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Reproductive Injustice? A County-Level Analysis of the Impact of Abortion Restrictions on Abortion Rates

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Abstract

Since *Planned Parenthood v. Casey* in 1992, state governments in the United States have been permitted to restrict abortion access up to the point where such restrictions do not place an ''undue burden" on those seeking abortion care. Since this ruling, abortion restrictions of various types and intensities have proliferated across the South and Midwest, especially since the 2010s. This paper uses a novel dataset of county-level abortion rates covering 20 years, as well as a database covering four types of restrictions which represent both "demand-side" restrictions (i.e., those which target abortion seekers) and "supply-side" restrictions (i.e., those which target abortion providers), to analyze the effect of abortion restrictions on abortion rates. Using a difference-in-differences design, the analysis finds that while both classes of abortion restrictions reduce the abortion rate, restrictions that target pregnant people seeking an abortion have a substantially larger effect on abortion rates. Leveraging the spatial heterogeneity of the county-level dataset, the analysis further finds that abortion restrictions have a substantially larger negative effect on abortion rates for counties which have a larger share of Black or Hispanic residents. When comparing high and low income counties, the results suggest that poorer counties experience a higher negative effect of abortion restrictions. Further, the study finds significant variation in the effect of different abortion restrictions by state. While demand-side laws consistently cause abortion rates to decrease, the results for supply-side laws are more heterogenous. Overall, the results suggest that repealing *Roe v. Wade* will have a significant and unequal effect on abortion rates, with marginalized communities experiencing a greater impact.

JEL Codes: I18, J13, B54

Keywords: Reproductive Health, Abortion Restrictions, Abortion, *Roe v. Wade*, Reproductive Justice

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1 Introduction

In June 2022, the U.S. Supreme Court ruled in *Dobbs v. Jackson Women's Health Organization* (2022) that ''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). This decision - which overturned *Roe v. Wade* (1973) along with the entire set of Supreme Court decisions which consistently affirmed *Roe* - allowed states to enact virtually unlimited restrictions on abortion care, up to and including outright bans. However, these increasingly dramatic restrictions reflect a culmination of a trend rather than a sharp break in reproductive health policy. Since *Planned Parenthood of Southeastern Pennsylvania v. Casey* (1992), states have been permitted to enact restrictions on abortion up to the point that they do not place an ''undue burden" on those seeking abortion care. Since this ruling, abortion restrictions of various types and intensities have proliferated across the South and Midwest. Over the last decade, however, the rate at which states have passed these restrictions has increased dramatically. Over 1300 abortion restrictions have been enacted since *Roe v. Wade*, with 44% of these being passed in the last decade. In 2021 alone, a record 108 abortion restrictions were passed in 19 states - by far the most since 1973 (Nash 2021). To shed light on the implications of the repeal of *Roe v. Wade* for reproductive justice, this paper analyzes the effect of these laws on abortion rates, using data on abortion restrictions with novel data on county-level abortion rates spanning a 20 year period from 2000 to 2020.

Abortion restrictions can broadly be classified into two categories: ''supply-side" restrictions, or Targeted Regulation of Abortion Providers (TRAP) laws, which are designed to target abortion providers and are often called Targeted Regulation of Abortion Providers (TRAP) laws, and ''demand-side" restrictions are laws which target pregnant people seeking abortions.[1] This paper focuses on Ambulatory Surgical Center (ASC) laws and Admitting Procedure (AP) laws, TRAP laws which have been the focus of widespread legal challenges throughout the late 2010s and early 2020s (*Whole Woman's Health v. Hellerstedt* 2016; *June Medical Services LLC v. Russo* 2020). On the demand-side, this paper focuses on Mandatory Waiting Period (MWP) laws and Texas's six-week gestational ban on abortion. It finds that while all abortion restrictions reduce the abortion rate, those which target pregnant people seeking an abortion have a much larger effect thant those which target abortion providers.

Reproductive Justice advocates have long argued that restrictions which increase the financial, social, and time costs in seeking an abortion fall disproportionally on the most marginalized (Ross and Solinger 2017). For example, while wealthier women may have the capacity to travel across state lines and rent a hotel room to avoid state-level abortion restrictions, poorer women may be unable to do so; women who live in the Deep South may face further hurdles in access than those who live closer to an unrestricted state, and younger women who do not own a vehicle may have to depend on limited public transit options. Using county-level demographic data, this analysis also compares the effect of abortion restrictions between counties which have relatively high shares of ethnic and racial minorities

1. This paper occasionally uses the gender-neutral term ''pregnant people" to refer to those who may seek to have an abortion.

to counties which have high white population shares. It finds that abortion restrictions can reduce the abortion rate of counties with large Black and Hispanic populations by over twice as much as counties with mostly white populations. When stratifying by county median household income, it finds more mixed effects: Once accounting for a cluster of high income counties, abortion restrictions decrease abortion rates more in poorer counties compared to wealthier counties.

Much popular and scholarly attention has focused on especially severe versions of abortion restrictions, such as H.B. 2 in Texas. However, these restrictions are in place all over the country. This paper also presents a state-by-state analysis for each type of law, examining the effect of a given restriction on the abortion rate for each state individually. While TRAP laws appear to have much more heterogenous effects across states - with certain states experiencing a large decrease in the abortion rate and others a null or even positive effect - MWP laws have a much more unambiguously negative effect on abortion rates. Furthermore, the state-by-state analysis presents suggestive evidence that abortion restrictions have become more pernicious in the last decade when compared to restrictions enacted in the early 2000s.

This paper contributes to recent literature which has applied causal methods to examine the effect of abortion restrictions. Much work has focused on the increased travel distance to a clinic that is caused by a decrease in the number of clinics as a result of a specific TRAP or demand-side law, such as H.B. 2 in Texas or Tennessee's MWP (Lindo et al. 2020; Fischer, Royer, and White 2018; Lindo and Pineda-Torres 2021). However, this literature is generally case-study based, making it difficult to generalize about the causes of these laws. Other work which has attempted to estimate the aggregate effect of abortion restrictions have used state-level abortion rate data, which makes measuring the effect of abortion policy difficult given the large number of state-specific, time-varying factors which need to be controlled for (Austin and Harper 2019b; Myers 2021a). State-level data also prevents the type of heterogeneity analysis by county characteristics which is crucial for understanding the differential impact of these restrictions on abortion rates, which is especially important to understand in the post-*Roe* era.

This paper makes several contributions to overcome these limitations. Firstly, it analyzes a broad range of abortion restrictions across a key twenty year period when abortion restrictions where rapidly spreading across the U.S. using a consistent empirical method. This allows for straightforward comparisons of the effect of these laws, and can broadly characterize the role that abortion restrictions played in reducing the abortion rate in the pre-*Dobbs* era. Secondly, it provides this analysis at the county-level, which allows for finer geographic comparisons, controls, and fixed effects than a state-level analysis of abortion restrictions would allow. This also allows for analysis of abortion rates by the spatial and demographic features of each county, a critical feature of the larger discussion on the effects of abortion restrictions which is largely missing from the causal literature. Lastly, it provides a causal estimate of the effect of an abortion ban in the United States. Given the rapid rate at which bans are being implemented as a result of ''trigger laws'', this analysis provides an early insight into the future of reproductive health in the wake of *Dobbs* (Nash and Cross 2021).

