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IZA DP No. 16608

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ABSTRACT

The Effects of the Dobbs Decision on Fertility*

The U.S. Supreme Court decision in Dobbs v. Jackson Women's Health Organization sparked the most profound transformation of the landscape of abortion access in 50 years. We provide the first estimates of the effects of this decision on fertility using a pre-registered synthetic difference-in-differences design applied to newly released provisional natality data for the first half of 2023. The results indicate that states with abortion bans experienced an average increase in births of 2.3 percent relative to states where abortion was not restricted.

JEL Classification: I11, I12, I18, J13, K23
Keywords: abortion, Dobbs, fertility, power analysis

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1 Introduction

In the landmark Dobbs v. Jackson Women's Health Organization decision issued on June 24, 2022, the United States Supreme Court overturned Roe v. Wade and, with it, the constitutional protection for abortion rights. Within hours of the decision, abortions were halted in 10 states, either in response to a ban triggered by the decision or to the expected enforcement of a pre-Roe abortion ban that was still on the books (Bui et al., 2022). Over the weeks and months that followed, the landscape of abortion access continued to shift as more states sought to enact and enforce abortion bans and as some of those bans were challenged in state courts. As of November 1, 2023, 14 states are enforcing bans on abortion in nearly all circumstances, and 23 percent of U.S. women of reproductive age have experienced an increase in driving distance to the nearest abortion facility, from an average of 43 miles one-way before Dobbs to 330 miles at present (Myers et al., 2023). This represents the most profound transformation of the landscape of U.S. abortion access in 50 years.

If the past foretells our present, the Dobbs decision will result in increases in unintended births and exacerbate economic inequality. The ability to control fertility has been associated with 40 decades of women's economic advancement (Goldin and Katz, 2002). The last dramatic change in U.S. abortion access occurred in 1969-1971 when abortion was legalized by 5 "repeal states" and the District of Columbia before being legalized in the rest of the country in 1973 with the Roe decision (Myers, 2022). The legalization of abortion in the early 1970s reduced births, particularly among young women, and forestalled "shotgun marriages" that otherwise would have resulted from unintended pregnancies (Levine et al., 1999; Myers, 2017).[1] In turn, access to legal abortion improved women's health and increased women's educational attainment, labor force participation, occupation prestige, and earnings (Klein, 1997; Angrist and Evans, 2000; Farin et al., 2021; Kalist, 2004; Oreffice, 2007; González et al., 2018; Abboud, 2019; Jones and Pineda-Torres, 2022).[2] Still, fifty years later, abortion

[1] The literature also documents the causal effects of abortion legality on fertility in the context of the 19th century U.S. (Lahey, 2014a,b) and 20th century Spain (González et al., 2018), Norway (Mølland, 2016), and Eastern Europe (Levine and Staiger, 2004) In the U.S., the literature documents that in the decades prior to Dobbs, demand-side restrictions including parental involvement laws and mandatory waiting periods increased births (Joyce and Kaestner, 2001; Myers and Ladd, 2020; Myers, 2021).

[2] The literature also documents effects of abortion access on health in the context of the liberalization of abortion access in Mexico (Clarke and Mühlrad, 2021).

remains common: In 2020, approximately 1 in 5 pregnancies ended in abortion (Jones et al., 2022). At the time they seek abortions, 75 percent of patients are low-income, 59 percent have previously given birth, and 55 percent report a recent disruptive life event such as falling behind on the rent or losing a job (Jones and Jerman, 2017a,b). Recent evidence suggests that diminished abortion access poses a risk to the health and financial stability of this vulnerable population (Muratori, 2021; Jones and Pineda-Torres, 2022; Gardner, 2022; Miller et al., 2023).

However, while Dobbs rewinds the country to the pre-Roe regulatory environment, there are reasons to think we may not watch these fertility and economic effects play in reverse. Whereas pre-Roe abortion had only been legalized in a handful of states, post-Dobbs, abortions remain legal in most circumstances in 30 states and the District of Columbia. Previous research demonstrates that many people seeking abortions will travel to states where it is legal to obtain one (Joyce et al., 2013; Quast et al., 2017; Fischer et al., 2018; Lindo et al., 2020; Venator and Fletcher, 2021; Myers, 2023a). Myers (2023a) estimates that in this landscape of access, roughly three-quarters of residents of ban states seeking abortions will travel to brick-and-mortar abortion facilities in non-ban states. Estimates of surging abortion volumes in states bordering ban states suggest that travel is indeed occurring (Guttmacher Institute, 2023b; Society of Family Planning, 2023). Moreover, even for those pregnant people who are unable to find a way to manage the logistics and costs of a lengthy trip to receive healthcare services, organizations such as Aid Access will supply medication abortion via mail to ban states for pregnant people to self-manage their abortions safely and effectively (Aiken et al., 2022). Evidence of surging requests to Aid Access suggests that this, too, is occurring (Aiken et al., 2022b). Furthermore, expanded access to the full range of contraceptive methods, including long-acting reversible contraceptives, may reduce unintended pregnancies (Ricketts et al., 2014; Finer and Zolna, 2016; Lindo and Packham, 2017; Kelly et al., 2020).

Thus, the question we address in this paper is: To what extent are state abortion bans affecting fertility? We provide the first empirical evidence by exploiting newly released provisional state resident birth counts (Centers for Disease Control and Prevention, National

Center for Health Statistics, 2023) to estimate how births are changing in ban states relative to states where abortion access has not been restricted or threatened since the Dobbs decision. We registered a pre-analysis plan and code at Open Science Framework in October 2023, before the release of the 2nd quarter of provisional birth data, in which we used a simulated power analysis in the pre-period following Black et al. (2022) to ensure that the method we choose for analysis is well-suited to detect effects within the range of what may be expected (Dench and Pineda-Torres, 2023). Based on the results and analysis plan, we utilize Arkhangelsky et al.'s (2021) Synthetic Difference-in-Differences (SDID) using bootstrap inference, which we found always provides for smaller minimum detectable effects (MDE) than two-way fixed effects (TWFE) with cluster robust standard errors.

The results indicate that birth rates increased by an average of 2.3 percent in ban states relative to protective states. Effects were especially large for Hispanic women (4.7 percent) and women aged 20-24 (3.3 percent). The estimated increases were larger in states such as Mississippi (4.4 percent) and Texas (5.1 percent), where the geography of bans renders interstate travel more costly.

2 Post-Dobbs abortion bans

Two landmark Supreme Court decisions—Roe v. Wade (1973) and Planned Parenthood v. Casey (1994)— established and upheld the finding that the due process clause of the Fourteenth Amendment to the U.S. Constitution protects the right to an abortion prior to fetal viability, a nebulous line that is drawn somewhere towards the end of the second trimester of pregnancy (The American College of Obstetricians and Gynecologists, 2017). In Dobbs v. Jackson Women's Health (2022), the Court overturned these precedents, finding: "The Constitution does not confer a right to abortion; Roe and Casey are overruled; and the authority to regulate abortion is returned to the people and their elected representatives" (p. 1).

The ruling in Dobbs allowed states to enforce pre-viability abortion bans. When it was released on June 24, 2022, 13 states had trigger bans in place designed for just such an eventuality to outlaw abortion under almost all circumstances.[3] In addition, several states had never repealed pre-Roe bans and threatened to enforce them, while in other states, legislatures moved to enact new bans. While many of these new bans are "total bans" on abortions under most circumstances, some are "gestational age bans," placing stricter limits on the allowable gestational ages for abortions. Of these, the strictest have been the 6-week gestational age bans. Because gestation is dated from the start of the last menstrual period, a 6-week ban provides a person with a 28-day menstrual cycle roughly two weeks from the time they could possibly learn they were pregnant until the deadline to schedule and obtain an abortion.

Appendix A documents and describes state abortion bans in the wake of Dobbs. The history of enforcement in some states is quite complicated because legal challenges resulted in delayed or intermittent enforcement of bans. For instance, North Dakota passed a trigger ban in 2007, and following Dobbs, the governor announced that the ban would take effect on July 28, 2022. However, the state's sole provider challenged the law, and the state supreme court enjoined enforcement before it could take effect on the grounds that it did not provide adequate protections for the preservation of the pregnant person's life or health as required by the state constitution. The legislature then repealed and revised the law, and a total ban took effect on April 24, 2023 (Center for Reproductive Rights, 2023). However, in the meantime, North Dakota's sole abortion facility relocated from Fargo, North Dakota, to Moorhead, Minnesota, less than two miles away but across the border into a state where abortion rights are expected to remain protected (Center for Reproductive Rights, 2023). Two other trigger bans, in Utah and Wyoming, remain unenforced due to legal challenges.

Adding another dimension of complexity, Texas's SB8 bill effectively banned abortions past six weeks gestation through civil penalties in September 2021, approximately ten months before Dobbs.[4] Oklahoma's copycat bill went into effect roughly two months before

[3]Exceptions to abortion bans generally fall into four categories: to save the life of a pregnant person, to prevent a substantial negative health outcome for the pregnant person, where the pregnancy is the result of rape or incest, and in cases of a lethal fetal anomaly. The set of exemptions varies across states. For instance, 10 of 14 total bans currently enforced do not include exceptions for rape or incest, and 11 of 14 do not include exceptions for fatal fetal anomalies (Felix et al., 2023). Moreover, even where exceptions to preserve the life or health of the pregnant person are codified, in practice, these are often unworkable and cause healthcare providers to delay providing care (Felix et al., 2023).

[4]This policy has been shown to have reduced abortions by half, increased appointment waiting times in

the Dobbs ruling in early May 2022. By the end of May, the state had effectively banned all abortions, and its facilities had shuttered.

We reduce this regulatory complexity by grouping states into three categories: (1) "Total ban" states enforced bans on abortion under almost all circumstances by the end of 2022. (2) "Protected" states are those that have not enacted or enforced a significant abortion restriction since Dobbs and are not viewed as likely to do so. (3) "Excluded" states attempted to enact or enforce a ban but did not effectively do so by the end of 2022, enacted only a gestational age ban by the end of 2022, or are viewed as hostile to abortion and at high risk of enforcing a ban.[5] These state categorizations are depicted in Figure 1 and provided as a list in Appendix Table A.1. See Appendix A for further details on the classifications.

3 Natality Data

We primarily rely on CDC Wonder data (Centers for Disease Control and Prevention, National Center for Health Statistics, 2022, 2023), accessed on November 6, 2023, for monthly births by state of residence covering the period January 2005 through June 2023. We use total resident birth counts and additionally estimate models for outcomes by age category (15-19, 20-24, 25-29, and 30-44) and by three categories of maternal race and ethnicity (non-Hispanic white alone, non-Hispanic Black alone, and Hispanic women of any race).[6] We divide these birth counts by the corresponding population counts, limiting to women age 15-44 for overall and by race/ethnicity estimates, in each state from census estimates using the single-race estimates of the resident population as of July 1 of each year (Census, 2016, 2021, 2022).[7]

out-of-state facilities (White et al., 2021), increased requests for self-managed medication abortions (Aiken et al., 2022a), and reduced mobility near abortion clinics in Texas (Andersen et al., 2023). In a preliminary analysis based on provisional data, it was also shown to increase fertility (Bell et al., 2023).

[5]North Dakota, Utah, and Wyoming, all states with trigger bans that were not enforced for most of 2022 are placed in the "excluded" category.

[6]We focus on mutually exclusive races and ethnicities because this way, we have the most distinct categories from each other. These analyses start in 2016 to consistently identify individuals with single races. Furthermore, due to limited sample sizes in other groups, we do not explore changes in fertility trends for other non-Hispanic groups.

[7]We apply an error of closure formula to smooth differences in estimates between census years (Census, 2000). Since 2023 population estimates are not yet available we project forward by assuming the same growth rate at the state level as occurred from 2021 to 2022.

Given the timing of Dobbs and the length of human gestation, births resulting from abortion bans would primarily begin to occur in early 2023. Final birth data for 2023 will not be published until 2024. To compare monthly and annual changes in fertility, we also calculate the annualized monthly birth rates as the number of births in each month divided by the corresponding estimated population in that month multiplied by 12 multiplied by 1,000.

4 Empirical Method

4.1 Synthetic Difference-in-Differences

Our analyses rely on Synthetic Difference-in-Differences (SDID) research design to compare changes in birth rates in "total ban" states to those in "protected" states (Figure 1). We treat all states that banned abortions in 2022 as becoming "treated" (i.e., subject to a total ban) as of January 2023, the earliest date we would expect to see births resulting from Dobbs.[8,9] We aggregate the first six months of fertility every year as our periods of analysis to eliminate any differential seasonal effects across states and because reliable data on the second half of 2023 is not yet available.

We estimate the effects of bans using models that alternatively exclude and include Texas from the sample of total ban states because it is partially treated in the pre-period due to the implementation of SB8 on September 1, 2021. When we include Texas, we code treatment for Texas as starting in January 2022. This makes the first treated fertility period for Texas more ambiguously treated since it includes variation in treatment intensity due enforcement of SB8 prior to the total ban. We also exclude states from the controls if they have gestational age limit changes, implement late bans, or were otherwise perceived as

[8]Prior to Dobbs, 45 percent of abortions occurred by 6 weeks gestation, and 93 percent occurred before 14 weeks gestation (Kortsmit et al., 2022). The average human gestation is 40 weeks. Hence, a pregnant person seeking an abortion just after Dobbs at 14 weeks gestation (considerably more advanced than most abortions) but who was unable to access one due to a ban would be expected to give birth approximately 28 weeks later in early January 2023. People seeking abortions at earlier gestational ages would be expected to have due dates later in 2023.

[9]Although abortion bans occurred in a staggered manner across the total ban states, there is evidence that abortion access was affected immediately in most if not all of these states due to ambiguity of old laws and anticipation of imminent bans by providers (Society of Family Planning, 2023).

actively hostile toward abortion, states (Figure 1) because these environments may have intermediate effects on fertility. For instance, the threat of potential bans may result in provider closures or relocations, such as the one that took place in North Dakota in advance of an anticipated ban.[10]

The SDID method combines features of Synthetic Control methods (SC) and Difference-in-Differences (DID). It reweights and matches on pre-exposure trends to weaken the reliance on parallel trends like SC while simultaneously being invariant to additive unit-level shifts and allowing for valid large-panel inference like DID (Arkhangelsky et al., 2021). Unlike SC methods, it does not select a weighted set of control units that minimize average differences in levels in the pre-period, but rather, it selects a weighted set of control units that minimize differences in trends in the pre-period. This addresses concerns raised and similarly addressed in Ferman and Pinto (2021) about the biasedness of SC when pre-treatment fit is imperfect and treatment correlated with unobserved confounders. In addition, SDID selects time weights that minimize the level difference in the post-period and the pre-period among all control units. Both procedures use only the outcomes in state and time for selection of weighting, leaving little for the researcher to select. Together, these features minimize variation between treatment and control units and time periods, improving statistical power while as best satisfying the fundamental assumption of DID— parallel trends—without introducing researcher degrees of freedom through selective deletion of treatment or control groups or choices of control variables. For concerns of contemporaneous confounding time-variant treatments, the method allows testing the robustness of the estimates to the inclusion of observable confounders in estimation.

Specifically, we estimate the average causal effect of *Dobbs* on birth rates by obtaining:

$$(\hat{\tau}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = \underset{\tau,\mu,\alpha,\beta}{argmin}\{\sum_{i=1}^{N}\sum_{t=1}^{T}(Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2\hat{\omega}_i^{sdid}\hat{\lambda}_t^{sdid}\} \tag{1}$$

where ω_i^{sdid} is chosen to minimize the average squared difference in trend between the treatment and control groups subject to a regularization parameter to increase dispersion

[10]In Appendix Table D.1 and D.2, we present robustness checks that include hostile states with no late ban or gestational age limit change in the control group.

and ensure the uniqueness of weights. In other words, regularization prevents overfitting to decrease estimator variance without a substantial increase in bias.

