio Grande region and the Panhandle.

specific fertility rates, the number of births to mothers of a given race are divided by the total number of women of reproductive age of that race in the county-year in thousands.

Fertility rates from 2010 to 2022 are shown in figure 6. All regions experience substantial declines in fertility over this period, although Texas has a consistently higher fertility rate than other regions of the country. Most regions also experience a slight increase in fertility in the early 2020s, which is consistent with the ‘'COVID baby bump" observed in national data (Bailey, Currie, and Schwandt 2023). However, Texas's increase in the fertility rate appears much larger than the rest of the country, and continues into 2022 despite the increases in fertility tapering off in other regions.[14]

5.4 Death Certificate Data

To compute mortality rates, I use restricted-use death certificate data from the NCHS. These data report demographic, location, and the underlying cause of death details for every death in the United States. Underlying causes of death are classify according to the International Classification of Diseases, Tenth Revision (ICD-10) codes. Underlying causes of death are assigned by the NCHS using algorithms which assign a primary cause of death according to the various conditions listed on the death certificate.

This analysis focuses on infant mortality. Infant mortality is defined as the number of deaths of infants under one year of age in a given county-year divided by the total number of live births in the county-year (in thousands). To calculate race and ethnicity-specific infant mortality rates, the number of deaths of infants under the age of one of a specific race or ethnicity in a given county-year combination is divided by the total number of live births to mothers of the same race or ethnicity in that county-year, divided by 1000.

Figure 7 shows infant mortality rates from 2010 to 2022 by region. Infant mortality rates decreased in all regions across the decade, with infant mortality rates in Texas lower than

14. Appendix figure C2 shows the average fertility rates from 2016–2020 by county of residence in Texas. The highest fertility rates are in the Panhandle and the Rio Grande region, especially along the border with Mexico. Fertility rates are relatively lower in East Texas and Central Texas, here abortion rates are relatively higher.

the rest of the South and the Midwest. However, infant mortality rates increased in most regions after 2020, increasing to the highest level in 20 years at the national level (Associated Press 2023). This increase appears to have been especially sharp in Texas.

5.5 Other Data

For control variables or other variables used in the analysis, a variety of sources are used. County-level population data from the Census Bureau County Intercensal estimates are used to calculate racial/ethnic shares and gender shares (U.S. Census Bureau 2021, 2023a). Data on county unemployment rates are from the Bureau of Labor Statistics Local Area Unemployment Statistics (U.S. Bureau of Labor Statistics 2022). Data for county-level Republican vote shares are from the MIT Election Data and Science Lab (2022). County-level poverty and median household income data are from the Census Bureau Small Area Income and Poverty Estimates (SAIPE) (U.S. Census Bureau 2023b). Counties are classified as rural or urban according to the 2013 Rural-Urban Continuum Codes from the Economic Research Service (U.S. Department of Agriculture 2020). Survey data on unintended births are from the National Survey of Family Growth (NSFG), which I describe in more detail in section 9. Additional details about the data are provided in the Appendix.

5.6 Descriptive Statistics by Race and Ethnicity

As is well-documented in the literature, large disparities in reproductive health are rife in the United States. In this section, these disparities in Texas are reported across the five years leading up to the ban. It is important to document initial disparities, as these disparities may be exacerbated by the ban. Alternatively, the ban could cause a convergence towards negative health outcomes, possibly eroding the relatively higher health incomes of more privileged groups.

Since abortion rates are reported at the county level, it is not possible to examine differences in abortion rates separately for racial groups. However, following Caraher (2023), these differences are approximated by using county-level racial and ethnic population shares. In order to classify counties based on population shares, all counties in Texas are ranked by the population share of Black non-Hispanic residents, Hispanic residents, and white non-Hispanic residents. Figure 8 shows the average abortion and fertility rates from 2016–2020 by county of residence in Texas for those counties which have populations shares above the median for Black non-Hispanic, Hispanic, and white non-Hispanic residents.[15] Also shown in the far right panel is the abortion to fertility ratio for these counties. The abortion to fertility ratio is calculated as the number of abortions divided by the number of births in a county-year. Counties with Black non-Hispanic population shares above the median have the highest abortion rate, compared to counties with Hispanic or white non-Hispanic population shares above the median, which have roughly equal abortion rates. On the other hand, Hispanic counties have the highest fertility rates, followed by Black non-Hispanic counties, and then white non-Hispanic counties. These two figures result in an abortion ratio that is highest in Black non-Hispanic counties, and lowest in Hispanic counties, suggesting that Hispanic residents of Texas have relatively fewer abortions compared to births.

Turning to health outcomes, since birth and death certificates report race, it is possible to examine differences in infant mortality directly. Total infant mortality in Texas from 2016–2020 is shown in figure 9. Infant mortality for Black non-Hispanics is about twice as high when compared to Hispanic or white non-Hispanics. This is consistent with the substantial literature documenting disparities in reproductive health as discussed above (Hoyert 2023; MacDorman, Declercq, and Thoma 2017). An important predictor of infant mortality is birth weight, which is also reported on the NCHS birth certificates. Figure 10 shows the proportion of infants born in Texas with low or very low birth weights from 2016–2020. [16] Black non-Hispanic infants are more likely to be born with low or very low birth weights compared to Hispanic or white non-Hispanic infants, with about 13 percent of Black non-

15. Appendix figure C3 shows the the population shares for Hispanic, White non-Hispanic, and Black non-Hispanic residents across Texas.

16. Low birth weight is defined as less than 2500 grams, and very low birth weight is defined as less than 1500 grams.

Hispanic infants born with low birth weights, and about 3 percent born with very low birth weights. White non-Hispanic infants are the least likely to be born with low or very low birth weights, with Hispanic babies in between.

6 Abortion and Fertility Rate Results

This section presents the results of the difference-in-differences analysis of the effect of Texas's abortion ban on abortion rates and fertility rates.

6.1 Abortion Rate Results

The baseline event study for the effect of Texas's abortion ban on abortion rates is shown in figure 11. The figure shows the estimated effect of the ban on abortion rates in Texas, from 2016 to 2022. The first year of treatment is 2021, the year the first ban was enacted, and the second year of treatment is 2022. The figure shows that the abortion rate in Texas was stable from 2016 to 2020, before dropping substantially in 2021 and plummeting in 2022. These declines are consistent with the enactment of SB 8 in 2021 and the total ban in 2022, with a smaller effect in 2021 representing the enactment of the first ban in September 2021, and the larger effect in 2022 representing the total ban enacted in August 2022. The initial drop in 2021 of about 0.68 abortions per women aged 15-44 represents a 13 percent decrease in the abortion rate relative to the pre-treatment average from 2016–2020, and the drop in 2022 of 3.96 abortions represents a decrease of 74 percent.

Table 1 summarizes the results of the difference-in-differences analysis of the effect of Texas's abortion ban on abortion rates across several specifications.[17] The average post-treatment outcome, where both post-treatment years are pooled, is reported. Column 1

17. Appendix figure C4 shows the event studies of the difference-in-differences analysis of the effect of Texas's abortion ban on abortion rates across the 6 different specifications. In the last specification, counties in Texas are matched to similar counties in control states based on the unemployment rate, poverty rate, teenage, adult aged 20-24, adult aged 25-34, Republican vote shares, and Black non-Hispanic, Hispanic, and white non-Hispanic population shares.

shows the results of the difference-in-differences analysis without any control variables, column 2 shows the results with county-level population weights, and columns 3-5 show the results with region-specific trends and county-level economic and population-based control variables, including county-level unemployment rates, poverty rates, log median household income, labor force participation rates, Republican vote shares in the most recent presidential election, and population shares of teenagers aged 15-19, adults aged 20-24, adults aged 25-34, adults aged 35-44, Black non-Hispanic, white non-Hispanic, Hispanic, and total women of reproductive age.

Overall, the results suggest a reduction in the abortion rate over the two year period of between -2.26 to -3.80 abortions per women aged 15-44, which implies a reduction in the abortion rate of approximately 40 percent. The synthetic control estimates suggest that the abortion rate decreased by an average of -3.65 in 2021 and 2022 as a result of the ban.[18]

Given that the total ban passed in the later half of 2022, there may be a concern that the substantial negative effect on abortion rates is primarily driven by the total ban rather than the 6-week abortion ban of SB 8. This concern is alleviated by reporting the average of the two post-treatment years, which since both bans were passed at around the same time, should reflect primarily the initial 2021 ban. Additionally, in appendix figure C5, I use seasonality in monthly abortion rate data to estimate a bi-annual abortion rate in Texas, and estimate the treatment effect using this bi-annual rate, focusing on the treatment effect on the first 6 months of 2022, relative to the abortion rate in the first 6 months of 2016 to 2020. The results are consistent with the main analysis, with a reduction in the abortion rate of about 44 percent.

18. The synthetic control estimate is presented in figure C6. The RMSPE ratio ranking in appendix figure C7 shows that root mean squared prediction errors for Texas and all placebo states.

6.2 Fertility Rate Results

The event study for the effect of Texas's abortion ban on overall fertility rates is shown in figure 12. The figure shows the estimated effect of the ban on fertility rates in Texas, from 2016 to 2022. In the years leading up to the ban and in 2021, fertility rates in Texas are relatively stable, before increasing substantially in 2022. Specifically, the treatment effect of the abortion ban in 2022 is about 2.25 additional births per 1,000 women of reproductive age.

Table 2 summarizes the results of the difference-in-differences analysis of the effect of Texas's abortion ban on fertility rates across several specifications.[19] Column 1 shows the results of the difference-in-differences analysis without any control variables, column 2 shows the results with county-level population weights, and columns 3-5 show the results with region-specific trends and county-level economic and population-based control variables, using the same matches as table 1 for column 6. The reported coefficients are those in the second year of treatment (2022). The coefficient estimates are relatively stable and range from 1.58 additional birth per 1000 women aged 15-44 to 3.30 additional births, The results in column 3 suggest that the abortion ban increased fertility rates by about 2.24 births per 1000 women, which is about a 4 percent increase relative to the pre-treatment average from 2016–2020 of about 63 births per 1000 women of reproductive age, and overall the estimates suggest a magnitude of between 2.5 percent to 5 percent. The synthetic control estimate suggests a slightly higher increase after the ban of an increase of 4.1 births per 1000 reproductive aged women.[20]

While the overall fertility rate increased, certain subgroups may have experienced differ-

19. Figure C8 shows the results of the difference-in-differences analysis of the effect of Texas's abortion ban on fertility rates across the four different specifications. Each color and shape represents a different specification. Once accounting for economic factors and population shares, the estimated effect on fertility increases considerably. The results are broadly similar, with stable fertility rates, especially from 2019 to 2021, before increasing substantially a year after the ban was enacted. While some of the specifications have a statistically significant pre-treatment period in 2017 and 2018, the matched sample mitigates these effects.

20. The synthetic control estimate is presented in figure C9. The RMSPE ranking in appendix figure C10 suggests the estimate is statistically significant at the 5 percent level.

ent effects. As outlined in section 3, certain groups may be more able to shift their fertility behavior in response to the abortion ban away from in-state abortions, and towards out-of-state abortions, or increased contraceptive use. Other groups may be less able to do so, and therefore may be more likely to experience an increase in fertility rates. Since the individual-level NCHS birth certificate data reports the birth of the mother, it is possible to estimate fertility rates separately by race for each county.

Figure 13 shows the event study estimates with weights and control variables for the effect of Texas's abortion ban on fertility rates by the racial or ethnic group of the mother for Black non-Hispanic, Hispanic, and white non-Hispanic women. While fertility rates for each group are relatively stable prior to the ban, there is a substantial increase in fertility rates in 2022 for Black non-Hispanic and White non-Hispanic women, but little to no effect for Hispanic women.

Table 3 shows the point estimates for the effect of the ban by racial group, with the first three columns corresponding to the baseline model, and the second three columns corresponding to the model with county-level economic and population-based control variables. As seen in column 4, the increase in fertility for Black non-Hispanic women is especially stark, with an increase of about 3 births per 1000 Black non-Hispanic women aged 15-44. This represents an increase of about 5 percent relative to the pre-treatment average of 59.8 births per 1000 Black non-Hispanic. For white non-Hispanic women, fertility rates increased by about 1 birth per 1000 white non-Hispanic women of reproductive age, or about 2 percent relative to the pre-treatment average of 60 births. Given these results, the overall fertility increases appear to be driven primarily by Black non-Hispanic women, who experienced the largest increase in fertility rates, followed by white non-Hispanic women.

In addition to examining the effect of the abortion ban on fertility rates by race, I also estimate the effect of the ban on fertility rates by distance to the nearest state with less restrictive abortion laws by interacting the treatment term in 2022 in equation 5 with each county's distance to the nearest state with less restrictive abortion laws, using the specification with control variables and population weights. I then compute the predicted effect of the abortion ban on the fertility rate as a function of distance. This specification allows me to test if counties closer to states with more liberal abortion laws, such as New Mexico, experienced a smaller increase in fertility rates after the ban, since residents in these counties may have been more likely to travel to another state for an abortion.

Figure 14 shows the estimated effect of the abortion ban on fertility rates as a function of distance to the nearest state with less restrictive abortion laws. The estimates suggest that as distance to the nearest state with less restrictive abortion laws increases, the Texas ban had a larger positive effect on the fertility rate. This is consistent with the idea that the abortion ban may have increased fertility rates by reducing the number of abortions in counties further away from a state with less restrictive abortion laws, since residents in these counties are less able to travel to another state for an abortion. The estimates range from about 1.4 additional births per 1,000 women of reproductive age for counties near a less restrictive abortion state, to about 2.5 additional births for counties between 800-900 miles from a state with more liberal abortion laws.

7 Unmet Reproductive Health Needs and the Texas Ban on Abortion

Before moving on to the county-specific RHNI results, I first describe the overall RHNI for Texas after the enactment of SB 8. Given the estimated effect of the ban on abortion rates in table 1 of about -3 abortions per 1000 women of reproductive age, and the estimated increase in fertility rates of about 2 births per 1000 women of reproductive age, then the average RHNI for Texas is about -1. This implies that for every three abortions that were prevented by the ban, only two births were added. This suggests that at least one potential birth that would have otherwise resulted in an abortion without the ban was instead shifted towards another outcome along the decision tree, such as through increased contraceptive use or a self-managed or travel abortion.

The county-level RHNI calculated using the county-specific difference-in-differences estimates of the effect of the ban on abortion rates and fertility rates is presented in figure 15. The figure shows the difference in the estimated effect of the ban on abortions and births relative to pre-treatment fertility rates using the average post-treatment abortion rate and fertility rate estimate in 2022. Given the small counts of births in some county-year combinations, county codes on the vertical axis are anonymized. I also limit the analysis to focus on RHNI less than zero. Most counties have a RHNI of less than 10 percent of the fertility rate, although there is considerable variation in the RHNI across counties. Counties with RHNI near zero are those which experienced roughly equal reductions in the abortion rate and increases in the fertility rate, which would suggest that the ban did not significantly alter outcomes further up along the abortion decision tree, such as contraceptive behavior or sexual activity. It also would suggest that these counties have relatively fewer recorded abortions replaced by travel to other states for an abortion or obtaining pills online.

To examine heterogeneity in this index, I group counties into quartiles based on poverty rates and demographics and compare the average difference in the RHNI for counties in the top quartile to all other counties. More specifically, I rank counties in Texas according to the share of the county population that is white non-Hispanic, Black non-Hispanic, and Hispanic, as well as the poverty rate in the county, and if the county is rural or urban using the 2013 Rural-Urban Continuum Codes (U.S. Department of Agriculture 2020). I then regress the RHNI on an indicator for being in the top quartile of a given variable.

RHNI by county type are shown in figure 16. A positive difference in the RHNI indicates that relatively more abortions are translated into births. Counties in the top quartile of white non-Hispanic population shares have slightly larger reproductive health indices, suggesting that the ban had a larger effect on these counties, although the difference is not statistically significant. Counties with Black non-Hispanic population shares above the median have substantially larger RHNI, suggesting that for these counties, considerably more abortions were unable to be shifted elsewhere on the decision tree, and instead resulted in birth. This is consistent with the finding above that Black non-Hispanic women also experienced the largest increase in fertility after the ban. Counties in the top quartile of Hispanic population shares have slightly smaller RHNI, though this is not statistically significant, and counties in the top quartile of poverty rates have slightly smaller RHNI, although this is also not statistically significant. Lastly, rural counties have slightly smaller RHNI, and this difference is statistically significant.

To examine the effect of distance to the nearest state with less restrictive abortion laws on the RHNI, I run a simple regression of the RHNI on the distance to the nearest state with less restrictive abortion laws. I then compute the RHNI as a function of distance to the nearest state with less restrictive abortion laws. The results are shown in figure 17. The estimates suggest that as distance to the nearest state with less restrictive abortion laws increases, the RHNI increases. Since residents in these counties are more likely to face larger costs in traveling for an abortion, they also may be more likely to carry a pregnancy to term after the ban. Residents in these counties are not as able to offset the effects of the ban by traveling to another county or state for an abortion, nor has behavior or contraception changed to reduce the number of pregnancies in these counties.

Overall, these results largely correspond to those found in section 6 above. Black non-Hispanics are affected by the ban in such a way that more abortions result in births, and this is especially true for counties further away from a state with less restrictive abortion laws. White non-Hispanics are also affected by the ban in such a way that more abortions result in births, but to a lesser extent, and the ban has little effect on Hispanic counties.

8 Infant Health Results

This section presents the results of the difference-in-differences analysis of the effect of Texas's abortion ban on infant health outcomes, specifically birth weight and infant mortality rates.

8.1 Birth Weight

I analyze the effect of Texas's ban on infant birth weights using individual-level birth certificate data from the NCHS as outlined in equation 6. I estimate the effect of the ban on the probability that a given birth is very low weight, defined as less than 1500 grams, which is a critical predictor of infant mortality and morbidity (Watkins, Kotecha, and Kotecha 2016).

Figure 18 shows the event study estimates for the effect of Texas's abortion ban on the proportion of infants born with very low birth weights in Texas. Prior to the ban, there is no difference in Texas between the proportion of infants born with very low birth weights and the rest of the country. However, after the ban, the proportion of infants born with very low birth weights increases substantially in Texas, especially in 2022 relative to the baseline year of 2020, with an increased probability of a birth being very low weight of about 0.08 percentage points.

I also estimate the effect of the ban on the proportion of infants born with very low birth weights by race and ethnicity of the mother, using the same individual-level birth certificate data. Figure 22 shows the event study by racial/ethnic group of the mother. With the exception of an outlier in 2017, there are not substantial differences in the proportion of infants born with very low birth weights within racial groups. After the ban, all racial groups experience an increase in the proportion of infants born with very low birth weights by 2022, especially for Black non-Hispanic babies, although the estimates are less precise. The increases are more modest but still significant for white non-Hispanic and Hispanic babies.

These results are summarized in table 4. Each column shows the estimated effect of the ban on the proportion of infants born with very low birth weights for all babies and Black non-Hispanic, Hispanic, and white non-Hispanic mothers for several specifications. For all infants, the results suggest that the ban increased the probability of a baby being born with very low birth weight by about 0.07 percentage points. The largest effect is for Black non-Hispanic babies, with a point estimate of about 0.15 percentage points. While these point estimates are small, relative to the pre-treatment average probability of a Black non-Hispanic baby being born with very low birth weight of about 2.8 percent, this point estimate represents an increase of about 5 percent. For white non-Hispanic babies, the increase is about 4.2 percent relative to a pre-treatment average of 1 percent, and for Hispanic babies, the increase is about 4.1 percent relative to a pre-treatment average of 1.2 percent, although this is not statistically significant when using economic and population-based control variables.

In addition to examining the effect of the abortion ban on the probability of a baby being born with very low birth by race and ethnicity, I estimate the effect of the ban on the probability of a baby being born with very low birth weight by distance to the nearest state with less restrictive abortion laws. Figure 20 shows the estimated effect of the ban as a function of distance. For those babies born in counties near states with less restrictive abortion laws, there is a very small increase in the probability of a baby being born with very low birth weight. The magnitude of this effect increases as distance increases, with the largest effect for babies born in counties between 800-900 miles from a state with less restrictive abortion laws with an estimated effect of about 0.15 percentage points, or a about a 7.5 percent increase relative to the pre-treatment rate of 1.4 percent of babies with very low birth weight. This positive distance gradient with respect to low birth weight rates not exist prior to the ban. As shown in appendix figure C19, the relationship between distance to a state with less restrictive abortion laws and the probability of a baby being born with very low birth weight is not statistically significant prior to the ban at any distance. This suggest that the positive distance gradient in the effect of the ban on very low birth weight rates is causally related to the abortion ban, and not some pre-existing trend in infant health outcomes.

Overall, the results suggest that the probability of a baby being born with very low birth weight increased in 2022 by about 6.4 percent as a result of the ban relative to the average rate from 2016–2020 of 1.5 percent.[21] The increase in the probability of a baby being born

21. The synthetic control estimate suggests a slightly larger increase of about 0.09 percentage points, as reported in figure C11. The RMSPE ranking in appendix figure C12 suggests that the estimate is statistically

with very low birth weight is especially stark for Black non-Hispanic mothers, in line with the fertility rate results which suggest that these mothers experienced the largest increase in fertility rates after the ban. Similarly, the effects are largest for counties further away from a state with less restrictive abortion laws, suggesting that the ban may have had a larger effect on infant health outcomes in these counties.

8.2 Infant Mortality

Figure 21 shows the event study estimates for the effect of Texas's abortion ban on infant mortality rates in Texas. Prior to the ban, there is no trend in infant mortality rates in Texas relative to the control counties. However, in 2022, there is a sharp increase in mortality, with an estimated increase of 0.4 additional infant deaths per 1000 live births.

In addition to examining the effect of the abortion ban on infant mortality rates overall, I also examine the effect of the ban on infant mortality rates by race and ethnicity. Racial and ethnic-specific infant mortality rates are calculated by dividing the total number of infant deaths of a given racial group over the total number of live births of a given racial group. Figure 9 shows the infant mortality event study by racial and ethnic group of the infant. The results show that after the ban, the infant mortality rate increases significantly for black non-Hispanic infants, and to a lesser extent for white non-Hispanic infants. There does not appear to be a statistically significant increase in infant mortality for Hispanic infants.

Results for the effect of the ban on infant mortality rates are summarized in table 5. Overall, infant mortality rates are estimated to increase by about 0.35 to 0.40 additional infant deaths per 1000 live births as a result of the ban, an increase of about 6.2-7.2 percent relative to the pre-treatment average of 5.5 infant deaths per 1000 live births. For black non-Hispanic infants, infant mortality increased by 0.8 additional infant deaths per 1000 live births, an increase of between 7.5 percent relative to the pre-treatment average of 10.7 infant deaths per 1000 live births. White non-Hispanic infants experienced an increase of about

significant at the 5 percent level.

0.20 additional infant deaths per 1000 live births, an increase of about 2 percent relative to the pre-treatment average. Hispanics did not experience a statistically significant increase in infant mortality rates, consistent with less pronounced effects on low birth weight and fertility rates for this group.

Figure 23 shows the estimated effect of the ban on infant mortality rates as a function of distance to the nearest state with less restrictive abortion laws. For counties near states with less restrictive abortion laws, there is no statistically significant effect of the ban on infant mortality rates. However, the magnitude of the effect increases as distance increases, again with the largest effect for counties furthest away from a state with less restrictive abortion laws. Infant mortality is not affected by the ban unless the county is about 350 miles away from a state with legal abortion, at which point the ban increases infant mortality rates by about 0.1 additional infant deaths per 1000 live births. Counties in the middle of the state experience an increase of about 0.3 additional infant deaths per 1000 live births, and those counties furthest away from a state with less restrictive abortion laws experience an increase of about 0.8 additional infant deaths per 1000 live births.

Crucially, before the ban was implemented, there is no significant correlation between a county's distance to the nearest state with less restrictive abortion laws and infant mortality rates. Appendix Figure C20 illustrates the estimated effect of distance on infant mortality rates prior to the ban's enactment. This figure shows the distance-mortality gradient, derived from regressing infant mortality rates in Texas on the distance to the nearest state with more liberal abortion laws, while controlling for economic and population variables, using only pre-ban data. Although a slight negative relationship between distance to a liberal abortion state and infant mortality rates exists before the ban, it is not statistically significant at any point. This further supports the conclusion that the positive distance gradient observed in the effect of the ban on infant health outcomes is causally related to the abortion ban.

8.3 Maternal Health Mechanisms

This section examines a medical mechanism linking abortion bans and adverse reproductive health outcomes: interpregnancy intervals. Medical literature suggests that short interpregnancy intervals (i.e., less than 18 months between births) are associated with worse infant health outcomes, such as preterm birth, low birth weight, and infant mortality, as well as adverse maternal health, such as uteroplacental bleeding disorders, endometritis, anaemia, and maternal morbidity (McKinney et al. 2017; Conde-Agudelo, Rosas-Bermúdez, and Ana Cecilia Kafury-Goeta 2006; Conde-Agudelo, Rosas-Bermúdez, and Ana C. Kafury-Goeta 2007; Conde-Agudelo and Belizán 2000).

There are a number of hypothesized medical causes for how short interpregnancy intervals affect infant health. A common hypothesis is Maternal Depletion Syndrome. This theory posits that short interpregnancy intervals do not allow the pregnant persons' body to fully recover from the physiological stressors of pregnancy and lactation before the next pregnancy begins, leading to fetal malnutrition and an overall weakened intrauterine environment which increases the risk of adverse health outcomes (Winkvist, Rasmussen, and Habicht 1992). Additional hypotheses include Folate Depletion, where the body does not have enough time to replenish folate resources between pregnancies, and Cervical Insufficiency, where the cervix cannot sufficiently recover muscle tone between pregnancies which inhibits the ability of the cervix to maintain the pregnancy prior to labor (Conde-Agudelo et al. 2012).

If pregnant people who may have needed to obtain an abortion to space out births prior to the ban are no longer able to do so, then the probability of a birth being preceded by a short interpregnancy interval may increase. I estimate the effect of the ban on the probability that a birth is preceded by a short interpregnancy interval, defined as less than 18 months between births, using the individual-level birth certificate data from the NCHS. I estimate the effect of the ban on the probability that a birth is preceded by a short interpregnancy interval using the same difference-in-differences framework outlined in equation 6. I limit the sample to second or higher order births, since first births cannot be preceded by a short interpregnancy interval. Plural births are also excluded from the analysis.

Figure 24 shows the effect of the ban on short interpregnancy intervals by racial and ethnic group. Prior to the abortion ban, rates of interpregnancy intervals less than 18 months were relatively stable. After the ban, the probability of a birth being preceded by a short interpregnancy interval increased for Black non-Hispanic and white non-Hispanic mothers, with a decrease for Hispanic mothers, and a null result for the aggregate estimate. This decrease for Hispanics may be partially explained by the slight decrease in fertility rates for this group after the ban, though that point estimate is not statistically significant. Table 6 shows the estimated effect of the ban on the probability of a birth being preceded by a short interpregnancy interval. The results suggest that the ban increased the probability of a birth being preceded by a short interpregnancy interval by about 0.3 percentage points for both Black non-Hispanic and white non-Hispanic mothers. Relative to pre-treatment means for interpregnancy intervals less than 18 months in Texas of about 10% percent for Black non-Hispanic pregnant people and 6.5% for white non-Hispanic pregnant people, these point estimates represent an increase of about 3% for Black non-Hispanic pregnant people and 5% for white non-Hispanic pregnant people. Given the associations between short interpregnancy intervals and adverse maternal and infant health outcomes, especially for white and Black non-Hispanic mothers, these results suggest that the increase in adverse infant health outcomes after the ban may be partially driven by an increase in shorter interpregnancy intervals.

9 Reproductive Health Spillovers

The results presented in section 8 suggest that the abortion ban had a substantial negative effect on infant health, primarily through changes in birth weight and infant mortality rates. Besides medical mechanisms, such as the increase in short interpregnancy intervals, there is another possible channel through which the ban eroded infant health outcomes: changes in the underlying fertility pool, or the demographic characteristics of who is giving birth in Texas.

As discussed above, the abortion ban resulted in some individuals who would have otherwise chosen abortion to instead carry their pregnancies to term. If this shift in fertility outcomes—towards birth—involves individuals who are more likely to experience poorer infant health outcomes on average, the rise in low birth weight and infant mortality rates following the ban could be attributed to changes in the composition of the fertility pool. Research has shown that unintended or mistimed births are associated with worse maternal and infant health outcomes, such as low birth weight (Shah et al. 2011; Mohllajee et al. 2007).. Therefore, it's possible that the increase in unintended births after the ban is contributing to the decline in infant health outcomes. In other words, the negative effects of the ban may stem from the addition of births to the fertility pool that would have otherwise been more likely to end in abortion.

On the other hand, the abortion ban might also negatively impact the health outcomes of those who wanted and intended to give birth, regardless of the ban. If a restrictive reproductive health policy, like the one in Texas, reduces the overall quality of reproductive healthcare, then adverse infant health effects could also occur among individuals who did not change their fertility behavior in response to the ban. This would suggest that abortion bans have spillover effects on reproductive health outcomes.

In order to examine if the abortion ban affect infant health primarily through compositional changes, or through broader changes in the reproductive health care system, I estimate the effect of Texas's abortion ban on both unintended and intended births. To do so, it is first necessary to define what qualifies as an unintended birth. The unintendedness of a birth is not recorded on the NCHS birth certificate data, or any other administrative vital statistics data. Therefore, it is necessary to estimate unintended births using a different data set. A commonly used survey used to estimate the rate of unintended births is the NSFG. The NSFG is a survey which gathers information about pregnancies, births, demographics, and other reproductive health data for a nationally-representative sample of women of reproductive age. For each pregnancy experienced by each respondent, the questionnaire also includes items about the wantedness and the timing of a birth, which I use to construct an indicator of unintendedness.