This paper will proceed as follows. Section 2 will discuss the relevant literature. Section 3 will introduce the difference-in-differences method used in this paper. Section 4 provides more details on the abortion restrictions studied in this analysis. It will outline the data sources used to compile the datasets on abortion restrictions and abortion rates, as well as the other data sources used in this paper. Section 5 will present the primary results on the effect of abortion restrictions on abortion rates. It first pools the effect of all types of restrictions, before disaggregating by supply-side and demand-side laws, and then by AP and ASC laws. This section also presents the heterogeneity analyses by racial, ethnic, and income county group, as well as by state. Section 6 will show the results for Texas's six-week ban on abortion. Lastly, section 7 will summarize and conclude.[2]

2 Literature Review

The passage of H.B. 2 in Texas led to an increased interest in supply-side abortion restrictions, and a modest literature has emerged to examine the effect of these laws.[3] The drop in clinics in Texas was quick and dramatic. Grossman et al. (2014) observed that after the passage of H.B. 2, the number of clinics providing abortions decreased from 41 to 22, resulting in significant increases in the number of women living 50, 100, and 200 miles from a provider.

Several papers have leveraged this extreme and exogenous drop in providers to estimate the effect of a reduction in abortion access on abortion rates and other outcomes. Lindo et al. (2020) and Fischer, Royer, and White (2018) both examine the effect of the sudden change in distance on abortion rates. They find that a change in distance from being close to a clinic to being 50 or more miles away decreases the abortion rate by about 16-17%. Importantly, the Lindo et al. (2020) and Fischer, Royer, and White (2018) analysis of birth rates after H.B. 2 are much smaller than what is expected based on the effect on abortion, implying a much less than one-to-one channel of abortion policy changes to fertility. In other words, pregnant people are finding other ways to obtain an abortion than those that show up in the official statistics, such as commuting to a different state, or self-inducing an abortion. Venator and Fletcher (2021) examines policies which shuttered clinics in Wisconsin and finds similar results.

The analysis in this paper extends these case study approaches to all states which have passed TRAP laws in the last 20 years to determine the average effect of these laws. A few other articles have moved beyond specific case studies of supply-side laws, instead opting for cross-state analysis. Austin and Harper (2019b) uses the panel dataset constructed in Austin and Harper (2019a) to examine the causal effect of TRAP laws on abortion rates. Using state-level data on abortion rates, they find that TRAP laws do not have a consistent statistically significant effect on abortion rates. However, the use of state-level data prevents the heterogeneity analysis that is necessary to examine the differential

2. The data and replication code used to generate the findings of this study will be made openly available for download in the Harvard Dataverse repository and will be found at the following persistent link upon publication: https://doi.org/10.7910/DVN/ZWOPNX.

3. See Austin and Harper (2018) for an early literature review of TRAP laws on health outcomes, including early analyses of H.B. 2 in Texas. Their assessment of the literature is that there was some contradictory evidence of the effect on abortion rates, but that the evidence for AP and ASC type laws were less ambiguous.

effects of these policies, making it difficult to address issues of reproductive justice, which the use of finer geographic level data allows in this article. The analysis presented here also disaggregates abortion restrictions by both type and state, illuminating how the effect of abortion restrictions has changed over time and varies by state. Myers (2021b) is another contribution which examines the effect of increasing distance to a clinic on abortion rates. Using a similar dataset as this paper on county-level abortion rates for all states where these data are available from 2009-2020, Myers (2021b) finds that an increase in travel distance from zero to 100 miles leads to a decrease in the abortion rate of about 20.5%, and an increase in birth rates of approximately 2.4%. While not explicitly examining TRAP laws, the large changes in provider numbers observed in Myers (2021b) broadly reflects the enactment of TRAP and similar laws across the country, though not all clinics may have closed due to an exogenous change in policy. This analysis explicitly examines such policy changes. It also is able to examine a larger number of law enactments given the larger sample size employed.

The demand-side literature is smaller, although there have been several important contributions analyzing the effect of these class of restrictions as well, again mostly employing a case study approach. Joyce, Henshaw, and Skatrud (1997) and Lindo and Pineda-Torres (2021) are case studies which examine the effect of Mandatory Waiting Period laws passed in Mississippi and Tennessee, respectively. Both articles find that these policies caused reductions in the abortion rate, and considerable increases in second trimester abortions.[4] Myers (2021a) codes the spread of both ''one-trip" and ''two-trip" mandatory waiting period laws, and uses the difference-in-differences approach to estimate the effect of these laws on abortion and birth rates. Using state-level data on abortion and county-level data on births, Myers (2021a) finds that ''two-trip" mandatory waiting period laws led to a decrease in the abortion rate by 8.9%, and increased birth rates by 1.5%. While Myers (2021a) examines heterogenous effects on birth rates, the use of state-level data prevents analysis of the differential effect of these MWP laws on abortion rates, a gap in the literature which this paper fills.

3 Empirical Method

Estimating the effect of abortion restrictions on abortion rates requires a comparison of counties which passed restrictions to relevant control counties. The general empirical approach is to use an event-study difference-in-differences (DiD) estimator. More specifically, I utilize the Stacked Difference-in-Differences (SDiD) model following Cengiz et al. (2019).

The baseline model is as follows:

$$Y_{itc} = \sum_{k=K}^{-2} \beta_k D_{itc}^k + \sum_{k=0}^{L} \beta_k D_{itc}^k + X_{itc}\Omega + \alpha_{ic} + \tau_{tc} + \epsilon_{itc} \tag{1}$$

where Y_{itc} is the abortion rate for county i in time t for a given treatment cohort c, α_{ic} are treatment

4. See Joyce et al. (2009) for a review of the early literature on mandatory waiting periods.

cohort-specific county fixed effects, τ_{tc} are treatment cohort-specific time fixed effects, X_{itc} is a vector of pre-treatment control and outcome variables interacted with an indicator for the post-treatment period, and ϵ_{itc} is the error term. The D_{it}^{k} are lead and lag indicator variables which equal 1 if a county is ''treated" with an abortion restriction k periods before or after treatment and 0 otherwise. Therefore, the β_k for $0 \leq k \leq L$ trace out the effect of abortion restrictions from the period of treatment ($k = 0$) up to L periods after treatment. The β_k for $K \leq k < -1$ trace out the ''effect" of restrictions before the restrictions are actually passed, which following the conventions in the literature act as a falsification test for the parallel trends assumption of the DiD model. An 11 period window is chosen around each policy, with 5 pre-treatment periods (with $k = -1$ standardized to zero), and 6 post-treatment periods.

Estimates where the 6-year post-treatment effects are pooled are also estimated. Specifically, rather than event study coefficients, a single post-treatment coefficient is estimated:

$$Y_{itc} = \beta D_{itc} + X_{itc}\Omega + \alpha_{ic} + \tau_{tc} + \epsilon_{itc} \tag{2}$$

where D_{itc} equals 1 if county i is treated at time t for a given cohort c.

The "stacked" element of the above equations refer to the shape of the data, where treated counties and control counties for each policy are subsetted and aligned to occur at the same relative time. A treatment cohort is defined as the set of counties which get treated in the same calender year. The ''stack" is then created by sub-setting the full data and selecting only that cohort of treated states for the K, L window, as well as all the ''clean control" counties, defined here as those which either never enforce a given restriction or enforce it at a minimum of 6 years after treatment.[5] These data sub-sets are then ''stacked" on top of each other, with the relevant window of the clean control state appearing in the stacked data c number of times.[6] An individual stack can be thought of as a case study for a single cohort of treated states, and the stacks combined thus represent an average treatment effect across the cohorts.

A benefit of the stacked DiD model is that it is robust to the ''negative weights" problem associated with treatment effect heterogeneity, which could result in the standard DiD producing an estimate that is biased (Goodman-Bacon 2021; Baker, Larcker, and Wang 2022). Various estimators have been proposed to correct for the bias associated with heterogenous treatment assignment (Sun and Abraham 2021; Chaisemartin and D'Haultfœuille 2020; Callaway and Sant'Anna 2021). As a robustness check, I compare the baselines estimates of the SDiD model to the estimator proposed in Callaway and Sant'Anna (2021) in appendix C.