λ_t^{sdid} is chosen to minimize the sum of squared differences between the time-weighted pre-period outcomes of the control states and the simple average of the post-period outcomes in the control states. This underweights values in the pre-treatment period, which are unusual for the control states relative to the post-period. For example, if an unexpected shock like a hurricane or a pandemic upsets the outcome in the pre-period for a short period of time so that they do not look like the post-period, but for other periods they do, SDID will down-weight the unusual periods. In practice, however, we find that SDID usually selects pre-period time periods in close proximity to the treatment period since downward trends in fertility rates make adjacent observations in time most like one another. For statistical inference, we rely on block bootstrap methods.[11]

To estimate SDID event studies with confidence intervals, we follow Clarke et al. (2023) and use the difference between the treatment and control group in each period relative to their time-weighted pre-period and bootstrap inference for the calculation of 95 percent confidence intervals. In all our analyses, we estimate the averaged treatment effect by treatment group in time compared to sets of never-treated control units. This is particularly relevant when including Texas since it allows addressing concerns related to staggered treatments (Goodman-Bacon, 2021), as is the suggested correction in Arkhangelsky et al. (2021).

We rely on SDID as our main empirical approach not just for its theoretically desirable properties but because in our simulated power analysis based on pre-period data, described in Appendix B, it dominates TWFE estimates when randomly assigning treatment to states in the pre-period data and when reassigning treatment to different time periods in the pre-

[11] Arkhangelsky et al. (2021) derives three methods for inference under different assumptions: block placebo inference, block bootstrap inference, and jackknife inference. Placebo inference can be used in all cases where control units outnumber treatment units. However, placebo inference assumes that the error distribution for the treatment groups has equal variance to the control groups, which is not testable in realized data. Jackknife standard errors are robust to this concern but carry the assumption that the time weights of the treatment unit absent treatment are similar to the control unit's selected time weights. Jackknife inference may also be overly conservative and, thus, underpowered. In contrast, block bootstrap methods can be used when the number of treated units and control units is sufficiently large and does not assume equal variance in treatment and control groups or equal time weights between treatment units and control groups. It can be computationally challenging in very large samples. Given our panel length and number of states, it is not prohibitively expensive and, therefore, our chosen method.

period. Specifically, in all our populations, under randomization of treatment at a single point in time, SDID achieves conventional power levels of 80 percent and 90 percent at lower MDE than TWFE. We also show that MDE is insensitive in SDID to the selection of pre-period time length by the researcher, while MDE is sensitive in TWFE to pre-period time length. In addition, when reassigning treatment to the Dobbs states in time, we observe that SDID similarly achieves conventional power levels with lower MDE than TWFE in demographic groups with parallel time trends in the pre-period. It also improves symmetry in detecting positive and negative effects on fertility in demographic groups with non-parallel time trends in the pre-period. Finally, applying Myers's (2023a) forecast, imposing the effect of distance on counties' birth numbers, and then aggregating it to the state level, we found SDID rejected the null in ten out of 11 time periods, while TWFE did so in only eight out of 11 instances.[12,13]

5 Results

5.1 Estimates of the effect of the average abortion ban on births

Figure 2 depicts the SDID event study results using state-level birth data for 2019-2023, excluding Texas. The results show that births trended similarly in ban states and the weighted set of control states in the years leading up to Dobbs before rising in the first half of 2023.[14]

Table 1 presents the SDID results for the level and log of births per 1,000 women in the corresponding age group indicated in the column label. When we do not include Texas as a total ban state, we observe that bans enforced in the first six months following Dobbs increased births by 1.1 births per 1,000 women. Using log models for relative effects, this corresponds to an increase in births to all reproductive-age women of roughly 2.3 percent. When we include Texas in the total ban states, these bans increase births by 1.3 births

[12]See Figures B.1 to B.9 in Appendix B for the power analyses using TWFE.

[13]We also explored SDID statistical power performance relative to Synthetic Control Methods, and it also dominated them. Those power analyses are available upon request.

[14]Appendix C includes event studies for including Texas.

per 1,000 women (2.7 percent) relative to non-ban states. These estimates are statistically significant at the one percent level. These are magnitudes our pre-analysis power calculations predicted we would be able to detect with greater than 80 percent probability.

While SDID limits design choices with respect to the selection of control states trending similarly in the pre-period, there is still considerable choice over frequency of data, controls for possible confounders, choice of uncontaminated control groups, selection of treatment groups, and the timing of treatment. Appendix D provides a series of results of alternative specifications, demonstrating that the conclusion that abortion bans increased births is robust to reasonable alternative choices regarding the research design, including using NVSS Rapid Release data rather than CDC Wonder for 2023, excluding controls for state economic conditions, adding detailed demographic controls, adjusting the pre-period, and aggregating the data to monthly rather than annual births. We also show that the estimated effects are slightly attenuated but continue to show substantial effects on births if we add the "hostile" states, excluding those with changes to gestational age bans (Figure 2), to the set of possible controls.

5.2 Estimates by Age and Race

Table 1 presents the SDID estimates by age and ethnicity, including and excluding Texas from the total ban states. The results do not show evidence of an increase in births to teenagers aged 15-19. Given the uncertainty, we cannot rule out an effect, but our pre-period power analysis would indicate that any effect is likely smaller than 5 percent. For older age groups, we estimate percentage effects of 3.3, 2.8, and 2 percent for women aged 20-24, 25-29, and 30-44, respectively; all these estimates are statistically significant at the one percent level. Given the evidence from Myers (2023a) that women aged 15-19 and 20-24 are more responsive to driving distances to abortion facilities than older women, it is striking that these results do not support the conclusion that teenage women were been more affected by abortion bans. If this finding is repeated as more data becomes available, one explanation may be that younger women are more likely to navigate online abortion finders or websites offering mail-order medication to self-manage abortions.[15]

When comparing the SDID estimates across race and ethnicity groups, we observe that fertility rates increased by 3, 3.8, and 4.7 percent for non-Hispanic White, non-Hispanic Black, and Hispanic women, respectively. However, the estimated effects for births to Black women are non-statistically significant at a conventional level. Nonetheless, these differential effects are consistent with the findings of previous studies that indicate the impacts of abortion restrictions on fertility are stronger for non-White women (Fischer et al., 2018; Myers and Ladd, 2020; Myers, 2021, 2023a).

5.3 Estimates of heterogeneous effects across ban states

We next estimate SDID log models for each ban state separately. The estimated effects, which are presented in Table 2, indicate that the effects of bans on birth rates vary substantially across ban states, from a 0.4 percent increase in births in Missouri to a 5.1 percent increase in births estimated in Texas.

One factor that likely contributes to the variation in the effects of state bans on births is the tremendous variation in the distances their residents must travel to reach a facility that remains open. Using the Myers Facility Database (Myers, 2023b) and the methodology described in Myers (2023a), we calculate the change in driving distance to the nearest abortion facility for the average resident of each ban state between May 1, 2022, and December 31, 2022. This average change in distance is reported in Table 2. In Missouri, the ban results in an average increase in driving distance of 2.2 miles, compared to a 453-mile increase in Texas, illustrating that states with the greatest increases in driving distance also tend to have the greatest estimated increases in births.

To further explore the potential role of driving distances as a mechanism, we compare the SDID estimates of the increases in births due to state bans to prior state-level forecasts based on variation in driving distances. Myers (2023a) uses a difference-in-differences research design exploiting county-by-year variation in distances to the nearest abortion facility over the decade leading up to Dobbs to estimate the effect of driving distance on abortions and

[15] Appendix B includes event study estimates related to the results by age and by race and ethnicity.

births. She then forecasts changes in driving distances due to Dobbs and uses the results to forecast changes in births due to Dobbs. We adapt this approach, updating the distance forecasts to match the baseline (May 1, 2022) and post-period (December 31, 2022) used in this analysis. Based on the changes in distance in each county and the estimated effects of distance on births in (Myers, 2023a), we forecast the change in births directly resulting from increased driving distances and aggregate these county-level forecasts to the state level, weighting each county's contribution by the number of births to residents of that county in 2021. The results are presented in Figure 3, which compares the estimated effects by state (y-axis) to the forecasted effects (x-axis). The dotted line indicates where estimated equals predicted. We observe a strong positive correlation (correlation coefficient is 0.66) between the forecasts and realized changes in births, which suggests that driving distances are a major factor underlying variation across ban states in the estimated effects of bans.

For example, Myers (2023a) forecasted a 0.04 percent increase in births in Missouri because the sole facility that closed due to the ban was located in St. Louis, and facilities remained in operation a short distance across the Illinois border. The present analysis estimates a 0.4 percent increase. Considering a state with a much larger forecasted increase, for the average Mississippi resident, driving distances to the nearest abortion facility increased from 81 miles in May 2022 to 321 miles in December 2022. Correspondingly, Myers (2023a) forecasted a 3.4 percent increase in births. The present analysis estimates a 4.4 percent increase.

The forecast errors (differences between the forecasted effects and realized effects) also provide some suggestive preliminary evidence on other dimensions of access beyond distance that may be relevant to the effects of bans on births. The three states (Arkansas, Louisiana, and Oklahoma) with increases in births that were less than forecasted, were among the states with the greatest reported increases to Aid Access for medications to self-manage abortion following Dobbs (Aiken et al., 2022b).

Turning to those states where the forecasting error is negative, meaning the model forecasts smaller effects on births than were realized, the two states that are the greatest outliers are Kentucky and West Virginia, where the realized increases in births are more than twice as large as the forecasted effects. One possible explanation is that after the facilities in these states closed due to their bans, the next nearest facilities had particularly limited appointment availability. The sole facility in southern Ohio that became the nearest destination for most Kentuckians had no available appointments within three weeks when contacted in September 2022 and none at all when contacted in December 2022 (Myers et al., 2023). Similarly, wait times until the next available appointment were 2 to 3 weeks at facilities in Pittsburgh, Pennsylvania, which became the nearest destination for many West Virginians (Myers et al., 2023).

In addition to providing state-by-state estimates of increases in births, Table 2 also reports resident abortions in 2020, the last full year for which these are reported (Maddow-Zimet and Kost, 2022). The final column reports the ratio of the estimated increase in births in 2023 resulting from Dobbs to the number of resident abortions in 2020. The numerator corresponds to the estimated number of residents who were prevented from obtaining desired abortions due to post-Dobbs bans. As a back-of-the-evelope calculation and plausibility check, the ratio of foregone abortions in 2023 to resident abortions in 2020 is a rough estimate of the fraction of people seeking abortions who were "trapped" by bans and unable to obtain them.[16] These estimates, which range from 2.4 percent in Missouri to 31.0 percent in Kentucky, are generally in line with the estimated effects of distance on abortion rates and forecasts in Myers (2023a). Aggregating across all ban states, the estimates suggest that approximately 23 percent (or 18 percent, excluding Texas) of people seeking abortions may have been prevented from obtaining care.

6 Discussion and Conclusion

As abortion bans took effect across a wide swath of the South and Midwest, abortions surged in border states where services remained available (Guttmacher Institute, 2023b; Society of Family Planning, 2023) even as requests to mail-order medication abortion providers in

[16]Abortions rose 8 percent between 2017 and 2020 (Jones et al., 2022). If abortions had continued to rise in the absence of Dobbs, then the ratio of foregone abortions in 2023 to total abortions in 2020 may modestly overestimate the fraction of abortion seekers who are trapped.

the informal healthcare system also increased (Aiken et al., 2022b). While these trends suggest that interstate travel and self-management of abortion may blunt the ultimate impacts of abortion bans on fertility, the question of the ultimate effect of bans on births has been unresolved. Using newly released provisional birth data and a pre-registered synthetic difference-in-differences design, we provide the first evidence of the effect of abortion bans on birth rates. We chose this method based on simulated power analysis that revealed that SDID dominates two-way fixed effects along several dimensions.

Our primary analysis indicates that in the first six months of 2023, births rose by an average of 2.3 percent in states enforcing total abortion bans compared to a control group of states where abortion rights remained protected, amounting to approximately 32,000 additional annual births resulting from abortion bans. These effects vary across demographic groups and tend to be larger for younger women and women of color. These effects also vary substantially across ban states, with much larger effects observed in states that are bordered by other ban states and hence have long travel distances to reach facilities that remain open. As a back-of-the-envelope calculation, we compare the estimated increases in births resulting from bans to the last available resident abortion counts prior to the Dobbs decision and estimate that roughly one-fifth to one-fourth of people seeking abortions did not receive them due to bans.

These analyses are based on provisional data for the first six months of 2023. Future changes to the landscape of bans, medication abortion access, and unintended pregnancy rates could further mediate the effects of bans. If future research using finalized data and additional policy variation reveals continued substantial effects on births, then we expect long-lasting and profound effects on the lives of affected pregnant people and their families, including effects on educational investment, employment, earnings, and financial security.

References

Abadie, A., S. Athey, G. W. Imbens, and J. M. Wooldridge (2023). When should you adjust standard errors for clustering? *The Quarterly Journal of Economics 138*(1), 1–35.

Abboud, A. (2019, November). The Impact of Early Fertility Shocks on Women's Fertility and Labor Market Outcomes.

Aiken, A. R. A., E. P. Romanova, J. R. Morber, and R. Gomperts (2022, June). Safety and effectiveness of self-managed medication abortion provided using online telemedicine in the United States: A population based study. *The Lancet Regional Health – Americas 10*. Publisher: Elsevier.

Aiken, A. R. A., J. E. Starling, J. G. Scott, and R. Gomperts (2022a, February). Association of Texas Senate Bill 8 With Requests for Self-managed Medication Abortion. *JAMA network open 5*(2), e221122.

Aiken, A. R. A., J. E. Starling, J. G. Scott, and R. Gomperts (2022b, November). Requests for Self-managed Medication Abortion Provided Using Online Telemedicine in 30 US States Before and After the Dobbs v Jackson Women's Health Organization Decision. *JAMA 328*(17), 1768–1770.

Andersen, M. S., C. Marsicano, M. Pineda Torres, and D. Slusky (2023). Texas Senate Bill 8 significantly reduced travel to abortion clinics in Texas. *Frontiers in Global Women's Health 4*.

Angrist, J. D. and W. N. Evans (2000, January). Schooling and labor market consequences of the 1970 state abortion reforms. In *Research in Labor Economics*, Volume 18 of *Research in Labor Economics*, pp. 75–113. Emerald Group Publishing Limited.

Arkhangelsky, D., S. Athey, D. A. Hirshberg, G. W. Imbens, and S. Wager (2021). Synthetic difference-in-differences. *American Economic Review 111*(12), 4088–4118.

Bailey, M. J., J. Currie, and H. Schwandt (2022, October). The Covid-19 Baby Bump: The Unexpected Increase in U.S. Fertility Rates in Response to the Pandemic.

Bell, S. O., E. A. Stuart, and A. Gemmill (2023). Texas' 2021 ban on abortion in early pregnancy and changes in live births. *JAMA 330*(3), 281–282.

Black, B., A. Hollingsworth, L. Nunes, and K. Simon (2022). Simulated power analyses for observational studies: An application to the affordable care act medicaid expansion. *Journal of Public Economics 213*, 104713.

Bui, Q., C. C. Miller, and M. Sanger-Katz (2022, June). How Abortion Bans Will Ripple Across America. *The New York Times*.

Census (2000). Methodology for national intercensal estimates.

Census (2016). Single race estimates for the resident population by single year age and sex for the years 2000-2010. Data are from the Census estimates based on the 2000 Census.

Census (2021). Single race estimates for the resident population by single year age and sex for the years 2010-2020. Data are from the Census estimates based on the 2020 Census.

Census (2022). Single race estimates for the resident population by single year age and sex for the years 2020-2022. Data are from the Census estimates based on the 2020 Census.

Center for Reproductive Rights (2023). After Roe Fell: Abortion Laws by State.

Centers for Disease Control and Prevention, National Center for Health Statistics (2022). National vital statistics system, natality, on cdc wonder online database. Data are from the Natality Records 2005-2022, as compiled from data provided by the 57 vital statistics jurisdictions through the Vital Statistics Cooperative Program.