However, there are also several drawbacks to using solely the NSFG for an analysis of abortion bans. Firstly, the most recent wave only covers up to 2019. Secondly, the survey is constructed to be representative only at the national, and not state-level. Lastly, the sample design itself is ill-suited for year-level difference-in-differences analysis.[22]

In order to overcome the shortfalls associated with the NSFG and the birth certificate's lack of question about unintendedness, I build on the combined-data strategy in Buckles, Guldi, and Schmidt (2022). Firstly, I use machine learning methods to develop a predictive model of which births are more likely to be unintended using the NSFG data. In training the model, I restrict the variables (i.e., characteristics of the mother and the birth) to only those which are included as items at the pregnancy-level for both the NSFG and the NCHS birth certificate data. Then, I deploy the model on the NCHS birth certificate data, generating a predicted probability that a given birth is unintended for nearly all births in the United States from 2016 to 2022.

For the data set I use to train and validate the model, I pool all pregnancy-level survey data from recent NSFG waves, including the 2006–2010, 2011–2013, 2013–2015, 2015–2017, and 2017–2019 waves (National Center for Health Statistics 2011, 2014, 2016, 2018, 2020).[23] I limit the NSFG data to only those pregnancies that resulted in a live birth, and where the mother was between the ages of 15–44 at the time of the birth. The data set comprised of over 41,000 live births across 19,000 mothers. A birth is classified as unintended using a combination of two responses in the NSFG survey, following Buckles, Guldi, and Schmidt (2022) and Guzzo (2017). The first is the response to the following question: "if you had to

22. These issues are pointed out in Buckles, Guldi, and Schmidt (2022). They show that compared to the birth certificate data, the NSFG data at the year-level is highly variable and sometimes quite different from the birth certificate data.

23. Limiting the NSFG data to only those waves in the 2010s does not affect the results.

rate how much you wanted or didn't want a pregnancy right before you got pregnant that time, how would you rate yourself?" Respondents indicated their desire to have a pregnancy using a 0 to 10 scale. I classify a birth as unwanted if the response was below a five. The second NSFG item I use asks if a pregnancy occurs sooner than intended. I also record a birth as unintended if it was wanted but was too soon by two years or more. Across the entire pooled NSFG pooled data set, about 35% of births are defined as unintended.

To predict the likelihood that a birth is unintended, I use the following variables: race, ethnicity, birth order, age, marital status, immigrant status, and if medicaid paid for the birth.[24] I also use all two-way interactions between all these variables, resulting in a total of over 350 features used to train the model. I train the following nine models: logistic regression, LASSO, Ridge, Elastic Net, Decision Tree, Random Forest, XGBoost, K-nearest-neighbors, and a neural network, using 10-fold cross-validation to find the optimal set of hyper-parameters for each class of model. I then evaluate the performance of each model using the area under the receiver operating characteristic curve (ROC-AUC). The Random Forest model performs the best, and I deploy this model on the individual-level NCHS birth certificate data to estimate if a birth is unintended. I classify a birth as intended if the predicted probability that a birth is intended is greater than 60%.[25] I compute state-level unintended fertility rates by dividing the total number of unintended births in a given state-year over the total number of women of reproductive age [26]

Figure 25 shows the unintended fertility rates overtime for Texas compared to all other states. This rate drops considerably for all regions throughout the late 2010s. However, as can be seen in 2022, Texas experiences a sharp increase in the rate of unintended births

24. While there are additional items in the NSFG about the characteristics of the mother, such as educational status, these items are only reported at the respondent-level, rather than the pregnancy-level, and therefore may not reflect the characteristics of the mother at the time of the birth.

25. Appendix figure C21 shows the ROC-AUC curves for each model. The ROC plots the true positive rate against the false positive rate for each model at different thresholds, and the area under the curve is a measure of the model's performance at correctly classifying births as intended or unintended. While most models perform similarly, logistic regression, K-nearest-neighbors, and the neural network perform relatively worse.

26. I use state-level counts rather than county-level counts to help mitigate some of the noise of the prediction process.

after the ban. Figure 26 shows the difference-in-differences estimates of the effect of the ban on unintended fertility rates. While these estimates are derived from a predictive model and should therefore be interpreted with caution, the estimate suggests that the unintended fertility rate in Texas increased by about 0.30 unintended births per 1,000 women aged 15-44 relative to control states, or an increase of about 5% relative to 2020. This increase in unintended births is consistent with the increase in fertility rates seen above, and is an important public health concern given the potential for abortion bans to reverse the substantial reductions in unintended births seen in the 2010s in figure 25 and as documented in the literature.

The event study results for the effect of the ban on the probability of a baby being born with very low birth weight by unintendedness are shown in figure 28. The results suggest that the ban increased the probability of a baby being born with very low birth weight for both unintended and intended births, but the effect is larger for unintended births.[27] The results suggest that the ban increased the probability of a baby being born with very low birth weight by about 0.06 percentage points for intended births, compared to a larger increase of about 0.09 percentage points for unintended births. Relative to the pre-treatment average probability of a baby being born with very low birth weight of about 1.5 percent, this represents an increase of about 4.0 percent for intended births, and about 6.0 percent for unintended births. While the effect is larger for unintended births, the effect of the ban on the probability of a baby being born with very low birth weight is still substantial. This result suggests that even for mothers who likely never intended to have an abortion, there may be spillover effects of the ban on their infant health outcomes.

One potential drawback with training a predictive model based on demographic features with pre-ban data is that the model may not be able to pick up shifts in demographic composition of unintendedness in the post-ban period. For example, if the abortion ban increased the cost of obtaining an abortion, then pregnant people in their mid-20s who

27. These differences in point estimates are statistically significant at the 5 percent level.

previously would have been able to afford an abortion may now be more likely to have an unintended birth. This would lead to an increase in the probability of a birth being unintended for those in their mid-20s in the post-ban period relative to the pre-ban period. If this is the case, the predictive model may be underestimating the probability of a birth being unintended in the post-ban period for those who are close to the threshold of unintendedness.

To help mitigate this issue, I split the estimated probability that a birth is unintended into quintiles, with those in the lowest quintile the least likely to have an unintended birth, and those in the highest quintile the most likely to have an unintended birth. Figure 27 presents a heatmap of the predicted probability that a birth is unintended by quintile for a given characteristic of the mother for Texas. The vibrancy of the color corresponds to the proportion of births in a given quintile of unintendedness for a given characteristic of the mother. Black non-Hispanic mothers are overrepresented in the highest quintile of unintendedness, and Hispanic mothers are most represented in the middle quintiles. Teenage mothers are also overrepresented in the highest quintile of unintendedness, as are mothers in their early 20s. Mothers in their late 20s are clustered in the middle quintile, and mothers in their early and late 30s are clustered in the lowest quintile of unintendedness. Those who did not complete highschool are more likely to have an unintended birth, while college graduates are more likely to have an intended birth. Nearly all mothers in the lowest quintile of unintendedness are married, while those in the highest quintile are more likely to be unmarried. Immigrant mothers are clustered in the middle quintiles of unintendedness.

In figure 29, I show the estimated effect of the ban on the likelihood of a baby being born with very low birth weight, broken down by quintile of unintendedness. The ban increased the probability of very low birth weight across all quintile groups, although some estimates are less precise. The point estimates grow larger as the likelihood of unintended birth increases, with the most significant effect observed in those most likely to have an unintended pregnancy, and smaller effects seen among those least likely. These findings indicate that even among mothers least likely to experience an unintended birth—those who likely would have continued their pregnancy regardless of the ban—the policy still led to worse infant health outcomes. This supports the notion that the ban negatively impacted infant health across the board in Texas, not just among those who would have chosen abortion but now remain in the fertility pool.

There are several possible mechanisms for how pregnant people who strongly desire to give birth may also have worse infant health outcomes after an abortion ban. Restrictive reproductive health regimes may lead to a gradual erosion in the quality of reproductive health care more generally, such as through a reduction in the quantity and quality of OB-GYNs due to the uncertain and restrictive legal environments. This could lead to closures of clinics that provide reproductive health care beyond just abortion, isolating pregnant people from the care they need to have a healthy pregnancy and baby. Further research is needed to clarify the how the ecology of a reproductive health care system may degrade in a restrictive reproductive health environment.

10 Conclusion

This paper examined the effect of Texas's 6-week abortion ban enacted in September 2021 on reproductive health outcomes, focusing on abortion rates, fertility rates, and infant health outcomes. The results suggest that abortion rates plummeted by over 40 percent after the ban, results broadly consistent with the small monthly panel used to estimate the immediate effect of the ban in Caraher (2023). Fertility rates increased by about 4 percent, with the largest increases in fertility rates for Black non-Hispanic women and white non-Hispanic women. This estimated fertility increase is slightly larger but consistent with the national estimate of post-*Dobbs* abortion bans presented in Dench, Pineda-Torres, and Myers (2023). It also finds that the effect of the ban on abortion and fertility rates was larger for counties further away from a state with legal abortion.

This analysis also constructs a county-level measure of unmet reproductive health needs after the Texas ban, using the observed changes in county-specific abortion and fertility rates. It finds that counties with a higher share of Black non-Hispanic residents, as well as counties further away from a state with legal abortion, experienced larger reproductive health needs after the enactment of the ban compared to other counties in Texas. Turning to infant health outcomes, the analysis finds that the ban increased the proportion of infants born with very low birth weights between about 4-5 percent, with the largest increases relative to the pre-treatment average for Black non-Hispanic infants. Given associations established in the literature between low birth weight and a wide range of health, educational, and economic outcomes in childhood and adult life, this finding suggests that the effect of the ban on infant health outcomes may have long-lasting consequences.

Mirroring increases in low birth weights, the analysis also finds that Texas's ban increased infant mortality rates by about 6-8 percent. This corresponds to about 130 additional infant deaths as a result of the ban. Again, the largest increase in infant mortality rates is for Black non-Hispanic infants. Additionally, the analysis finds that the effect of the ban on infant health outcomes was largest for counties further away from a state with legal abortion. Given the distance-mortality gradient, the abortion ban only increased infant mortality for those counties at least 350 miles away from a state with legal abortion. This threshold is intuitive, as a distance of 300-400 miles is likely the point at which a roundtrip drive to an out-of-state abortion clinic could no longer be done in a single day. Women who live outside of this range may therefore be less able to shift their fertility choices after an abortion ban towards a travel abortion, and therefore may be more likely to carry the pregnancy to term and have a birth which results in a severe, adverse infant health outcome.

In investigating the mechanisms underlying these disparities in infant health outcomes, the analysis demonstrates that the abortion ban increased the likelihood of births occurring after a short interpregnancy interval—defined as less than 18 months between births—by approximately 0.3 percentage points for both non-Hispanic white and Black mothers. Additionally, employing a predictive model to classify births as intended or unintended, the study finds that the ban had a disproportionately negative effect on health outcomes for unintended births, while also adversely affecting health outcomes for intended births. Although those with limited capacity to modify their fertility behavior in response to the ban are the most significantly impacted, the results suggest that the ban may exert spillover effects on infant health outcomes across all pregnant individuals in Texas. These broader effects may stem from a general deterioration in the reproductive healthcare system following the ban, potentially resulting in worsened health outcomes for the entire population of pregnant individuals in the state.

The results in this paper suggest that the abortion ban in Texas had substantial effects on reproductive health outcomes, especially those groups whose abortion and fertility outcomes were most impacted by the abortion ban. The effects are driven primarily by Black non-Hispanic women, followed by white non-Hispanic women. The ban appears to have had more mixed to little effects on Hispanic women. This may be for a couple of reasons. Hispanic residents of Texas initially had lower abortion rates and higher fertility rates. Given this distribution of pre-treatment outcomes, it may be that an abortion ban might be less salient for this group in this specific instance, since this group is already less likely to have a recorded abortion and more likely to give birth. For example, this group may initially have been more likely to have a different abortion decision tree, perhaps as a result of previous abortion restrictions passed in Texas. The counties in Texas with the largest Hispanic population shares are in the west of state near the border with Mexico, and are therefore more likely to be closer to a state with legal abortion. As a result, Hispanic women may have been more likely to travel for an abortion even before the ban was implemented, leading to a relatively smaller effect of the ban on this group. This may also be why the effect of the ban on infant health outcomes was smaller for Hispanic infants, since spillovers on other reproductive health outcomes may also be smaller.[28]

28. Texas has a long history of restrictive abortion laws, such as House Bill 2 in 2013, which required abortion providers to have admitting privileges at a nearby hospital. This law was later struck down, but the subsequent decline in abortions may have altered the abortion decision tree for Hispanic women and others in Texas relative to other states.

Lastly, given that the infant health outcomes are lower for the same sub-groups that experienced the largest increases in fertility rates and the most dramatic unmet reproductive health needs, it lends more credibility to the claim that the estimated effects are causal, rather than driven by some other unobserved factor. Future work should continue to delve more deeply into the social and biological mechanisms driving these disparities in reproductive health outcomes after abortion bans.

As states continue to pass abortion bans and restrictions, such as Florida's recently imposed 6-week ban, it is critical to understand how these laws effect not only the most direct outcomes of abortion and fertility, but also outcomes further up the abortion decision tree (Mazzei 2024). Texas's abortion ban created substantial unmet reproductive health needs, especially for Black women. This group also experienced the largest increases in infant mortality rates, suggesting that these unmet needs can translate into the most dire health consequences.

By restricting access to abortion, reproductive health disparities in Texas were exacerbated even further, and the health of pregnant people and infants was put at risk. States which enacted abortion bans in the wake of the *Dobbs v. Jackson* decision may see similar effects, creating further fractures in reproductive health for those who are already the most marginalized.

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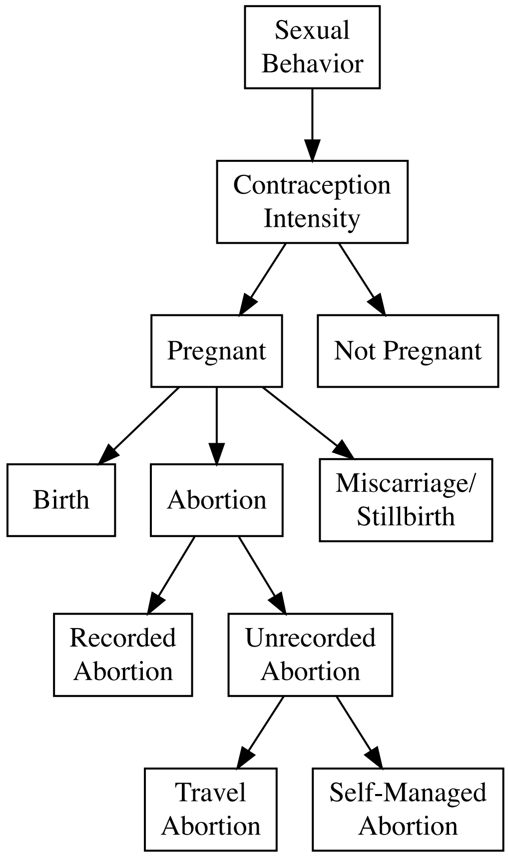
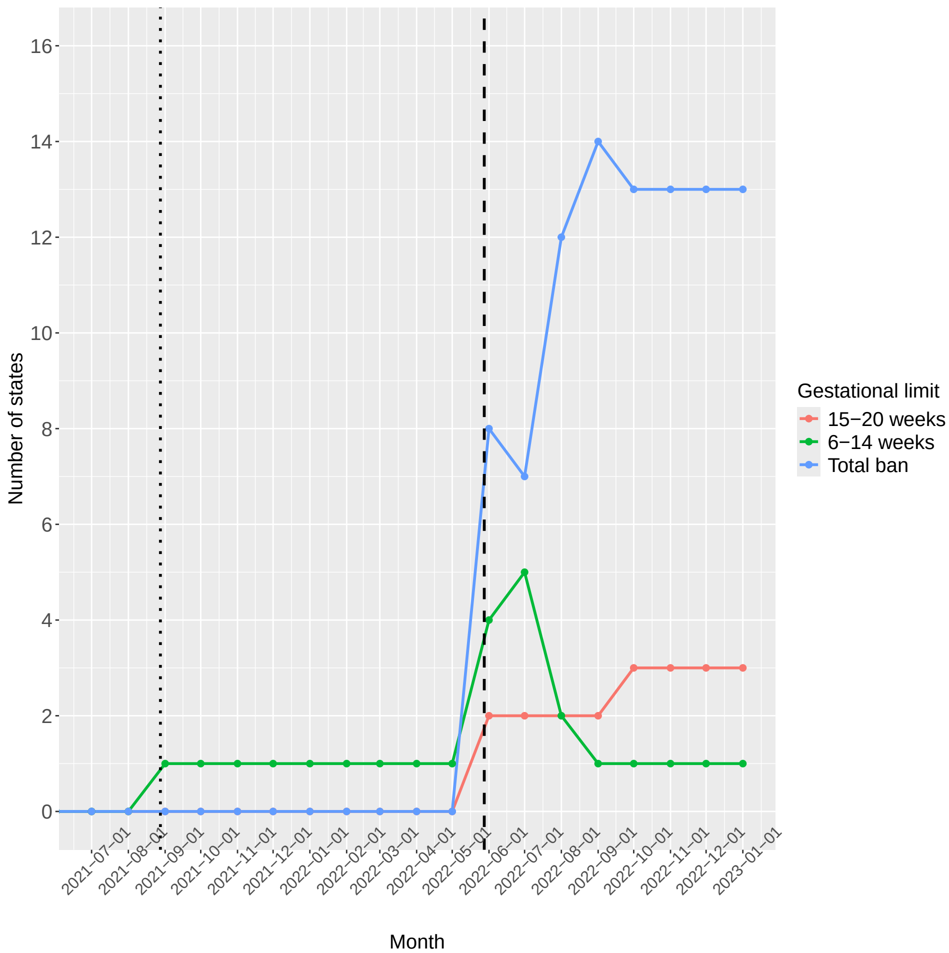
Figures

Figure 1: The Abortion decision tree in a restrictive reproductive health regime



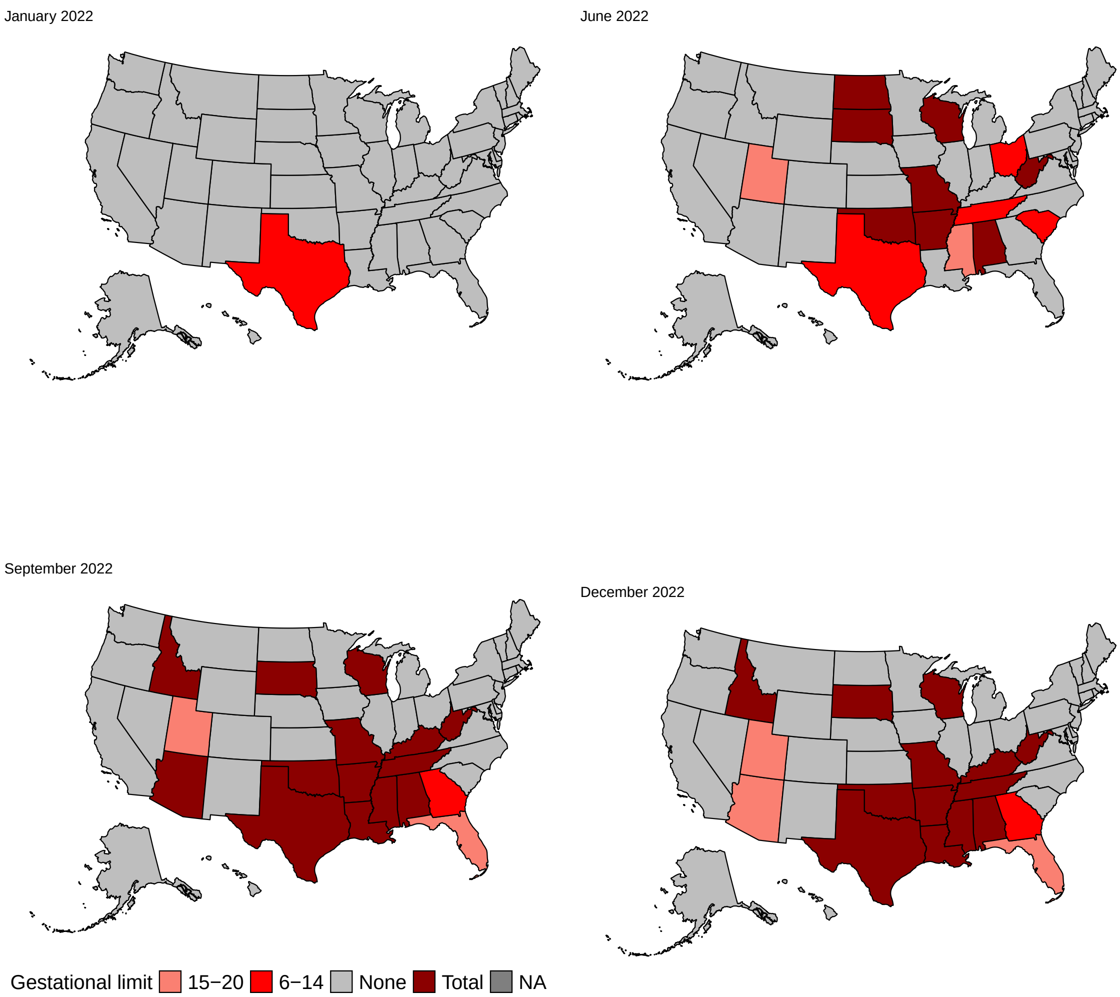
Notes: This figure shows a diagram outlining the abortion decision tree. Each node represents a choice that a pregnant person must make along the tree, and each edge shows the possible consequence of that choice.

Figure 2: Abortion ban trends, 2021–2023



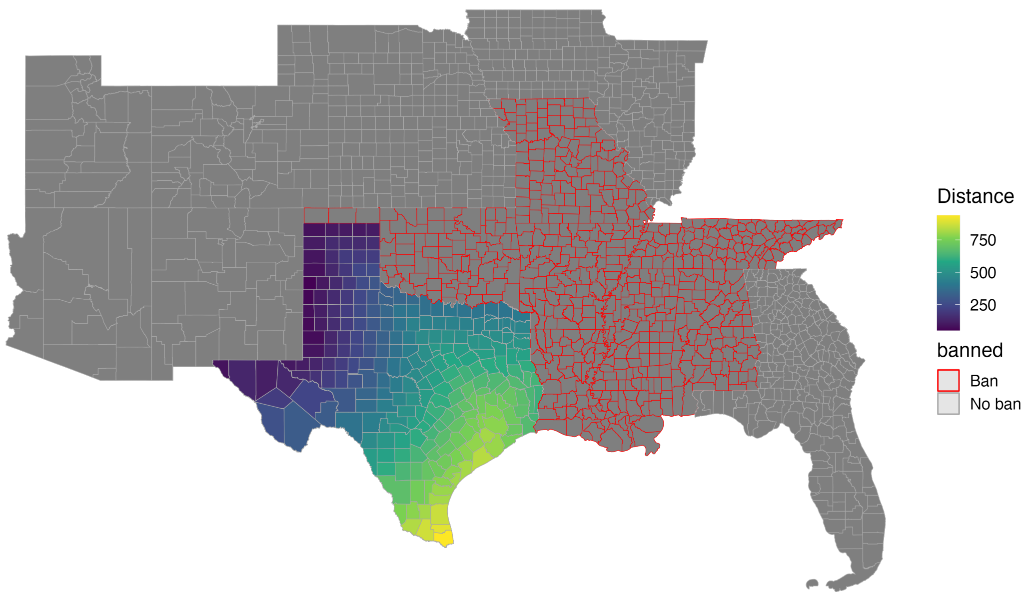
Notes: The figure shows the number of abortion bans by gestational limit across the United States from September 2021 to January 2023. Each color represents a different gestational limit. States with bans may allow some exceptions for extreme medical situations. The dotted line represents the passage of SB 8 in Texas in September 2021, and the dashed line represents the *Dobbs* decision in June 2022. Source: Author's calculations from Policy Surveillance Program and Advancing New Standards in Reproductive Health Care (2023) and a variety of local sources.

Figure 3: Map of abortion bans by gestational limit



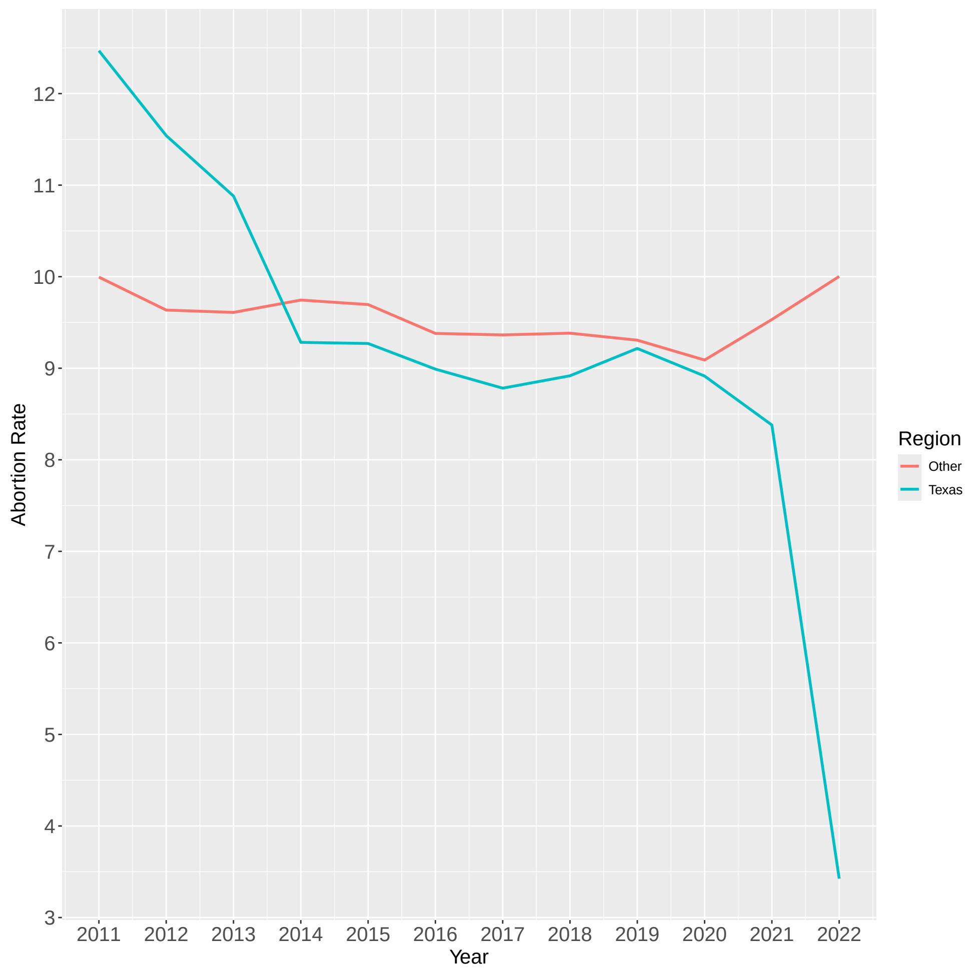
Notes: The figure shows the spread of abortion bans by gestational limit in January 2022, June 2022, September 2022, and December 2022. The colors represent the severity of the abortion ban. Source: Author's calculations from Policy Surveillance Program and Advancing New Standards in Reproductive Health Care (2023) and a variety of local sources.

Figure 4: Distance to states with legal abortion by county



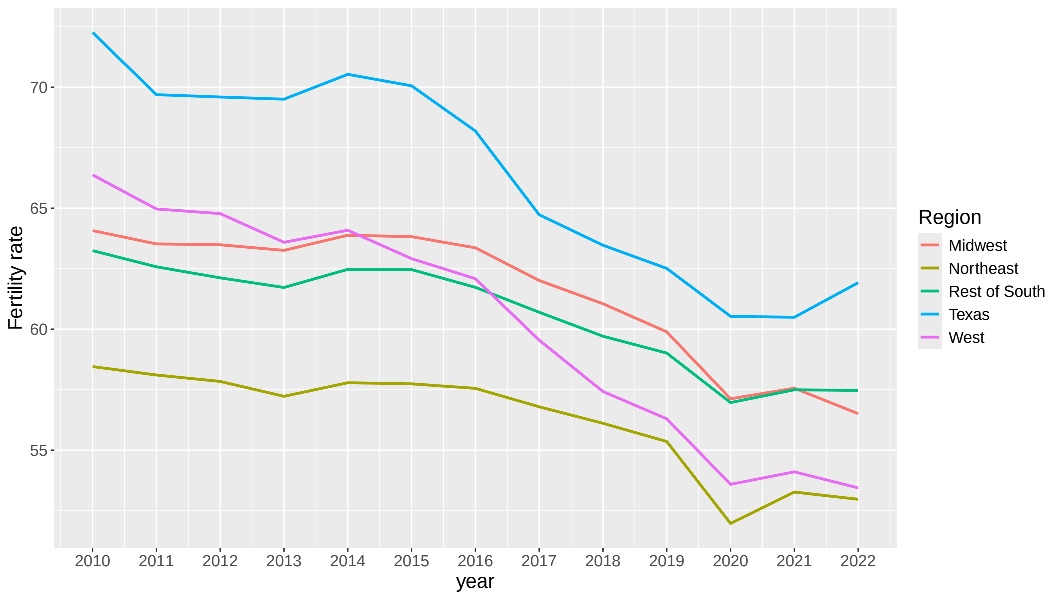
Notes: This figure shows the distance from each county to the nearest state with a gestational limit greater than Texas in 2022. Distances are calculated using the geographic center of each county. Counties are shaded based on the distance to the nearest state with a gestational limit greater than Texas. Counties wih red outlines are in state which banned abortion after the *Dobbs* decision.