Identification is derived from the assumption that the treated and untreated counties follow parallel

5. The implication of this selection of controls in the language of Callaway and Sant'Anna (2021) is that both ''never-treated" and ''not-yet-treated" controls are included as comparison units. Also included are states which enacted a restriction, but due to some legal hurdle it was blocked in the court system. The logic here is that states which either will enforce a given restriction at a later point or states which attempted to are intuitively better controls than states which never attempt to enact an abortion restriction, and therefore important to include in the DiD estimate.

6. An example and a visualization of the shape of the data is presented in appendix figure C1.

trends prior to the point of treatment. An ideal experiment would randomly assign abortion restrictions and compare the treated and control groups, but that is not possible for most policy studies. Further, abortion restrictions are not spread evenly throughout the country. Specifically, they are clustered in the South and Midwest, with the Northeast and West Coast having relatively few restrictions. These regions have highly differentiated political, social, demographic, and economic trends that are likely correlated with both a tendency to restrict abortion as well as abortion and other health outcomes. This threatens the parallel trends assumption that the DiD model imposes for a legitimate causal interpretation of the coefficient estimates. This uneven distributution of policy treatments is not unique to abortion restrictions. For example, state-level minimum wages are also clustered unevenly across regions, with higher minimum wages most common in the Northeast and West Coast, and least likely in the South. In order to address this issue, one strategy used in the minimum wage literature is to control for certain variables in order to better match treated and control counties, or to include state-specific time trends (Allegretto et al. 2017). Following these innovations in the minimum wage literature, I explicitly allow for a number of pre-treatment control variables that might capture any variation not caught by the fixed effects. Specifically, I use the year-before-treatment values for total population, racial and ethnic population shares, and the share of the population who are women of reproductive age (15-44) to match counties with initial differences in population composition that may influence abortion rates or policy changes.[7] I also use the pre-treatment state-level minimum wage as a proxy to capture political attitudes which may similarly drive differences in either variable. Lastly, I use the county-level poverty rate, median household income, and unemployment rate to capture differences in economic conditions, as well as the pre-treatment abortion rate to capture any initial possible exogenous differences in abortion demand.[8]

4 Data and Descriptive Statistics

In order to investigate the effect of various restrictions on abortion rates, two primary data sources are needed. First, a dataset which captures the start of these restrictions, and second, a dataset with abortion rate data at a fine geographic level. A major contribution of this paper is to assemble these sources.

4.1 Data on Abortion Restrictions

In this paper, I mainly focus on three separate restrictions: Admitting Privilege, Ambulatory Surgical Center laws, and Mandatory waiting period laws.

The supply-side laws considered here are TRAP (Targeted Regulation of Abortion Provider) laws.

7. An alternative would be to use time-varying controls. However, changes in reproductive health policy could plausibly differentially shift population shares, and perhaps even economic and political variables as well. Using pre-treatment values for the controls mitigates this problem.

8. I also estimate a variant of equations 1 and 2 allowing for state-specific or county-specific linear trends in the appendix.

While initially confined to only a handful of states, by the end of the last decade a plurality of states in the U.S. South and Midwest had attempted to pass through such laws, often facing intense legal blowback. Supporters argue that these regulations are necessary in order to protect the women seeking abortions. However, there is no evidence that TRAP laws in any way improve health outcomes (American Public Health Association 2015). These actions by state governments culminated in the Supreme Court case *Whole Woman's Health v. Hellerstedt* (2016), which ruled that a particularly restrictive set of TRAP laws in Texas known as H.B. 2 were unconstitutional and placed an undue burden on women seeking an abortion. This ruling was upheld with a more conservative bench in *June Medical Services LLC v. Russo* (2020).

The TRAP law abortion restrictions data will come from Austin and Harper (2019a). They trace the origin for three types of TRAP laws for each state which has passed one from 1970 to 2017. This makes it possible to identify moments where states went from having no or minimal TRAP laws to substantial ones, which is ideal for the DiD approach used here. Austin and Harper (2019a) used policy documents and a large range of secondary sources to identify TRAP enactment, enforcement, and if it was legally blocked for three of the main types of laws which may effect clinic closures: Ambulatory Surgical Center (ASC) laws, Admitting Privilege (AP) laws, and Transfer Agreement (TA) laws. ASC laws require abortion clinics to adhere to the same strict facility and personnel regulations of ambulatory surgical centers. These laws often require clinics to either undergo expensive and medically unnecessary renovations in order for the clinic to meet the standard, or to close. AP laws require clinics to have admitting privileges at a nearby hospital. These laws were relatively rare until the early 2010s, and were the focus of *Whole Woman's Health v. Hellerstedt* (2016). Paradoxically, in order to obtain admitting privileges a clinic must meet a minimum threshold for number of patients admitted to the hospital. Since abortion procedures are very safe, this threshold is often difficult to meet. TA laws are similar to AP laws in that they require an agreement with a hospital, but are generally much easier to secure and are often a component of ASC laws. Therefore, I exclude TA laws from the analysis. However, as emphasized in American Public Health Association (2015), none of these laws are medically necessary.

I augment the Austin and Harper (2019a) with data from Temple University's Policy Surveillance Program (Policy Surveillance Program and Advancing New Standards in Reproductive Health Care 2021a, 2021b, 2021c). The Policy Surveillance Program data starts in 2016 and ends in 2021. The Austin and Harper (2019a) data is merged with the Policy Surveillance Program data based on the procedure outlined in Appendix B. These two datasets provide a complete measure of AP and ASC laws passed in the U.S. from 2000 to 2020.

Mandatory Waiting Period (MWP) laws have become increasingly common across the country. These laws require those seeking an abortion to wait for anywhere between 18 hours and 3 days from pre-abortion consultation and the abortion procedure. Further, some states require an in-person appointment (rather than over the phone or online), which then requires women to make two separate trips to the abortion clinic (Guttmacher Institute 2020). This can increase costs for women seeking an abortion, as they are now required to make multiple trips to the clinic. Data on Mandatory Waiting Periods is from Myers (2021a). In this paper, I focus on the more extreme version of this law, which requires two separate trips to an abortion clinic.

These three separate data sources together provide an important overview of both supply-side and demand-side laws. Figure 1 shows the growth in AP, ASC, and MWP laws from 2000-2020. While ASC laws saw more consistent growth over the period, AP laws rapidly spread across the country than collapsed in the 2010s in the wake of *Whole Woman's Health v. Hellerstedt* (2016), while two-period MWP laws also grew rapidly through the 2010s, but broadly remained in place. Figure 2 shows the geographic spread of these laws by decade. The South and Midwest, are the states which have primarily implemented abortion restrictions, with a few exceptions in the Northeast and Southwest. Further, again the rapid spread of restrictions in the 2010s can clearly be seen in figure 2 as well, especially for AP and MWP laws.

4.2 Data on Abortion Rates

Existing datasets of abortion counts and rates, such as the CDC Abortion Surveillance Program and the Guttmacher Institute, do not contain data at the county-level. County-level data is useful in a difference-in-differences setup, since it allows finer geographic controls and fixed effects than state-level data, as well as allowing for heterogeneity analysis by county characteristics, which is important for understanding the implications of post-*Roe* changes in abortion access.