Centers for Disease Control and Prevention, National Center for Health Statistics (2023). National vital statistics system, provisional natality on cdc wonder online database. Data are from the Natality Records for births occurring in 2023 through last month, as compiled from data provided by the 57 vital statistics jurisdictions through the Vital Statistics Cooperative Program.

Clarke, D. and H. Mühlrad (2021). Abortion laws and women's health. *Journal of Health Economics 76*(C). Publisher: Elsevier.

Clarke, D., D. Pailañir, S. Athey, and G. Imbens (2023, February). Synthetic Difference In Differences Estimation. arXiv:2301.11859 [econ].

Dench, D. and M. Pineda-Torres (2023, Oct). Effect of the dobbs decision on fertility. *Open Science Foundation*.

Dench, D. L., W. Li, T. J. Joyce, H. Minkoff, and G. Van Wye (2023, March). Fertility in the Heart of the COVID-19 Storm.

Farin, S. M., L. Hoehn-Velasco, and M. Pesko (2021, September). The Impact of Legal Abortion on Maternal Mortality.

Felix, M., L. Sobel, and A. S. Published (2023, May). A Review of Exceptions in State Abortion Bans: Implications for the Provision of Abortion Services.

Ferman, B. and C. Pinto (2021). Synthetic controls with imperfect pretreatment fit. *Quantitative Economics 12*(4), 1197–1221.

Finer, L. B. and M. R. Zolna (2016). Declines in unintended pregnancy in the united states, 2008–2011. *New England journal of medicine 374*(9), 843–852.

Fischer, S., H. Royer, and C. White (2018). The impacts of reduced access to abortion and family planning services on abortions, births, and contraceptive purchases. *Journal of Public Economics 167*(C), 43–68. Publisher: Elsevier.

Gardner, G. (2022, October). The Maternal and Infant Health Consequences of Restricted Access to Abortion in the United States. *Working Paper*.

Goldin, C. and L. F. Katz (2002). The power of the pill: Oral contraceptives and women's career and marriage decisions. *Journal of political Economy 110*(4), 730–770.

González, L., S. Jiménez-Martín, N. Nollenberger, and J. Vall-Castello (2018, April). The effect of abortion legalization on fertility, marriage and long-term outcomes for women. Technical Report No. 1035, Barcelona Graduate School of Economics. Publication Title: Working Papers.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics 225*(2), 254–277.

Guttmacher Institute (2023a). Interactive Map: US Abortion Policies and Access After Roe.

Guttmacher Institute (2023b). Monthly abortion provision study. Accessed on 2023-11-12.

Jones, K. and M. Pineda-Torres (2022, May). Trap'd Teens: Impacts of Abortion Provider Regulations on Fertility & Education.

Jones, R. K. and J. Jerman (2017a). Abortion incidence and service availability in the united states, 2014. *Perspectives on sexual and reproductive health 49*(1), 17–27.

Jones, R. K. and J. Jerman (2017b). Characteristics and circumstances of us women who obtain very early and second-trimester abortions. *PloS one 12*(1), e0169969.

Jones, R. K., M. Kirstein, and J. Philbin (2022, December). Abortion incidence and service availability in the United States, 2020. *Perspectives on Sexual and Reproductive Health 54*(4), 128–141.

Jones, R. K., J. Philbin, M. Kirstein, E. Nash, and K. Lufkin (2022, June). Long-Term Decline in US Abortions Reverses, Showing Rising Need for Abortion as Supreme Court Is Poised to Overturn Roe v. Wade.

Joyce, T., R. Tan, and Y. Zhang (2013). Abortion before & after roe. *Journal of health economics 32*(5), 804–815.

Joyce, T. J. and R. Kaestner (2001). The Impact of Mandatory Waiting Periods and Parental Consent Laws on the Timing of Abortion and State of Occurrence among Adolescents in Mississippi and South Carolina.

Kalist, D. (2004). Abortion and female labor force participation: Evidence prior to Roe v. Wade. *Journal of Labor Research 25*(3), 503–514. Publisher: Transaction Publishers.

Kearney, M. S. and P. B. Levine (2023). The us covid-19 baby bust and rebound. *Journal of Population Economics*, 1–24.

Kelly, A., J. M. Lindo, and A. Packham (2020, December). The power of the IUD: Effects of expanding access to contraception through Title X clinics. *Journal of Public Economics 192*, 104288.

Klein, M. H. H. I. (1997). *The effects of abortion legislation on women's educational attainment in the United States*. Ph.D., University of California, Berkeley, United States – California.

Kortsmit, K., A. T. Nguyen, M. G. Mandel, E. Clark, L. M. Hollier, J. Rodenhizer, and M. K. Whiteman (2022). Abortion surveillance—united states, 2020. *MMWR Surveillance Summaries 71*(10), 1.

Lahey, J. N. (2014a, June). Birthing a Nation: The Effect of Fertility Control Access on the Nineteenth-Century Demographic Transition. *The Journal of Economic History 74*(2), 482–508. Publisher: Cambridge University Press.

Lahey, J. N. (2014b, April). The Effect of Anti-Abortion Legislation on Nineteenth Century Fertility. *Demography 51*(3), 939–948.

Levine, P. and D. Staiger (2004, April). Abortion Policy and Fertility Outcomes: The Eastern European Experience. *The Journal of Law and Economics 47*(1), 223–243. Publisher: The University of Chicago Press.

Levine, P. B., D. Staiger, T. J. Kane, and D. J. Zimmerman (1999). Roe v Wade and American fertility. *American Journal of Public Health 89*(2), 199–203. Publisher: American Public Health Association.

Lindo, J. M., C. K. Myers, A. Schlosser, and S. Cunningham (2020, October). How Far Is Too Far? New Evidence on Abortion Clinic Closures, Access, and Abortions. *Journal of Human Resources 55*(4), 1137–1160. Publisher: University of Wisconsin Press.

Lindo, J. M. and A. Packham (2017, August). How Much Can Expanding Access to Long-Acting Reversible Contraceptives Reduce Teen Birth Rates? *American Economic Journal: Economic Policy 9*(3), 348–376.

Maddow-Zimet, I. and K. Kost (2022). Even before roe was overturned, nearly one in 10 people obtaining an abortion traveled across state lines for care. *Guttmacher Institute 21*.

Miller, S., L. R. Wherry, and D. G. Foster (2023, February). The Economic Consequences of Being Denied an Abortion. *American Economic Journal: Economic Policy 15*(1), 394–437.

Muratori, C. (2021). The Impact of Abortion Access on Violence Against Women. Technical report, University of Turin.

Myers, C. K. (2017). The power of abortion policy: Reexamining the effects of young women's access to reproductive control. *Journal of Political Economy 125*(6), 2178 – 2224. Publisher: University of Chicago Press.

Myers, C. K. (2021, June). Cooling Off or Burdened? The Effects of Mandatory Waiting Periods on Abortions and Births.

Myers, C. K. (2022). Confidential and legal access to abortion and contraception in the usa, 1960–2020. *Journal of Population Economics 35*(4), 1385–1441.

Myers, C. K. (2023a). Forecasts for a post-roe america: The effects of increased travel distance on abortions and births. *Journal of Policy Analysis and Management*.

Myers, C. K. (2023b, November). Myers abortion facility database.

Myers, C. K., L. Bennett, F. Vale, and A. Nieto (2023, September). Abortion Access Dashboard.

Myers, C. K. and D. Ladd (2020, May). Did parental involvement laws grow teeth? The effects of state restrictions on minors' access to abortion. *Journal of Health Economics 71*, 102302.

Mølland, E. (2016). Benefits from delay? The effect of abortion availability on young women and their children. *Labour Economics 43*, 6–28. Publisher: Elsevier.

Oreffice, S. (2007). Did the legalization of abortion increase women's household bargaining power? Evidence from labor supply. *Review of Economics of the Household 5*(2), 181–207. Number: 2.

Quast, T., F. Gonzalez, and R. Ziemba (2017, January). Abortion Facility Closings and Abortion Rates in Texas. *INQUIRY: The Journal of Health Care Organization, Provision, and Financing 54*, 0046958017700944. Publisher: SAGE Publications Inc.

Ricketts, S., G. Klingler, and R. Schwalberg (2014, September). Game change in Colorado: widespread use of long-acting reversible contraceptives and rapid decline in births among young, low-income women. *Perspectives on Sexual and Reproductive Health 46*(3), 125–132.

Society of Family Planning (2023, June). #WeCount Report.

Sun, L. and S. Abraham (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics 225*(2), 175–199.

The American College of Obstetricians and Gynecologists (2017, October). Periviable Birth. *Obstetric Care Consensus 6*.

UW CORE (2022, December). Changes to abortion access in Wisconsin following the June 2022 Dobbs decision. CORE Brief, University of Wisconsin Madison.

Venator, J. and J. Fletcher (2021). Undue Burden Beyond Texas: An Analysis of Abortion Clinic Closures, Births, and Abortions in Wisconsin. *Journal of Policy Analysis and Management 40*(3), 774–813. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/pam.22263.

White, K., E. Vizcarra, L. Palomares, A. Dane'el, A. Beasley, T. Ogburn, J. E. Potter, and S. L. Dickman (2021). Initial Impacts of Texas' Senate Bill 8 on Abortions in Texas and at Out-of-State Facilities.

Figures

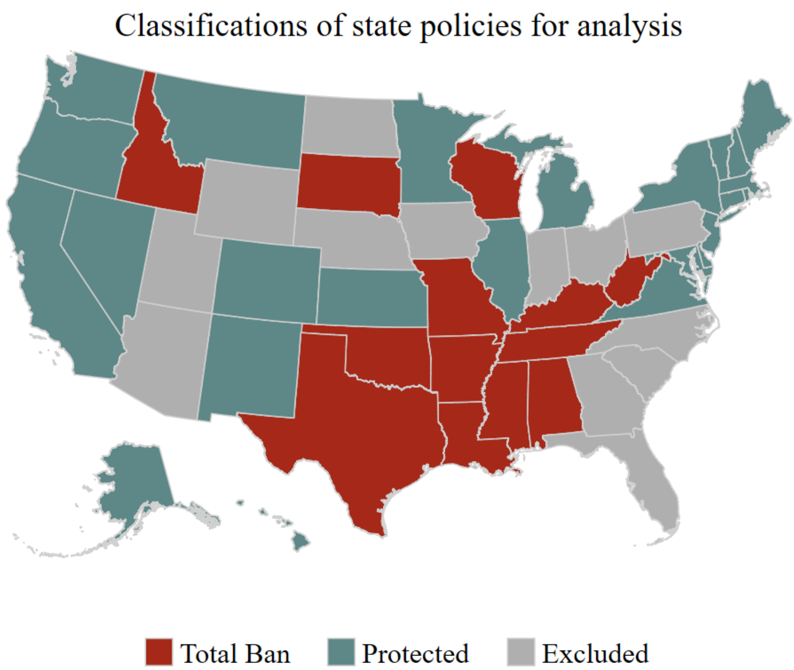


Figure 1: State level map of classifications of state policies for analysis.

Notes: Total Ban states are those that enacted a total ban by the end of 2022, Protected states either kept abortion policies in place or expanded abortion rights, while Excluded states are a mix of states that enacted bans too late to be effective for fertility in our analysis, have enforced gestational-age bans, or have legislatures hostile towards abortion. See Appendix A for details.

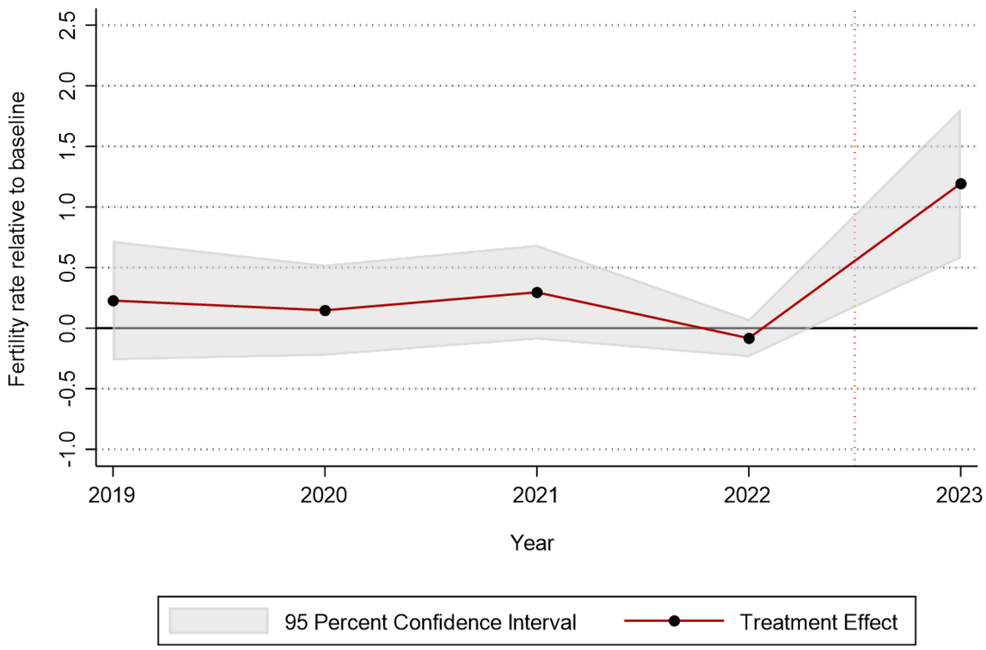


Figure 2: Synthetic difference-in-differences event study estimates of fertility in Dobbs ban states relative to protected control states for all women aged 15-44 for the first six months of each year, 2019-2023.

Notes: The graph shows six-month estimates of the difference between Dobbs ban states and the unit-weighted set of non-ban control states relative to the difference in the average time-weighted pre-period. They depict the first 6-month, January to June, fertility rate results for every period from 2019-2023, including the first six months of provisional births in 2023 from CDC Wonder. The unit weights and time weights are selected based on procedures developed in Arkhangelsky et al. (2021) and implemented by Clarke et al. (2023). The event study estimates are produced using the procedure outlined in Clarke et al. (2023). See section 4 for more details on the methods. These analyses exclude Texas because of *SB8*'s implementation. See Figure C.2 in Appendix C for a staggered version including Texas.

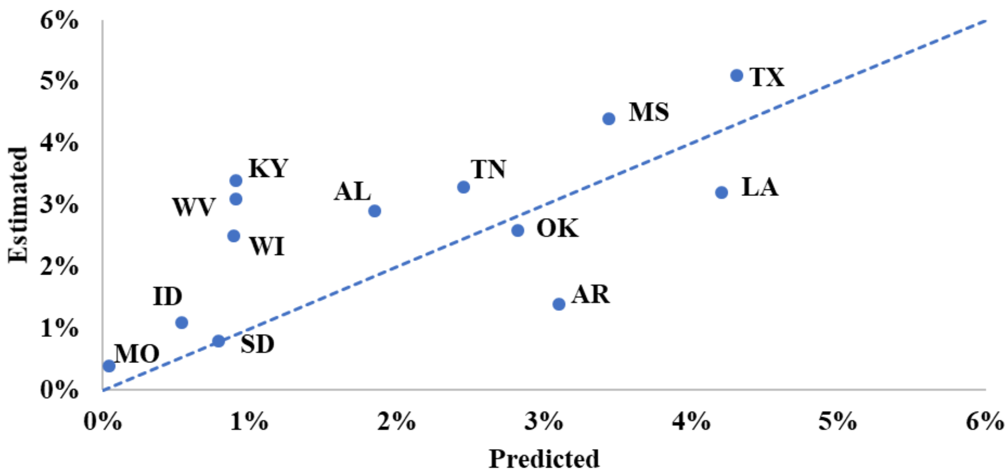


Figure 3: Estimated effects by state compared to their predicted effects based on distance.

Notes: The estimated effects come from an SDID model for each treated state separately using Protected states as potential controls and controlling for state unemployment rates lagged one year. Predicted effects come from a distance model at the county level following estimated effects of distance in the pre-Dobbs era in Myers (2023a) on fertility forecasted to post-Dobbs distance changes from May 2022 to December 2022, averaging effects at the state level, and weighting for births in a county in 2021.