Figure 5: Abortion rates for Texas and all other states, 2010–2022



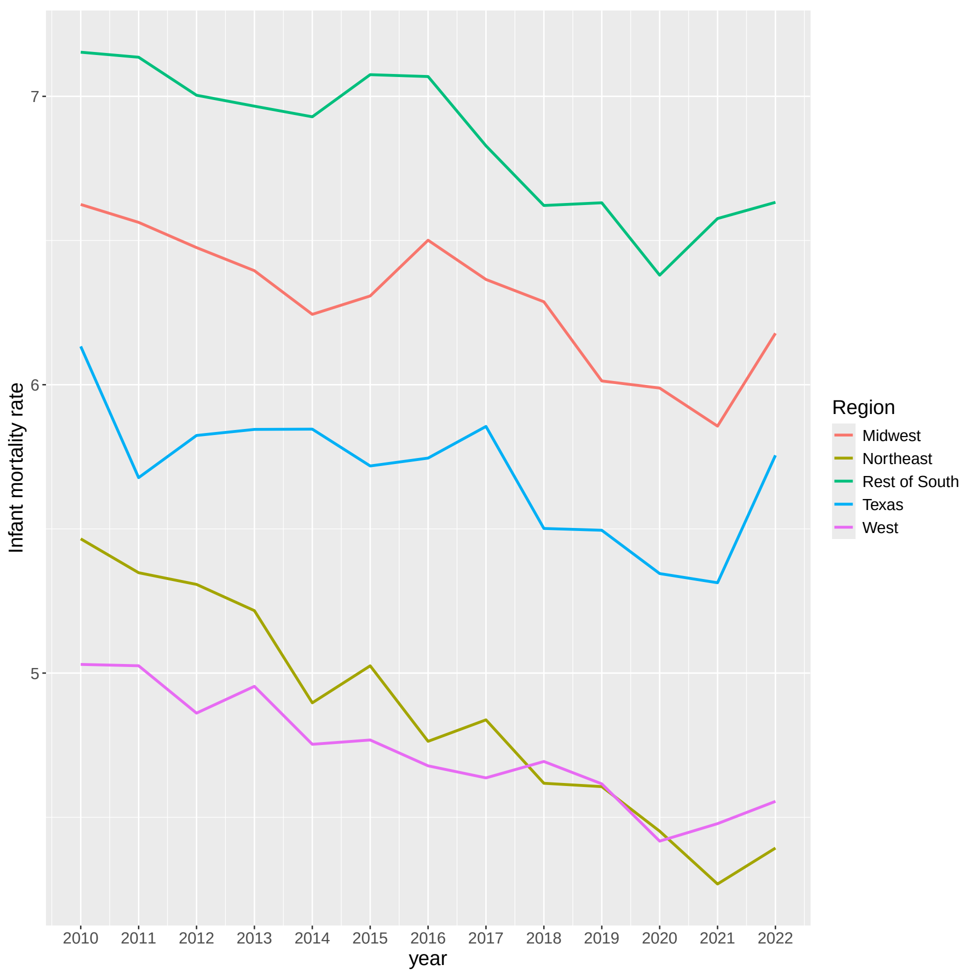
Notes: This figure shows the abortion rates (the number of abortions per 1,000 women aged 15-44) for Texas and all other states from 2010 to 2022. Each color represents either Texas or non-Texas states. Only states with complete data from 2010 to 2022 are included. Source: Author's calculations using county-level abortion data updated from Caraher (2023).

Figure 6: Fertility rates by region, 2010–2022



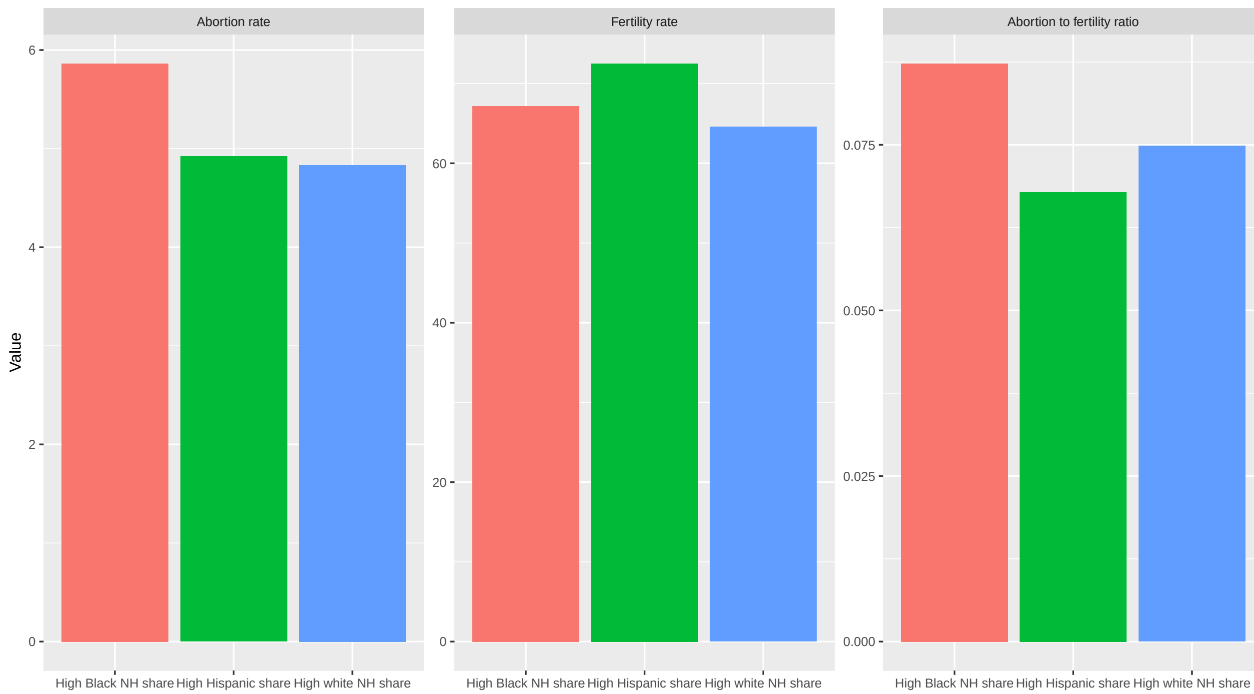
Notes: This figure shows the fertility rates (births per 1,000 women aged 15-44) by region from 2010 to 2022. Each color represents a different region of the United States, with Texas plotted separately. Only states with complete data from 2010 to 2022 are included. Source: Author's calculations from NCHS data and Census data.

Figure 7: Infant mortality rates by region, 2010–2022



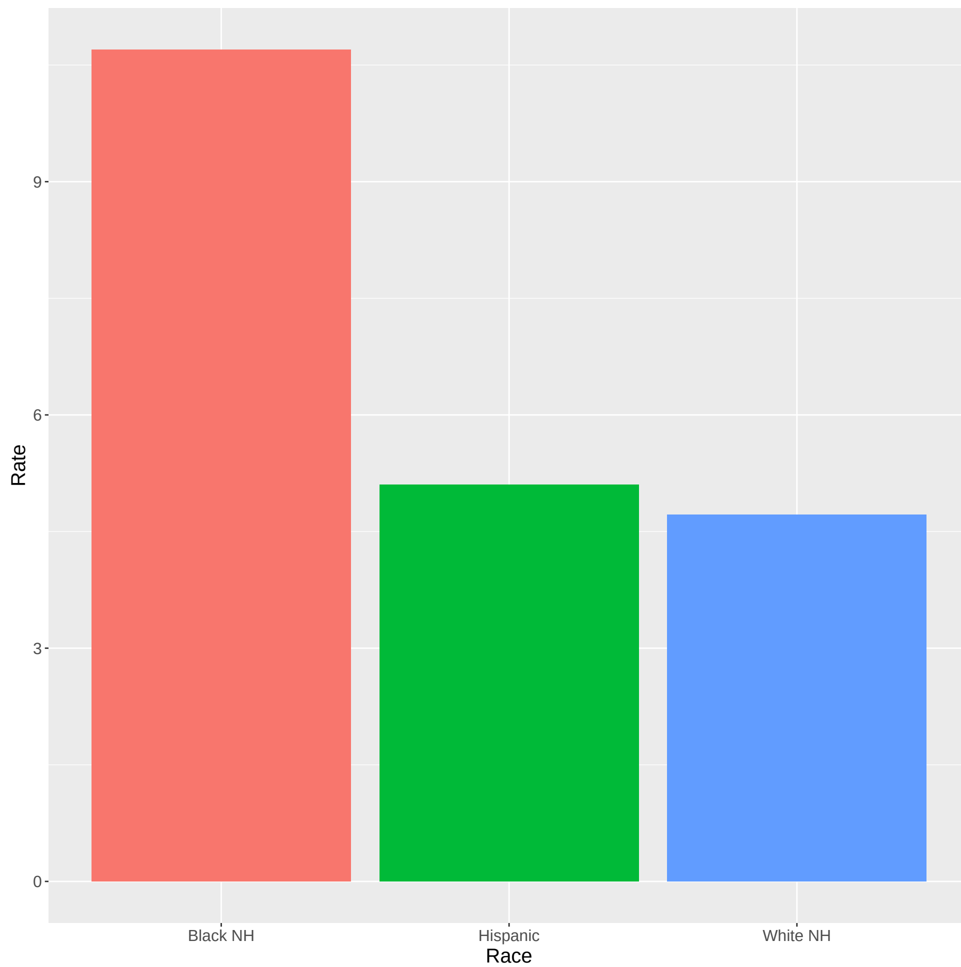
Notes: This figure shows the infant mortality rates by region from 2010 to 2022. Each color represents a different region of the United States, with Texas plotted separately. Only states with complete data from 2010 to 2022 are included. Source: Author's calculations from NCHS data.

Figure 8: Abortion and fertility rates by county demographics, 2016–2020



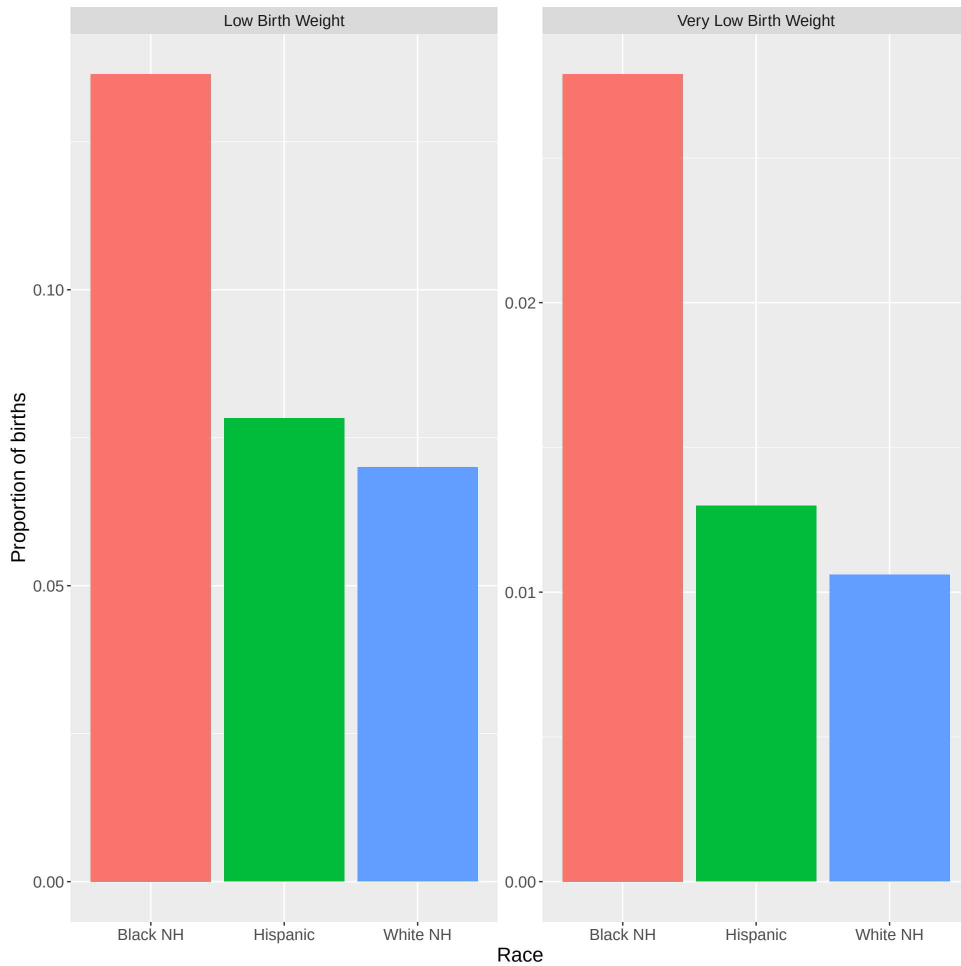
Notes: This figure shows the average abortion rates (the number of abortions per 1,000 women aged 15-44), fertility rates (the number of births per 1,000 women aged 15-44), and abortion ratios (abortion rate divided by fertility rate) by county demographics from 2016–2020. Each color represents the average rate for counties in Texas above the median population share for a given demographic group. White NH refers to white non-Hispanic, Black NH refers to Black non-Hispanic. Source: Author's calculations using county-level abortion data from various state-specific sources, NCHS data, and Census data.

Figure 9: Infant mortality by race and ethnicity, 2016–2020



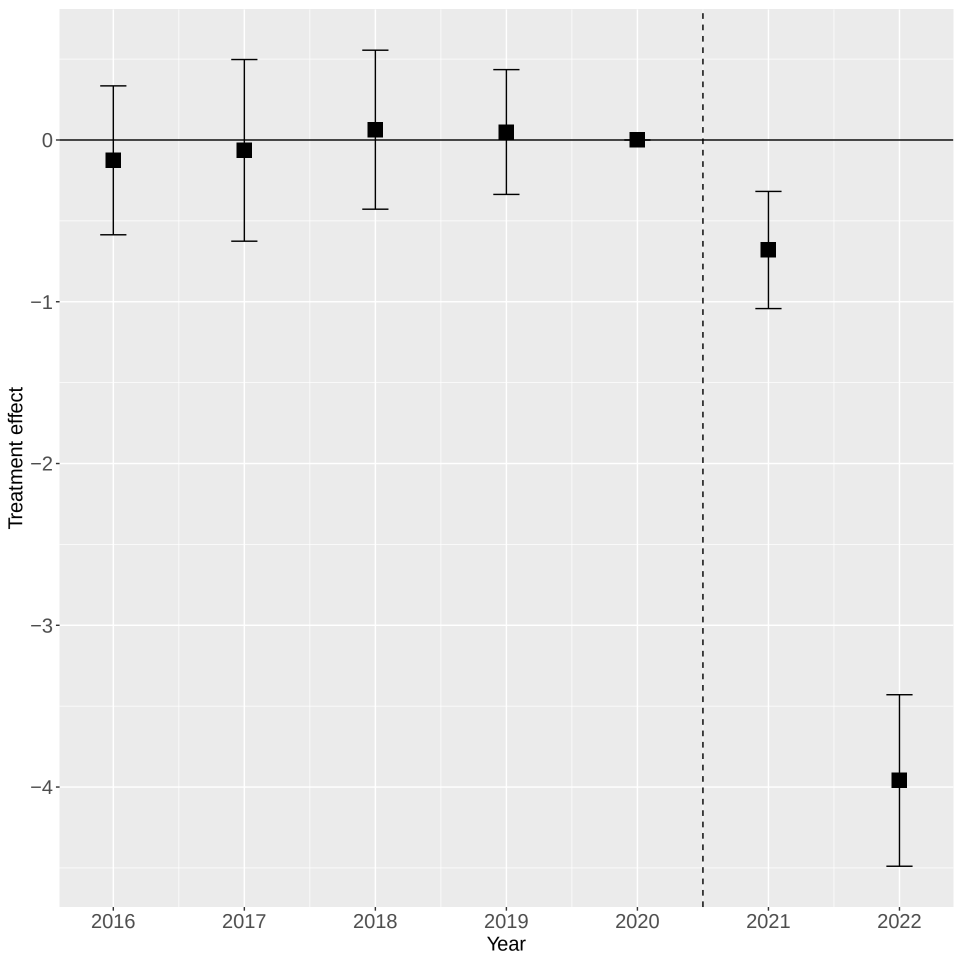
Notes: This figure shows the total infant mortality rates for Black non-Hispanic, Hispanic, and White non-Hispanic births in Texas from 2016–2020. Each color represents the total number of deaths per 1,000 live births for a given racial/ethnic group. Source: Author's calculations using NCHS data and Census data.

Figure 10: Low birth weight by race and ethnicity, 2016–2020



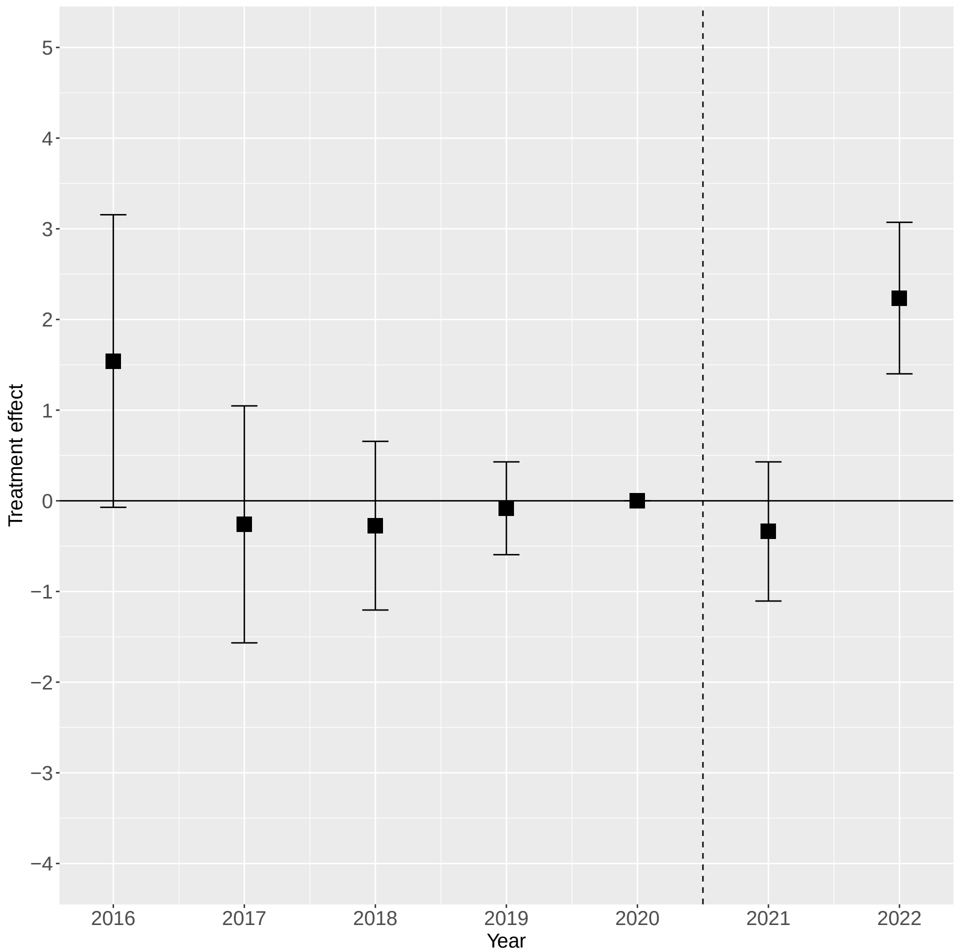
Notes: This figure shows the proportion of infants born at low birth weight (less than 2500 grams) or very low birth weight (less than 1500 grams) for Black non-Hispanic, Hispanic, and White non-Hispanic births in Texas from 2016–2020. Each color represents a different racial/ethnic group. Source: Author's calculations using NCHS data and Census data.

Figure 11: Abortion rate event study



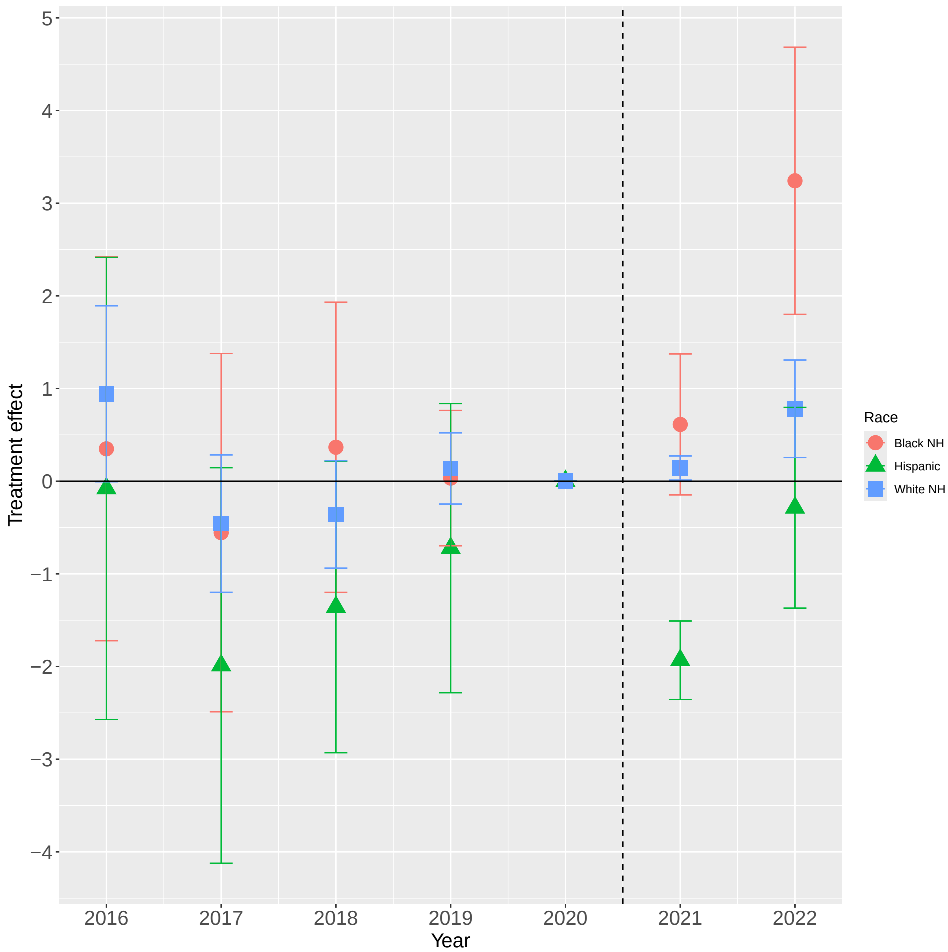
Notes: This figure shows the difference-in-differences event study results of the effect of the abortion ban in Texas on abortion rates. The vertical axis is measured in (change in) abortions per 1,000 women aged 15-44. The dashed line represents the enactment of the abortion ban in Texas in September 2021. Female population aged 15-44 in thousands in 2020 is used as a constant denominator. The sample is restricted to counties with more than 1000 women of reproductive age in 2020. The event study is estimated using the baseline specification with no weights or control variables. Standard error bars clustered at the county and state-year are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources and Census data.

Figure 12: Fertility rate event study



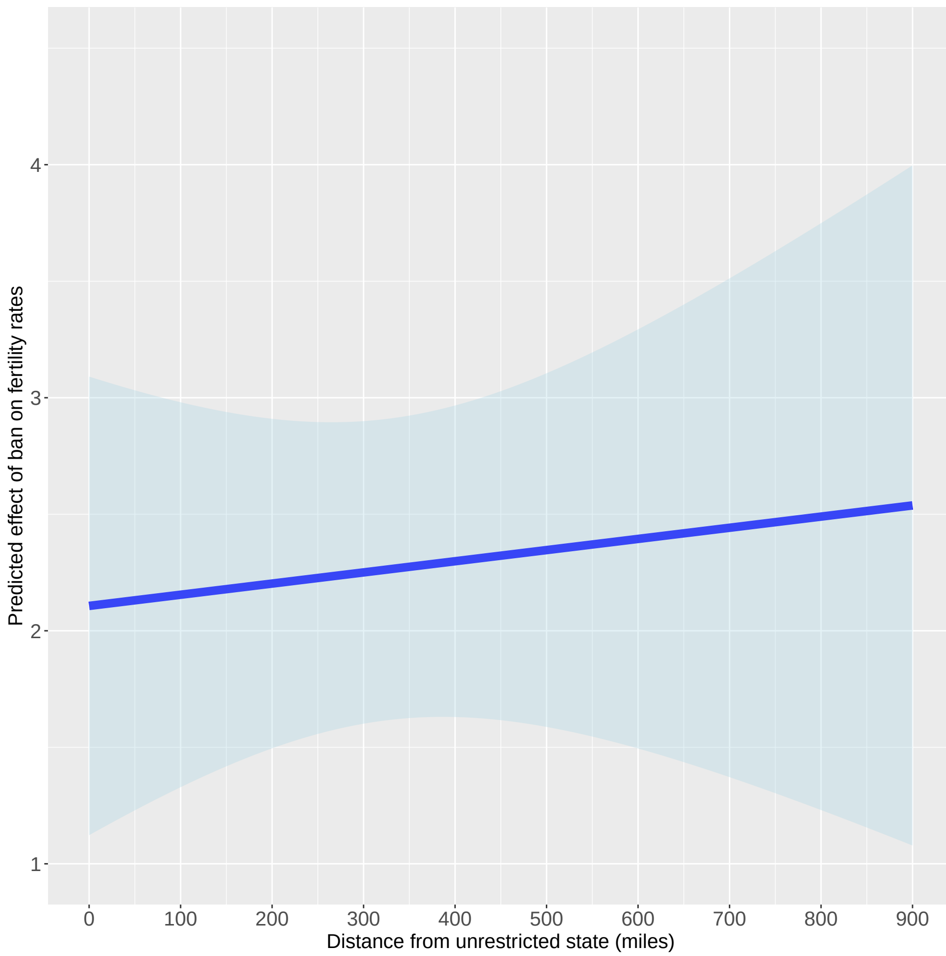
Notes: This figure shows the difference-in-differences event study results of the effect of the abortion ban in Texas on fertility rates. The vertical axis is measured in (change in) births per 1,000 women aged 15-44. The dashed line represents the enactment of the abortion ban in Texas in September 2021. Female population aged 15-44 in thousands in 2020 is used as a constant denominator. The sample is restricted to counties with more than 1000 women of reproductive age in 2020. The event study is estimated with region-specific linear trends. Standard error bars clustered at the county and state-year are reported at the 95% level. Source: Author's calculations using NCHS birth certificate data and Census data.