This paper presents a novel dataset of county-level abortion rates, gathered from a variety of state-specific sources including Vital Statistics Reports, State Public Health Databases, and Public Records Requests. Importantly, these data are collected by county of residence of the woman who had the abortion, rather than the county where the procedure occurred. The complete dataset contains data from 36 states, the majority of which have data available from at least 2000 (often earlier) to 2019 or 2020. In this paper the sample is from 2000-2020. Figure 3 shows a map of states with available county-level data. Crucially, there does not appear to be any obvious selection into the data by the restrictiveness of the state. In other words, there is considerable representation of both restrictive and non-restrictive states, which is essential for the difference-in-differences approach. Additional details on the construction and contents of this dataset is presented in Appendix A.[9]

Figure 4 shows the national and regional trends in the abortion rate using the county-level data for states with available data over the majority of the period from 2000-2019.[10] Abortion rates in the Northeast are much larger than either the those in the rest of the country. While there is a large, secular decline in the abortion rate across the regions for most of the period, this decline is slightly reversed for most regions - as well as nationally - in the later years of the sample, a phenomenon which has been observed in other abortion rate datasets (Jones, Kirstein, and Philbin 2022).

9. The county-level abortion data, while gathered independently of Myers (2021b), was checked for consistency with a pre-publication version of the Myers (2021b) data for the years and states where the datasets overlap.

10. While not an issue for the difference-in-differences models, the absolute values of these figures should be interpreted with some caution, given that large states such as California are missing from the data.

4.3 Additional Data

The abortion count data is merged with the Census Bureau County Intercensal datasets to compute the county-specific abortion rate, the number of abortions per 1,000 women aged 15-44 (U.S. Census Bureau 2011, 2021a). The Intercensal data are also used to construct racial and ethnic population shares, as well as the share of women who are of reproductive age, and total population. County unemployment rate data is from the Local Area Unemployment Statistics (U.S. Bureau of Labor Statistics 2022). Household income and poverty data is from the Small Area Income and Poverty Estimates (U.S. Census Bureau 2021b). State minimum wage data are from Vaghul and Zipperer (2021).

5 Results

5.1 The Effect of Restrictions on Overall Abortion Rates

First, the average effect of abortion restrictions on abortion rates is estimated in order to understand the overall impact of these laws. To estimate this overall effect, the AP, ASC, and MWP stacked data are themselves stacked, excluding control states which pass a restriction within the 11 year window. If states enacted multiple restrictions within the 11 year window, only the first event is included. Figure 5 shows the baseline event study SDiD results for the effect of abortion restrictions overall, pooling the three policies together. Prior to the enactment of a policy, there is no clear evidence of a pre-trend, and abortion restrictions appear to have an immediate and statistically significant negative effect on abortion rates which increases overtime, from an initial reduction in the abortion rate of about 0.4 to a reduction after 6 years of about 1.6 abortions per 1000 women of reproductive age.

The first level of disaggregation separately examines the effect of supply-side and demand-side restrictions. The pooled TRAP law estimates are derived from the AP and ASC data stacks, again removing control states which pass a restriction within the time frame, and including only the first event if multiple occur in the window. Figure 8 shows the event study when disaggregating abortion restrictions into TRAP laws and demand-side laws. Neither law exhibits evidence of a pre-trend prior to the adoption of a TRAP or MWP law, and both types of laws have an immediate negative effect on abortion rates. In the first 5 years after treatment, TRAP laws reduce the abortion rate by about 0.8 abortions per 1000 women aged 15-44, before decreasing in the final year, as shown in the left panel. MWP laws decrease the abortion rate gradually and stabilize at around 3 years after treatment with a reduction in the abortion rate of about 2.25, as presented in the right panel.

The event study presented in figure 7 further disaggregates TRAP laws into AP and ASC laws in order to examine the effect of these laws individually. Neither policy exhibits clear evidence of a pre-trend, as the event study coefficients are not statistically different from zero in the years leading up to the enactment of the policy. For AP laws, as shown in the left panel, the restrictions reduce the abortion rate in the second year after treatment, stabilizing at the third year after treatment at a value of approximately -0.6. ASC laws immediately reduce the abortion rates by about 0.5, although the coefficients increase in value and are on the verge of statistical significance, before decreasing substantially in the 6th year after treatment. This would suggest that while AP laws will close clinics all at once, for ASC laws the effect is more gradual. Clinics may be able to cover the cost of renovating in the short term, but in the long run are unable to maintain their operation.

While the effects of AP and ASC laws appear to be of similar size, the effects of MWP laws are several times larger in magnitude. Table 1 presents the results when pooling the post-treatment period coefficients. These estimates thus represent the average effect of these laws over the six year period after a law was enacted. Columns 1, 3, and 5 present the baseline results of the effect of abortion restrictions on abortion rates for all laws, TRAP laws, and MWP laws, respectively. As seen in the first column, abortion restrictions in general reduce the abortion rate by a highly statistically significant 1.1 abortions per 1000 women age 15-44. Relative to the start-of-sample population weighted abortion rate of 14.6, this represents a drop in the abortion rate of about 8%. When examining supply-side and demand-side laws separately, the estimate in column 3 suggests TRAP laws reduce the abortion rate by 0.90. MWP laws reduce the abortion rate by over 2, a point estimate over twice as large as TRAP laws. This represents a drop in the abortion rate relative to the mean of about 6% and 14%, respectively. These results suggest that while both types of abortion restrictions have a substantial and statistically significant negative effect on abortion rates, restrictions which target pregnant people seeking abortions have a much larger effect than laws which target abortion providers.[11] When adding pre-treatment controls, as shown in columns 2, 4, and 6, the estimates are slightly attenuated but the magnitudes remain robust.[12] The point estimates imply any restriction, TRAP laws, and MWP laws reduced the abortion rate by 7%, 6%, and 12%, respectively.[13]

5.2 The Effect of Restrictions on Abortion Rates by Race

Literature has also identified differential effect of abortion access by race and ethnicity. This section seeks to explore the differential effects of abortion policy by utilizing the demographic composition of each county. First, I identify counties which are in the top quartile in the country in terms of black, hispanic, and white population shares using 2010 U.S. Census Bureau data. Then, separate treatment effects are estimated for each demographic group of counties. Appendix figures C14, C15, C16 show a map of counties which are in the top quartile of Black, Hispanic, and white population shares, respectively. In

11. Another method to deal with heterogenous treatment effects is presented in Callaway and Sant'Anna (2021), which does not rely on the method of ''stacking'' control states. Appendix figures C2, C3, and C4 compare the event study estimates from the SDiD and Callaway and Sant'Anna (2021). The point estimates in nearly all cases highly similar, though slightly less so for MWP laws.

12. Event study figures for these specifications for AP, ASC, and MWP laws are presented in figures C5, C8, and C11.

13. Given the large secular trend observed in figure 4, it could be that the SDiD estimate may be picking up the general decline in abortion rates, rather than declines as a result of policies. Appendix tables C1, C2, and C3 add state or county linear time trends, for AP, ASC, and MWP laws, respectively. The point estimates show that this is not the case, and the magnitude of the effect increases when using state-specific linear trends, and grow slightly larger when using county-specific linear trends. Event study estimates for these specifications with state or county linear trends are presented in figures C6 and C7 for AP laws, figures C9 and C10 for ASC laws, and figures C12 and C13 for MWP laws.

this analysis, I focus on the disaggregation of abortion restrictions which separates polices into demand-side restrictions represented by MWP laws and supply-side laws represented by TRAP laws.