Tables

Table 1: Synthetic difference in differences estimate of the impact of the Dobbs decision on fertility using the first six months of every period, 2019-2023

		Age Categories				Race/Ethnicity		
	Overall	15-19	20-24	25-29	30-44	W	B	H
Panel A: Without Texas								
Effect of ban (levels)	1.1	0.0	1.7	3.0	1.1	1.3	1.8	4.0
	(0.3)	(0.3)	(0.8)	(1.0)	(0.4)	(0.3)	(2.2)	(1.3)
Effect of ban (logs)×100	2.3	0.8	3.3	2.8	2.0	3.0	3.8	4.7
	(0.6)	(1.6)	(1.1)	(0.8)	(0.8)	(0.7)	(2.4)	(1.6)
2022 fertility rate in ban states	57.2	18.8	74.2	109.7	46.9	54.7	58.8	81.3
Panel B: With Texas								
Effect of ban (levels)	1.3	0.0	1.7	3.3	1.3	1.3	1.8	3.7
	(0.4)	(0.2)	(0.8)	(0.9)	(0.4)	(0.3)	(1.9)	(1.2)
Effect of ban (logs)×100	2.7	1.1	3.4	3.4	2.5	3.0	3.7	4.5
	(0.6)	(1.3)	(1.0)	(0.9)	(0.8)	(0.7)	(2.2)	(1.5)
2022 fertility rate in ban states	57.4	18.9	74.0	109.2	47.4	54.7	58.4	80.1

Notes: The reported coefficients are estimated effects of Dobbs ban states relative to protected states where the effects are estimated using Synthetic Difference-in-Differences from Arkhangelsky et al. (2021) and implemented by Clarke et al. (2023) in Stata. Fertility is measured based on the first six months of every period in each state in each group and measured as 1,000 multiplied by the number of births in each group divided by the number of women in each group multiplied by two to annualize the estimates. Panel A excludes Texas, while Panel B includes Texas as a treated state. The treatment turns on for all Dobbs ban states in 2023 in Panel A. The treatment turns on for all states except Texas in 2023 in Panel B, while it turns on in 2022 in Texas since SB8 may have affected fertility rates starting in that year. We present separate models in levels and logs. Level models were in the pre-analysis plan, while logs are an exploratory analysis. Staggering in Panel B is addressed in the manner described in Clarke et al. (2023) averaging estimates of Texas compared to never treated groups in the two post-periods, 2022 and 2023, with estimates for the other treated states in the single post-period 2023 and receiving different unit weights for Texas and the rest. Standard errors are obtained through block bootstrapping with 1,000 bootstraps as outlined in Arkhangelsky et al. (2021) to account for common treatment of a ban on abortion to all women who reside in the state (Abadie et al., 2023). Overall refers to the birth rates of women ages 15-44 as the population base. W, B, and H refer to Non-Hispanic White, Non-Hispanic Black, and Hispanic women, respectively.

Table 2: Change in driving distance, SDID estimates of impact by state, resident abortions in 2020, and relative increase in births to abortions.

State	Increase in average driving distance Miles	Estimated increase in births due to total abortion ban %	Estimated increase in births due to total abortion ban Level	Resident abortions in 2020 Level	Increase in births/abortions %
Alabama	100.5	2.9	1,689	9,060	18.6
Arkansas	225.9	1.4	504	4,510	11.2
Idaho	25.7	1.1	237	2,130	11.1
Kentucky	44.9	3.4	1,762	5,690	31.0
Louisiana	408.6	3.2	1,806	7,760	23.3
Mississippi	240.0	4.4	1,550	5,760	26.9
Missouri	2.2	0.4	280	11,710	2.4
Oklahoma	154.2	2.6	1,229	8,330	14.7
South Dakota	32.9	0.8	87	680	12.7
Tennessee	130.2	3.3	2,573	10,450	24.6
Texas	452.9	5.1	18,594	61,500	30.2
West Virginia	45.9	3.1	528	1,780	29.7
Wisconsin	43.8	2.5	1,503	8,290	18.1

Notes: Column 1 lists the 13 states classified as ”total ban” states in the analyses. The estimated increase in driving distance from May 2022 to December 2022 as reported in Myers (2023b) is listed in column 2. Using data from the first six months of every period, 2019-2023, column 3 reports the estimated reduction in births based on 13 separate SDID models comparing changes in log births in each ban state to changes in log births in a weighted set of control states. Except for Texas all states are considered treated in 2023, while Texas is considered treated starting in 2022. Column 4 reports the annualized estimated increase in births using column 3 log changes multiplied by 2020 births. Column 5 reports total resident abortions in 2020 (the latest year available) based on estimates from the Guttmacher Institute (Maddow-Zimet and Kost, 2022). Column 6 divides the change in births in column 4 by the number of abortions in column 5.

Appendix A: Details on states' abortion ban classification

We use as a starting point for our state legal coding the information collected by the Center for Reproductive Rights (Center for Reproductive Rights, 2023). In particular, we rely on their classification of abortion bans and protective landscapes. Then, we cross-validate this information with the Guttmacher Institute's classification of abortion policies and access after Roe (Guttmacher Institute, 2023a). Both sources are continuously updated, but our classifications reflect the state abortion landscapes as of October 2022. In those instances in which it was not clear how accessible abortion is in a state, we relied on specific statutes in the law surrounding the case text of abortion policy laws and proposals, as well as news articles. This is with the aim of tracking down the evolution of abortion policy proposals and their corresponding approvals or blockings to classify these states in the category that most accurately reflected abortion access in those states.

If a state had a ban on abortions under nearly all circumstances in effect as of October 2022, we code the state as enforcing a near-total ban on abortions, which is our treatment. From the 13 states we include in this category, 11 had a trigger law or a pre-Dobbs law that took effect with the Dobbs decision, i.e., by late June 2022.[17] West Virginia did not have a trigger law but banned abortion after Dobbs. The 13th state we consider as a ban state is Wisconsin. Although it did not have a ban in effect as of October 2022, the legal environment has been highly hostile, and existing abortion policies are unclear. As a result, all Wisconsin abortion providers ceased providing services due to Dobbs. Two facilities resumed services in 2023, but this is outside our study period(UW CORE, 2022).

The next category of states we consider are those that have enacted a pre-viability gestational-age ban at any point through the present and/or enacted a total abortion ban after October 2022. In the first case, states with gestational age limits are highly restrictive, but abortion access has not been completely banned, as in the case of the states in the previous paragraph. In the second case, although abortion access is not legal anymore in this state, the change happened late enough not to affect abortion access and, therefore,

[17] These states are Alabama, Arkansas, Idaho, Kentucky, Louisiana, Mississippi, Missouri, Oklahoma, South Dakota, Tennessee, and Texas

births during 2022 and the first quarter of 2023, our period of study.

In addition, although some other states have not implemented abortion bans or gestational age limits, their state legislature proposals and decisions around abortion access have been hostile. Therefore, we consider these states in a separate category because abortion access has been in a grayer area relative to ban states, states with gestational age limit changes, or protective states.

Finally, the remaining states either did not change their abortion legislation after Dobbs or have implemented policies that protect abortion access.[18]

Table A.1 presents the states' classification across the abovementioned categories. Below, we briefly describe the policies on which our legal coding is based for each state.

Alabama

Ala. Code § 26-23H-4 makes it illegal to perform an abortion unless it is deemed medically necessary by a licensed physician, which will be verified by a second physician 180 days after the end of the abortion.

This statute went into effect on June 24, 2022.

Classification: Total Ban.

Alaska

Planned Parenthood of The Great Nw, 375 P.3d at 1129 ruled that the privacy provision of Alaska's constitution protects the right to an abortion.

Classification: Protected.

Arizona

Id. §§ 13-3603, 13-3605 is a pre-*Roe* era ban on abortion that is currently enjoined. In the immediate aftermath of Dobbs, it was unclear whether this law should take precedence. A ruling in December 2022 on *Planned Parenthood v. Brnovich* clarified that it should not take precedence over state regulations of abortion.

Separately, a statute § 36-2322, which went into effect in September 2022, bans abortion

[18] These states are Alaska, California, Colorado, Connecticut, Delaware, Hawaii, Illinois, Kansas, Maine, Maryland, Massachusetts, Michigan, Minnesota, Montana, Nevada, New Hampshire, New Jersey, New Mexico, New York, Oregon, Rhode Island, Vermont, Virginia, Washington, and the District of Columbia.

after 15 weeks gestational age.

Classification: Excluded. GA Change or late ban.

Arkansas

§ 5-61-301 to –304 bans abortions in all cases except to save the life of the mother.

This statute went into effect on June 24, 2022.

Classification: Total Ban.

California

HSC § 123468 allows abortion up to fetal viability. Further, Prop 1 in November 2022 passed by popular vote and clarified the state constitution's right to privacy to include a right to an abortion and contraceptives.

classification: Protected.

Colorado

There is no gestational age limit to abortion in Colorado. Further §§ 25-6-403, effective April 2022, guarantees a right to abortion in Colorado.

Classification: Protected.

Connecticut

§ 19a-602(a) leaves the decision to have an abortion to a pregnant woman.

Classification: Protected.

Delaware

tit. 24, § 1790 (b) expressly allows abortion up to fetal viability.

Classification: Protected.

District of Columbia

D.C. CODE § 2-1401.06 recognizes a right to an abortion.

Classification: Protected.

Florida

Fla. Stat. § 390.0111 was modified on July 21, 2022, and limits abortions to 15 weeks. At various points, this law has been enjoined or enforced. Currently under review by Florida's Supreme Court., S.B. 300, 2023 would enforce a 6-week ban in the event that Florida's Supreme Court allows the 15-week ban to continue.

Classification: Excluded. GA Change or late ban.

Georgia

H.B. 481, 2019, made it illegal to perform an abortion after a 6-week gestational age. This law was enjoined until November 2022, when it was allowed to take effect.

Classification: Excluded. GA change or late ban.

Hawaii

§ 453-16(b) allows abortion until viability.

Classification: Protected.

Idaho

Idaho Code § 18-622(1)(a) bans abortion with exceptions for the life of the mother and in the case of rape or incest reported to law enforcement. The law became effective on August 25, 2022.

Classification: Total Ban.

Illinois

775 ILL. COMP. STAT. 55/1-25(a) allows abortion until viability.

Classification: Protected.

Indiana

S.B. 1, 122nd Leg., 1st Spec. Sess. (Ind. 2022) made it illegal to perform an abortion. This law was enjoined until June 30, 2023, and took effect on August 1, 2023. Since the law didn't take effect until 5 months before the end of 2023, we are considering it not to have an effect on fertility in 2023, but the law serves as evidence of general hostility towards abortion over this period.

Classification: Excluded. Moves to Total Ban in 2024.

Iowa

S.F. 597, 2023 Leg., Spec. Sess. (Ia.. 2023) passed in July 2023 limited abortion to 6 weeks or less gestational age but was enjoined. The law serves as evidence of hostility towards abortion.

Classification: Excluded.

Kansas

Hodes & Nauser, MDsS, P.A. v. Schmidt, 440 P.3d 461, 502 clarified that the state constitution guarantees a right to an abortion. A ballot measure H.C.R. 5003 failed that would have changed this in August 2022.

Classification: Protected.

Kentucky

Ky. Rev. Stat. § 311.772 took effect on June 24, 2022, and bans abortion except to prevent the death or substantial risk of death due to a physical condition or to prevent the serious, permanent impairment of a life-sustaining organ of a pregnant woman.

Classification: Total Ban.

Lousiana

LA. Stat. Ann. §§ 40.87.7, 14.87.8, 40:1061 took effect on June 24, 2022, and bans abortion except for the death or substantial risk of death due to a physical condition or to prevent the serious, permanent impairment of a life-sustaining organ of a pregnant woman.

Classification: Total Ban.

Maine

Tit. 22 §1598 ensures the right to an abortion up to viability.

Classification: Protected

Maryland

CODE, HEALTH-GEN. § 20-209 ensures the right to an abortion up to viability.

Classification: Protected.

Massachusetts

The decision in *Moe v. Secretary of Administration and Finance* ruled that abortion is protected under the due process clause of the state constitution. In addition, Gen. Laws ch. 112, § 12L. ensures a right to an abortion.

Classification: Protected.

Michigan

Id. § 333.17015 allows abortion with informed consent up to the point of viability.

Under Article I § 28 of the state constitution protects the right to an abortion.

Classification: Protected.

Minnesota

Women of State of Minnesota represented by Doe v. Gomez ruled that women have a right to an abortion.

Classification: Protected.

Mississippi

Effective June 27, 2022, Miss. Code Ann. § 41-41-45 bans all abortion except to save the life of pregnant persons or in cases of rape or incest reported to law enforcement.

Classification: Total Ban.

Missouri

Effective June 24, 2022 o. Rev. Stat. § 188.017 bans all abortions except to save the life of the mother.

Classification: Total Ban.

Montana

The right to privacy under MONT. CONST., ART. II, § 10. Armstrong v. State ruled that this right includes the right to an abortion pre-viability.

Classification: Protected.

Nebraska

LB574 banned abortion after 12 weeks of gestational age in May 2023 in time to possibly have an effect on fertility in 2023. However, since we do not the extent of this effect, we consider it hostile during our study period.

Classification: Excluded. Would be GA change or late ban by end of 2023.

Nevada

NEV. REV. STAT. § 442.250. allows abortion before 24 weeks.

Classification: Protected.

New Hampshire

N.H. REV. STAT. § 329:34 bans abortion after 24 weeks. No law expressly allows abortion, and neither does a law prohibit it.

Classification: Protected.

New Jersey

S.B. 49/A6260 made abortion a right in January 2022.

Classification: Protected.

New Mexico

Partial birth abortion is prohibited under N.M. STAT. ANN. § 30-5A-3, but there are no express legal prohibitions on abortion. There are also no express legal rights to abortions.

Classification: Protected.

New York

§ 2599-aa guarantees a right to an abortion.

Classification: Protected.

North Carolina

N.C. Gen. Stat. § 90-21.81B(2), which was enacted on July 1, 2023, prohibits abortion after 12 weeks. It did not pass in time to substantially affect fertility rates in 2023, as it was 6 months before the end of the year. It was a demonstration of its hostile status towards abortion, though.

Classification: Excluded, but would be GA change or late ban for 2024.

North Dakota

On April 24, 2023, North Dakota began enforcing a total ban on abortion under S.B. 2150, 68th Leg. Sess. This ban took place at a time that could partially affect fertility in late 2023.

Classification: Excluded. GA change or late ban.

Ohio

REV. CODE ANN. § 2919.195(A) prohibits abortion after six weeks. It is currently enjoined and will not take effect until a review of *Preterm-Cleveland v. Yost* determines the legality of the statute post-Dobbs but was enforced for a few months Post-Dobbs.

Classification: Excluded. Noted that it has a pre-viability abortion ban which is enjoined but was effective for a couple months.

Oklahoma

S.B. 1503, 58th Leg. created private citizen enforcement of a 6-week ban making abortions after 6 weeks prohibitively costly on May 3, 2022. Under H.B. 4327, 58th Leg. Oklahoma began enforcing a total ban on abortions under the same private citizen enforcement mechanism on May 26, 2022. S.B. 1555, 58th Leg., 2nd Reg. Sess., which made abortion illegal throughout pregnancy, took effect on June 24, 2022.

Classification: Total Ban.

Oregon

§ 435.305 ensures abortion as a right.

Classification: Protected.

Pennsylvania

Pennsylvania has a governor supportive of abortion but a senate that is actively hostile towards abortion. It also has many abortion restrictions in place. CRR classifies them as hostile, although not much has changed post-Dobbs. Our coding is consistent with the Center for Reproductive Rights, but we can see an argument for abortion access to be considered as protected.

Classification: Excluded. Bordering Protected.

Rhode Island

§ 23-4.13-2(a) ensures a right to an abortion.

Classification: Protected.

South Carolina

§§ 44-41-610 et seq. limits abortion to six weeks and was in effect from June 24, 2022, to August 17, 2022, and then enjoined. A separate law S. 474, 125th Gen. Assemb., Spec. Sess. passed in May 2023 and took effect in August 2023 at a point where it would not affect fertility in 2023. South Carolina may have been ambiguously affected in 2023 due to the early enforcement of the original 6-week abortion law before it was enjoined.