Figure 13: Fertility rate event study by race and ethnicity



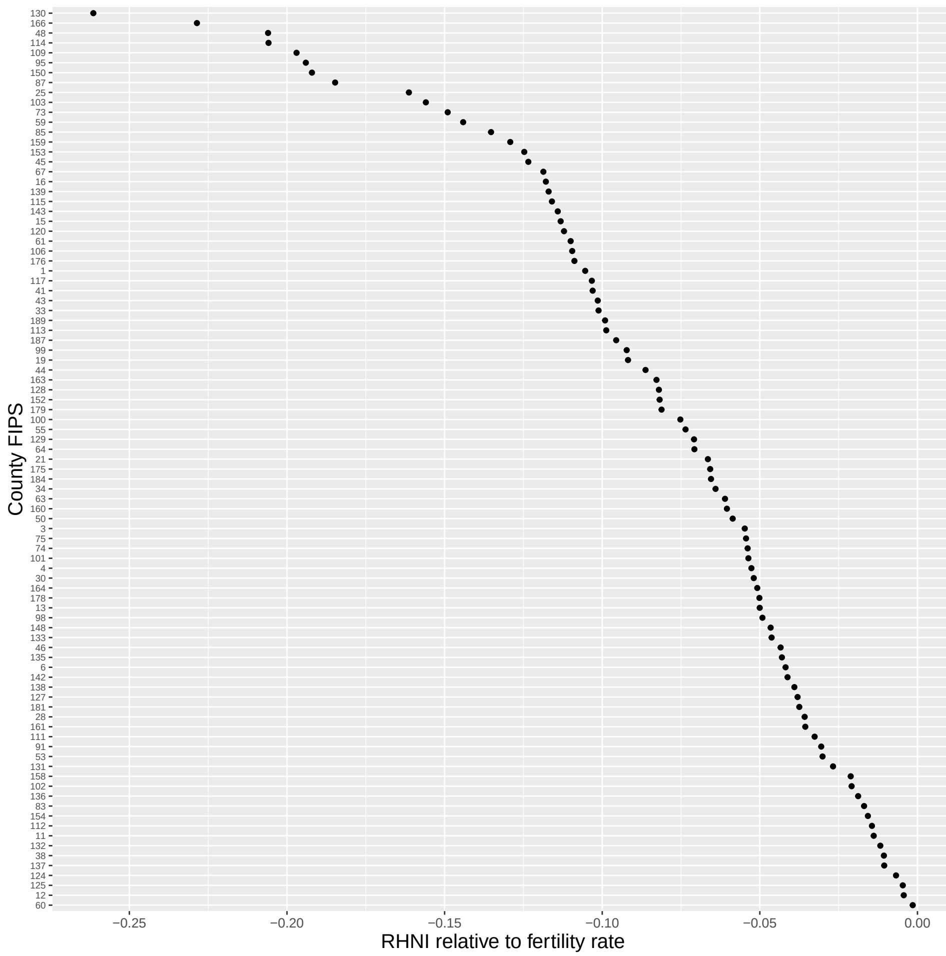
Notes: This figure shows the difference-in-differences event study results of the effect of the abortion ban in Texas on fertility rates. The vertical axis is measured in (change in) births per 1,000 women of a given race and ethnicity aged 15-44. The dashed line represents the enactment of the abortion ban in Texas in September 2021. Each color represents an estimate for a different race and ethnic group, with Black NH referring to Black non-Hispanic, and White NH referring to White non-Hispanic. Race/ethnic group-specific female population aged 15-44 in thousands in 2020 is used as a constant denominator. The sample is restricted to counties with more than 1000 women of reproductive age in 2020 for a given race/ethnic group. Control variables include county-level unemployment rates, poverty rates, log median household income, labor force participation rates, Republican vote shares, as well as county-level population shares of teenagers, adults in age bin, Black non-Hispanic women of reproductive age, white non-Hispanic women of reproductive age, Hispanic women of reproductive age, total women of reproductive age, and the total number of women of reproductive age. Estimates for white non-Hispanics include region-specific linear trends. Population weights refer to total county population of a given race/ethnic group. Standard error bars clustered at the county and state-year are reported at the 95% level. Source: Author's calculations using NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure 14: Effect of the abortion ban on fertility rates by distance



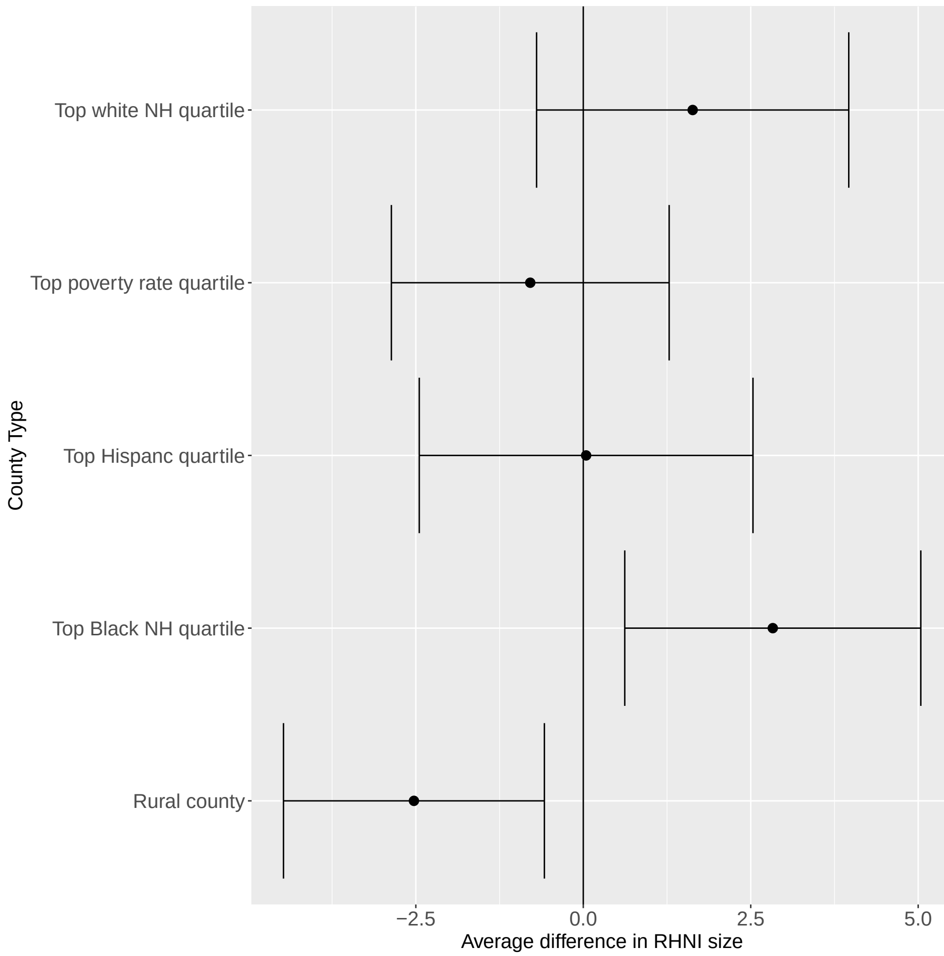
Notes: This figure shows the predicted effect of the abortion ban in Texas on fertility rates by distance to the nearest state with legal abortion. The vertical axis is measured in (change in) births per 1,000 women of a given race and ethnicity aged 15-44. The horizontal axis is measured in miles to the nearest state with less restrictive abortion laws. The shaded area represents the 95% confidence interval. Standard errors are calculated using the delta method. Source: Author's calculations using Census data, Policy Surveillance Program data, NCHS birth certificate data, and control variables sources listed in the text.

Figure 15: County-specific Reproductive Health Needs Index



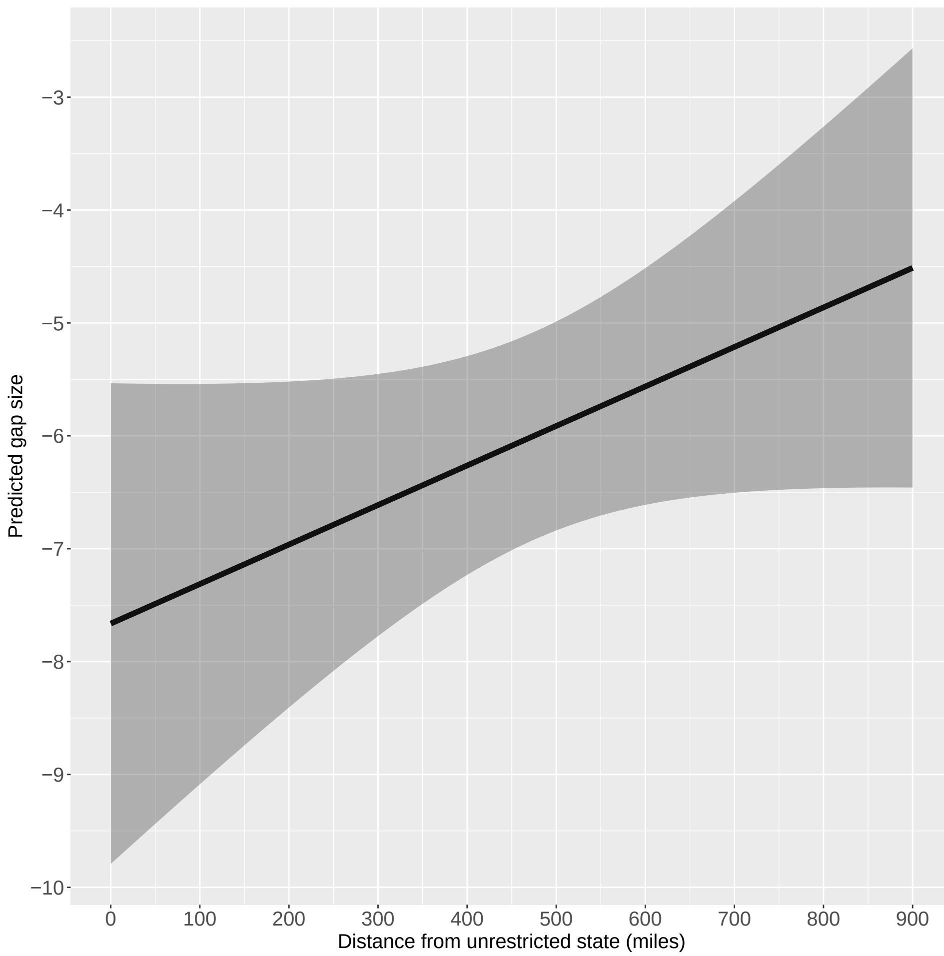
Notes: This figure shows the county-specific Reproductive Health Needs Index as described in the text. Each point represents a county in Texas, with the values along the x-axis representing the size of the RHNI, or the difference between the change in births and the change in abortions after the enactment of an abortion ban. These values are scaled by the total pre-treatment fertility rate in a given county. Counties with a larger RHNI (closer to zero) are more likely to have more unmet reproductive health needs after the ban. Counties with a smaller RHNI (further from zero) are more likely to have fewer unmet reproductive health needs after the ban. Source: Author's calculations using NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure 16: County-specific Reproductive Health Needs Index by county type



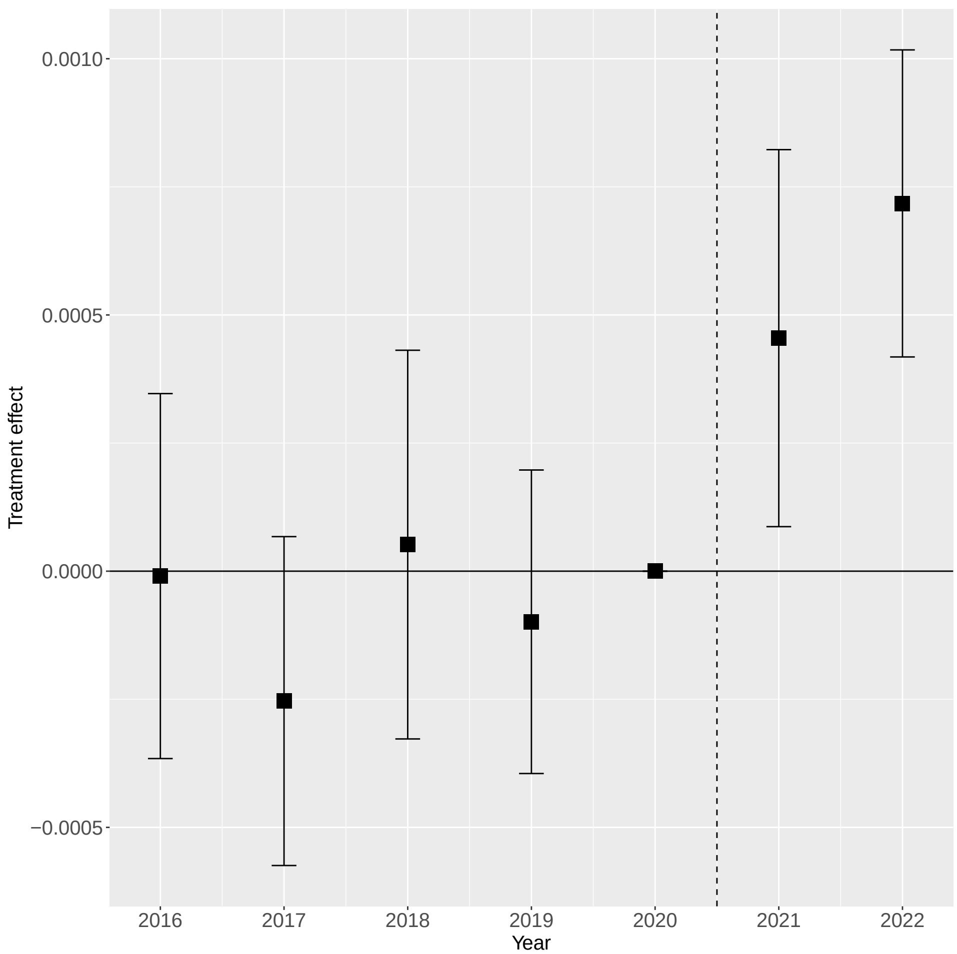
Notes: This figure shows the average difference in County-specific Reproductive Health Needs Index by county type after the enactment of Texas's abortion ban. County types are assigned based on if a certain county has a poverty rate, distance, or population share is in the 4th quartile. Each point represents the the difference in average index size between counties of a given type and all other counties, for example counties in the 4th quartile of poverty rates compared to all other counties in Texas. The horizontal axis represents the average difference in the index size, with positive values indicating that counties of a given type have higher unmet reproductive health needs relative to all other counties. Standard error bars are reported at the 95% level. Source: Author's calculations using NCHS birth certificate data, Census data, Policy Surveillance Program data, state-specific abortion data, and control variables sources listed in the text.

Figure 17: County-specific Reproductive Health Needs Index by distance



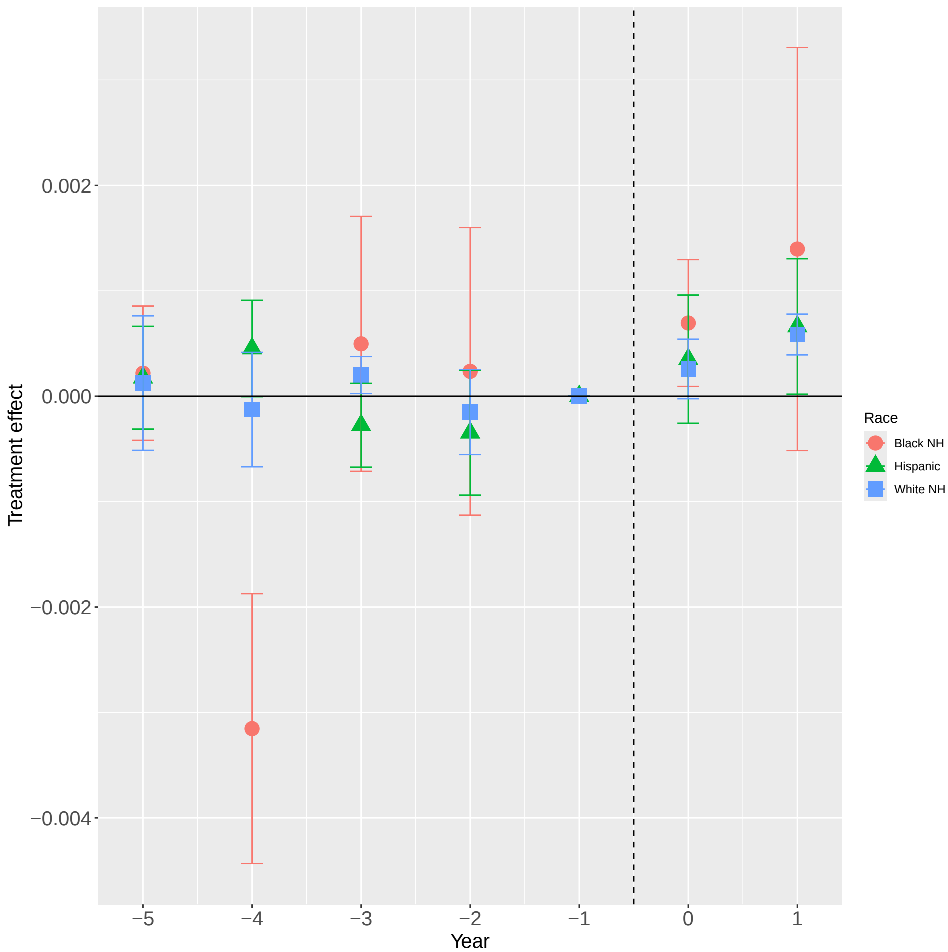
Notes: This figure shows the predicted Reproductive Health Needs Index by distance to the nearest state with liberal abortion laws after the enactment of Texas's abortion ban. The vertical axis is measured in (change in) the RHNI. The horizontal axis is measured in miles to the nearest state liberal abortion laws. Standard error bars calculated using the delta method are reported at the 95% level. Source: Author's calculations using NCHS birth certificate data, Census data, Policy Surveillance Program data, state-specific abortion data, and control variables sources listed in the text.

Figure 18: Very low birth weight event study



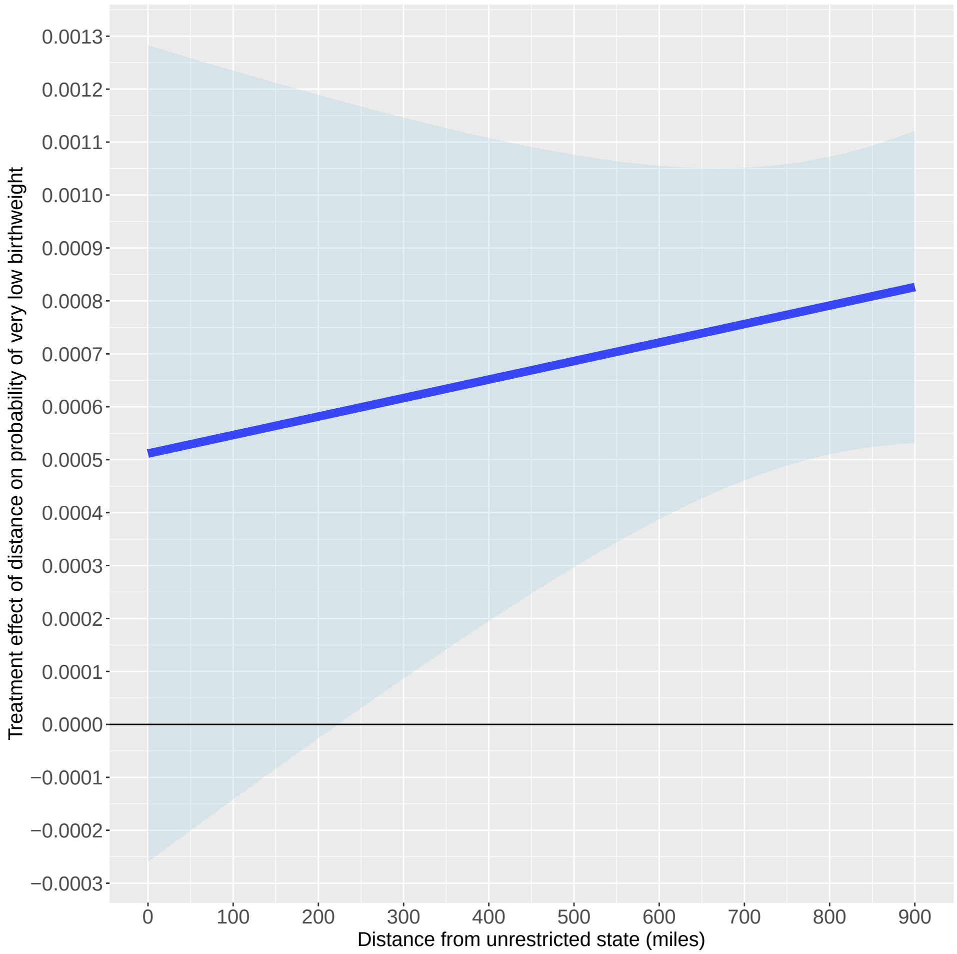
Notes: This figure shows the difference-in-differences event study results of the effect of the abortion ban in Texas on the probability of an infant being born with very low birth weight. The vertical axis is measured in (change in) the probability of a birth being very low birth weight (less than 1500 grams). The dashed line represents the enactment of the abortion ban in Texas in September 2021. The pre-treatment probability in Texas of a very low birth weight is about 1 percent. The sample is restricted to mothers aged 15-44, and counties with more than 1000 women of reproductive age in 2020. The event study is estimated using the baseline specification with no weights or control variables. Standard error bars clustered at the county and state-year are reported at the 95% level. Source: Author's calculations using NCHS data and Census data.

Figure 19: Very low birth weight event study by race and ethnicity



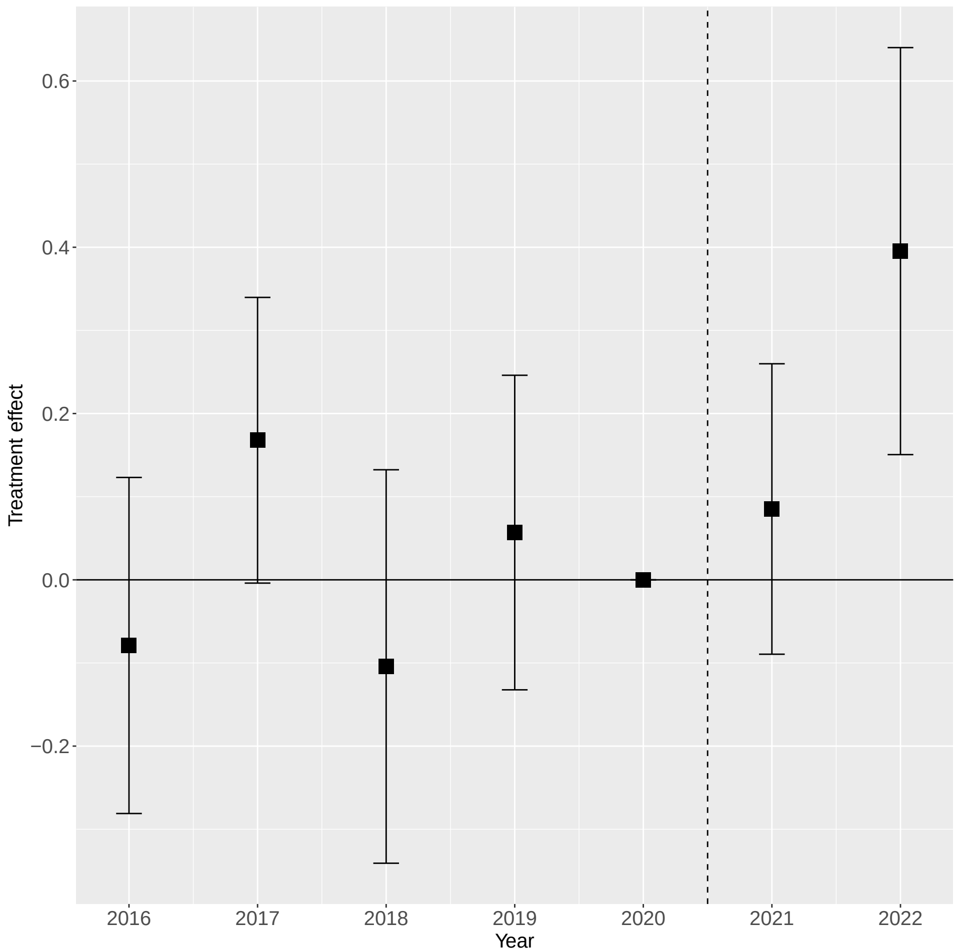
Notes: This figure shows the difference-in-differences event study results of the effect of the abortion ban in Texas on the probability of very low birth weight. The vertical axis is measured in (change in) the probability of a birth being very low birth weight (less than 1500 grams). The dashed line represents the enactment of the abortion ban in Texas in September 2021. Each color represents an estimate for a different race and ethnic group, with Black NH referring to Black non-Hispanic, and White NH referring to White non-Hispanic. The sample is restricted to counties with more than 1000 women of reproductive age in 2020 for a given race/ethnic group. Standard error bars clustered at the county and state-year are reported at the 95% level. Source: Author's calculations using NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure 20: Effect of the abortion ban on very low birth rate probability by distance



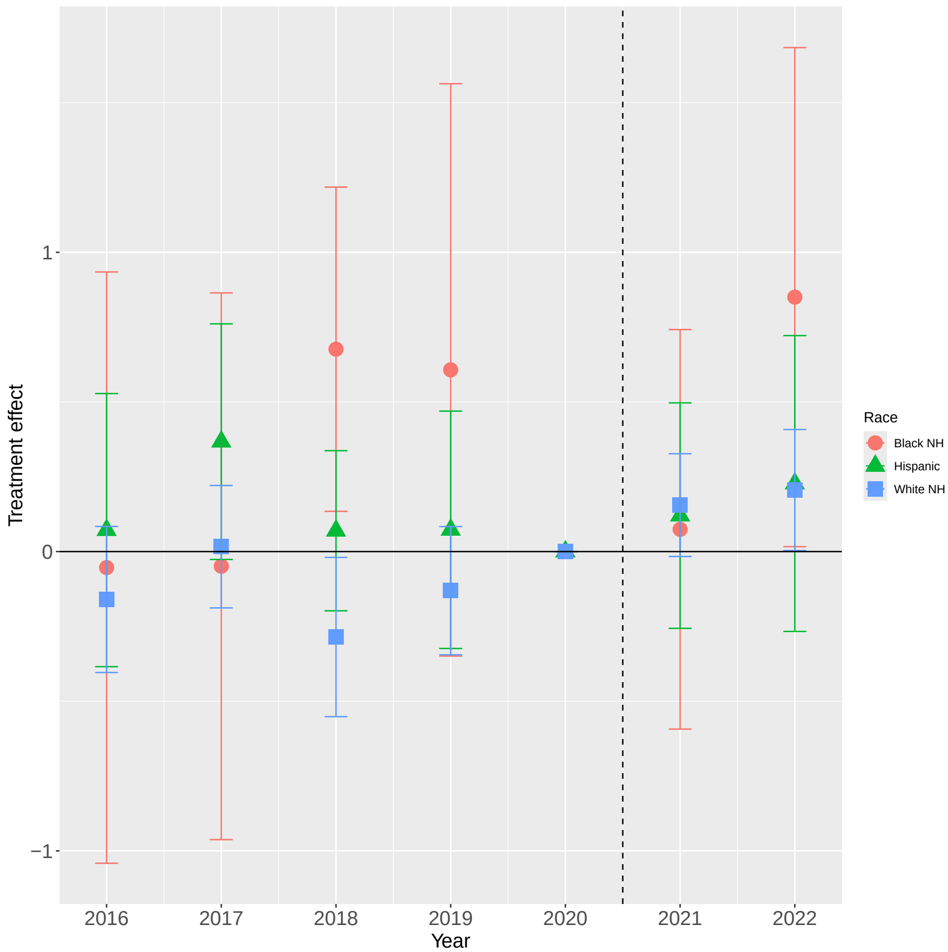
Notes: This figure shows the predicted effect of the abortion ban in Texas on very low birth weight probabilities by distance to the nearest state with legal abortion. The vertical axis is measured in (change in) probability of very low birth weight. The horizontal axis is measured in miles to the nearest state liberal abortion laws. The shaded area represents the 95% confidence interval. Standard errors are calculated using the delta method. Source: Author's calculations using Census data, Policy Surveillance Program data, NCHS birth certificate data, and control variables sources listed in the text.