Columns 1,2, and 3 in table 3 presents the baseline estimates of the effect of TRAP laws on abortion rates for Black, Hispanic, and white demographic counties, respectively. For counties which are in the top quartile of the Black population share, TRAP laws reduce the abortion rate by a about 0.77, while the effect is substantially larger at -2.2 for counties in the top quartile of Hispanic population shares. Counties which have a relatively high white population share, however, experience a much smaller and not statistically significant drop in the abortion rate of 0.2. When adding control variables, as shown in columns 4,5, and 6, the point estimates increase slightly for Black counties and decrease slightly for Hispanic counties, but maintain the same relative magnitude. The treatment effect for abortion rates in white counties increases and magnitude and becomes statistically significant.

Table 4 presents the pooled treatment effects for MWP laws. As shown in columns 1-3, although all demographic county groups experience considerable declines in the abortion rate after the passage of an MWP law. For counties with high minority population shares, the effect is much larger. The estimates suggest that for counties with high Black and Hispanic populations, MWP laws reduce the abortion rate by 2.6 and 3.2, respectively, compared to a reduction of about 1.1 for counties which are mostly white. When adding controls, the results in columns 4-6 show that while the difference in treatment effects among the demographic groups becomes less pronounced, it remains considerably large.

Figure 8 shows the event study from equation 1 by race and ethnicity of the county. The left panel presents the results for TRAP laws, and the right panel shows the results for MWP laws. The point estimates for each racial group are distinguished by color. For TRAP law, Hispanic counties clearly exhibit the largest drop in abortion rates after the passage of a TRAP law. The abortion rate for these counties falls immediately after treatment, though the coefficients stay relatively consistent.[14] Counties in the top quartile of Black population shares see a more gradual decline in the abortion rate, increasing steadily over the six year post-treatment period. Counties which are highly white, however, see little to no change in the abortion rate after treatment. The story is similar for MWP laws. Prior to treatment, the coefficient estimates for the counties in the top quartiles of Black, Hispanic, and white population shares are all highly similar and there is no evidence of a pre-trend for either group. After the enactment of MWP laws, however, the treatment effects diverge, though all groups are affected considerably by the law. For white counties, the coefficients drop and stabilize at about -1.5 around three periods after treatment. For counties with a high Black population share, the reduction in the abortion rate after the passage of a MWP law is steeper, and it continues to fall until up to five periods after treatment. For counties with relatively high Hispanic populations, the drop in the abortion rate is the largest among the three demographic groups, with the estimates stabilizing after three post-treatment periods at around -4, several times larger than for largely white counties.

The estimates presented here provide substantial evidence that for both supply-side and demand-side

14. There is one statistically significant pre-treatment value for Hispanic counties. However, this occurs 5 years before treatment, and the other pre-treatment values are much closer to zero.

abortion restrictions, counties which have a relatively higher share of Black and Hispanic populations experience a much more dramatic reduction in the abortion rate relative to counties which are predominantly white. In fact, the point estimates suggest that this decrease can be over twice as large for counties with large minority shares compared to counties with relatively higher white population shares.

5.3 The Effect of Restrictions on Abortion Rates by Income

The other geographic heterogeneity which is explored in this paper is the relationship between abortion restrictions and household income. Specifically, counties are ranked by 2010 median household income, and the effect of abortion restrictions for the top quartile of county incomes are compared to the bottom quartile. Household income data is from the U.S. Census Bureau's SAIPE (U.S. Census Bureau 2021b). A map of counties which are designated as high and low income is presented in appendix figure C17.

Table 5 presents the results for TRAP laws for high and low income counties, respectively. Population density is additionally included as a continuous control to account for the how urban or rural the county is. Columns 1 and 2 show the results for low and high income counties, respectively. As can be seen, TRAP laws reduce the abortion rate by about 1.1 in low income counties, and 1.5 high income counties. When adding control variables, the difference between the point estimates shrinks, but the results still holds. Table 6 presents the results for MWP laws. Columns 1 and 2 again appear to suggest that high income counties experience a larger decrease in abortion rates due to abortion restrictions compared to low income counties.

However, this result appears to be driven by the cluster of high income counties in Northern Virginia near Washington, DC. This counties both experienced a substantial drop in their abortion rate compared to the low income counties in Virginia, and are also very high income. Table 7 re-examines the differential effect of TRAP laws by county income group after removing Virginia from the sample. Column 1 suggests that for low income counties, abortion restrictions reduce the abortion rate by nearly 1 abortion per 1000 women of reproductive age, compared to an statistically insignificant -0.8 for high income counties. When including control variables, as seen in columns 3 and 4, the results are similar, though the drop in abortion rates for high income counties is marginally statistically significant. Table 8 presents the results for MWP laws. As can be seen in columns 1 and 2, while high income counties experience a drop in the abortion rate of about 1.9, low income counties see a drop in the abortion rate of 2.3. When accounting for control variables, the difference between these types of counties decreases, with estimates of about -1.94 for low income counties, and -1.92 for high income counties.

Figure 9 presents the event study estimates by county income group. The results for TRAP laws are presented in the left panel, and MWP laws in the right panel. The point estimates for low income counties are generally lower than those in high income counties for the post-treatment period.

The section has presented evidence on the relative difference in the effect of abortion restrictions for high and low income counties. Once accounting for the high income counties in Northern Virginia, abortion restrictions have a larger effect on abortion rates for low income counties relative to high income counties.

5.4 Examining Law Heterogeneity

Another benefit of multi-state approaches, rather than the case study approach often conducted in the literature, is that with county-level data it becomes possible to examine heterogeneity within each type of law. For example, while AP laws were especially harsh in Texas with H.B. 2, it may be the case that they are less extreme or somehow less salient in other states. In other words, not all laws which on the surface imply the same restriction operate identically in practice, given the different institutional, geographic, political, and cultural contexts across states. While the stacked DiD approach outlined in equation 1 can manage the mechanical bias due to this type of heterogeneity, it may be more informative to look at laws passed in individual states rather than the overall effect.

In order to examine the heterogeneity for each type of law, treatment effects are estimated using equation 2 with controls for each state that passed a given restriction. Operationally, this entails estimating the treatment effect separately for each ''stack" of the data. If multiple states passed the same law at a given time (i.e., multiple treated states within a stack), then the treatment effect is estimated on subsets of the stack, with one treated state and all control states comprising each stack subset. This approach is a slightly modified version of the ''event-by-event" estimator of Cengiz et al. (2019).

Figure 10 presets the state-by-state estimates for AP laws. As can be seen, there is substantial heterogeneity in terms of the effect of these restrictions on abortion rates. The negative overall effect of these laws as seen in figure 7 appears to be driven primarily by H.B. 2 in Texas, and to a smaller extent the AP law in Tennessee. Several states even experience a small increase in the abortion rate after the passage of an AP law.

A similar degree of heterogeneity also exists for ASC laws, as presented in figure 11. While most laws appear to have a zero or small positive or negative effect on abortion rates, Virginia and Tennessee, the ASC laws passed in the 2010s, have large significant, negative effects on abortion rates.

Lastly, the state-by-state estimates for MWP laws are plotted in figure 12. While ASC and AP laws have considerable heterogeneity in terms of their effect on abortion rates, MWP laws have an unambiguously negative effect on abortion rates across states, excepting a few states with statistically insignificant estimates. This is also the case for MWP periods passed both early and late in the 2000-2020 sample period, although the MWP laws which have the largest negative effect were passed in the 2010s.

While TRAP laws appear may have substantially different effects on the abortion rate, MWP laws appear to have much more consistently negative effect. There is also some evidence that those laws passed in the 2010s had a relatively larger negative effect on abortion than those passed in the 2000s. However, answering why this heterogeneity exists is not possible in this dataset. More details about the type of restriction passed in each state, or how a given type of restriction may be more or less salient in each state or questions left to be explored in additional research.