Classification: Excluded. Moving to GA change or late ban by 2024. Noted that it had a 6 week ban that was enforced temporarily but was late enjoined.

South Dakota

§ 22-17-5.1 made performing an abortion a felony except in cases to save the life of the mother on June 24, 2022.

Classification: Total Ban.

Tennessee

§ 39-15-213 bans abortion except in limited medical emergency exceptions and became effective on August 25, 2022.

Classification: Total Ban.

Texas

SB8 went into effect in September 2021 and allowed private citizens to sue anyone suspected of assisting an abortion that occurred after six weeks of pregnancy. §§ 170A.001-7 officially went into effect starting August 25, 2022.

Classification: Total Ban. Early Implementation of stringent gestational age ban.

Utah

§§ 76-7-302 bans abortion at 18 weeks and went into effect on June 26, 2022. A full ban, § 76-7a-201, went into effect from June 24, 2022, to June 27, 2022, but was enjoined.

Classification: Excluded. GA change or late ban.

Vermont

Id. § 9493 ensures a right to an abortion. Vt. S. Const. Amend. No. 5 further ensures this right.

Classification: Protected.

Virginia

§§ 18.2-71, 18.2-74 states abortion is legal up to viability.

Classification: Protected.

Washington

§ 9.02.110 ensures a right to an abortion up to viability.

Classification: Protected.

West Virginia

§16-2R-3 bans abortion except for non-viable fetuses, ectopic pregnancy, or medical emergencies and became effective on September 13, 2022, following the passage of state law.

Classification: Total Ban.

Wisconsin

Abortion providers have been acting under an ambiguous legal environment where it is undetermined whether an 1849 law that bans abortion should take precedence since June 24, 2022. This ambiguity will remain until *Kaul et al. v. Kapenga et al.* is decided, and so abortion is de facto banned in Wisconsin until this is resolved.

Classification: Total Ban.

Wyoming

§ 35-6-102 bans abortion but has not taken effect as it has been enjoined. It is evidence of clear hostility towards abortion.

Classification: Excluded.

Table A.1: State Abortion Dispositions After Dobbs

(1) Total Ban	**(2) Protected**	**(3) Excluded**
Alabama	Alaska	**Arizona**
Arkansas	California	**Florida**
Idaho	Colorado	**Georgia**
Kentucky	Connecticut	Indiana
Louisiana	Delaware	Iowa
Mississippi	DC	Nebraska
Missouri	Hawaii	North Carolina
Oklahoma	Illinois	**North Dakota**
South Dakota	Kansas	Ohio
Tennessee	Maine	Pennsylvania
Texas	Maryland	South Carolina
Wisconsin	Massachusetts	**Utah**
West Virginia	Michigan	Wyoming
	Minnesota	
	Montana	
	Nevada	
	New Hampshire	
	New Jersey	
	New Mexico	
	New York	
	Oregon	
	Rhode Island	
	Vermont	
	Virginia	
	Washington	

Notes: Bolded states had a gestational age ban that may be relevant for the first six months of 2023 or a full ban at a later time that may have created ambiguity for providers that may be relevant for the first six months of fertility in 2023. Two states in the Excluded list, Ohio and South Carolina had relevant 6-week gestational age limits that were temporarily enforcement before being enjoined.

Appendix B: Power Analysis

B.1 Simulated Power Analysis Method

To estimate the minimum detectable effect size on the fertility of abortion bans at various levels of power, we follow the methods presented by Black et al. (2022).

Like Black et al. (2022), we assign a pseudo period like the Dobbs period in the main analysis. For the main results of our paper, we rely on the four years leading into Dobbs in the pre-period and one-year post, which is 2019-2022 and 2023, respectively, for the Dobbs period. For the pseudo period, we rely on 2015-2019. We set the period of analysis to 2015-2019 to exclude any actual effects in differential fertility that might have occurred due to the COVID-19 pandemic across states (Bailey et al., 2022; Kearney and Levine, 2023; Dench et al., 2023). We randomly assign treatment to 12 states to match the number of states with bans going into effect shortly after Dobbs but excluding Texas for the reasons discussed in the main body of the paper. We then impose varying effects starting from the null and increasing out to 7 percent positive and 7 percent negative effects of the mean fertility rate in each population in whole percentage point increments on the last year of the pseudo-treatment period, 2019. We estimate synthetic difference-in-differences (SDID) and two-way fixed effects (TWFE) models, where pseudo-treatment turns on in 2019. For synthetic difference-in-differences models, we use clustered bootstrap standard errors with 1,000 bootstrap samples. For two-way fixed models, we clustered standard errors at the state level. Then, we repeat this randomization and analysis 200 times and report the percent of samples at each effect size where we have t-statistics either greater than 1.96 or less than -1.96, representing the power of the test at that effect size corresponding to a rejection rate of 0.05 on a two-sided hypothesis.

Our method differs from Black et al. (2022) in the following ways. First, in some analysis Black et al. (2022) adjust the weighting of their analysis by applying inverse propensity weighting based on observable characteristics (IPW). This is with the aim that the weighted randomized pseudo-treated look more like the set of groups that are actually treated and the randomized pseudo-control groups look more like the set of groups that are actually control groups. In our case, we do not think it is reasonable to apply this adjustment since ban states will vary on many unobservable as well as observable characteristics that would make such reweighting implausible. In addition, SDID adjusts for the most obvious and important difference between treated and control states, which is differential trends, without the need to arbitrarily select reweighting control variables to meet this condition. Second, we consider a two-tailed instead of a one-tailed test. While we believe treatment effects should be positive, given the substantial literature in support of this, we do not want to impose that given the uncertainty around *Dobbs'* effects on mitigating behaviors. Second, because this is a state-level analysis, there is no need to randomly increase births such as Black et al. (2022) removed deaths based on their probability of occurring in each county. Instead, we simply increase or decrease the fertility rate by the selected percent of the state-year fertility rates. Third, we do not remove states where there could be pre-treatment contamination from the analysis. Given ban states are frequent regulators of abortion, we would have very few treatment states from which to draw inference in randomization. Instead, we rely on the parallel trends assumption inherent in difference-in-differences which holds on average under randomization.

To assess sensitivity to the selection of pre-period, in another set of power analyses, we lengthen our pre-period to go back to 2005. This is to show the extent to which power may be affected in two-way fixed effects or SDID by arbitrary selection of the pre-period. The caveat is that SDID might still select a weighted set of pre-periods itself. In that case, there is no subjective judgment in selection, but rather it is based on the algorithm defined in Arkhangelsky et al. (2021). Randomization, in this case, will still impose parallel trends on average.

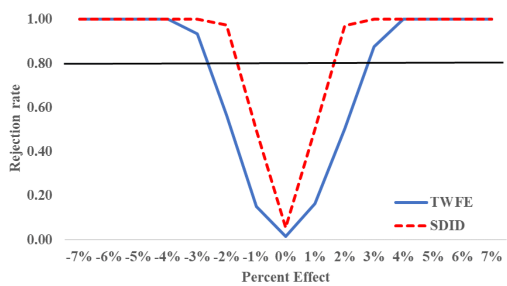
Our power analysis illustrates the effect sizes we could detect if treatment were randomized across states. It should be noted that randomization imposes the assumption, on average, that the treated group is trending similarly to the control group. It therefore guarantees the underlying assumption in difference-in-differences analysis while this might not play out in the real world if there are differential trends between treatment and control groups. These power calculations should therefore be considered in the context of where this underlying assumption holds.

To address this concern, we conduct a secondary analysis assessing effects assigned to the Dobbs ban states over time. We reassign the period of analysis to every 5-year period from 2005 to 2019 (e.g. 2005-2009, 2006-2010), generating eleven pseudo-periods, imposing the effects in the last year of treatment. The rest of the power analysis follows similarly to the randomized designs.

The final analysis is to take into account the potential for heterogeneous effects across our states since power may be different than when the effect is uniform. We rely here on modeled forecasts from Myers (2023a). While these estimates are based on travel distances to abortion clinics before Dobbs applied to post Dobbs travel distances, which might exclude effects of bans generated by other mechanisms, they serve as a way of generating plausible effect size heterogeneity across states. For this analysis, we take the estimates from model (6) of Table 2 and apply them to formula (2) for each to modify each county's number of births in each year. We then aggregate to the state level and sequentially impose effects to every five-year period from 2005-2019 and estimate SDID and TWFE models. We apply this analysis only to all women aged 15-44 since Myers (2023a) only provides the effects of a change in distance from 0-100 miles for these groups.

B.2 Power analysis results

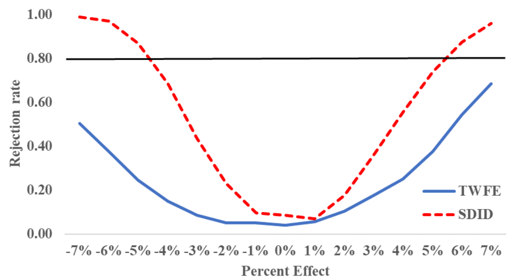
Our primary power analysis in Table B.1 and Figures B.1 to B.3 shows the rejection rate imposing each randomized treatment effect of between -7 to 7 percent limited to the period 2015-2019. We report ranges for MDE at conventional levels of 0.8 power levels and only on the positive side. In the case of randomization, however, positive and negative rejection MDE are quite symmetric. As expected, the rejection rate when there is zero imposed effect is at or around 0.05 for both methods due to randomization. The main difference between TWFE and SDID is that SDID achieves the conventional rate of rejection of 80 percent or more much more quickly, both overall and in each of our subpopulations of interest. For the overall population, SDID reaches the conventional power level between 1-2 percent imposed effects, whereas TWFE reaches this level between 2-3 percent imposed effects. To be more specific, SDID, the more powerful method, crosses the 80 percent threshold between 1.4 to 1.6 percent effects. For the age group 15-19, TWFE reaches the conventional power level after 7 percent imposed effects, whereas SDID reaches the conventional power level between 5 to 6 percent. For ages 20-24, the conventional power level is reached between 3 to 4 percent but 2 to 3 percent for SDID. For ages 25-29, TWFE hits the conventional power level at between 4 and 5 percent, whereas SDID hits that level between 2 to 3 percent. For non-Hispanic White women, TWFE hits the conventional power level between 2 to 3 percent, whereas for SDID, the MDE is between 1 to 2 percent. For non-Hispanic Black women, we hit the conventional level closer to six percent, while for SDID, we hit the conventional level closer to 5 percent. Finally, for Hispanic women, we cross the conventional power level between 4 to 5 percent for TWFE and 3 to 4 percent for SDID.



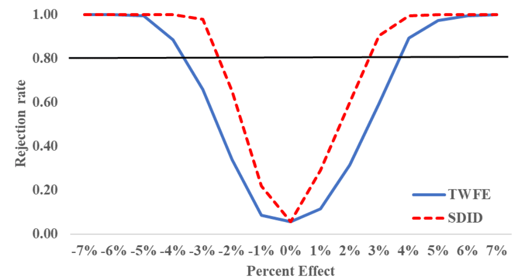
(a) All women

Figure B.1: Synthetic difference-in-differences and two-way fixed effects power analysis rejection rates imposing effect sizes on the period 2015-2019 in a random set of 12 states that mimic the bans in the twelve Dobbs ban states, excluding Texas for the overall population. Notes: We use fertility rates in each year-state as the outcome imposing effects from -7 to 7 percent of that year-state in the 12 randomly selected states in 2019, the last year of the power analysis. We count the number of rejected effects with t-statistics greater than 1.96 or less than -1.96 when the last year is considered treated.

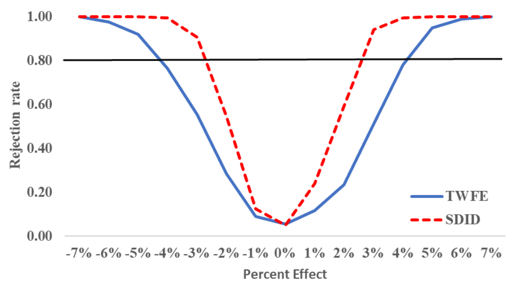
In Table B.2 and Figures B.4 to B.6, we report how extending the pre-period of analysis affects MDEs for each group of interest. The MDE are all higher in the case of OLS, for some groups substantially so, but practically unchanged for SDID. This is likely because of SDID's automatic selection of time weights to reduce the difference in the average post-period and pre-period for the control group. In this way, for power, SDID is rather insensitive to the



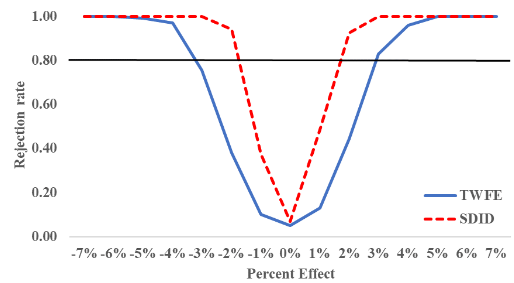
(a) Ages 15-19



(b) Ages 20-24



(c) Ages 25-29

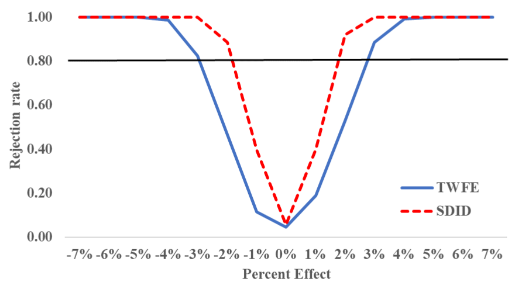


(d) Ages 30-34

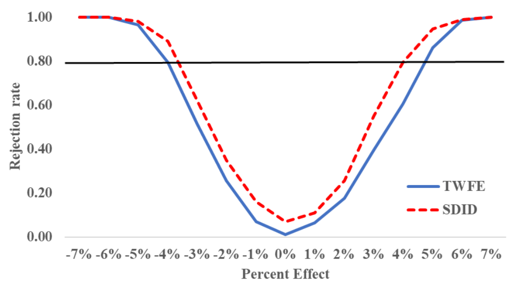
Figure B.2: Synthetic difference-in-differences and two-way fixed effects power analysis rejection rates imposing effect sizes on the period 2015-2019 in a random set of 12 states that mimic the bans in the twelve Dobbs ban states excluding Texas by age group.
Notes: We use fertility rates in each year-state as the outcome imposing effects from -7 to 7 percent of that year-state in the 12 randomly selected states in 2019, the last year of the power analysis. We count the number of rejected effects with t-statistics greater than 1.96 or less than -1.96 when the last year is considered treated.

selection of the pre-period.