Figure 21: Infant mortality event study



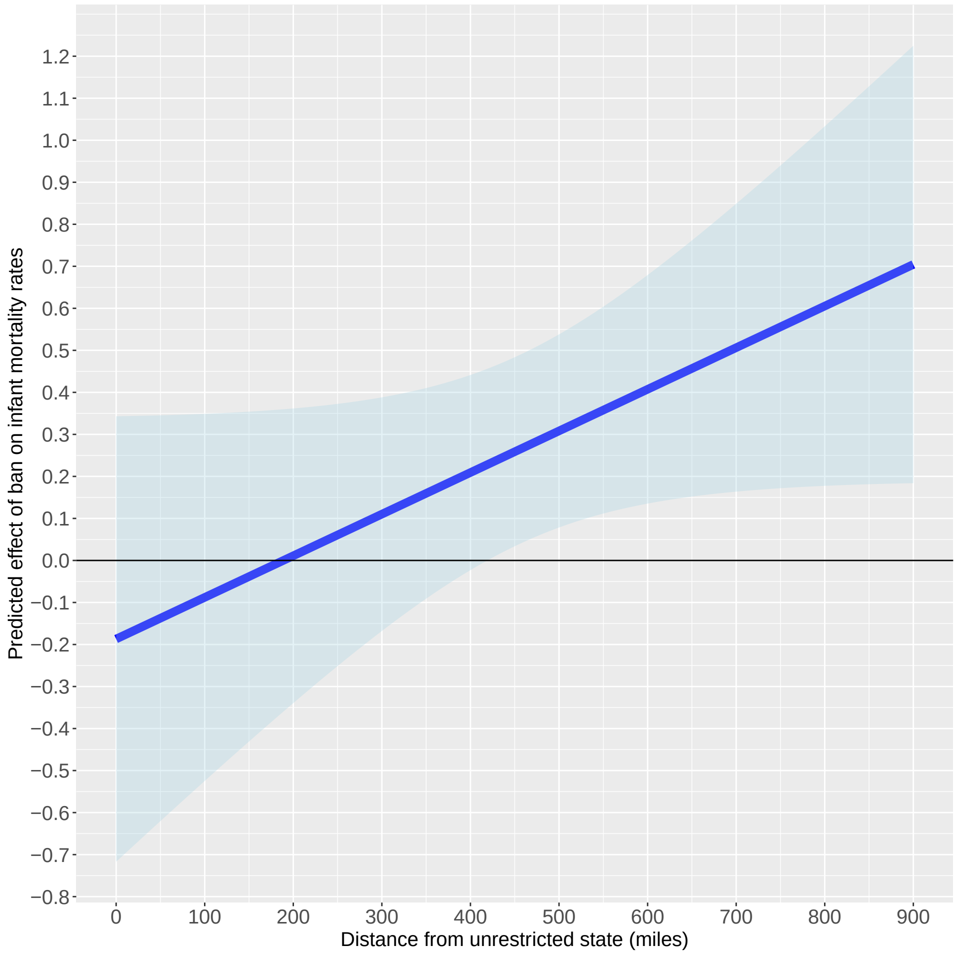
Notes: This figure shows the difference-in-differences event study results of the effect of the abortion ban in Texas on the infant mortality rate. The vertical axis is measured in (change in) the infant mortality rate (the number of infant deaths per 1,000 births). The dashed line represents the enactment of the abortion ban in Texas in September 2021. The sample is restricted to counties with more than 1000 women of reproductive age in 2020. Control variables include county-level unemployment rates, poverty rates, log median household income, labor force participation rates, Republican vote shares, as well as county-level population shares of teenagers, adults aged 20-24, adults aged 25-34, adults aged 35-44, Black non-Hispanic women of reproductive age, white non-Hispanic women of reproductive age, Hispanic women of reproductive age, the total share of women of reproductive age, and the total number of women of reproductive age. Population weights refer to total county population. Standard error bars clustered at the county and state-year are reported at the 95% level. Source: Author's calculations using NCHS death certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure 22: Infant mortality event study by race and ethnicity



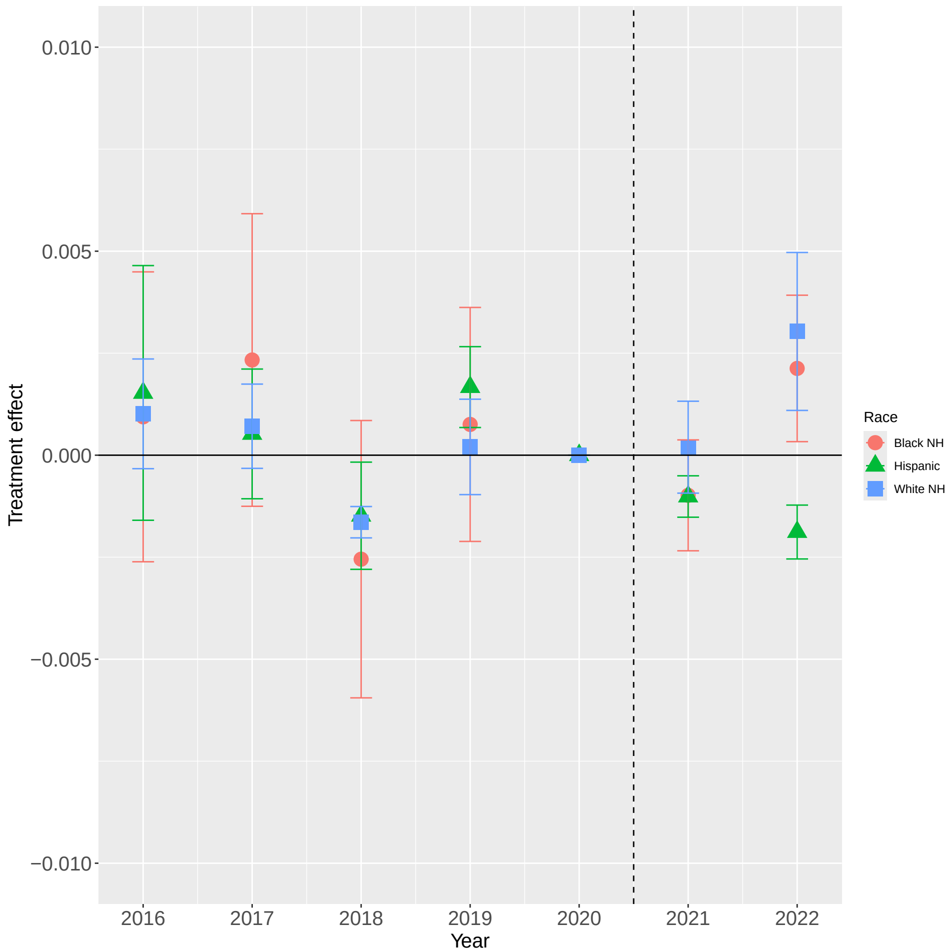
Notes: This figure shows the difference-in-differences event study results of the effect of the abortion ban in Texas on infant mortality rates. The vertical axis is measured in (change in) the infant mortality rate (the number of infant deaths per 1,000 births of a given race and ethnicity). The dashed line represents the enactment of the abortion ban in Texas in September 2021. Each color represents an estimate for a different race and ethnic group, with Black NH referring to Black non-Hispanic, and White NH referring to White non-Hispanic. The sample is restricted to counties with more than 1000 women of reproductive age in 2020. Each color and shape represents a different specification. Control variables include county-level unemployment rates, poverty rates, log median household income, labor force participation rates, Republican vote shares, as well as county-level population shares of teenagers, adults aged 20-24, adults aged 25-34, adults aged 35-44, Black non-Hispanic women of reproductive age, white non-Hispanic women of reproductive age, Hispanic women of reproductive age, the total share of women of reproductive age, and the total number of women of reproductive age. Population weights refer to total county population of a given race/ethnic group. Standard error bars clustered at the county and state-year are reported at the 95% level. Source: Author's calculations using NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure 23: Effect of the abortion ban on infant mortality rates by distance



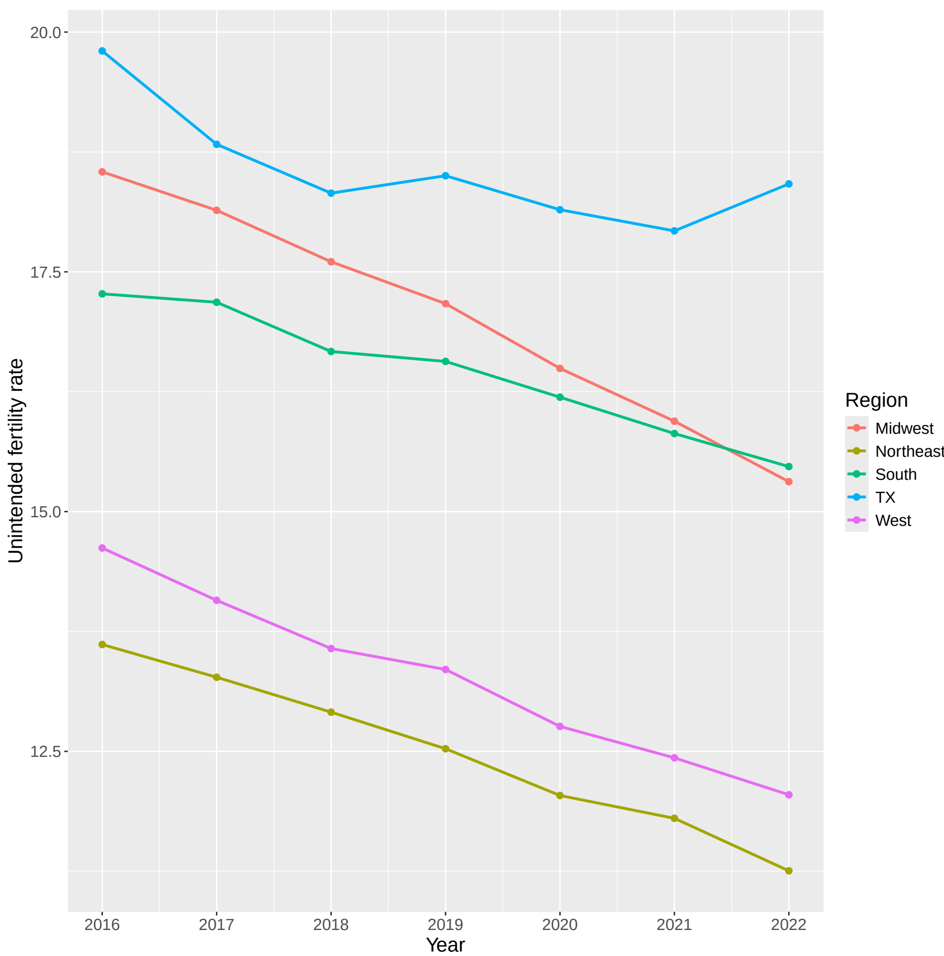
Notes: This figure shows the predicted effect of the abortion ban in Texas on infant mortality rates by distance to the nearest state with legal abortion. The vertical axis is measured in (change in) the infant mortality rate (the number of infant deaths per 1,000 births). The horizontal axis is measured in miles to the nearest state liberal abortion laws. The shaded area represents the 95% confidence interval. Standard errors are calculated using the delta method. Source: Author's calculations using Census data, Policy Surveillance Program data, NCHS birth certificate data, and control variables sources listed in the text.

Figure 24: Short birthing interval event study by race and ethnicity



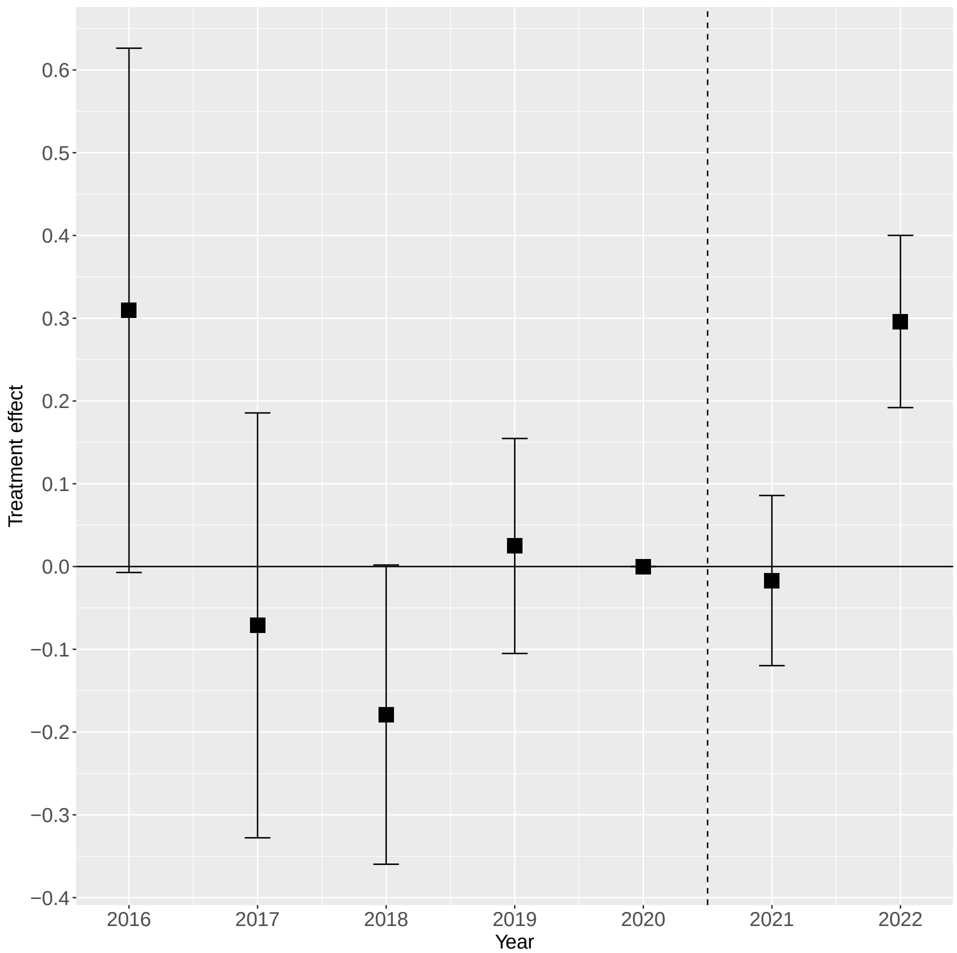
Notes: This figure shows the difference-in-differences event study results of the effect of the abortion ban in Texas on the probability of a very short birthing interval (less than 18 months). The vertical axis is measured in (change in) the probability of a birth being very low birth weight (less than 1500 grams). The dashed line represents the enactment of the abortion ban in Texas in September 2021. Each color represents an estimate for a different race and ethnic group, with Black NH referring to Black non-Hispanic, and White NH referring to White non-Hispanic. The sample is restricted to counties with more than 1000 women of reproductive age in 2020 for a given race/ethnic group. Standard error bars clustered at the state-level are reported at the 95% level. Source: Author's calculations using NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure 25: Unintended fertility rates by region



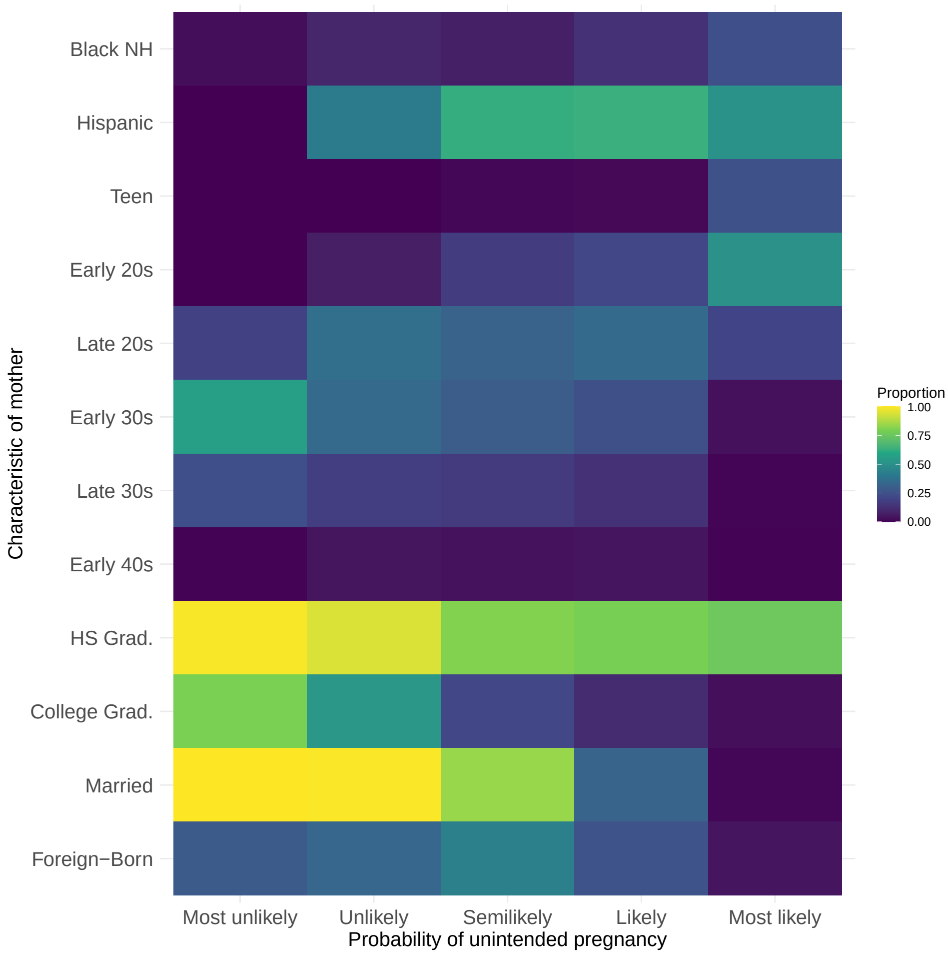
Notes: This figures shows the predicted unintended fertility rates overtime for Texas and for all other states by region, from 2016 to 2021. The vertical axis is measured in unintended births per 1,000 women aged 15-44. Unintended births are estimated using a Random Forest model. Each color represents a different region of the United States, with Texas plotted separately. Source: Author's calculations using NCHS birth certificate data, Census data, and NSFG data.

Figure 26: Unintended Fertility rate event study



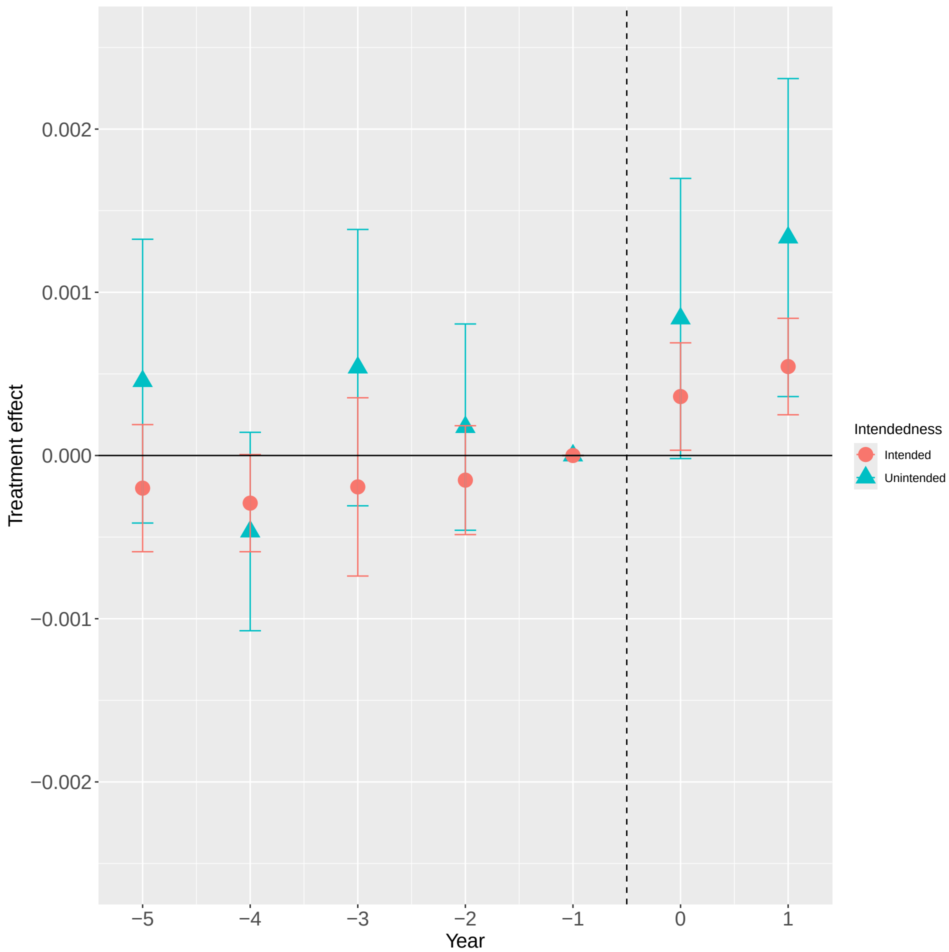
Notes: This figure shows the difference-in-differences event study results of the effect of the abortion ban in Texas on predicted unintended fertility rates. The vertical axis is measured in (change in) unintended births per 1,000 women aged 15-44. The dashed line represents the enactment of the abortion ban in Texas in September 2021. Female population aged 15-44 in thousands in 2020 is used as a constant denominator. The sample is restricted to counties with more than 1000 women of reproductive age in 2020. The event study is estimated using the baseline specification with region-specific trends. Standard error bars clustered at the state-year level are reported at the 95% level. Source: Author's calculations using NCHS birth certificate data, Census data, and NSFG data.

Figure 27: Demographic characteristics of mothers by likelihood quintile of an unintended birth



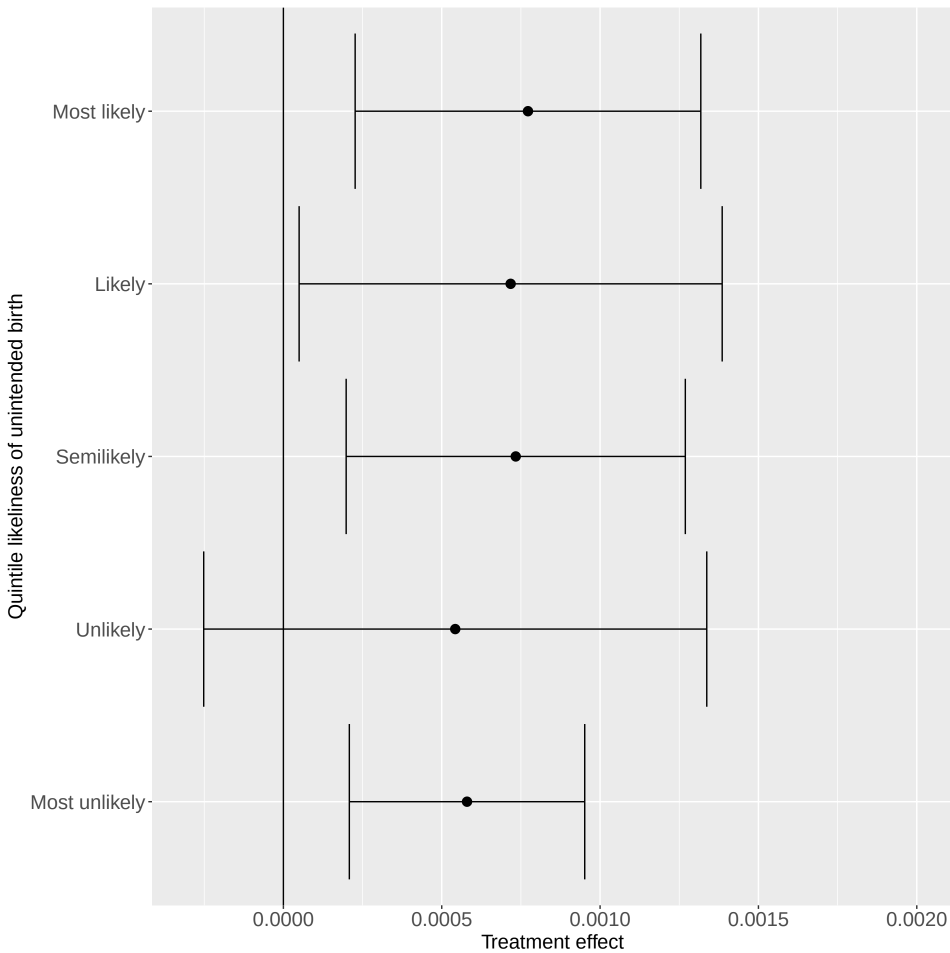
Notes: This figure shows the demographic characteristics of mothers by quintile of the prediction probability of an unintended birth. The probability of an unintended birth is estimated using a predictive model on NSFG data. Births in the lowest likelihood quintile are the least likely to be unintended, while births in the highest likelihood quintile are the most likely to be unintended. Colors that are more vibrant represent higher proportions of mothers with a given characteristic in a given quintile. Source: Author's calculations using NCHS birth certificate data, Census data, and NSFG data.

Figure 28: Very low birth weight event study by unintendedness of birth



Notes: This figure shows the difference-in-differences event study results of the effect of the abortion ban in Texas on the probability of very low birth weight. The vertical axis is measured in (change in) the probability of a birth being very low birth weight (less than 1500 grams). The dashed line represents the enactment of the abortion ban in Texas in September 2021. Each color represents an estimate for a different predicted intendedness of birth group, with intended births referring to births that are intended as predicted by a model trained on NSFG data, and unintended births referring to births that are unintended as predicted by the same model. The sample is restricted to counties with more than 1000 women of reproductive age in 2020 for a given race/ethnic group. Standard error bars clustered at the county and state-year are reported at the 95% level. Source: Author's calculations using NCHS birth certificate data, Census data, and NSFG data.

Figure 29: Effect of the abortion ban on very low birth rate probability by likeliness of unintended birth quintile



Notes: This figure shows the difference-in-differences estimate of the effect of the abortion ban in Texas on the probability of very low birth weight by quintile of unintendedness of birth prediction probability. The probability of an unintended birth is estimated using a predictive model on NSFG data. Those in the first quintile are the least likely to have an unintended birth, while those in the fifth quintile are the most likely to have an unintended birth. The horizontal axis is measured in (change in) the probability of a birth being very low birth weight (less than 1500 grams), averaged over the post-treatment period. The sample is restricted to counties with more than 1000 women of reproductive age in 2020 for a given race/ethnic group. Standard error bars clustered at the county and state-year level are reported at the 90% level. Source: Author's calculations using NCHS birth certificate data, Census data, and NSFG data.

Tables

Table 1: The Effect of the Abortion Ban on Abortion Rates

Dependent Variable:	Abortion rate					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Abortion ban	-2.2622**	-3.0740**	-3.8068**	-2.7988**	-3.6507**	-2.6468***
	(0.8954)	(1.4516)	(1.5017)	(1.4057)	(1.4352)	(0.5788)
Controls	No	No	No	Yes	Yes	Yes
Region-specific trends	No	No	Yes	No	Yes	No
Population weights	No	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
County	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	6,826	6,826	6,826	6,826	6,826	1,810
R^2	0.8477	0.9393	0.9427	0.9450	0.9480	0.8186

Clustered (fips & state_year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table shows the pooled treatment effect of the abortion ban in Texas on abortion rates. The abortion rate is measured as the number of abortions per 1,000 women aged 15-44. Female population aged 15-44 in thousands in 2020 is used as a constant denominator. The sample is restricted to counties with more than 1000 women of reproductive age in 2020. Standard errors are clustered at the state level. Control variables include county-level unemployment rates, poverty rates, log median household income, labor force participation rates, Republican vote shares, as well as county-level population shares of teenagers, adults aged 20-24, adults aged 25-34, adults aged 35-44, Black non-Hispanic women of reproductive age, white non-Hispanic women of reproductive age, Hispanic women of reproductive age, the total share of women of reproductive age, and the total number of women of reproductive age. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Table 2: The Effect of the Abortion Ban on Fertility Rates

Dependent Variable:	Fertiltiy rate					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Abortion ban	1.7602***	3.2974***	2.2359***	2.3884***	1.5787***	2.8433**
	(0.4186)	(0.3554)	(0.4240)	(0.3657)	(0.3537)	(1.3399)
Controls	No	No	No	Yes	Yes	Yes
Region-specific trends	No	No	Yes	No	Yes	No
Population weights	No	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
County	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	10,191	10,191	10,191	10,100	10,100	1,932
R^2	0.8780	0.9251	0.9303	0.9480	0.9510	0.8452

Clustered (fips & state_year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table shows the pooled treatment effect of the abortion ban in Texas on fertility rates. The fertility rate is measured as the number of births per 1,000 women aged 15-44. Female population aged 15-44 in thousands in 2020 is used as a constant denominator. The sample is restricted to counties with more than 1000 women of reproductive age in 2020. Standard errors are clustered at the state level. Control variables include county-level unemployment rates, poverty rates, log median household income, labor force participation rates, Republican vote shares, as well as county-level population shares of teenagers, adults aged 20-24, adults aged 25-34, adults aged 35-44, Black non-Hispanic women of reproductive age, white non-Hispanic women of reproductive age, Hispanic women of reproductive age, the total share of women of reproductive age, and the total number of women of reproductive age. Source: Author's calculations using NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Table 3: The Effect of the Abortion Ban on Fertility Rates by Racial/Ethnic Group

Dependent Variable:	Fertiltiy rate					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Abortion ban	0.4965	-2.6308**	1.3798***	3.2420***	-0.2864	0.7815***
	(0.9660)	(1.3290)	(0.4031)	(0.7308)	(0.5495)	(0.2670)
Group	Black NH	Hispanic	White NH	Black NH	Hispanic	White NH
Controls	No	No	No	Yes	Yes	Yes
Population weights	No	No	No	Yes	Yes	Yes
Fixed-effects						
County	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,709	4,186	9,324	2,703	4,165	9,275
R^2	0.8740	0.8600	0.8652	0.9080	0.9102	0.9381

Clustered (County & State-year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table shows the pooled treatment effect of the abortion ban in Texas on fertility rates by racial and ethnic group. The fertility rate is measured as the number of births per 1,000 women of the given race and ethnicity aged 15-44. Race/ethnic group-specific female population aged 15-44 in thousands in 2020 is used as a constant denominator. The sample is restricted to counties with more than 1000 women of reproductive age in 2020 for a given race/ethnic group. Control variables include county-level unemployment rates, poverty rates, log median household income, labor force participation rates, Republican vote shares, as well as county-level population shares of teenagers, adults aged 20-24, adults aged 25-34, adults aged 35-44, Black non-Hispanic women of reproductive age, white non-Hispanic women of reproductive age, Hispanic women of reproductive age, and the total share of women of reproductive age. Population weights refer to total county population of a given race/ethnic group. Estimates for white non-Hispanics include region-specific linear trends. Standard error bars clustered at the county and state-year are reported at the 95% level. Source: Author's calculations using NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Table 4: The Effect of the Abortion Ban on the Probability of Low Birth Weight by Race/Ethnicity

Dependent Variable:	Very low birthweight							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Abortion ban	0.0007***	0.0015**	0.0005*	0.0004*	0.0007***	0.0013**	0.0003	0.0008***
	(0.0002)	(0.0007)	(0.0003)	(0.0002)	(0.0002)	(0.0007)	(0.0003)	(0.0002)
Group	All	Black NH	Hispanic	White NH	All	Black NH	Hispanic	White NH
Controls	No	No	No	No	Yes	Yes	Yes	Yes
Fixed-effects								
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	17,446,210	2,073,436	4,879,099	8,363,644	17,375,472	2,068,490	4,867,291	8,325,272
R^2	0.0007	0.0012	0.0006	0.0006	0.0007	0.0012	0.0006	0.0006

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table shows the pooled treatment effect of the abortion ban in Texas on the probability of very low birth weight overall and by racial and ethnic group. The pre-treatment probability of very low birth weight in Texas is about 1 percent. The sample is restricted to counties with more than 1000 women of reproductive age in 2020, and women between the ages of 15 and 44. Control variables include county-level unemployment rates, poverty rates, log median household income, labor force participation rates, Republican vote shares, as well as county-level population shares of teenagers, adults aged 20-24, adults aged 25-34, adults aged 35-44, Black non-Hispanic women of reproductive age, white non-Hispanic women of reproductive age, Hispanic women of reproductive age, the total share of women of reproductive age, and the total number of women of reproductive age. Population weights refer to total county population of a given race/ethnic group. Standard error bars clustered at the county and state-year are reported at the 95% level. Source: Author's calculations using NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Table 5: The Effect of the Abortion Ban on Infant Mortality Rates by Racial/Ethnic Group

Dependent Variable:	Infant mortality rate							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Abortion ban	0.3515***	0.7999**	0.1648	0.1873**	0.3954***	0.8503**	0.2275	0.2057**
	(0.1153)	(0.3558)	(0.1994)	(0.0804)	(0.1242)	(0.4230)	(0.2508)	(0.1026)
Group	All	Black NH	Hispanic	White NH	All	Black NH	Hispanic	White NH
Controls	No	No	No	No	Yes	Yes	Yes	Yes
Population weights	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects								
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	10,191	8,467	10,039	10,191	10,100	8,409	9,950	10,100
R^2	0.3221	0.2105	0.2126	0.2764	0.3230	0.2117	0.2180	0.2769