6 The Effect of Abortion Bans an Abortion Rates: An Early Look at Texas

While the *Dobbs v. Jackson Women's Health Organization* (2022) Supreme Court decision turned over regulation of abortion fully to the States, an earlier decision foreshadowed the Supreme Court's intent. On May 19, 2021, the Governor of Texas signed S.B. 8 into law. This law, on top of allowing vigilante lawsuits against citizens who provide or assist with abortion care, banned nearly all abortions after approximately six weeks of pregnancy (Center for Reproductive Rights 2021). Despite a legal challenge, the Supreme Court allowed the ban to pass into law in *Whole Woman's Health v. Jackson* (2021), and on September 1, 2021, the state of Texas enacted the strictest abortion restriction since *Roe v. Wade* (1973).

The effect of the ban was dramatic and immediate. Figure 13 shows the number of abortions in Texas by month from January 2017 to June 2022. While prior to the ban, abortions averaged about 4600 per month with a slight upward trend, after the ban, abortions plummeted to an average of 2700 per month, a drop of about 41%.

While the ban in Texas was implemented recently, it is possible to obtain a ''first-pass" causal estimate of the effect of S.B. 8 on abortion rates using monthly abortion data. Texas, along with Oregon, Indiana, Kentucky, Minnesota, Nebraska, and North Dakota, release abortion data by the month and have made these data publicly available up to December 2021. This makes it possible to estimate the effect of the Texas ban from September 2021 to the end of the year. To estimate the effect of Texas's ban relative to abortion trends in these other States, I first gather monthly abortion count data from January 2017 (the first year Texas released monthly data) to December 2021 for these 7 states.[15] I then compute abortion rates for each year by dividing the number of abortions for a given month by the yearly number of women within a state aged 15-44 using U.S. Census Bureau data (U.S. Census Bureau 2021a, 2022). Then, I estimate the following event study DiD model:

$$Y_{it} = Pre_{it} + \sum_{k=-8}^{-1} \beta_k D_{it}^k + \sum_{k=0}^{3} \beta_k D_{it}^k + \alpha_i + \tau_t + \epsilon_{it}, \tag{3}$$

where Y_{it} is the abortion rate for state i in month t, and Pre_{it} is an indicator which equals one if the state i is Texas and the month t is any time prior to January 2021 and zero otherwise. The D_{it}^k are lead and lag indicator variables which equal one if the state is Texas k periods before or after treatment and zero otherwise, and the β_k estimate the effect of the ban eight months before and 4 months after

15. While county-level data by county of residence was used in section 5, Kentucky, Nebraska, North Dakota, and Minnesota report only occurrences by month. While this is not ideal, most occurrences in these states are obtained by state residents.

the law is enacted. I set the base period to $t = -3$ rather than the conventional $t = -1$ as in equation 1 due to the clear anticipation effects seen in figure 13. The terms α_i, τ_t, and ϵ_{it} are state fixed effects, year-month fixed effects, and error terms, respectively.

Figure 14 shoes the results of the event study. In the months leading up to Texas's ban, the trend in the abortion rate in Texas roughly follows that of the six other states included in the panel. There is again some evidence of anticipation prior to the enactment of the ban, as the abortion rate is relatively higher and is statistically significant in Texas in the month before the ban takes place. After the ban, however, the abortion rate plummets permanently, with a highly statistically significant treatment effect of approximately -0.45 in the months after the ban. Relative to Texas's abortion rate in June 2021 of about 0.82 abortions per 1000 women aged 15-44, this represents a massive 45% drop in the abortion rate as a result of the ban. While only an initial attempt to estimate the effect of this ban, the unprecedented drop in abortions seen in Texas after the ban appears to be nearly entirely caused by the law itself.

The U.S. Supreme Court overturned *Roe v. Wade* (1973) with their decision in *Dobbs v. Jackson Women's Health Organization* (2022) in June 2022. Texas has a so-called "trigger" law which would ban abortion in nearly all circumstance already in place, which was meant to go into place immediately following the repeal of *Roe v. Wade* (1973). Although the law did not formally get enforced until August of 2022, providers in Texas had essentially stopped providing abortions immediately after *Dobbs v. Jackson Women's Health Organization* (2022) (Klibanoff 2022).

For the month of July 2022 - the last month that Texas has data available as of writing - there were 68 abortions in Texas: a 99% drop in the number of abortions relative to the pre-S.B. 8 average.

7 Conclusion

This paper sought to quantify the effect of abortion restrictions on abortion rates. It finds that while all restrictions reduce the abortion rate, restrictions which target abortion seekers have much larger effects. While abortion restrictions of both types on average reduce the abortion rate by 8%, TRAP laws reduce the abortion rate by about 6%, MWP laws reduce the abortion rate by about 14%. The estimates are robust to including pre-treatment controls and state or county linear time trends.

It also explores heterogenous effects of these laws by geography, race, and income. Abortion restrictions have a larger negative effect on the abortion rate for counties with larger populations of racial and ethnic minorities, compared to counties which are heavily white. This is especially the case for MWP laws, where the effect is nearly twice as large compared to white counties. Additionally, when differentiating by county median household income, counties which are poorer experience a larger reduction in the abortion rate relative to richer counties once accounting for high several high income counties in Virginia, especially for TRAP laws. Furthermore, the different types of supply-side laws have highly heterogenous effects, and it is likely that the overall negative effect of these laws is driven by a handful of especially harsh versions of them in Texas and a few other states. MWP laws, on the other hand, consistently reduce the abortion rate in nearly all states where they are implemented. Initial evidence on Texas's 6-week gestational limit suggests that it reduced the abortion rate by a staggering 45% in the months after its enactment. While this analysis is limited, additional gestational limits and outright bans are now being rolled out across the U.S. The dramatic fall in abortions as estimated in Texas here will likely follow in other States which enact such restrictions.

This analysis has made clear what qualitative and some quantitative evidence has already found: that abortion restrictions generally have a much stronger effect on those who are most marginalized.

There are several limitations to this study. Firstly, county demographic data rather than the demographic data of pregnant people who obtained abortions are used to examine the heterogenous effects of these laws. While some states do collect and share individual demographic data at the county-level, it is relatively rare, making it difficult to perform a cross-state analysis using individual demographic data. Additionally, not all states are included in this sample. While both restrictive and non-restrictive states are included, there may be particularly pernicious or mild versions of these laws which are omitted from the estimates that could have an impact on the average effect of these laws. Lastly, The recent proliferation of abortion medication which can be bought online may limit the utility of abortion count data in the future. Murtagh et al. (2018) found that abortion pills online often sold for considerably cheaper than the price of getting the procedure at a clinic. However, the websites where they can be bought are often shutdown. There is also some observational evidence that online searches for abortion pills are higher in states with relatively more restrictions, and that the plurality of women searching for this information are pregnant and seeking to end their pregnancy (Jerman, Onda, and Jones 2018).

Further work should consider the other health and socio-economic effects of abortion restrictions. For example, recent work has found legal abortion led to substantial decreases in maternal mortality for non-white women, and that abortion bans in the U.S. will lead to substantial increases in maternal deaths (Farin, Hoehn-Velasco, and Pesko 2021; Stevenson, Root, and Menken 2022). Additionally, Bahn et al. (2020) found that TRAP laws, such as AP and ASC laws considered here, reduced occupational mobility for women, and data from the Turnaway Study suggests that women who are denied access to an abortion experienced increased likelihood of unemployment and poverty (Foster et al. 2018). Exploring the effects of past abortion restrictions can help researchers fully understand the detrimental effects of the repeal of *Roe v. Wade*, and the extent to which these effects differ by race and class.