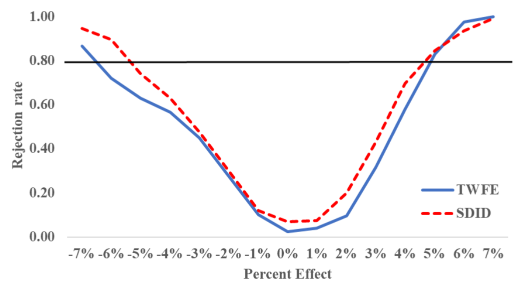
The results in B.3 and B.7 to B.9 show the result of imposing an effect on the Dobbs states at the end of each set of five-year periods from 2005-2019. Keep in mind that this is more akin to a placebo in time analysis than a simulated power analysis in the spirit of Black et al. (2022). If there are any actual differential effects between Dobbs states and non-Dobbs states during the last year of these periods or non-parallel trends in the pre-period, then it will contaminate the analysis and create skewed overrejection in either the positive or negative direction. Also, keep in mind that there are 11 potential time periods, so there is potentially substantial sampling variance, and thus the results of this power analysis will



(a) Non-Hispanic White



(b) Non-Hispanic Black

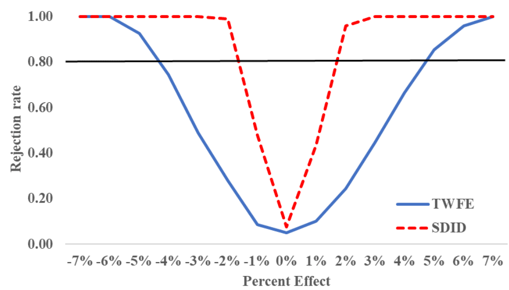


(c) Hispanic

Figure B.3: Synthetic difference-in-differences and two-way fixed effects power analysis rejection rates imposing effect sizes on the period 2015-2019 in a random set of 12 states that mimic the bans in the twelve Dobbs ban states, excluding Texas by race group.
Notes: We use fertility rates in each year-state as the outcome imposing effects from -7 to 7 percent of that year-state in the 12 randomly selected states in 2019, the last year of the power analysis. We count the number of rejected effects with t-statistics greater than 1.96 or less than -1.96 when the last year is considered treated.

inherently contain more noise than the randomization analysis. What we see is that for all women aged 15-44, for both TWFE and SDID, it is still very unlikely to reject the null hypothesis around the null. Like with randomization power analysis in B.1, we can obtain conventionally powered levels around 1 to 2 percent for SDID and 2 to 3 for TWFE. This is because the trends in fertility over the entire period 2005-2019 for women aged 15-44 in the Dobbs states and non-Dobbs states were parallel, as can be seen in Appendix **??** in TWFE and SDID event studies.

In the case of women aged 15-19, we reject the null hypothesis in TWFE with zero imposed effects 55 percent of the time. This is not unexpected given the trends observed in TWFE event studies in Appendix 6 in the pre-period. We also fail to ever reject the

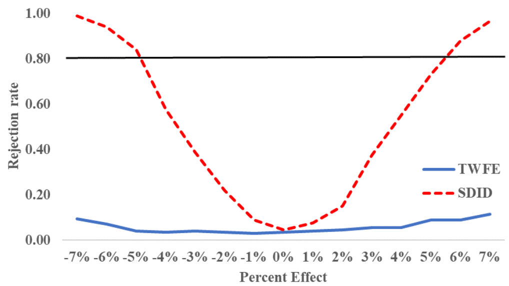


(a) All women

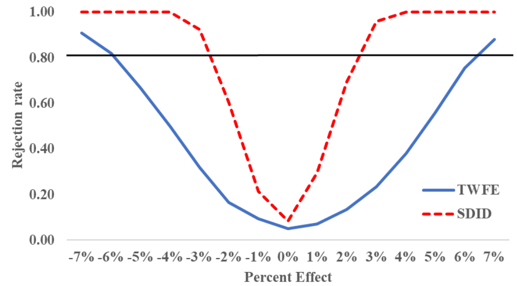
Figure B.4: Synthetic difference-in-differences and two-way fixed effects power analysis rejection rates imposing effect sizes on the period 2005-2019 in a random set of 12 states that mimic the bans in the twelve Dobbs ban states, excluding Texas for the overall population. Notes: We use fertility rates in each year-state as the outcome imposing effects from -7 to 7 percent of that year-state in the 12 randomly selected states in 2019, the last year of the power analysis. We count the number of rejected effects with t-statistics greater than 1.96 or less than -1.96 when the last year is considered treated.

null hypothesis for 15-19-year-old women using TWFE on the positive end. In contrast, in SDID, we reject the null with zero imposed effect only two out of 11 times and can detect effects on both sides of the distribution. With positive imposed effects, we reject the null hypothesis at greater than an 80 percent rate between 5 to 6 percent, which is similar to the rejection rates in the randomization power analysis. In all age groups, rejections are more symmetric in SDID than in TWFE, and in almost all cases where there is not severe skew in one direction with TWFE, conventional power rates are crossed earlier for SDID than for TWFE. One other thing to note is that, as is the case for the age group 25-29 as seen in related event studies when no weighted set of control states have similar trends to the treatment group, rejection at the null is quite common and may hinder our ability to interpret causality in this group. It should be noted that rejection at the null is also very high for TWFE.

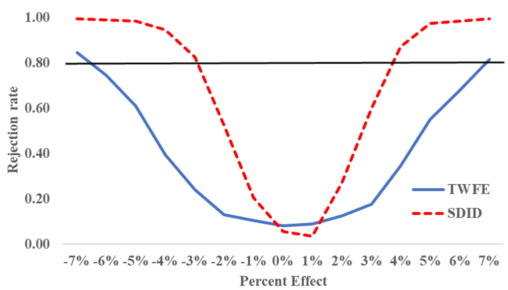
The final set of results pertains to allowing the effects to be heterogeneous across the ban and non-ban states using Myers (2023a)'s estimated effects of distance applied to post-Dobbs travel distance as our guide. In the case of SDID, imposing these effect sizes at the end of each five-year period from 2005-2019, we reject the null hypothesis ten out of 11



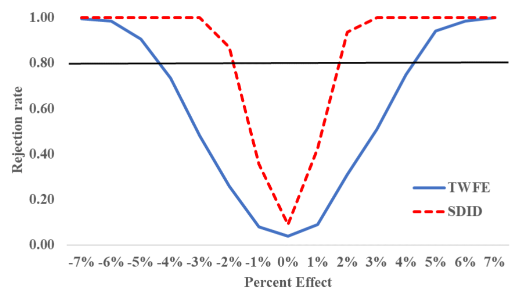
(a) Ages 15-19



(b) Ages 20-24



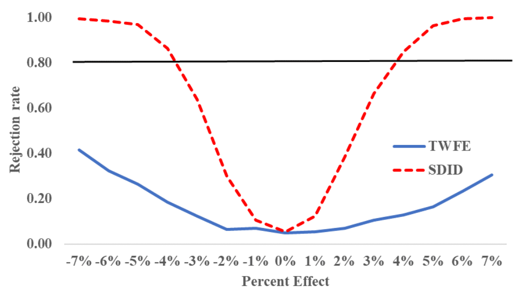
(c) Ages 25-29



(d) Ages 30-34

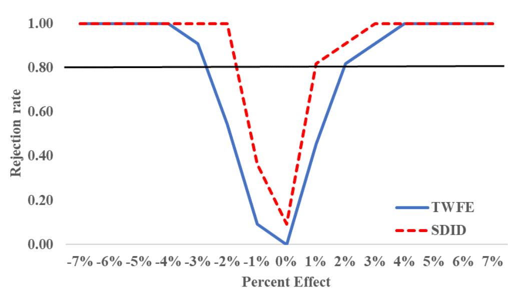
Figure B.5: Synthetic difference-in-differences and two-way fixed effects power analysis rejection rates imposing effect sizes on the period 2005-2019 in a random set of 12 states that mimic the bans in the twelve Dobbs ban states, excluding Texas by age group.
Notes: We use fertility rates in each year-state as the outcome imposing effects from -7 to 7 percent of that year-state in the 12 randomly selected states in 2019, the last year of the power analysis. We count the number of rejected effects with t-statistics greater than 1.96 or less than -1.96 when the last year is considered treated.

times. Using TWFE, we reject the null hypothesis eight out of 11 times.



(a) Hispanic

Figure B.6: Synthetic difference-in-differences and two-way fixed effects power analysis rejection rates imposing effect sizes on the period 2005-2019 in a random set of 12 states that mimic the bans in the twelve Dobbs ban states, excluding Texas for Hispanic women.
Notes: We use fertility rates in each year-state as the outcome imposing effects from -7 to 7 percent of that year-state in the 12 randomly selected states in 2019, the last year of the power analysis. We count the number of rejected effects with t-statistics greater than 1.96 or less than -1.96 when the last year is considered treated.



(a) All women

Figure B.7: Synthetic difference-in-differences and two-way fixed effects power analysis rejection rates imposing effect sizes on 12 states, excluding Texas at the end of every 5-year period from 2005-2019 for the overall population.
Notes: We use fertility rates in each year-state as the outcome imposing effects from -7 to 7 percent of that year-state in the 12 randomly selected states in 2019, the last year of the power analysis. We count the number of rejected effects with t-statistics greater than 1.96 or less than -1.96 when the last year is considered treated.

Table B.1: Two-way fixed effects versus synthetic difference-indifferences simulated power analysis rejection rates on randomly imposing *Dobbs*, 2015-2019

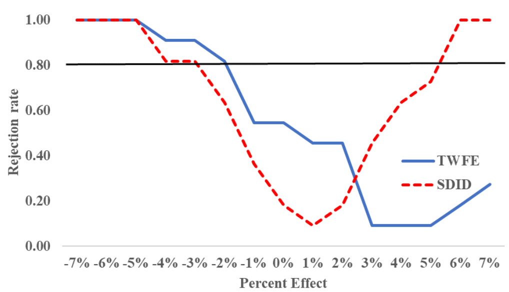
Percent Effect	Overall	Ages 15-19	Ages 20-24	Ages 25-29	Ages 30-44	White	Black	Hispanic
				Two-way Fixed Effects				
-7	1.00	0.51	1.00	1.00	1.00	1.00	0.87	1.00
-6	1.00	0.38	1.00	0.98	1.00	1.00	0.72	1.00
-5	1.00	0.25	1.00	0.92	1.00	0.99	0.63	0.97
-4	1.00	0.15	0.89	0.77	0.99	0.95	0.45	0.80
-3	0.94	0.09	0.66	0.56	0.83	0.76	0.45	0.52
-2	0.57	0.05	0.34	0.29	0.47	0.38	0.28	0.26
-1	0.15	0.05	0.09	0.09	0.12	0.10	0.10	0.07
0	0.02	0.04	0.06	0.06	0.05	0.05	0.03	0.01
1	0.17	0.06	0.12	0.12	0.19	0.13	0.04	0.07
2	0.51	0.11	0.32	0.24	0.53	0.45	0.1	0.18
3	0.88	0.18	0.60	0.51	0.89	0.83	0.32	0.40
4	1.00	0.25	0.90	0.78	0.99	0.96	0.58	0.61
5	1.00	0.38	0.98	0.95	1.00	1.00	0.83	0.86
6	1.00	0.55	1.00	0.99	1.00	1.00	0.98	0.99
7	1.00	0.69	1.00	1.00	1.00	1.00	1.00	1.00
				Synthetic Difference-in-differences				
-7	1.00	0.99	1.00	1.00	1.00	1.00	0.94	1.00
-6	1.00	0.97	1.00	1.00	1.00	1.00	0.89	1.00
-5	1.00	0.87	1.00	1.00	1.00	1.00	0.74	0.98
-4	1.00	0.69	1.00	1.00	1.00	1.00	0.63	0.89
-3	1.00	0.44	0.98	0.91	1.00	1.00	0.48	0.62
-2	0.98	0.23	0.65	0.55	0.89	0.95	0.30	0.35
-1	0.50	0.10	0.22	0.13	0.40	0.38	0.12	0.16
0	0.06	0.09	0.06	0.05	0.06	0.07	0.07	0.07
1	0.50	0.07	0.29	0.24	0.40	0.49	0.08	0.11
2	0.97	0.18	0.60	0.59	0.92	0.93	0.20	0.26
3	1.00	0.36	0.91	0.94	1.00	1.00	0.43	0.55
4	1.00	0.56	1.00	1.00	1.00	1.00	0.69	0.80
5	1.00	0.74	1.00	1.00	1.00	1.00	0.84	0.95
6	1.00	0.88	1.00	1.00	1.00	1.00	0.94	0.99
7	1.00	0.96	1.00	1.00	1.00	1.00	0.99	1.00

Table B.2: Two-way fixed effects versus synthetic difference-indifferences simulated power analysis rejection rates on randomly imposing *Dobbs*, 2005-2019

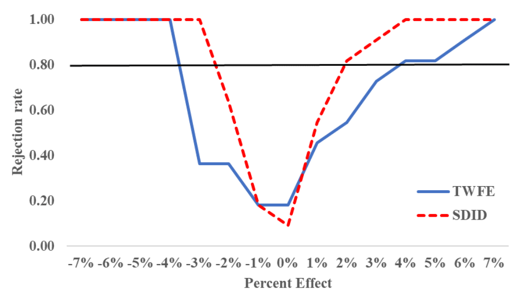
Percent Effect	Overall	Ages 15-19	Ages 20-24	Ages 25-29	Ages 30-44	Hispanic
			Two-way Fixed Effects			
-7	1.00	0.10	0.85	0.91	1.00	0.42
-6	1.00	0.07	0.75	0.82	0.99	0.33
-5	0.93	0.04	0.61	0.67	0.94	0.27
-4	0.75	0.04	0.40	0.50	0.76	0.19
-3	0.49	0.04	0.24	0.32	0.47	0.13
-2	0.28	0.04	0.13	0.17	0.22	0.07
-1	0.09	0.03	0.11	0.10	0.09	0.07
0	0.05	0.04	0.08	0.05	0.06	0.05
1	0.10	0.04	0.09	0.07	0.14	0.06
2	0.25	0.05	0.13	0.14	0.31	0.07
3	0.45	0.06	0.18	0.24	0.58	0.11
4	0.67	0.06	0.35	0.38	0.82	0.13
5	0.86	0.09	0.55	0.56	0.94	0.17
6	0.96	0.09	0.68	0.76	0.99	0.24
7	1.00	0.12	0.82	0.88	1.00	0.31
			Synthetic Difference-in-differences			
-7	1.00	0.99	1.00	1.00	1.00	1.00
-6	1.00	0.94	0.99	1.00	1.00	0.99
-5	1.00	0.84	0.99	1.00	1.00	0.97
-4	1.00	0.58	0.95	1.00	1.00	0.87
-3	1.00	0.39	0.83	0.93	1.00	0.64
-2	0.99	0.22	0.53	0.61	0.96	0.30
-1	0.48	0.09	0.21	0.22	0.41	0.11
0	0.08	0.05	0.06	0.09	0.03	0.06
1	0.44	0.08	0.04	0.30	0.34	0.13
2	0.96	0.15	0.27	0.70	0.91	0.39
3	1.00	0.38	0.60	0.96	1.00	0.67
4	1.00	0.55	0.87	1.00	1.00	0.85
5	1.00	0.73	0.98	1.00	1.00	0.97
6	1.00	0.88	0.99	1.00	1.00	1.00
7	1.00	0.97	1.00	1.00	1.00	1.00

Table B.3: Two-way fixed effects versus synthetic difference-in-differences simulated power analysis rejection rates on randomly imposing *Dobbs* in a different period, 2005-2019

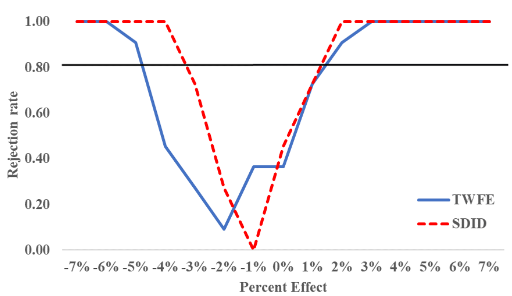
Percent Effect	Overall	Ages 15-19	Ages 20-24	Ages 25-29	Ages 30-44	Hispanic
			Two-way Fixed Effects			
-7	1.00	1.00	1.00	1.00	1.00	0.73
-6	1.00	1.00	1.00	1.00	1.00	0.73
-5	1.00	1.00	1.00	0.91	1.00	0.64
-4	1.00	0.91	1.00	0.45	0.82	0.64
-3	0.91	0.91	0.36	0.27	0.64	0.18
-2	0.55	0.82	0.36	0.09	0.18	0.18
-1	0.09	0.55	0.18	0.36	0.00	0.18
0	0.00	0.55	0.18	0.36	0.09	0.18
1	0.45	0.45	0.45	0.73	0.64	0.18
2	0.82	0.45	0.55	0.91	0.91	0.36
3	0.91	0.09	0.73	1.00	1.00	0.55
4	1.00	0.09	0.82	1.00	1.00	0.55
5	1.00	0.09	0.82	1.00	1.00	0.55
6	1.00	0.18	0.91	1.00	1.00	0.55
7	1.00	0.27	1.00	1.00	1.00	0.64
			Synthetic Difference-in-differences			
-7	1.00	1.00	1.00	1.00	1.00	0.91
-6	1.00	1.00	1.00	1.00	1.00	0.82
-5	1.00	1.00	1.00	1.00	1.00	0.73
-4	1.00	0.82	1.00	1.00	1.00	0.55
-3	1.00	0.82	1.00	0.73	1.00	0.45
-2	1.00	0.64	0.64	0.27	0.73	0.36
-1	0.36	0.36	0.18	0.00	0.18	0.18
0	0.09	0.18	0.09	0.45	0.18	0.18
1	0.82	0.09	0.55	0.73	0.73	0.18
2	0.91	0.18	0.82	1.00	0.91	0.27
3	1.00	0.45	0.91	1.00	1.00	0.64
4	1.00	0.64	1.00	1.00	1.00	0.73
5	1.00	0.73	1.00	1.00	1.00	0.82
6	1.00	1.00	1.00	1.00	1.00	0.91
7	1.00	1.00	1.00	1.00	1.00	0.91