Clustered (state_year & fips) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table shows the pooled treatment effect of the abortion ban in Texas on infant mortality rates overall and by racial and ethnic group. The infant mortality rate is measured as the number of infant deaths per 1,000 live births of a given race and ethnicity. The sample is restricted to counties with more than 1000 women of reproductive age in 2020, and women between the ages of 15 and 44. Control variables include county-level unemployment rates, poverty rates, log median household income, labor force participation rates, Republican vote shares, state minimum wages, as well as county-level population shares of teenagers, adults aged 20-24, adults aged 25-34, adults aged 35-44, Black non-Hispanic women of reproductive age, white non-Hispanic women of reproductive age, Hispanic women of reproductive age, the total share of women of reproductive age, and the total number of women of reproductive age. Population weights refer to total county population of a given race/ethnic group. Standard error bars clustered at the county and state-year are reported at the 95% level. Source: Author's calculations using NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Table 6: The Effect of the Abortion Ban on Short Birthing Intervals by Racial/Ethnic Group

Dependent Variable:	Short birth interval							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Abortion ban	0.0001	0.0021**	-0.0019***	0.0030***	-0.0001	0.0025*	-0.0018***	0.0032***
	(0.0005)	(0.0009)	(0.0003)	(0.0010)	(0.0005)	(0.0015)	(0.0006)	(0.0010)
Group	All	Black NH	Hispanic	White NH	All	Black NH	Hispanic	White NH
Controls	No	No	No	No	Yes	Yes	Yes	Yes
Fixed-effects								
County	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	16,611,349	1,936,661	4,664,450	7,987,800	16,543,574	1,931,955	4,653,126	7,951,091
R^2	0.0041	0.0082	0.0041	0.0043	0.0041	0.0082	0.0041	0.0043

Clustered (County & state_year) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table shows the pooled treatment effect of the abortion ban in Texas on the probability of a very short birthing interval (less than 18 months) overall and by racial and ethnic group. The sample is restricted to counties with more than 1000 women of reproductive age in 2020, and women between the ages of 15 and 44. Control variables include county-level unemployment rates, poverty rates, log median household income, labor force participation rates, Republican vote shares, state minimum wages, as well as county-level population shares of teenagers, adults aged 20-24, adults aged 25-34, adults aged 35-44, Black non-Hispanic women of reproductive age, white non-Hispanic women of reproductive age, Hispanic women of reproductive age, and the total share of women of reproductive age. Population weights refer to total county population of a given race/ethnic group. Standard error bars clustered at the county and state-year are reported at the 95% level. Source: Author's calculations using NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Appendices

A Abortion Policy Changes after *Dobbs v. Jackson* Through January 2023

1. Alabama
   - June 24, 2022: Total ban goes into effect
   - Sources: `https://reproductiverights.org/maps/state/alabama/`
2. Arizona
   - September 23, 2022: Pre-*Roe* total ban goes into effect
   - October 7, 2022: Total ban is blocked, but a 15 week ban passed in March 2022 goes into effect
   - Sources: `https://www.acluaz.org/en/issues/abortion-arizona#:~:text=On%20December%2030%2C%202022%2C%20a,care%20without%20state%2Drequired%20credentials`
3. Arkansas
   - June 24, 2022: Near-total ban goes into effect
   - Sources: `https://reproductiverights.org/maps/state/arkansas/`
4. Florida
   - July 1, 2022: Law banning abortion at 15 weeks goes into effect
   - Sources: `https://reproductiverights.org/maps/state/florida/`, `https://www.aclufl.org/en/legislation/sb-146-hb-5-banning-abortion-after-15-weeks`, `https://www.flsenate.gov/Session/Bill/2022/146`
5. Georgia
   - July 20, 2022: A 6-week ban goes into effect

- August 15, 2022: Fulton County refuses to block ban as litigation continues
- November 15, 2022: Fulton County blocks ban
- November 23, 2022: Georgia Supreme Court allows ban to come back into effect as litigation plays out
- Sources: `https://reproductiverights.org/case/post-roe-state-abortion-ban-litigation/sistersong-v-state-georgia/`

6. Idaho
   - August 25, 2022: Trigger law banning abortion in nearly all cases goes into effect
   - Sources: `https://reproductiverights.org/maps/state/idaho/`

7. Indiana
   - September 15, 2022: Total ban goes into effect
   - September 22, 2022: Total ban is blocked
   - August 21, 2023: Total ban is re-instated
   - Sources: `https://www.aclu-in.org/en/abortion-access-indiana`

8. Iowa
   - Iowa's pre-*Dobbs* heartbeat bill was enjoined in 2019 and continues to be enjoined
   - Sources: `https://reproductiverights.org/maps/state/iowa/`

9. Kentucky
   - June 24, 2022: Total ban goes into effect
   - June 30, 2022: Injunction is granted on total ban
   - August 1, 2022: Injunction on ban is lifted and ban goes into effect

- November, 2022: Voters reject amendment which stated abortion was not protected by the state constitution
- Sources: https://reproductiverights.org/maps/state/kentucky/, https://abcnews.go.com/Health/total-abortion-bans-reinstated-kentucky/story?id=87801481

10. Louisiana

    - June 24, 2022: Total ban goes into effect
    - June 27, 2022: Total ban is enjoined
    - August 1, 2022: Total ban is re-instated
    - Sources: https://reproductiverights.org/maps/state/louisiana/, https://reproductiverights.org/case/post-roe-state-abortion-ban-litigation/june-medical-services-v-landry/

11. Michigan

    - June 24, 2022: Governor files motion to prevent a 1931 law from coming into effect
    - November 8, 2022: 1931 law banning abortion is overturned in a ballot
    - Sources: https://www.aclu.org/news/reproductive-freedom/in-michigan-a-historic-victory-for-abortion-rights, https://lwvmi.org/wp-content/uploads/2023/04/History-of-Repro-Health-Care-in-MI-4.20.23.pdf

12. Minnesota

    - Law banning abortion after viability never goes into effect
    - May, 2023: Law banning abortion after viability is repealed

- Sources: https://reproductiverights.org/maps/state/minnesota/

13. Mississippi

    - June 24, 2022: State of Mississippi wins the case in *Dobbs v. Jackson* and a 15 week gestational limit goes into effect
    - July 7, 2022: After a lawsuit, a law banning abortions comes into effect
    - Sources: https://reproductiverights.org/maps/state/mississippi/, https://abcnews.go.com/Health/abortion-trigger-law-effect-mississippi-case-overturned-roe/story?id=86366550

14. Missouri

    - June 24, 2022: Trigger law total ban goes into effect
    - Sources: https://reproductiverights.org/maps/state/missouri/

15. Montana

    - The 2021 law banning abortion after 20 weeks is enjoined
    - Sources: https://law.justia.com/cases/montana/supreme-court/2022/da-21-0521-0.html, https://reproductiverights.org/maps/state/montana/

16. Nebraska

    - May 22, 2023: Nebraska enacts a 12 week ban
    - Sources: https://governor.nebraska.gov/press/governor-pillen-signs-lb574-law-abortion-ban-takes-effect-immediately

17. North Dakota

    - June 24, 2022: Trigger law banning abortion comes into effect; 6 week ban is permanently enjoined

- July 27, 2022: Trigger law banning abortion in nearly all cases is blocked and remained so through early 2023
- Sources: `https://www.reuters.com/world/us/judge-temporarily-blocks-north-dakotas-trigger-ban-abortions-2022-07-27/`

18. Ohio

- June 27, 2022: Ohio enforces its 6-week ban
- September 14, 2022: Ohio blocks its 6-week ban, allowing abortion up to 22 weeks
- November 7, 2023: Ohio votes to protect reproductive rights in the state constitution
- Sources: `https://www.aclu.org/press-releases/ohio-lower-court-blocks-six-week-abortion-ban-restoring-reproductive-rights-across`

19. Oklahoma

- June 24, 2022: Trigger law goes into effect re-instating a pre-*Roe* near-total ban
- Sources: `https://www.oklahoman.com/story/news/2022/06/24/roe-v-wade-scotus-means-oklahoma-abortion-trigger-law/7623055001/`, `https://reproductiverights.org/maps/state/oklahoma/`

20. South Carolina

- June 27, 2022: A 6-week ban passed in 2021 goes into effect
- August 16, 2022: The 6-week ban is enjoined
- January 5, 2023: The 6-week ban is struck down by the State Supreme Court
- May 12, 2023: A new 6-week ban is passed
- The new 6-week ban is allowed to be enacted

- Sources: https://apnews.com/article/abortion-health-ap-news-alert-south-carolina-c5b7e63f564a8408a8a12e691cb10ab1, https://apnews.com/article/abortion-politics-health-south-carolina-state-government-6cd1469dbb550c70b64a30f183be203c, https://reproductiverights.org/maps/state/south-carolina/

21. South Dakota
    - June 24, 2022: Trigger law banning abortion in nearly all cases goes into effect
    - Sources: https://reproductiverights.org/maps/state/south-dakota/

22. Tennessee
    - June 28, 2022: A 6-week ban which was previously enjoined goes into effect
    - August 25, 2022: A near-total ban goes into effect
    - Sources: https://abcnews.go.com/US/tennessee-trigger-law-banning-abortions-effect/story?id=88787662, https://www.aclu.org/press-releases/tennessee-six-week-abortion-ban-takes-effect#:~:text=NASHVILLE%2C%20Tenn.,even%20know%20they%20are%20pregnant, https://reproductiverights.org/maps/state/tennessee/

23. Texas
    - September 1, 2021: Senate Bill 8 goes into effect, banning abortion after 6 weeks
    - August 25, 2022: Near-total abortion ban from a trigger law passed in 2021 goes into effect
    - Sources: https://www.aclutx.org/en/know-your-rights/abortion-texas, https://reproductiverights.org/maps/state/texas/

24. Utah

- June 24, 2022: Utah begins enforcing its 2020 trigger ban, banning abortions in nearly all cases
- June 26, 2022: Utah's 18-week ban injunction is lifted
- June 27, 2022: Utah's total ban is enjoined, but 18-week ban is allowed to go into effect
- Sources: `https://www.acluutah.org/en/news/understanding-ongoing-litigation-abortion-care-utah`

25. West Virginia

- June 29, 2022: Attorney General states the 1849 law which banned and criminalized abortion is enforceable, but there was considerable uncertainty around the law and providers stopped the procedure
- Preliminary injunction is granted on the 1849 law
- September 13, 2022: Governor signs modern law banning abortion in nearly all cases
- Sources: `https://mountainstatespotlight.org/2022/07/25/west-virginia-lawmakers-first-step-banning-abortions/`, `https://web.archive.org/web/20220811212629/https://www.acluwv.org/sites/default/files/field_documents/22-c-556_opinion_and_order_filed_7.20.22.pdf`, `https://www.politico.com/news/2022/09/16/west-virginia-jim-justice-abortion-ban-law-00057255`, `https://web.archive.org/web/20221205033442/https://ago.wv.gov/Documents/Final%20Dobbs%20Memorandum.pdf`

26. Wisconsin

- June 24, 2022: Providers stop abortion care given uncertainty around enforceability of 1849 law criminalizing procedure

- June 28, 2022: Attorney General sues State seeking judgement that the 1849 ban is not enforceable, but uncertainty remained and providers limited procedure
- September 23, 2023: Dane County Circuit Court rules the 19th century law applies to infanticide, encouraging providers to re-start care

- Sources: https://www.jsonline.com/story/news/politics/2022/06/24/overturning-roe-sets-stage-wisconsins-1849-ban-take-effect/7703590001/, https://clearinghouse.net/case/43586/, https://www.npr.org/sections/health-shots/2023/09/21/1200610927/abortions-resume-in-wisconsin-after-15-months-of-legal-uncertainty

27. Wyoming

    - March 10, 2022: Wyoming passes a near-total abortion ban which is unenforceable
    - July 22, 2022: Governor certifies the near-total ban
    - July 27, 2022: District Court Judge grants temporary restraining order hours after the law goes into effect
    - August 10, 2022: Preliminary injunction is issued to continue to prevent ban from coming into effect
    - Sources: https://reproductiverights.org/maps/state/wyoming/, https://wyofile.com/abortion-in-wyoming/

B Additional Details on Data

B.1 Abortion Rate Data

Table B1 shows the availability of county-year abortion data by state. Certain states have yet to update their data to 2022, and others have chosen to stop reporting county-level abortion data. More details about the abortion rate data are provided in the appendix of Caraher (2023).

B.2 Birth Certificate Data

The birth certificate data used in this study is from the National Center for Health Statistics (NCHS). The use of this data is restricted, and is available to researchers through an application process. This data includes individual-level data from birth certificates from all 50 states and the District of Columbia. This data includes information on the mother, father, and child, as well as information on the birth itself. To calculate fertility rates, the number of births in a given county-year combination is divided by the total female population of reproductive age in that county-year combination divided by 1000. The number of births is calculated by counting the individual number of birth certificates. The race and ethnicity of the infant is determined by the entry for the mother's race and ethnicity as reported on the birth certificate. To calculate race and ethnic-specific fertility rates, the number of births to a mother of a specific race and ethnicity in a given county-year combination is divided by the total number of women of reproductive age of that race or ethnicity divided by 1000. Birth weights are reported in grams on the birth certificates, and very low birth weight is defined as a birth weight of less than 1500 grams, with births meeting that condition being assigned a value of one and all others being assigned a value of zero.

B.3 Death Certificate Data

The death certificate data used in this study is from the National Center for Health Statistics (NCHS). The use of this data is restricted, and is available to researchers through an application process. This data includes individual-level data from death certificates from all 50 states and the District of Columbia. This data includes information on the deceased individual including age, race, and ethnicity, as well as information on the cause and location. Infant deaths are calculated by counting the individual number of death certificates for infants under the age of one. To calculate infant mortality rates, the total number of deaths of infants under the age of one in a given county-year combination is divided by the total number of live births in that county-year, divided by 1000. The total number of live births in a given county-year combination is from the birth certificate data. To calculate race and ethnicity-specific infant mortality rates, the number of deaths of infants under the age of one of a specific race or ethnicity in a given county-year combination is divided by the total number of live births to mothers of the same race or ethnicity in that county-year, divided by 1000.

B.4 Population Data

The population data is from the Census Bureau's Population Estimates Program, specifically the intercensal estimates of county-level population by race, ethnicity, and age groups. The most recent intercensal estimates, based on the 2020 census, are used to compute county-level populations. To calculate population shares, I divide the race-specific, ethnicity-specific, or race-age-ethnicity-specific population by the total population of the county.

B.5 Economic and Political Data

Data on county-level unemployment rates are from the Bureau of Labor Statistics' Local Area Unemployment Statistics (LAUS) program. These data report annual unemployment rates for each county.

To compute county-level Republican vote shares, I use the presidential election results from the MIT Election Data and Science Lab. The Republican vote share is the percentage of votes cast for the Republican candidate in the most recent presidential election, implying this variable changes at the county-level every four years. The vote share is calculated as the number of votes cast for the Republican candidate divided by the total number of votes cast in the county.

I use data on county-level poverty rates from the Census Bureau's Small Area Income and Poverty Estimates (SAIPE) program. I also use data on county-level median household income from the Census Bureau's Small Area Income and Poverty Estimates (SAIPE) program. These data report annual estimates of poverty rates and median household income for each county in the United States. I use the API version of the SAIPE data to access the most recent estimates.

Data on the rural or urban status of the counties are from the 2013 Rural-Urban Continuum Codes from the Economic Research Service of the U.S. Department of Agriculture. These data classify counties into one of nine categories based on the population size of the county and the proximity of the county to a metropolitan area. I define counties as rural if they are classified as any non-metropolitan county.

I use the R package tigris (`https://cran.r-project.org/package=tigris`) to access shapefiles of the United States and its counties. I also use this package for data on the geographic center of each county.

B.6 National Survey for Family Growth Data

The National Survey for Family Growth (NSFG) is a nationally representative survey conducted by the National Center for Health Statistics (NCHS). These data reported at the pregnancy-level, meaning that each observation is a pregnancy, and women in the survey can have multiple pregnancies, meaning the same women can appear in the data multiple times.

I drop all pregnancies that are not live births, since those are the only pregnancies that would be recorded in the birth certificate data. I also limit the variables I train my model to those that fit the following conditions: i) they are available in the birth certificate data with similar or matching coding schemes, ii) they are reported for all waves of the NSFG data, and iii) they are reported in the NSFG data at either a) the pregnancy-level, or b) the mother-level, but are constant across pregnancies for the same mother. This includes variables like race, ethnicity, and in what country they are born. This also means that education, which is only reported at the time of the NSFG interview, is not included in the model, despite being in the birth certificate data.

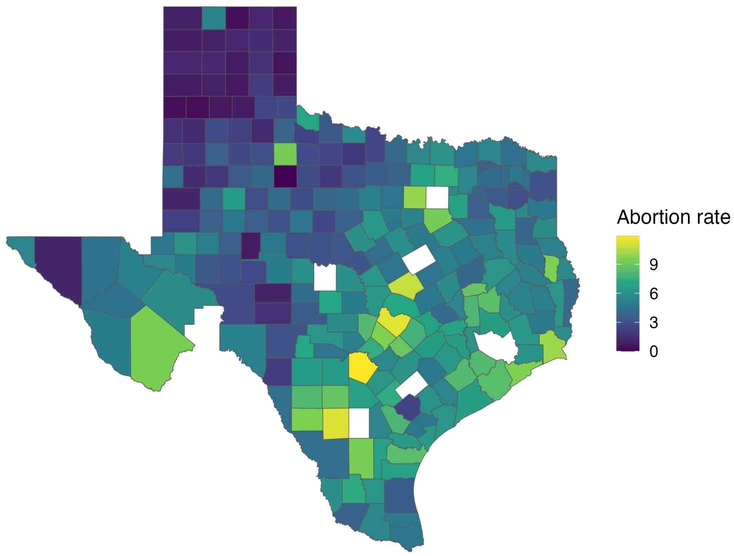
Table B1: County-year availability of abortion data

	State	Start Year	End Year
1	Alabama	1998	2020
2	Arizona	1990	2021
3	Colorado	2000	2022
4	Delaware	2000	2021
5	Florida	2017	2022
6	Georgia	1994	2020
7	Hawaii	1996	2021
8	Idaho	1992	2021
9	Illinois	1995	2020
10	Indiana	2000	2022
11	Kansas	1998	2022
12	Louisiana	2004	2021
13	Massachusetts	1999	2022
14	Michigan	1998	2022
15	Minnesota	1999	2022
16	Mississippi	1980	2021
17	Missouri	1999	2021
18	Montana	1998	2021
19	Nebraska	2013	2022
20	Nevada	2000	2021
21	New Mexico	2011	2022
22	New York	1997	2020
23	North Carolina	2000	2022
24	North Dakota	1998	2022
25	Ohio	1995	2021
26	Oklahoma	2002	2011
27	Oregon	1989	2022
28	Pennsylvania	1995	2021
29	South Carolina	1998	2020
30	South Dakota	1997	2022
31	Tennessee	2008	2020
32	Texas	2001	2022
33	Utah	1998	2022
34	Vermont	1998	2021
35	Virginia	1995	2020
36	Washington	1997	2022
37	Wisconsin	1994	2021

Notes: This table shows availability of county-year abortion data by state. Source: Author's calculations using county-level abortion data from various state-specific sources, and Caraher (2023).

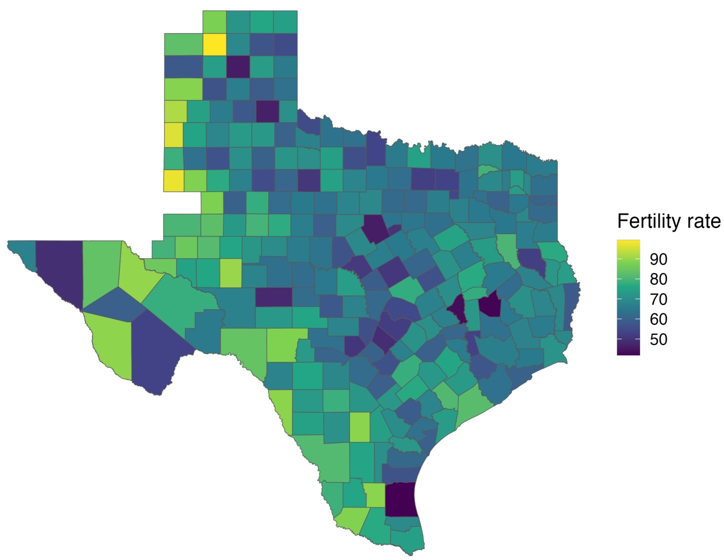
C Additional Figures

Figure C1: Average abortion rates in Texas counties, 2016–2020



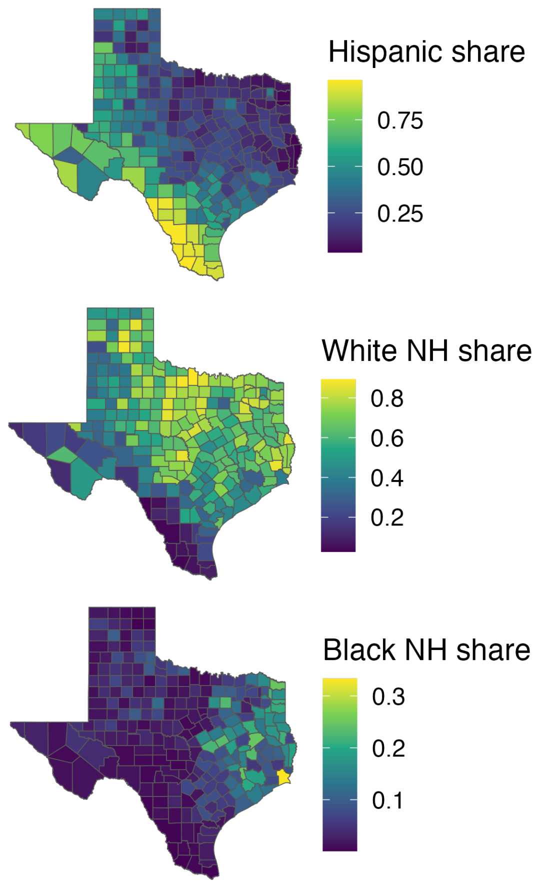
Notes: This figure shows the average abortion rates from 2016–2020 by county of residence in Texas. Abortion rates are measured as the number of abortions per 1,000 women aged 15-44. Counties with large outliers (abortion rates greater than 12) are omitted. Source: Author's calculations using county-level abortion data updated from Caraher (2023) and Census data.

Figure C2: Average fertility rates in Texas counties, 2016–2020



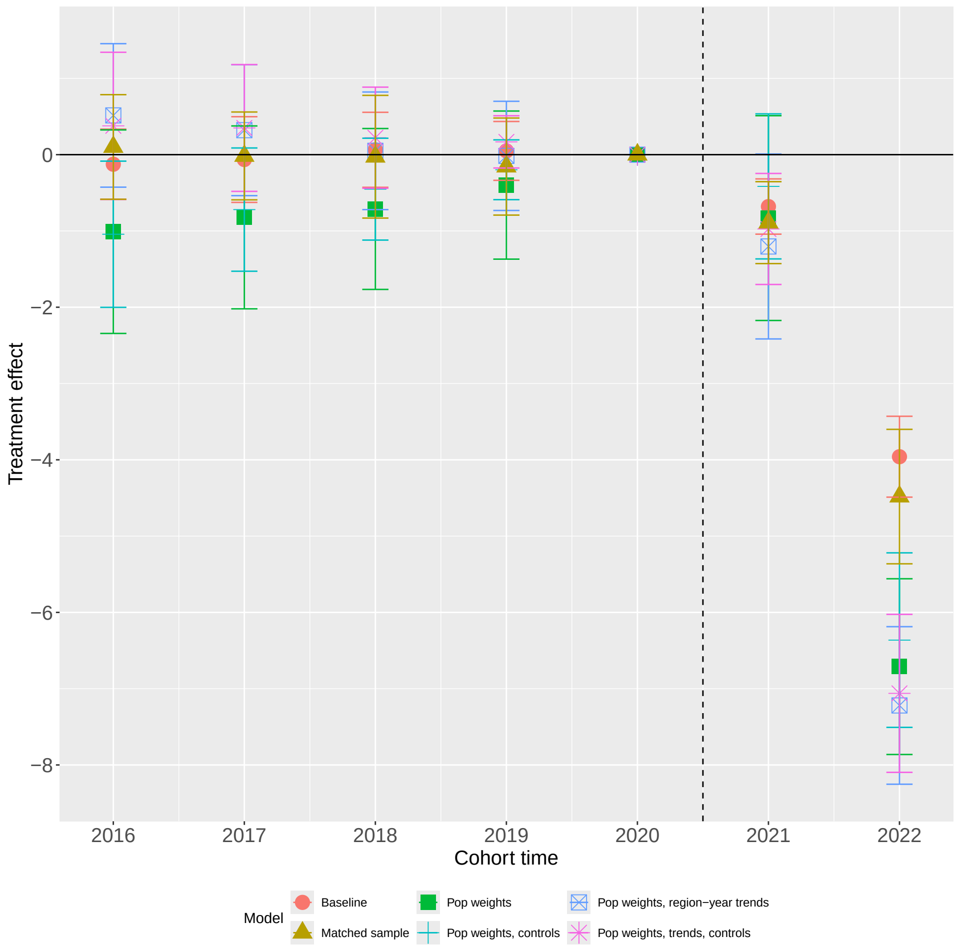
Notes: This figure shows the average fertility rates from 2016–2020 by county of residence in Texas. Fertility rates are measured as the number of births per 1,000 women aged 15-44. Counties with large outliers (fertility rates less than 100) are omitted. Source: Author's calculations using NCHS and Census data.

Figure C3: Racial/ethnic population shares by county, 2016–2020



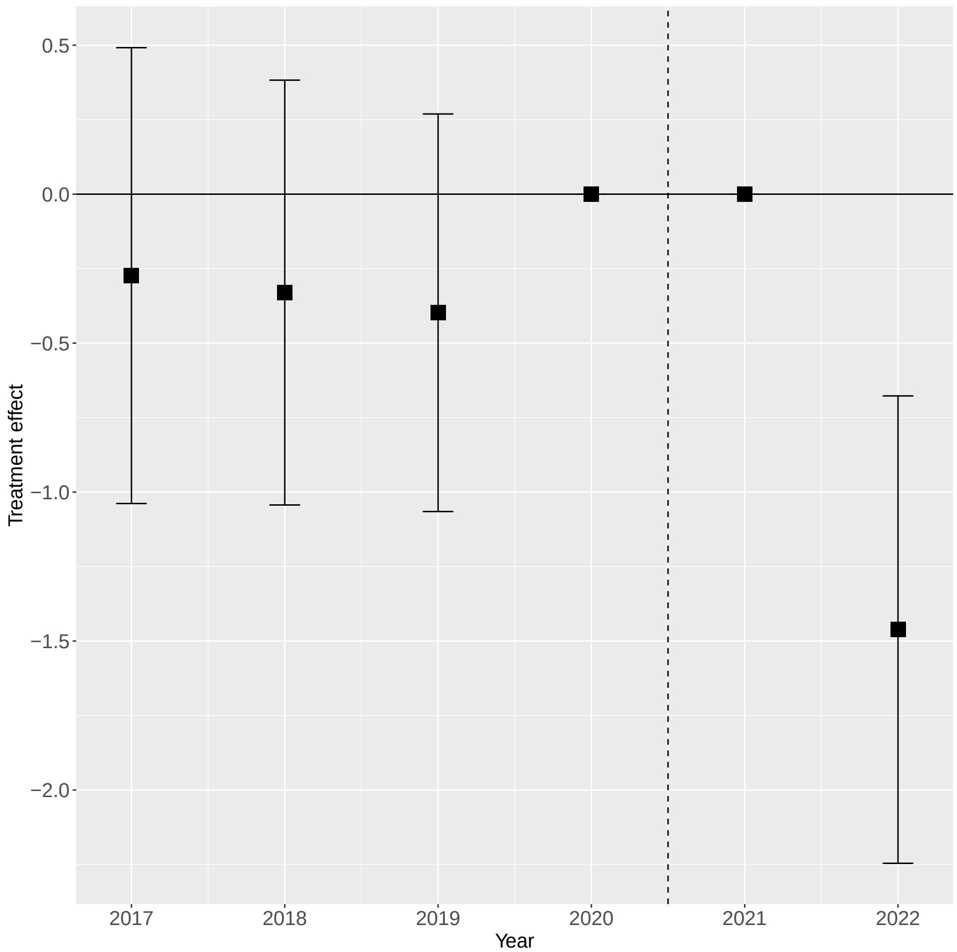
Notes: This figure shows the population shares by county averaged from 2016–2020. The top panel shows the population shares for Hispanic residents, the middle panel shows the population shares for White non-Hispanic residents, and the bottom panel shows the population shares for Black non-Hispanic residents.