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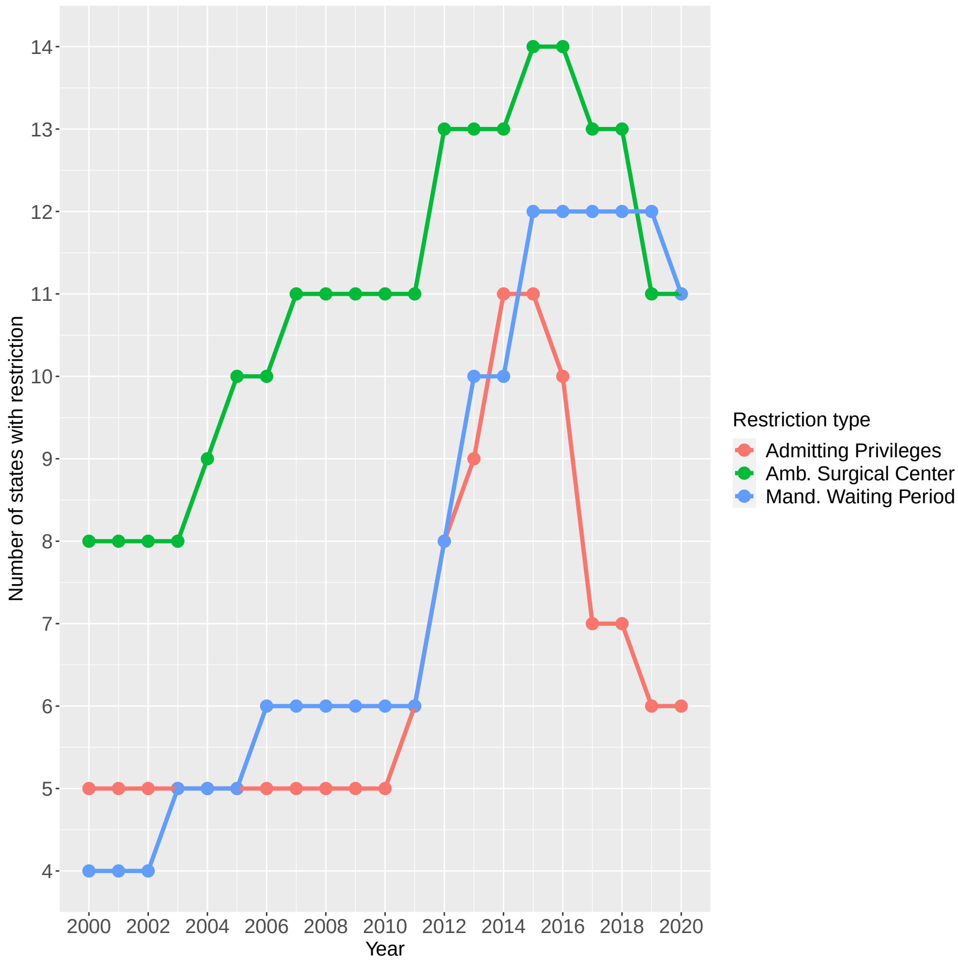
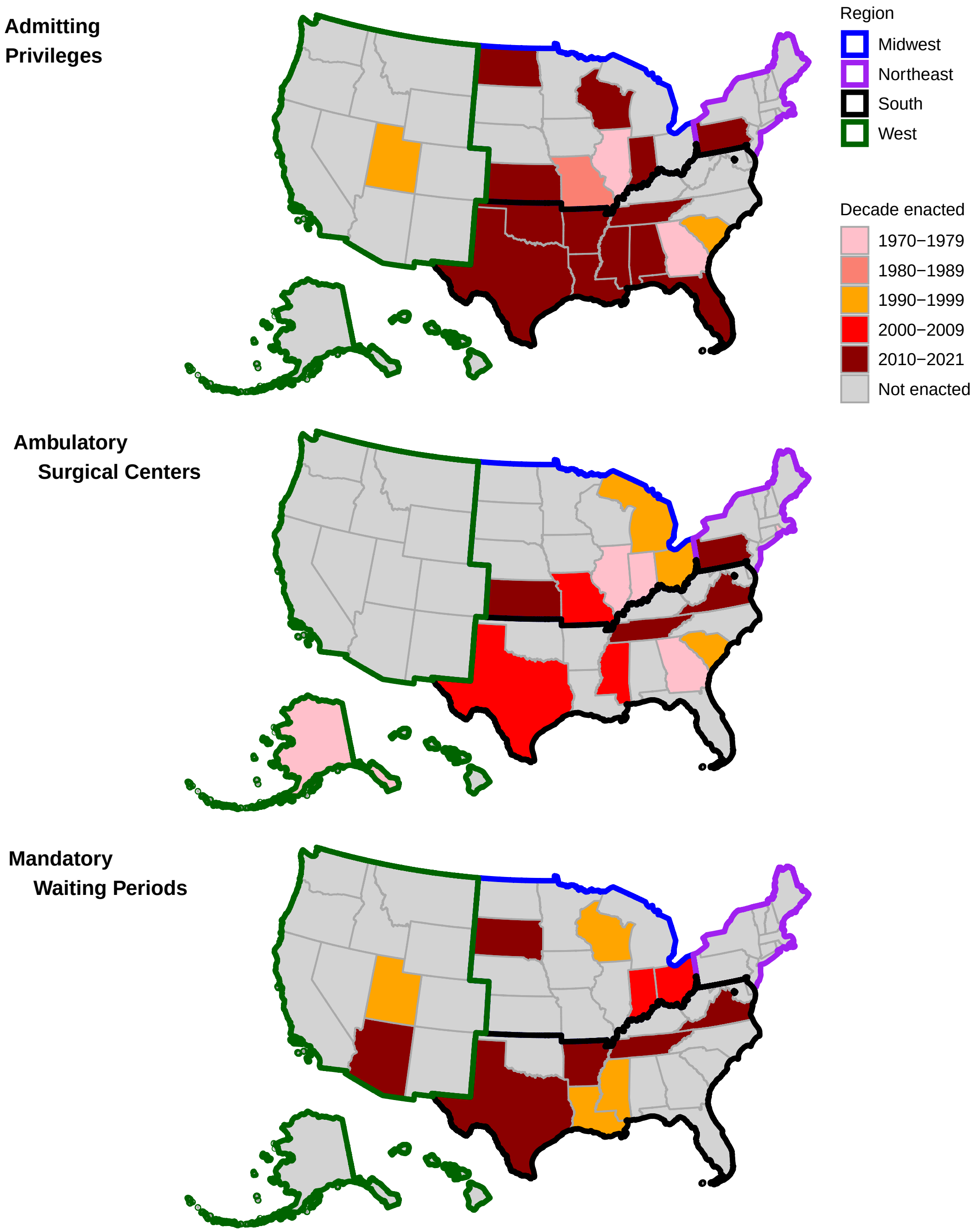
Figures