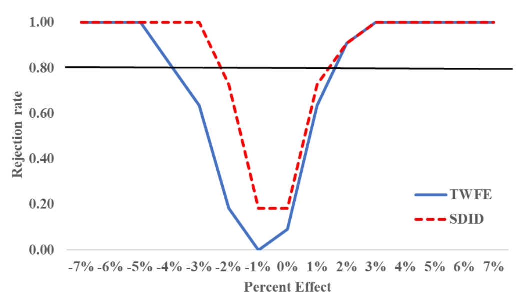
(a) Ages 15-19



(b) Ages 20-24

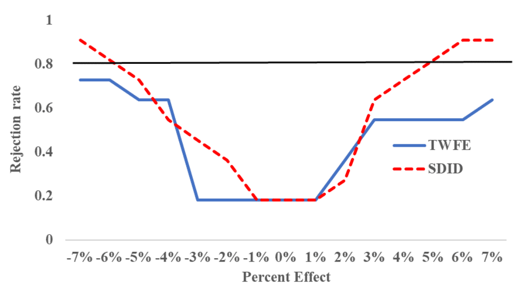


(c) Ages 25-29



(d) Ages 30-34

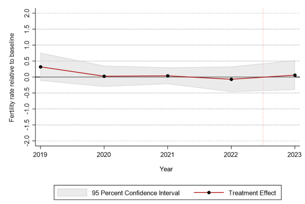
Figure B.8: Synthetic difference-in-differences and two-way fixed effects power analysis rejection rates imposing effect sizes on 12 states, excluding Texas at the end of every 5-year period from 2005-2019 by age group.
Notes: We use fertility rates in each year-state as the outcome imposing effects from -7 to 7 percent of that year-state in the 12 randomly selected states in 2019, the last year of the power analysis. We count the number of rejected effects with t-statistics greater than 1.96 or less than -1.96 when the last year is considered treated.



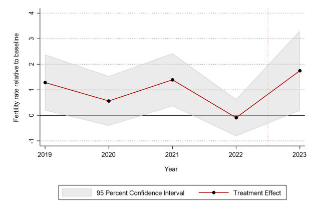
(a) Hispanic

Figure B.9: Synthetic difference-in-differences and two-way fixed effects power analysis rejection rates imposing effect sizes on 12 states, excluding Texas at the end of every 5-year period from 2005-2019 for Hispanic women.
Notes: We use fertility rates in each year-state as the outcome imposing effects from -7 to 7 percent of that year-state in the 12 randomly selected states in 2019, the last year of the power analysis. We count the number of rejected effects with t-statistics greater than 1.96 or less than -1.96 when the last year is considered treated.

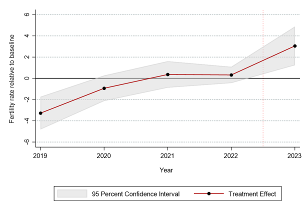
Appendix C: Additional Figures and Tables



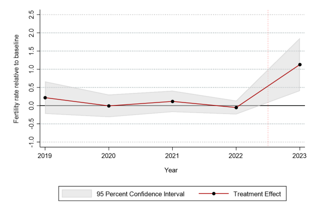
(a) Ages 15-19



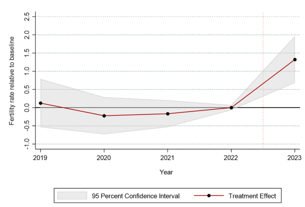
(b) Ages 20-24



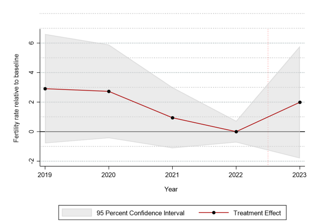
(c) Ages 25-29



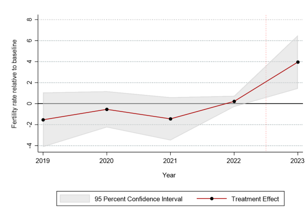
(d) Ages 30-44



(e) Non-Hispanic White



(f) Non-Hispanic Black



(g) Hispanic

Figure C.1: Synthetic difference-in-differences event study estimates of fertility in Dobbs ban states relative to protected control states for all women by age group or by race and ethnicity for the first six months of every period.

Notes: See notes to Figure 2 for details. All estimates are based on the CDC Wonder reporting system.

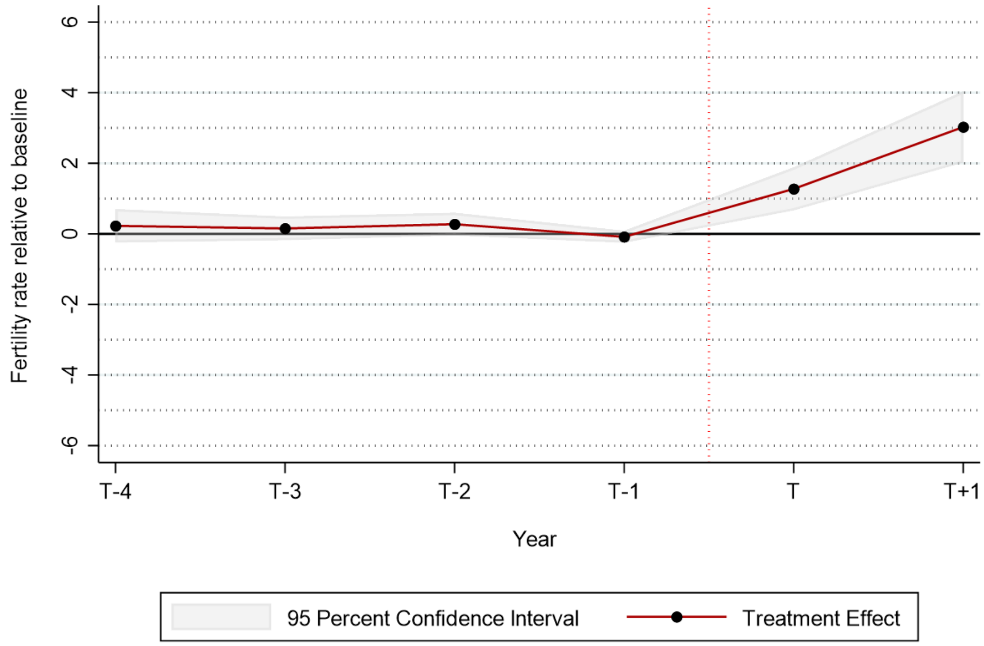


Figure C.2: Synthetic difference-in-differences event study estimates of fertility in Dobbs ban states relative to protected control states for all women aged 15-44, including Texas, for the first six months of each year.

Notes: We implement Sun and Abraham (2021) weights for staggered designs in difference-in-differences but applied to Synthetic Differences-in-Differences as suggested in Clarke et al. (2023). We allow Texas's ban to affect fertility starting in 2022 when the vast majority of births that took place as a result of SB8 would occur. See notes to Figure 2 for more details.

Appendix D: Robustness Checks

While SDID limits design choices with respect to the selection of control states trending similarly in the pre-period, there is still considerable choice over frequency of data, controls for possible confounders, choice of uncontaminated control groups, selection of treatment groups, and the timing of treatment. In this section, we present robustness checks to these considerations.

Table D.1 and Table D.2 show alterations to many of these design decisions. All iterations of design choices are shown with and without control for state economic conditions proxied through the six-month unemployment rate. All results are robust to the inclusion or exclusion of this control variable.

Another concern may be that we have arbitrarily selected our pre-period. We present extensions and robustness to pre-period selection, starting the analysis in 2005. Figures D.1 and rows (3) and (4) of Table D.1 show the results for this analysis. If anything, baseline results get a bit larger when you extend the pre-period to 2005.[19] Although aggregating to the yearly level reduces variance and negates the need to apply seasonal adjustment, it is yet another design choice. The seasonal adjustment we apply is to estimate the effect of monthly indicators and a linear trend term from 2019-2022 for each state separately, removing only the effect of the monthly indicators before estimating SDID. We show results at the monthly level in rows (5) and (6) of Table D.1 and Figure D.2. Results are a bit smaller, 0.7 instead of 1.1 per 1,000 women aged 15-44 at this level of aggregation. Correctly allowing Oklahoma's treatment to turn on in November 2022 instead of January 2023 in columns (7) and (8) of Table D.1 and figure D.6 increases the effect at this level a bit to 0.8-0.9 births per 1,000 women.

Returning to estimates aggregating effects to the first six months of every year, in rows (9) and (10) of Table D.1, we find the inclusion of hostile states with no gestational age ban or late total bans shrinks estimated effects to 0.8 to 0.9 births per 1,000 women of reproductive age but remain significant. Pennsylvania, although listed as a hostile state by Center for Reproductive Rights (2023), has a Democratic governor, and access remains pretty well in place during our period of interest. We therefore run exploratory analysis just including Pennsylvania in the potential list of controls. We find including Pennsylvania as a "Protected" state in rows (11) and (12) of Table D.2 makes no practical difference to our results.

Our choice to use SDID in our analysis, we believe, is well-founded by pre-period power analysis. The realized estimated effect size in the analysis is on the border of being able to be detected using Two-way fixed effects according to our pre-period power analysis in

[19]The results presented by race for non-Hispanic Black and non-Hispanic White only go back to 2016 instead of 2005. We could only go back to 2016 for Non-Hispanic Black and White groups due to the changes in definitions of races to report multiple race categories that rolled out over different groups over time but were available in all states in the CDC Wonder data system by 2016.

Appendix B. We present results for TWFE in rows (13)-(16) of Table D.2 and figures D.4 and D.5 for an extended version. While the magnitudes of the overall results are consistent with our findings, the standard errors are quite a bit larger, especially for the extended pre-period analysis.

One common control in the literature is for inclusion of the demographic makeup of a state's population. Given that SDID matches on pre-trends, there would have to be a sharp change in the demographic makeup of a state in the treatment period in order to substantially affect results. In rows (17) and (18), we include controls for the percent of women of reproductive age in each age category, 15-19, 20-24, 25-29, and 30-44, along with each race/ethnicity category, non-Hispanic White alone, non-Hispanic Black alone, and Hispanic. They make no practical difference to our results, but they do increase imprecision a bit.

Finally, we show results from a totally different system for provisional data release we are calling Rapid Release in rows (19) and (20) of Table D.2, accessed on October 23, 2023. Unlike Wonder, it does not contain the actual residence of each birth, but rather it estimates birth by state of residence based on the number of birth certificates that occur in states and adjusts this occurrence rate for the ratio of occurrences to residency in each state from prior birth certificate data. While this process may be faster than fully processing the birth certificate data for inclusion in CDC Wonder, it may also be less accurate in residency and does not contain information by demographic group. Overall, the estimates are consistent with CDC wonder data, showing an effect of 1.4-1.5 births per 1,000 women rather than 1.1.

Table D.1: Synthetic difference in differences estimate of the impact of the *Dobbs* decision on fertility using the first six months of every period, Robustness Checks

		Age Categories				Race/Ethnicity			
	Overall	15-19	20-24	25-29	30-44	W	B	H	UR control
(1) Baseline	1.1	0.0	1.7	3.0	1.1	1.3	1.8	4.0	Yes
	(0.3)	(0.3)	(0.8)	(1.0)	(0.4)	(0.3)	(2.2)	(1.3)	
(2) Baseline	1.2	0.1	1.8	3.2	1.1	1.3	2.0	4.0	No
	(0.3)	(0.2)	(0.7)	(1.0)	(0.4)	(0.3)	(1.9)	(1.3)	
(3) Extended	1.4	0.8	2.1	4.6	1.3	1.4	1.6	4.1	Yes
Pre-period	(0.4)	(0.3)	(0.8)	(1.4)	(0.4)	(0.3)	(2.3)	(1.3)	
(4) Extended	1.1	0.1	1.8	4.6	1.1	1.3	1.5	4.0	No
Pre-period	(0.3)	(0.2)	(0.6)	(1.4)	(0.4)	(0.3)	(2.1)	(1.3)	
(5) Monthly	0.7								Yes
	(0.4)								
(6) Monthly	0.7								No
	(0.4)								
(7) Oklahoma	0.8								Yes
staggered monthly	(0.4)								
(8) Oklahoma	0.9								No
staggered monthly	(0.4)								
(9) Hostile	0.8	0.1	1.0	1.9	0.8	1.0	2.5	3.1	Yes
control included	(0.3)	(0.3)	(0.7)	(0.9)	(0.4)	(0.3)	(1.8)	(1.3)	
(10) Hostile	0.9	0.2	1.1	2.0	0.8	1.0	2.9	3.1	No
control included	(0.3)	(0.2)	(0.7)	(0.9)	(0.4)	(0.3)	(1.6)	(1.4)	

Notes: See table 1 for notes on estimation. All even models present results without control for unemployment. Model (1)-(2) presents results from our baseline estimation without Texas. Model (3)-(4) present results using an extended pre-period. Model (5)-(6) estimate effects at the monthly level. Model (7)-(8) presents results where Oklahoma's treatment starts in November 2022 instead of January 2023. This is because Oklahoma's private citizen enforcement law took effect at the beginning of May 2022 instead of the end of June 2022. Models (9) and (10) include hostile states, Indiana, Iowa, Nebraska, North Carolina, Ohio, Pennsylvania, South Carolina and Wyoming that did not implement a gestational age limit or total ban by the time 2023 fertility might have been affected.

Table D.2: Synthetic difference in differences estimate of the impact of the *Dobbs* decision on fertility using the first six months of every period, Robustness Checks

		Age Categories				Race/Ethnicity			
	Overall	15-19	20-24	25-29	30-44	W	B	H	UR control
(11) Pennsylvania	1.1	0.0	1.7	2.9	1.1	1.3	1.9	4.0	Yes
control included	(0.3)	(0.3)	(0.8)	(0.9)	(0.4)	(0.3)	(2.1)	(1.3)	
(12) Pennsylvania	1.2	0.1	1.7	3.2	1.1	1.3	2.1	4.0	No
control included	(0.3)	(0.2)	(0.7)	(0.9)	(0.4)	(0.3)	(1.9)	(1.3)	
(13) TWFE	0.9	-0.1	-0.2	4.6	1.0	1.4	-0.6	5.6	Yes
	(0.5)	(0.3)	(0.8)	(1.2)	(0.5)	(0.6)	(2.3)	(2.2)	
(14) TWFE	0.9	-0.1	-0.2	4.6	1.0	1.4	-0.6	5.6	No
	(0.5)	(0.3)	(0.8)	(1.3)	(0.5)	(0.6)	(2.3)	(2.2)	
(15) TWFE Extended	1.5	-2.7	-0.0	11.6	2.2	1.3	-1.1	6.2	Yes
Pre-period (2005-2023)	(1.1)	(1.0)	(1.8)	(2.6)	(0.9)	(0.8)	(2.5)	(2.9)	
(16) TWFE Extended	1.7	-2.5	0.2	11.7	2.3	1.4	-1.1	6.4	No
Pre-period (2005-2023)	(1.2)	(1.1)	(1.9)	(2.6)	(0.9)	(0.8)	(2.5)	(3.0)	
(17) Demographic	1.3	0.3	1.7	2.8	1.3	1.3	1.7	5.1	Yes
controls	(0.5)	(0.4)	(0.9)	(1.4)	(0.6)	(0.4)	(2.4)	(1.7)	
(18) Demographic	1.3	0.4	1.7	2.9	1.3	1.4	1.8	5.1	No
controls	(0.4)	(0.4)	(0.9)	(1.4)	(0.5)	(0.4)	(2.2)	(1.7)	
(19) Rapid	1.4								Yes
Release	(0.4)								
(20) Rapid	1.5								No
Release	(0.4)								

Notes: See table 1 for details about estimation. Model (11)-(12) include Pennsylvania as an additional control without the other hostile states. We do this because PA, unlike the other hostile states, is very unlikely to implement a ban until after the governor race in 2026 and had no new regulation of abortion in 2022. These models are exploratory analysis since they were not in the pre-analysis plan. Model (13)-(14) present results using two-way fixed effects. Model (15)-(16) present results using TWFE with an extended pre-period. Model (17)-(18) present results controlling for percent in each age category 15-19, 20-24, 25-29 and 30-44, as well as percent White non-Hispanic, Black non-Hispanic and Hispanic. Model (19)-(20) uses an alternate provisional data release system, Rapid Release, for the birth data in 2023. This system provides information only for overall births in a state, is an estimate of resident births based on historical ratios of occurrence to residence ratios, and counts of birth certificates received from states based on occurrence in a state.