Figure C4: Abortion rate event study combined specifications



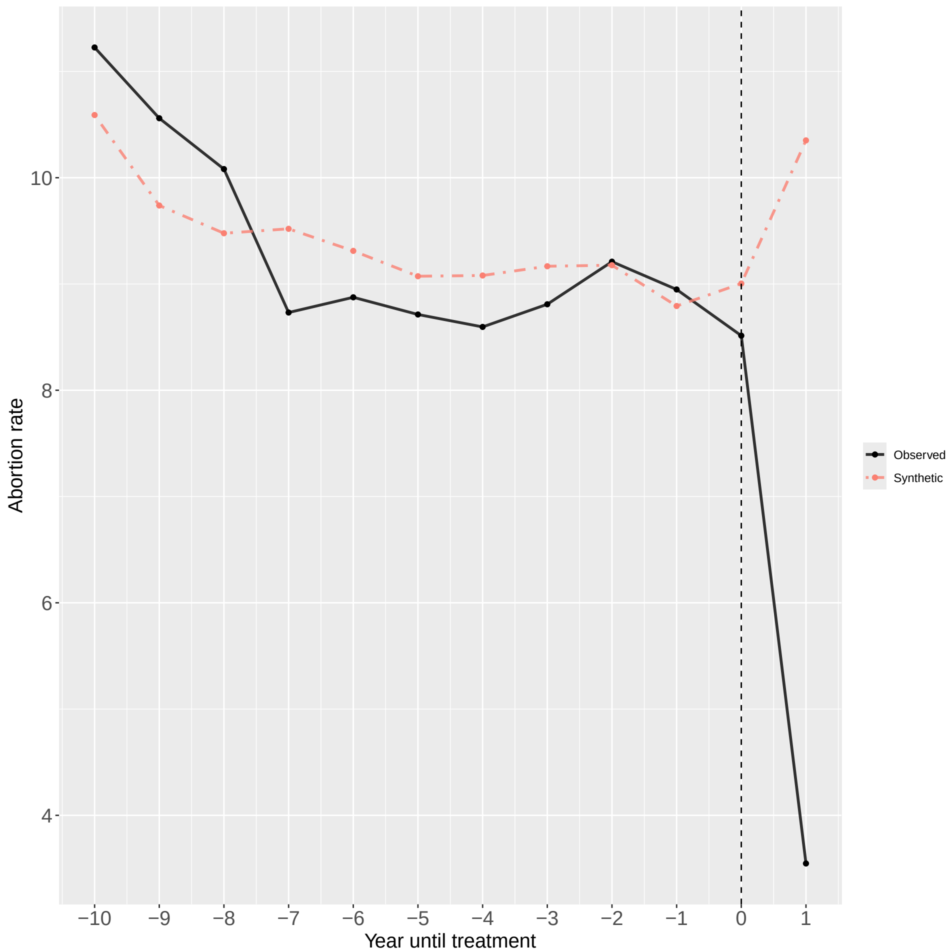
Notes: This figure shows the difference-in-differences event study results of the effect of the abortion ban in Texas on abortion rates. Abortion rates are measured as the number of abortions per 1,000 women aged 15-44. Female population aged 15-44 in thousands in 2020 is used as a constant denominator. The sample is restricted to counties with more than 1000 women of reproductive age in 2020. Each color and shape represents a different specification. Control variables include county-level unemployment rates, poverty rates, log median household income, labor force participation rates, Republican vote shares, as well as county-level population shares of teenagers, adults aged 20-24, adults aged 25-34, adults aged 35-44, Black non-Hispanic women of reproductive age, white non-Hispanic women of reproductive age, Hispanic women of reproductive age, the total share of women of reproductive age, and the total number of women of reproductive age. Population weights refer to total county population. Standard error bars clustered at the county and state-year are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure C5: Abortion ban event study specification using estimated 6-month (Jan-June) abortion rates



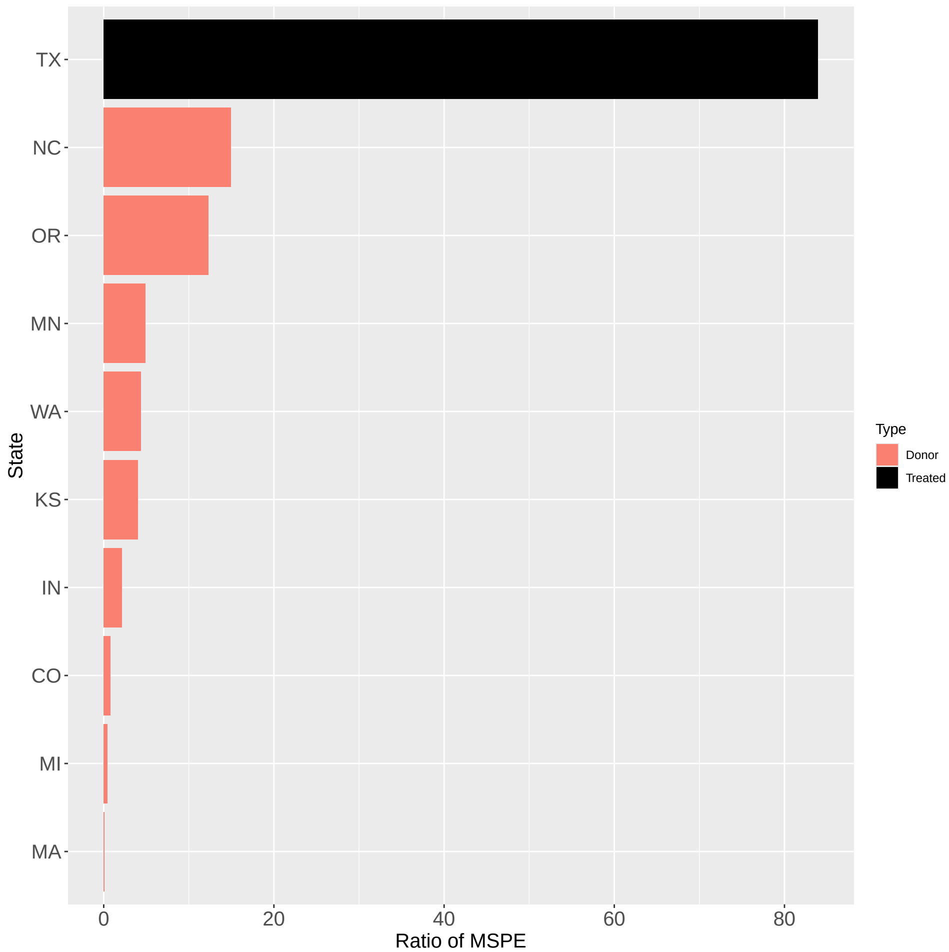
Notes: This figure event study results of the effect of the abortion ban in Texas on abortion rates using an estimated first half of the year (Jan-June) abortion rate. The first half of the year (Jan-June) abortion rate is estimated using state-month data on abortion rates from the Texas Department of Health and Human Services. Abortion rates are measured as the number of abortions per 1,000 women aged 15-44. First, for each year, the proportion of total state abortion performed from January to June is calculated. Then, the total number of abortions in each county is multiplied by this proportion to estimate the number of abortions in the first 6 months of the year in Texas for 2017-2020. The difference-in-differences is then estimated using these computed 6-month rates for 2017-2020, compared to the entire year of 2022. Since the number of abortions after September 2022 is near zero, the 6-month rate is a good approximation of the total year rate. The sample is restricted to counties with more than 1000 women of reproductive age in 2020. Standard error bars clustered at the county and state-year are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, the Texas Department of Health and Human Services, and Census data.

Figure C6: Synthetic control estimate of the effect of the abortion ban on abortion rates



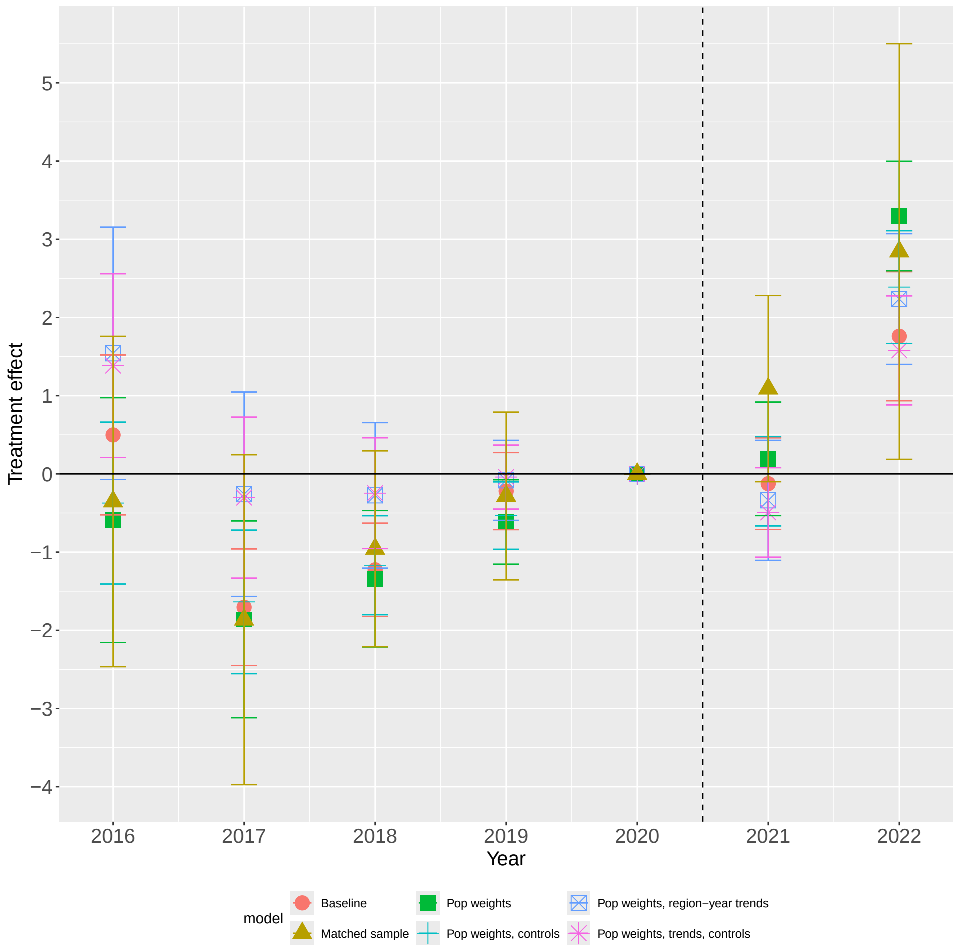
Notes: This figure shows the synthetic control estimate of the effect of the abortion ban in Texas on abortion rates. Abortion rates are measured as the number of abortions per 1,000 women aged 15-44. The black line shows the actual abortion rate in Texas, and the red line shows the synthetic control estimate of the abortion rate in Texas, which is a weighted average of the abortion rates in comparable control states. The pool of control states are those which did not pass an abortion ban in 2022. The weights are selected by matching outcomes in Texas to outcomes in control states based on pre-treatment abortion rates, unemployment rates, poverty rates, log median household income, labor force participation rates, Republican vote shares, as well as state-level population shares of teenagers, adults aged 20-24, adults aged 25-34, adults aged 35-44, Black non-Hispanic women of reproductive age, white non-Hispanic women of reproductive age, Hispanic women of reproductive age, the total share of women of reproductive age, and the total number of women of reproductive age. Source: Author's calculations using county-specific abortion rates from various state sources, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure C7: Synthetic control estimate of the effect of the abortion ban on abortion rates ranked mean squared prediction error



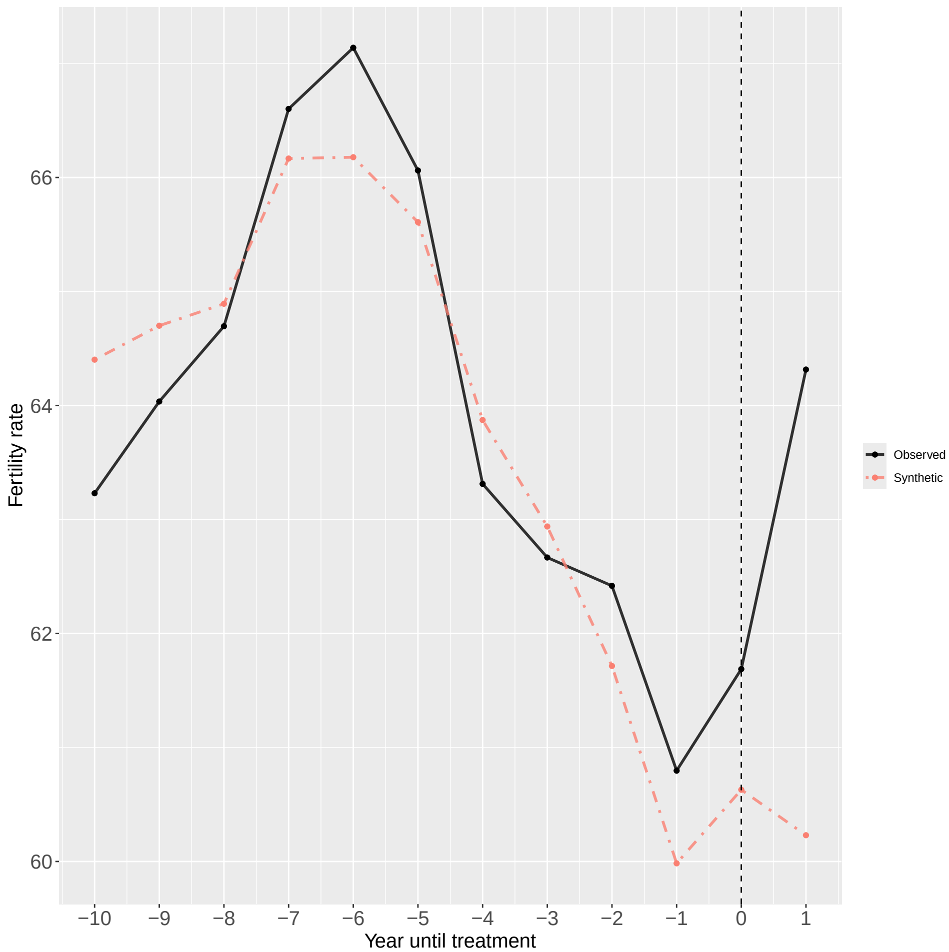
Notes: This figure shows the ranked root mean squared prediction error (RMSPE) of the synthetic control estimate of the effect of the abortion ban in Texas on abortion rates. Abortion rates are measured as the number of abortions per 1,000 women aged 15-44. The RMSPE for each state is estimated as a placebo test, where the abortion ban is assigned to each state in the pool of control states, and the synthetic control estimate is calculated. The black line shows the actual RMSPE for Texas, and the red lines show the RMSPE for each placebo. Source: Author's calculations using NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure C8: Fertility rate event study - combined specifications



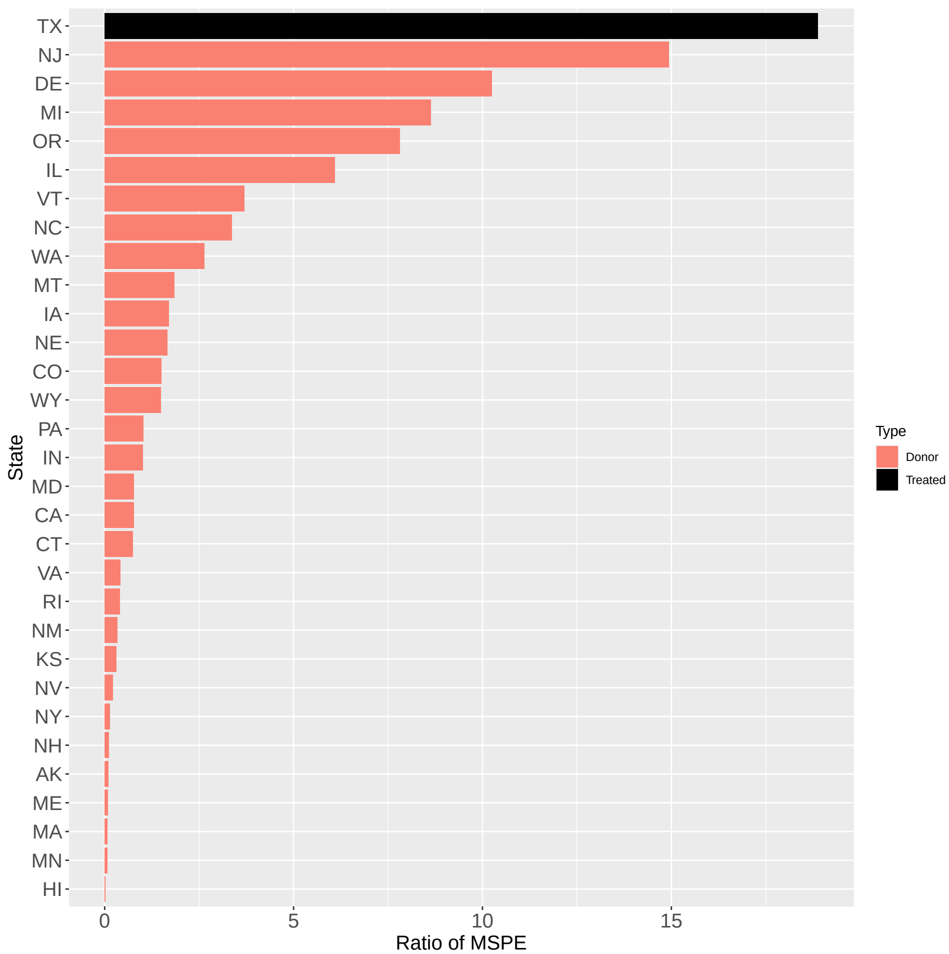
Notes: This figure shows the difference-in-differences event study results of the effect of the abortion ban in Texas on fertility rates. Fertility rates are measured as the number of births per 1,000 women aged 15-44. Female population aged 15-44 in thousands in 2020 is used as a constant denominator. The sample is restricted to counties with more than 1000 women of reproductive age in 2020. Each color and shape represents a different specification. Control variables include county-level unemployment rates, poverty rates, log median household income, labor force participation rates, Republican vote shares, as well as county-level population shares of teenagers, adults aged 20-24, adults aged 25-34, adults aged 35-44, Black non-Hispanic women of reproductive age, white non-Hispanic women of reproductive age, Hispanic women of reproductive age, the total share of women of reproductive age, and the total number of women of reproductive age. Population weights refer to total county population. Standard error bars clustered at the county and state-year are reported at the 95% level. Source: Author's calculations using NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure C9: Synthetic control estimate of the effect of the abortion ban on fertility rates



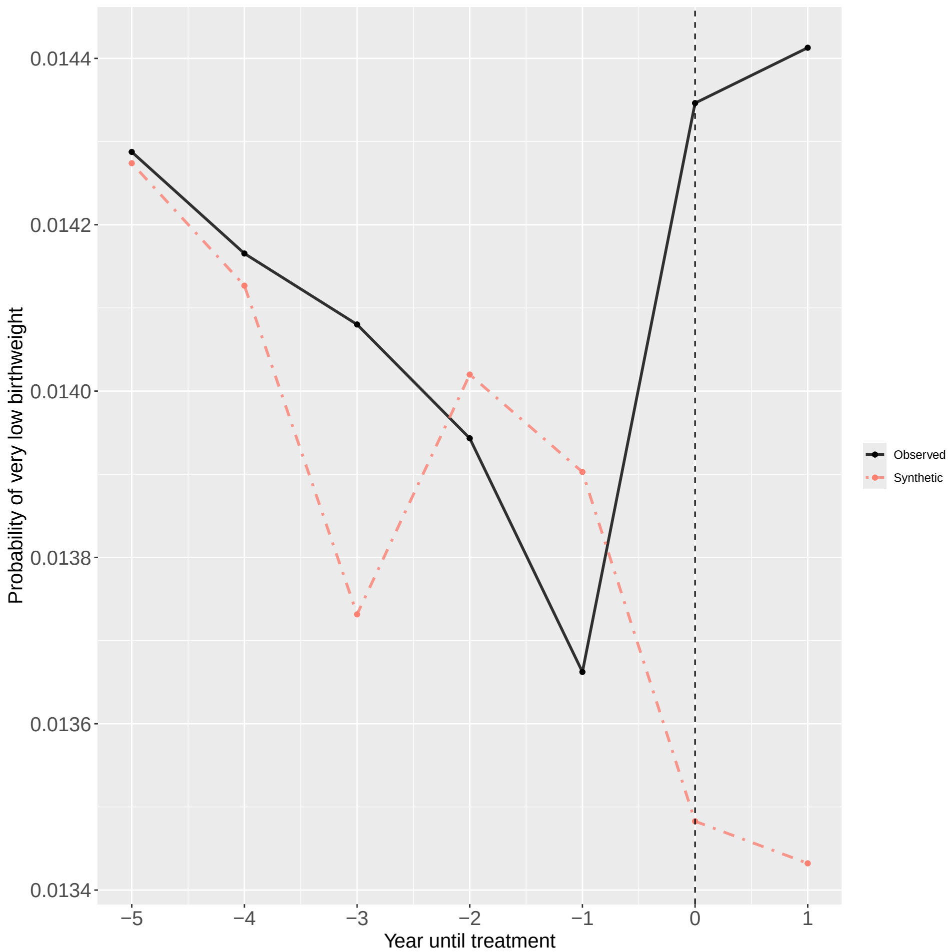
Notes: This figure shows the synthetic control estimate of the effect of the abortion ban in Texas on fertility rates. Fertility rates are measured as the number of births per 1,000 women aged 15-44. The black line shows the actual fertility rate in Texas, and the red line shows the synthetic control estimate of the fertility rate in Texas, which is a weighted average of the fertility rates in comparable control states. The pool of control states are those which did not pass an abortion ban in 2022. The weights are selected by matching outcomes in Texas to outcomes in control states based on pre-treatment fertility rates, unemployment rates, poverty rates, log median household income, labor force participation rates, and Republican vote shares. Source: Author's calculations using NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure C10: Synthetic control estimate of the effect of the abortion ban on fertility rates ranked mean squared prediction error



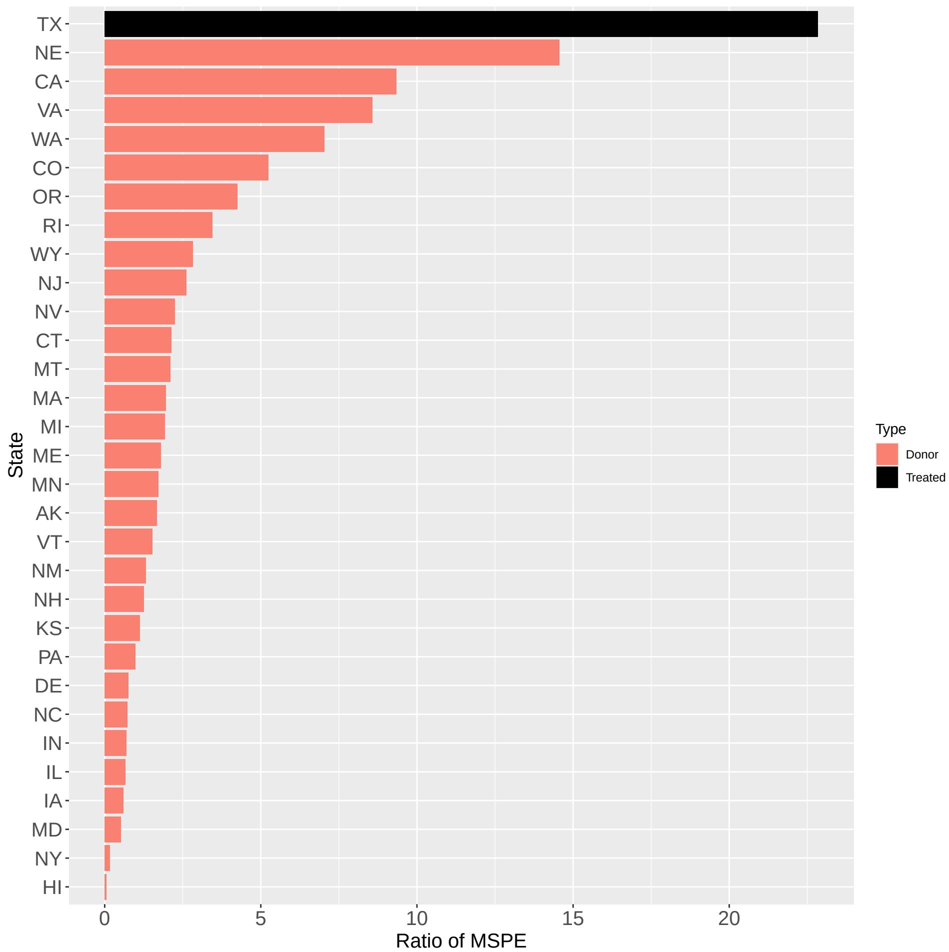
Notes: This figure shows the ranked root mean squared prediction error (RMSPE) of the synthetic control estimate of the effect of the abortion ban in Texas on fertility rates. Fertility rates are measured as the number of births per 1,000 women aged 15-44. The RMSPE for each state is estimated as a placebo test, where the abortion ban is assigned to each state in the pool of control states, and the synthetic control estimate is calculated. The black line shows the actual RMSPE for Texas, and the red lines show the RMSPE for each placebo. Source: Author's calculations using NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure C11: Synthetic control estimate of the effect of the abortion ban on very low birth weights



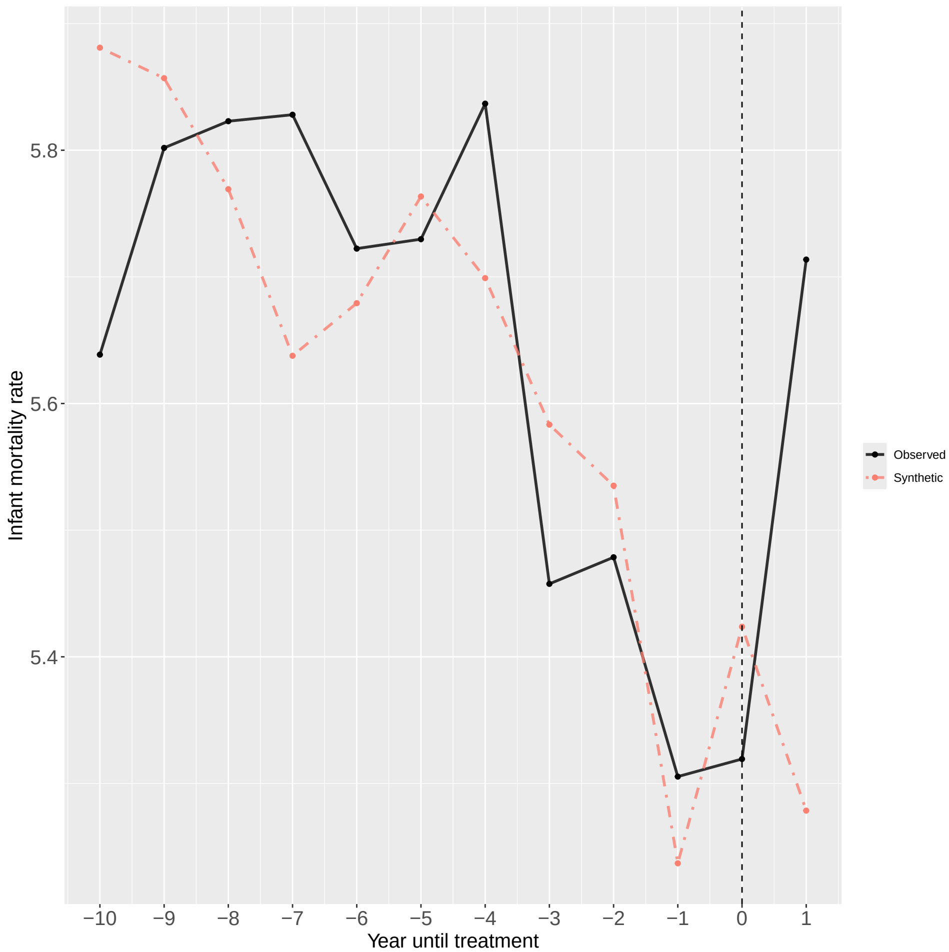
Notes: This figure shows the synthetic control estimate of the effect of the abortion ban in Texas on rates of babies with very low birth weight. Very low birth weight rates are calculated as the proportion of births with a birth weight of less than 1500 grams. The black line shows the actual rate in Texas, and the red line shows the synthetic control estimate of the rate in Texas, which is a weighted average of the rates in comparable control states. The pool of control states are those which did not pass an abortion ban in 2022. The weights are selected by matching outcomes in Texas to outcomes in control states based on pre-treatment rates of infants with very low birth weight, unemployment rates, poverty rates, log median household income, labor force participation rates, and Republican vote shares. Source: Author's calculations using NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure C12: Synthetic control estimate of the effect of the abortion ban on very low birth weight rates ranked mean squared prediction error