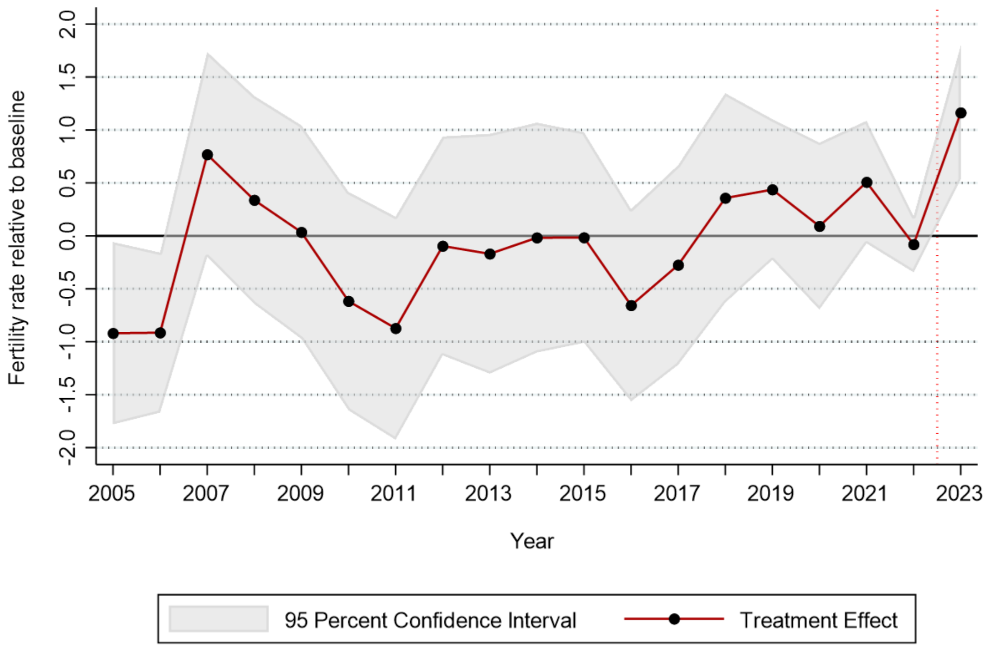


Figure D.1: Synthetic difference-in-differences event study estimates of fertility in Dobbs ban states relative to protected control states for all women aged 15-44 with extended pre-period 2005-2022 for the first six months of each year.

Notes: See notes to Figure 2 for more details.

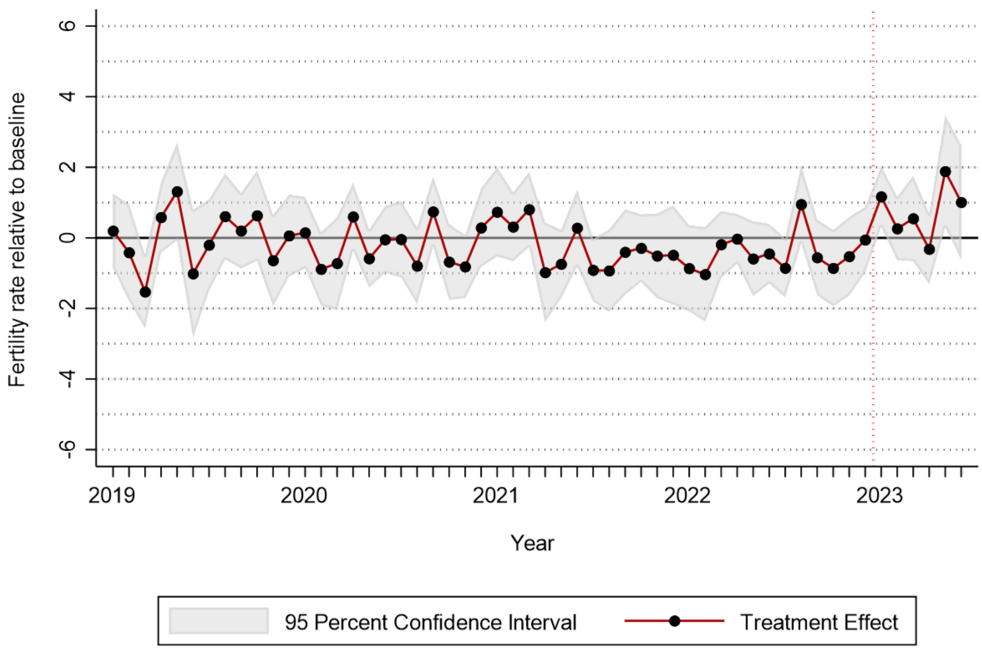


Figure D.2: Synthetic difference-in-differences event study estimates of fertility in Dobbs ban states relative to protected control states for all women aged 15-44 by month.

Notes: Treatment still turns on in January 2023 for all states. Estimates are deseasonalized by regressing each state's month-year fertility rate from 2019-2022 on a set of monthly indicators and a trend term. All month-year fertility from 2019-2023 is then subtracted by the corresponding monthly indicator. See notes to Figure 2 for details.

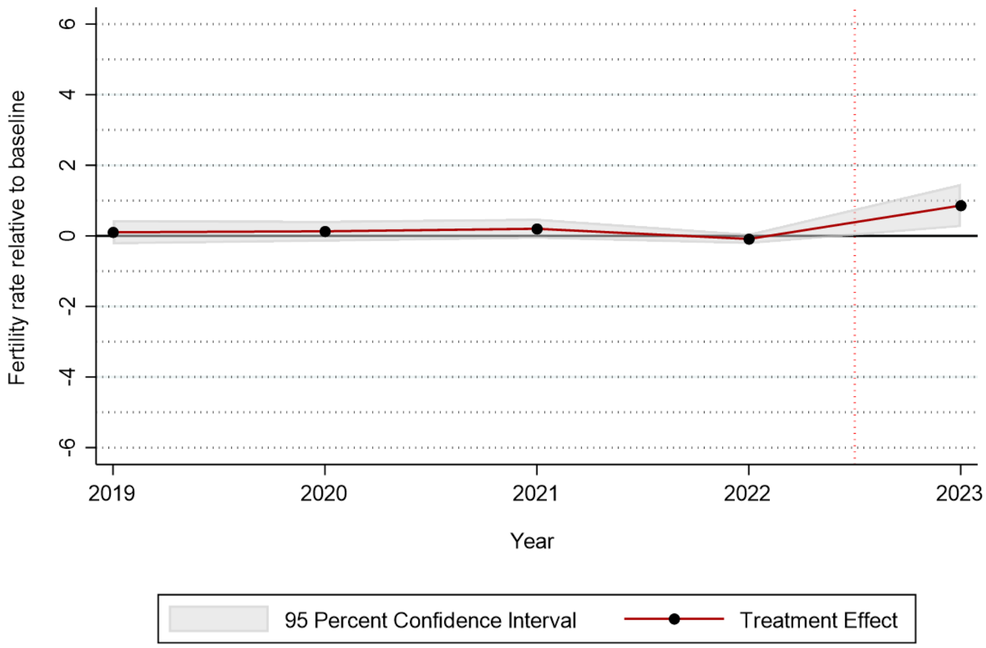


Figure D.3: Synthetic difference-in-differences event study estimates of fertility in Dobbs ban states relative to all states that do not implement a change in gestational age limit that could affect births in 2023 for all women aged 15-44.

Notes: Includes the *Protected* and *Excluded* states in the control group. Still excludes any states with gestational age or late bans that could affect 2023 fertility rates. See notes to Figure 2 for details.

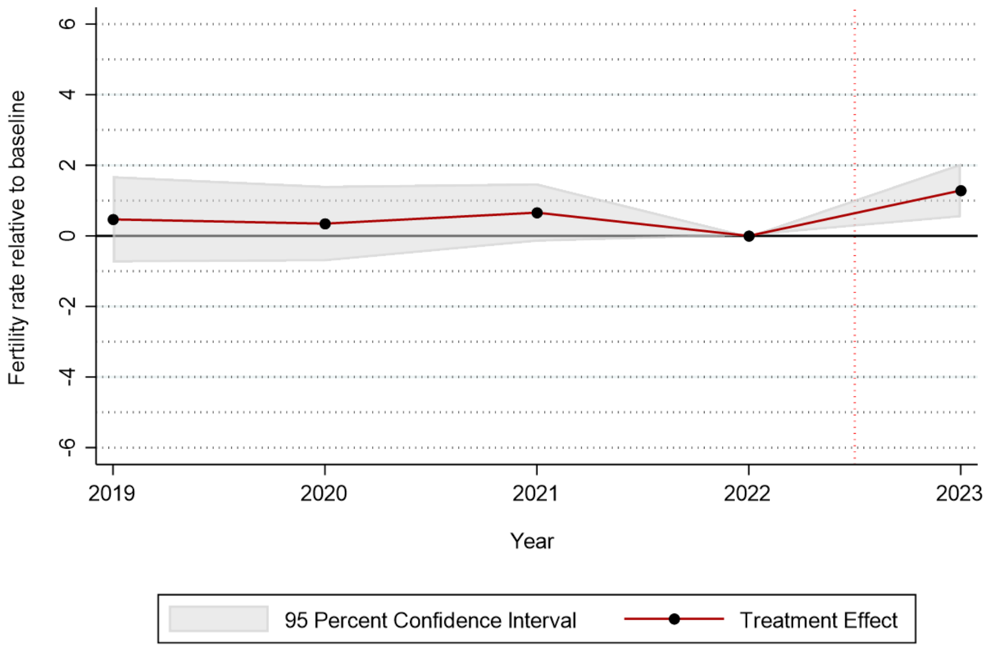


Figure D.4: Two-way fixed effects event study estimates of fertility in Dobbs ban states relative to protected control states with 2022 as the reference year for all women aged 15-44 for the first six months of every year.

Notes: See notes to Figure 2 for details. Estimates come from a standard TWFE model, and standard errors are clustered at the state level.

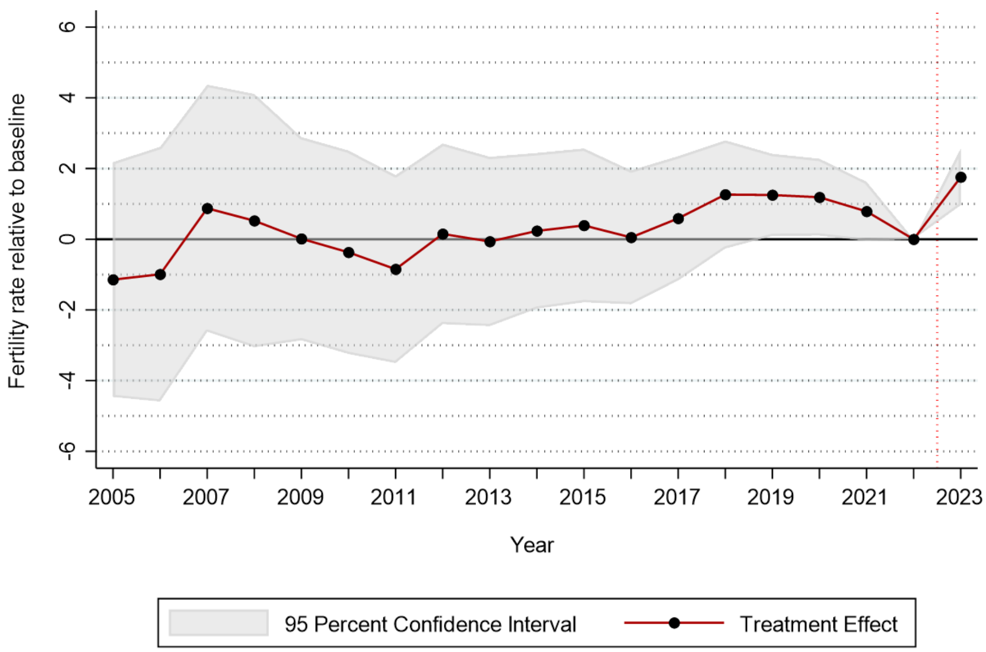


Figure D.5: Two-way fixed effects event study estimates of fertility in Dobbs ban states relative to protected control states with 2022 as the reference year and an extended pre-period for all women aged 15-44 for the first six months of every year.

Notes: See notes to Figure 2 for details.

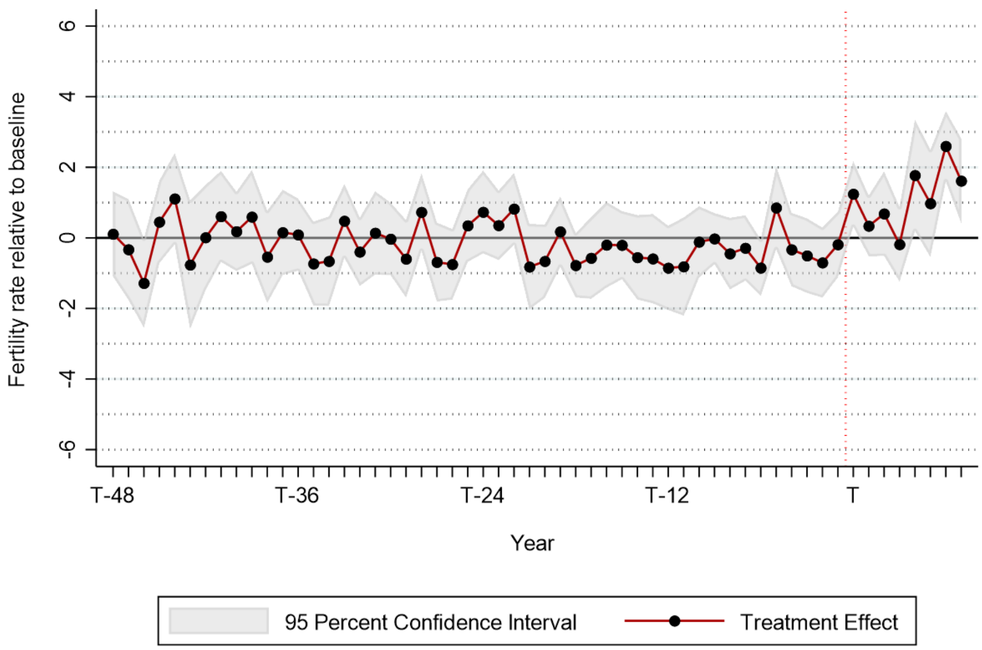


Figure D.6: Synthetic difference-in-differences event study estimates of fertility in Dobbs ban states relative to protected control states for all women aged 15-44 shown by month, but where Oklahoma begins two months earlier due to its six weeks gestational age ban at the beginning of May and full ban by the end of May.

Notes: See notes to Figure C.2 for details.