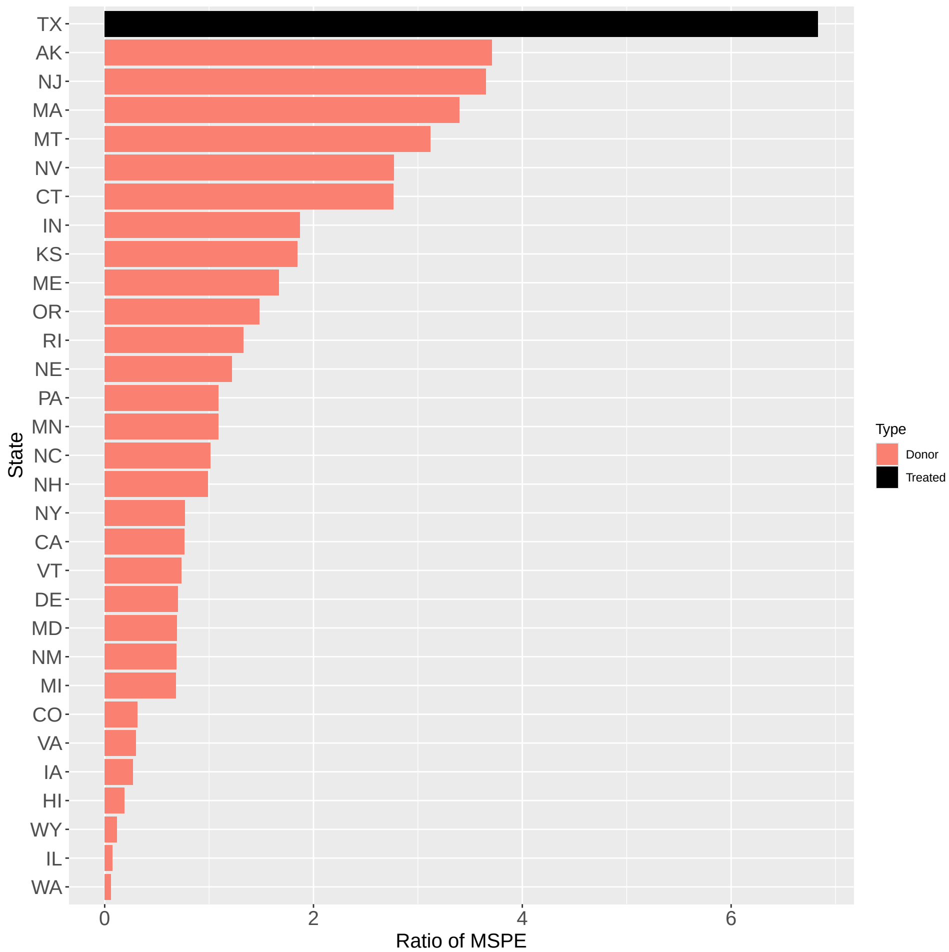
Notes: This figure shows the ranked root mean squared prediction error (RMSPE) of the synthetic control estimate of the effect of the abortion ban in Texas on very low birth weight rates. Very low birth weight rates are calculated as the proportion of births with a birth weight of less than 1500 grams. The RMSPE for each state is estimated as a placebo test, where the abortion ban is assigned to each state in the pool of control states, and the synthetic control estimate is calculated. The black line shows the actual RMSPE for Texas, and the red lines show the RMSPE for each placebo. Source: Author's calculations using NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure C13: Synthetic control estimate of the effect of the abortion ban on infant mortality rates



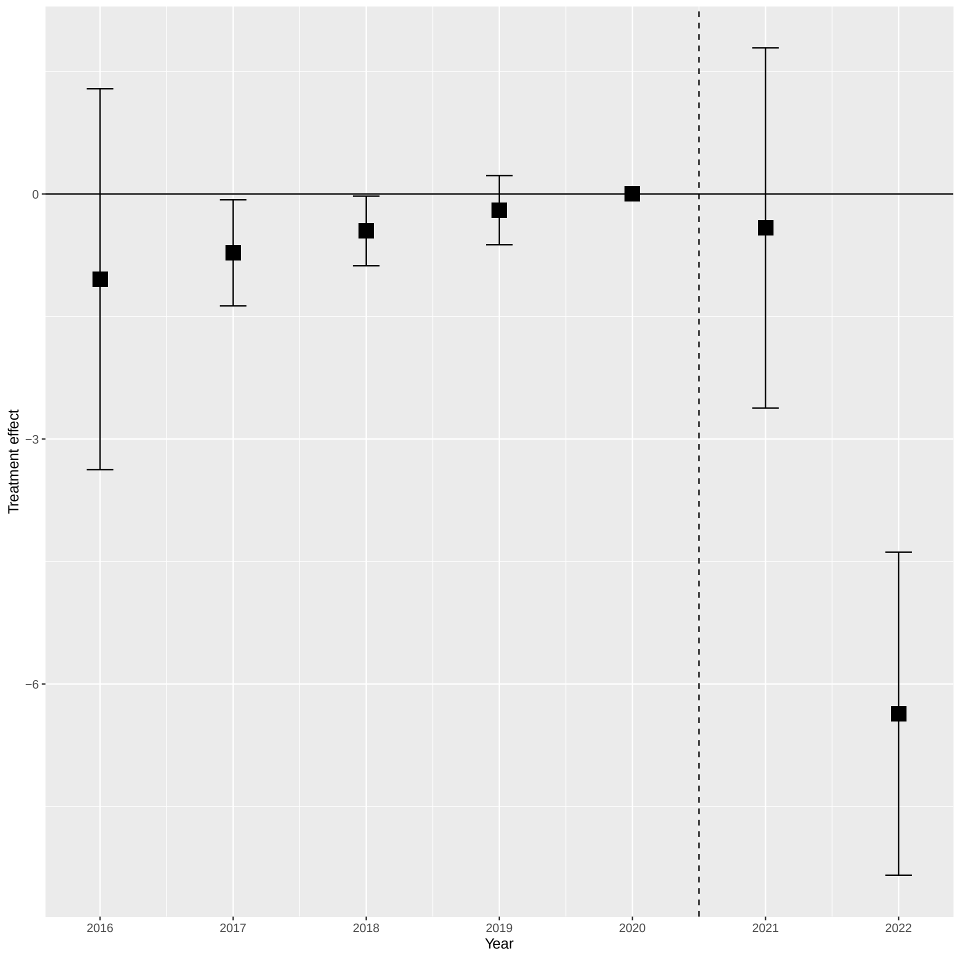
Notes: This figure shows the synthetic control estimate of the effect of the abortion ban in Texas on infant mortality rates. Infant mortality rates are calculated as the number of infant deaths per 1,000 live births. The black line shows the actual rate in Texas, and the red line shows the synthetic control estimate of the rate in Texas, which is a weighted average of the rates in comparable control states. The pool of control states are those which did not pass an abortion ban in 2022. The weights are selected by matching outcomes in Texas to outcomes in control states based on pre-treatment infant mortality rates, unemployment rates, poverty rates, log median household income, labor force participation rates, Republican vote shares, state minimum wages, as well as state-level population shares of teenagers, adults aged 20-24, adults aged 25-34, adults aged 35-44, Black non-Hispanic women of reproductive age, white non-Hispanic women of reproductive age, Hispanic women of reproductive age, the total share of women of reproductive age, the total number of women of reproductive age, and the total number of live births. Source: Author's calculations using NCHS death certificate data, NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure C14: Synthetic control estimate of the effect of the abortion ban on infant mortality rates ranked mean squared prediction error



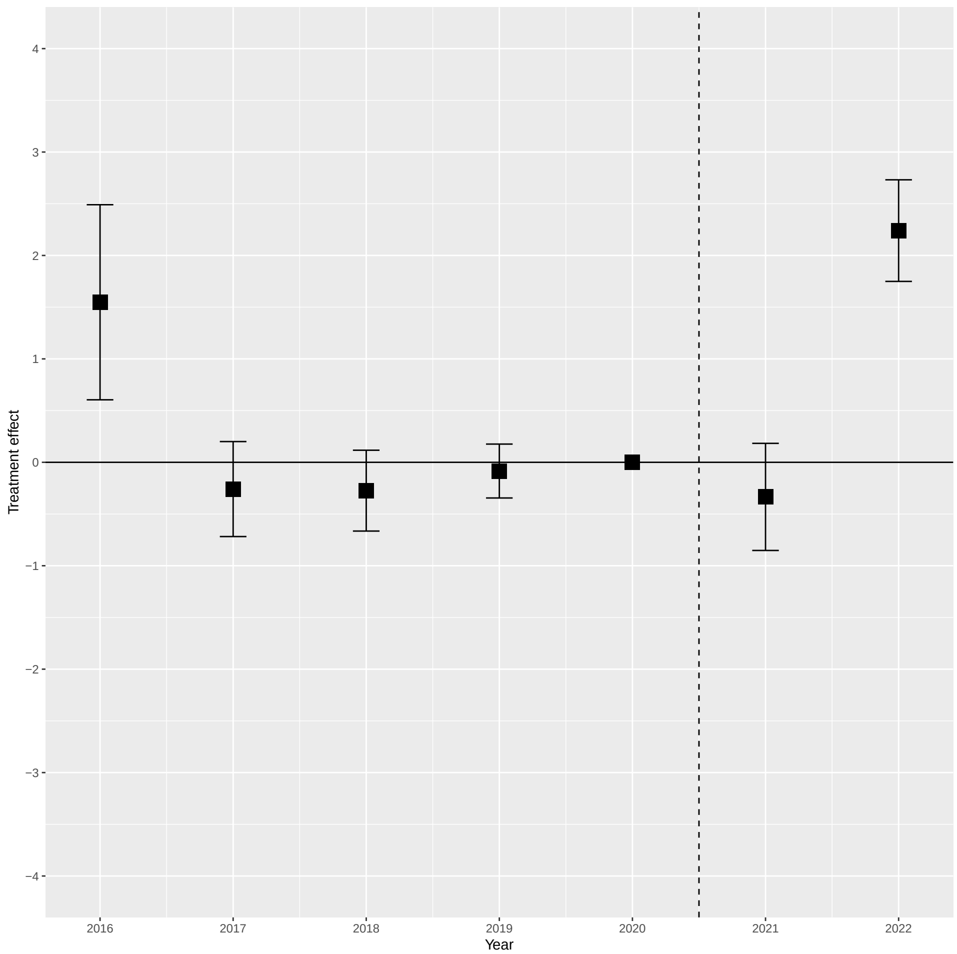
Notes: This figure shows the ranked root mean squared prediction error (RMSPE) of the synthetic control estimate of the effect of the abortion ban in Texas on infant mortality rates. Infant mortality rates are calculated as the number of infant deaths per 1,000 live births. The RMSPE for each state is estimated as a placebo test, where the abortion ban is assigned to each state in the pool of control states, and the synthetic control estimate is calculated. The black line shows the actual RMSPE for Texas, and the red lines show the RMSPE for each placebo. Source: Author's calculations using NCHS death certificate data, NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure C15: Event study estimates of the effect of the abortion ban on abortion rates using alternative standard errors



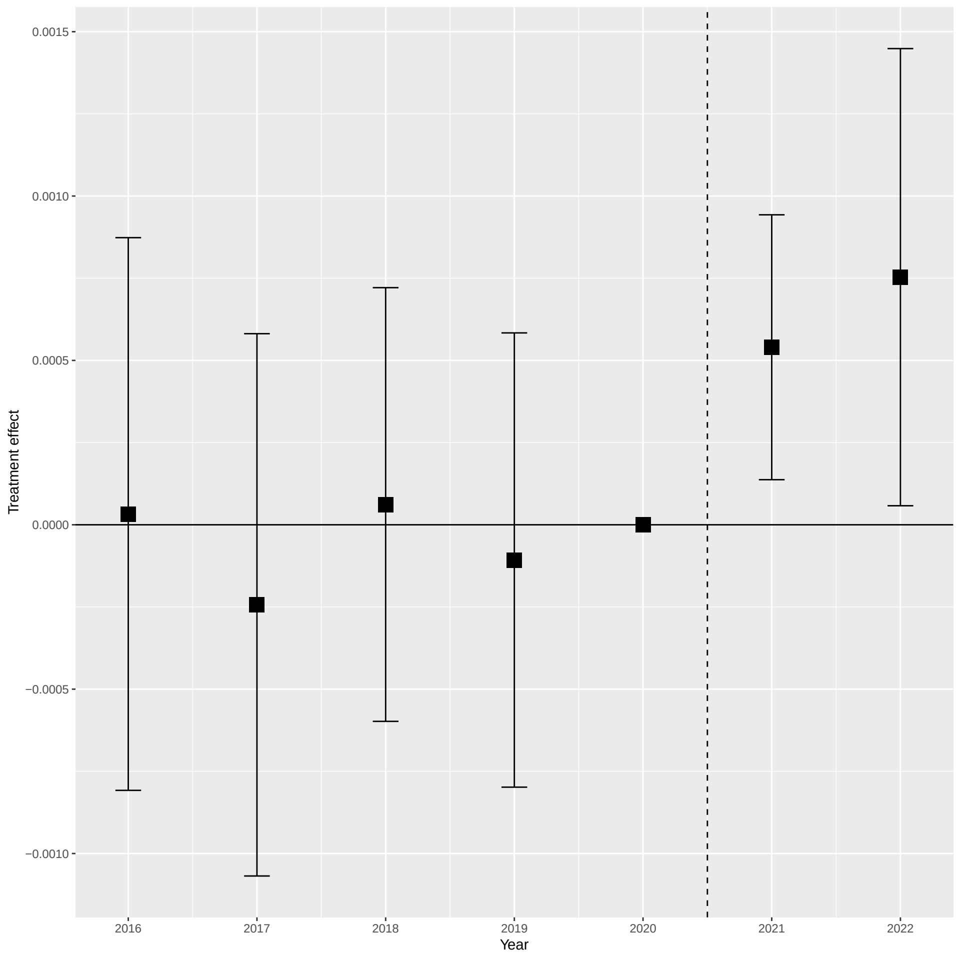
Notes: This figure shows the difference-in-differences event study results of the effect of the abortion ban in Texas on abortion rates. The vertical axis is measured in (change in) abortions per 1,000 women aged 15-44. The dashed line represents the enactment of the abortion ban in Texas in September 2021. Female population aged 15-44 in thousands in 2020 is used as a constant denominator. The sample is restricted to counties with more than 1000 women of reproductive age in 2020. The event study is estimated using the baseline specification with no weights or control variables. Standard error bars clustered at the state-level are reported at the 95% level using the Ferman and Pinto (2019) method. Source: Author's calculations using county-level abortion data from various state-specific sources and Census data. and control variables sources listed in the text.

Figure C16: Event study estimates of the effect of the abortion ban on fertility rates using alternative standard errors



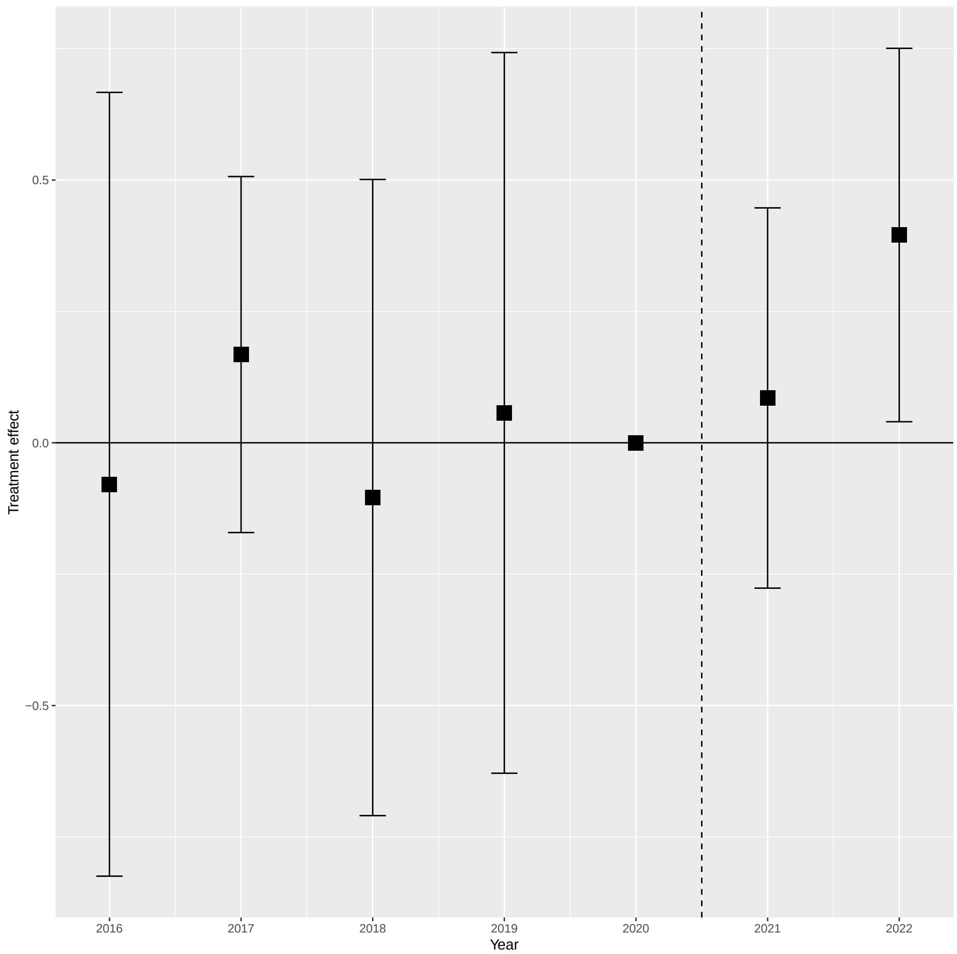
Notes: This figure shows the difference-in-differences event study results of the effect of the abortion ban in Texas on fertility rates. The vertical axis is measured in (change in) births per 1,000 women aged 15-44. The dashed line represents the enactment of the abortion ban in Texas in September 2021. Female population aged 15-44 in thousands in 2020 is used as a constant denominator. The sample is restricted to counties with more than 1000 women of reproductive age in 2020. The event study is estimated with region-specific linear trends. Standard error bars clustered at the state-level are reported at the 95% level using the Ferman and Pinto (2019) method. Source: Author's calculations using NCHS birth certificate data and Census data.

Figure C17: Event study estimates of the effect of the abortion ban on very low birth weight rates using alternative standard errors



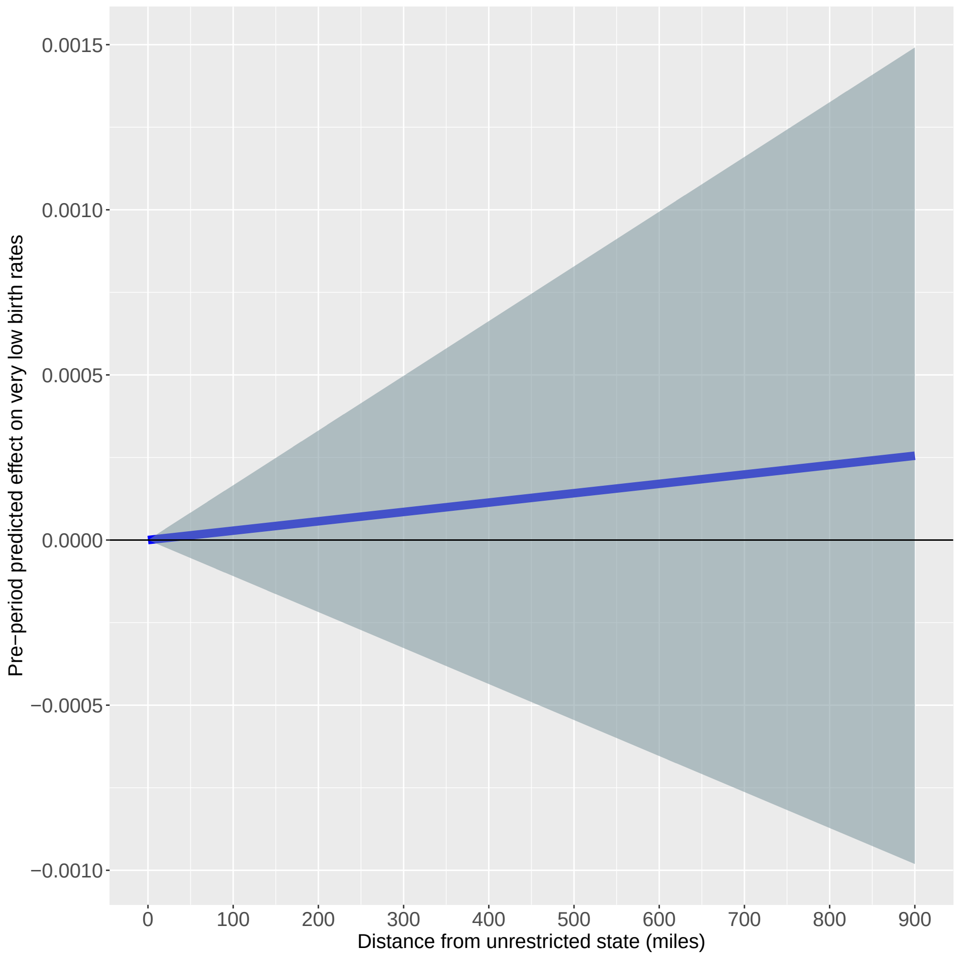
Notes: This figure shows the difference-in-differences event study results of the effect of the abortion ban in Texas on the probability of an infant being born with very low birth weight. The vertical axis is measured in (change in) the probability of a birth being very low birth weight (less than 1500 grams). The dashed line represents the enactment of the abortion ban in Texas in September 2021. The pre-treatment probability in Texas of a very low birth weight is about 1 percent. The sample is restricted to mothers aged 15-44, and counties with more than 1000 women of reproductive age in 2020. The event study is estimated using the baseline specification with no weights or control variables. Standard error bars clustered at the state-level are reported at the 95% level using the Ferman and Pinto (2019) method. Source: Author's calculations using NCHS data and Census data.

Figure C18: Event study estimates of the effect of the abortion ban on infant mortality rates using alternative standard errors



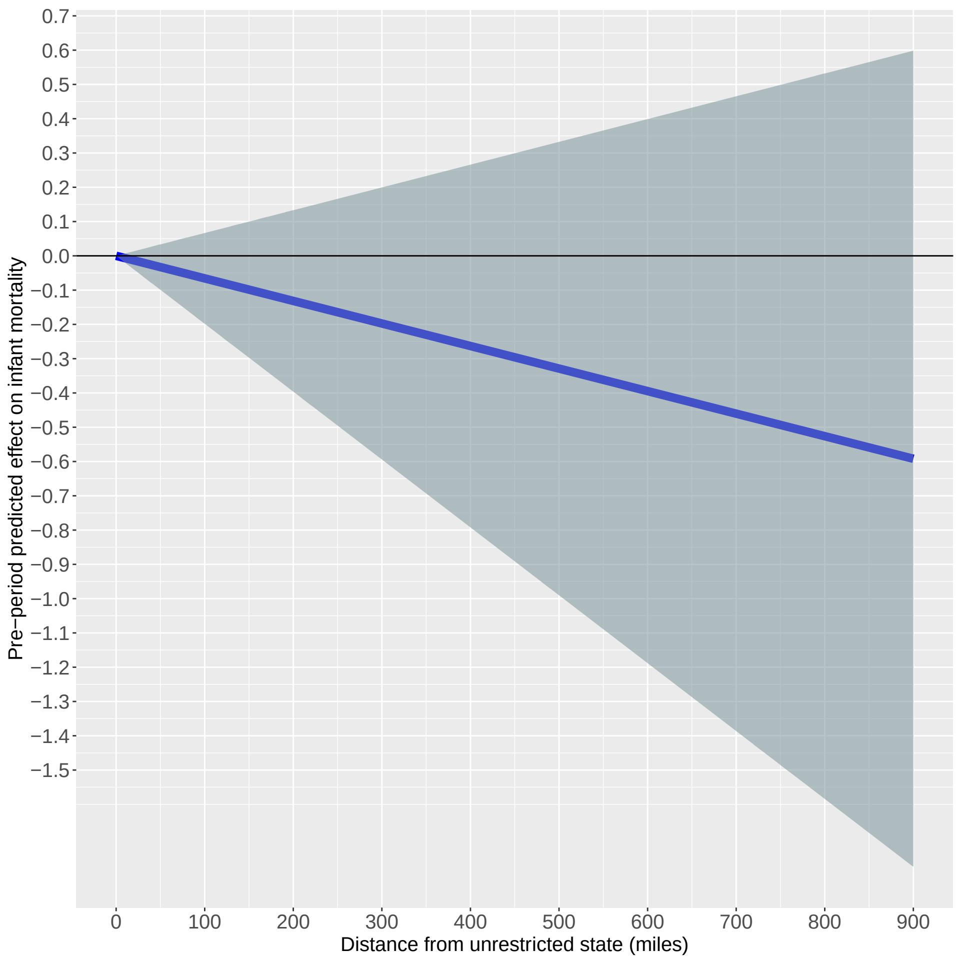
Notes: This figure shows the difference-in-differences event study results of the effect of the abortion ban in Texas on the infant mortality rate. The vertical axis is measured in (change in) the infant mortality rate (the number of infant deaths per 1,000 births). The dashed line represents the enactment of the abortion ban in Texas in September 2021. The sample is restricted to counties with more than 1000 women of reproductive age in 2020. Control variables include county-level unemployment rates, poverty rates, log median household income, labor force participation rates, Republican vote shares, as well as county-level population shares of teenagers, adults aged 20-24, adults aged 25-34, adults aged 35-44, Black non-Hispanic women of reproductive age, white non-Hispanic women of reproductive age, Hispanic women of reproductive age, the total share of women of reproductive age, and the total number of women of reproductive age. Population weights refer to total county population. Standard error bars clustered at the state-level are reported at the 95% level using the Ferman and Pinto (2019) method. Source: Author's calculations using NCHS death certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure C19: Predicted effect of distance to nearest state with unrestricted abortion access on very low birth rates prior to the abortion ban



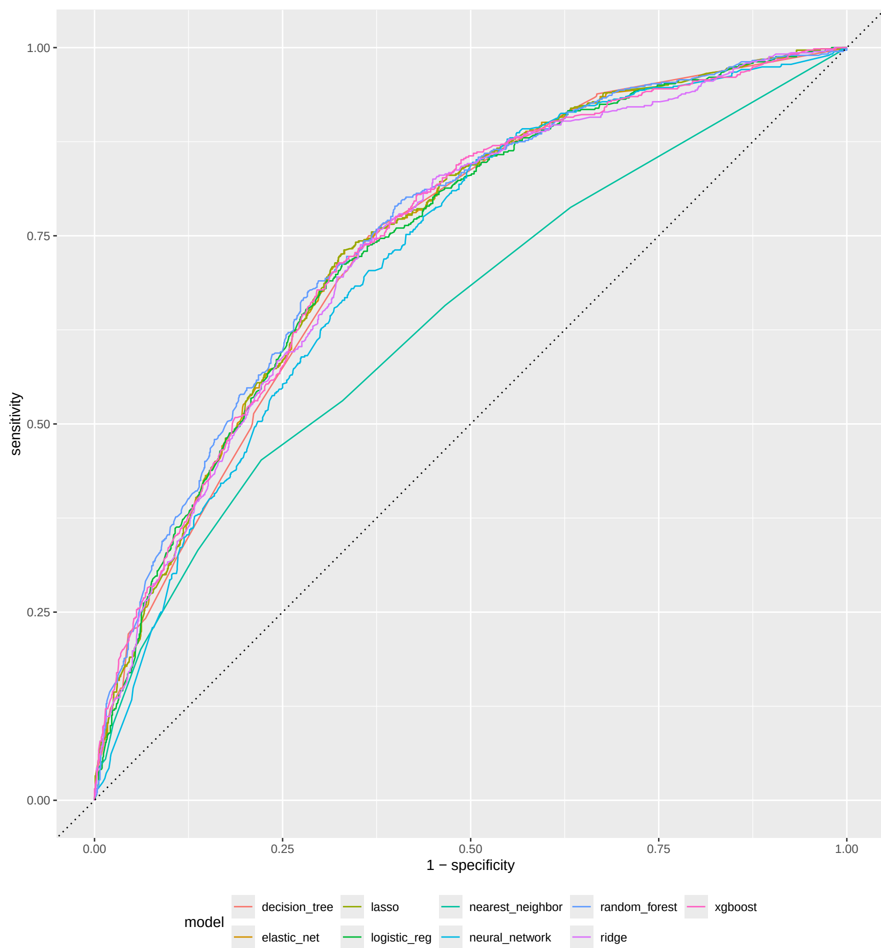
Notes: This figure shows the estimated effect of distance to the nearest state with unrestricted abortion access on likelihood of very low birth weight prior to the abortion ban in Texas. The effect is estimated using a linear regression of infant mortality rates on distance to the nearest state with unrestricted abortion access, limiting the sample to only those in Texas and limiting the years to 2016–2020. Control variables include county-level unemployment rates, poverty rates, log median household income, labor force participation rates, Republican vote shares, as well as county-level population shares of teenagers, adults aged 20-24, adults aged 25-34, adults aged 35-44, Black non-Hispanic women of reproductive age, white non-Hispanic women of reproductive age, Hispanic women of reproductive age, and the total share of women of reproductive age. Source: Author's calculations using NCHS death certificate data, NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure C20: Predicted effect of distance to nearest state with unrestricted abortion access on infant mortality rates prior to the abortion ban



Notes: This figure shows the estimated effect of distance to the nearest state with unrestricted abortion access on infant mortality rates prior to the abortion ban in Texas. Infant mortality rates are calculated as the number of infant deaths per 1,000 live births. The effect is estimated using a linear regression of infant mortality rates on distance to the nearest state with unrestricted abortion access, limiting the sample to only those in Texas and limiting the years to 2016–2020. Control variables include county-level unemployment rates, poverty rates, log median household income, labor force participation rates, Republican vote shares, as well as county-level population shares of teenagers, adults aged 20-24, adults aged 25-34, adults aged 35-44, Black non-Hispanic women of reproductive age, white non-Hispanic women of reproductive age, Hispanic women of reproductive age, the total share of women of reproductive age, and the total number of women of reproductive age. Source: Author's calculations using NCHS death certificate data, NCHS birth certificate data, Census data, Policy Surveillance Program data, and control variables sources listed in the text.

Figure C21: ROC curves for predictive models



Notes: This figure shows the ROC curves for nine different predictive models of unintended pregnancies. For each model, the optimal hyper-parameters were chosen using 10-fold cross-validation. Each color corresponds to a different predictive model. Source: Author's calculations using NSFG data.