Figure 1: Abortion Restrictions Growth, 2000-2020



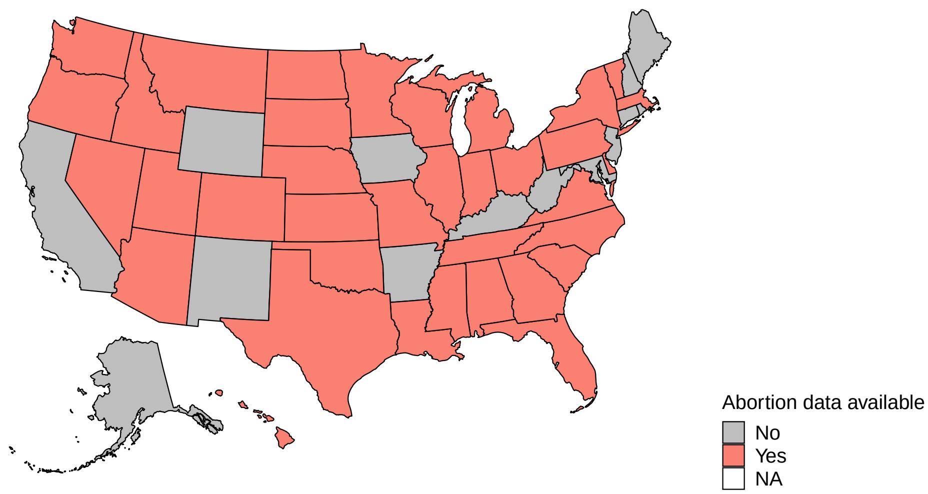
Notes: This figure shows the trend in the number of Admitting Privilege, Ambulatory Surgical Center, and Mandatory Waiting Period laws enforced in the U.S. from 2000 to 2020. This figure is an extension of that in Austin and Harper (2019a). Source: Author's construction from Austin and Harper (2019a) and Myers (2021a) data.

Figure 2: Abortion Law Passage, 1970-2020



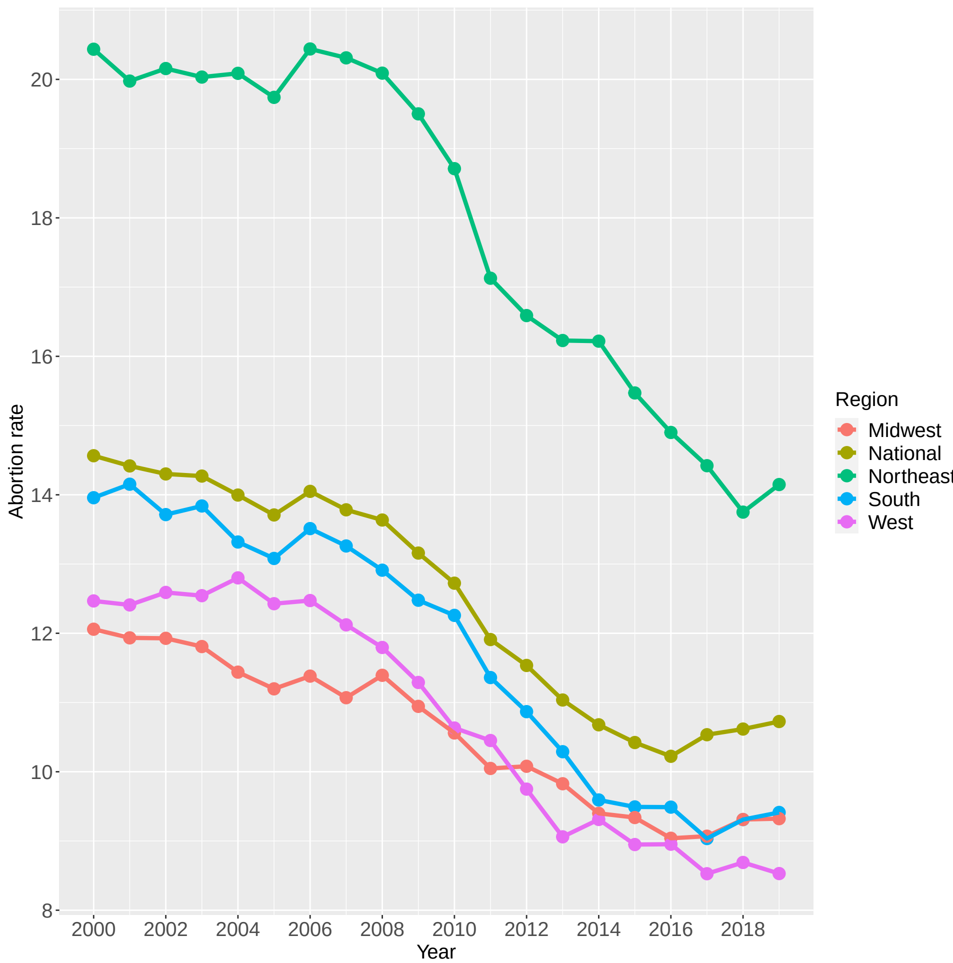
Notes: This figure shows the growth in Admitting Privilege, Ambulatory Surgical Center, and Mandatory Waiting Period laws geographically. Each state interior color represents the decade in which the restriction was enacted. Each state boundary color shows the region that each state belongs in. The top panel shows the growth in Admitting Privilege laws by state, the middle panel Ambulatory Surgical Center laws, and the bottom panel Mandatory Waiting Period laws. This figure is an extension of that in Austin and Harper (2019a). Source: Author's construction from Austin and Harper (2019a) and Myers (2021a) data.

Figure 3: County-level Abortion Rate Data Availability



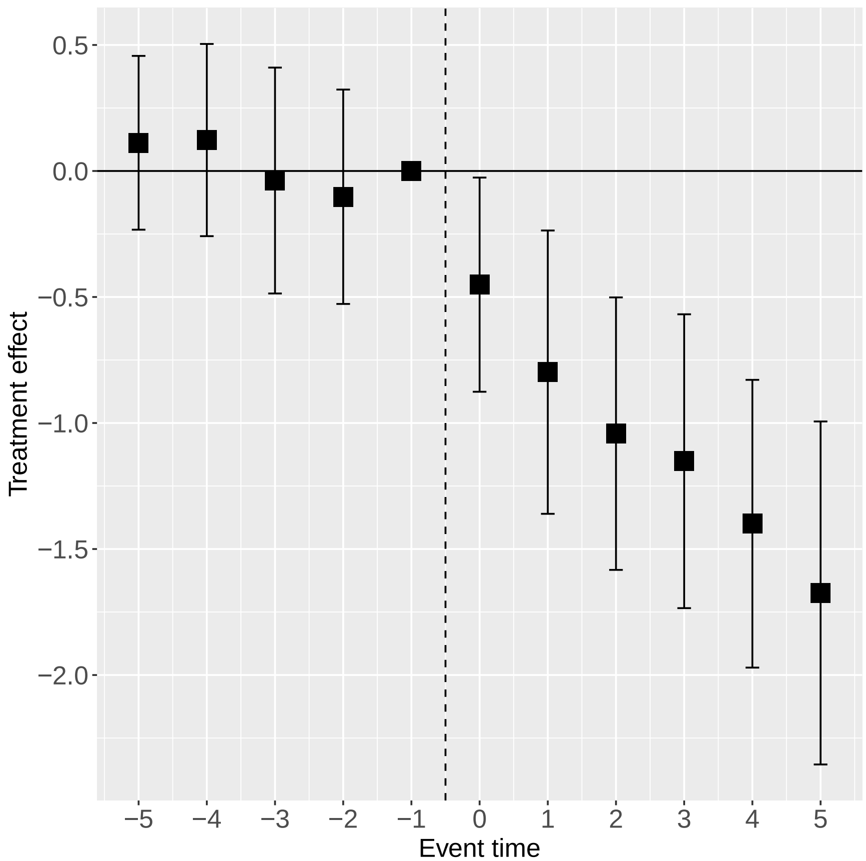
Notes: This figure shows a map for which state have county-level abortion data available in the sample. Some states shown may not have data available for the full sample period (2000-2020). Appendix A has more details on the data availability for each state. Source: Author's construction using county-level abortion data from various state-specific sources.

Figure 4: Abortion Rate Trends, 2000-2019



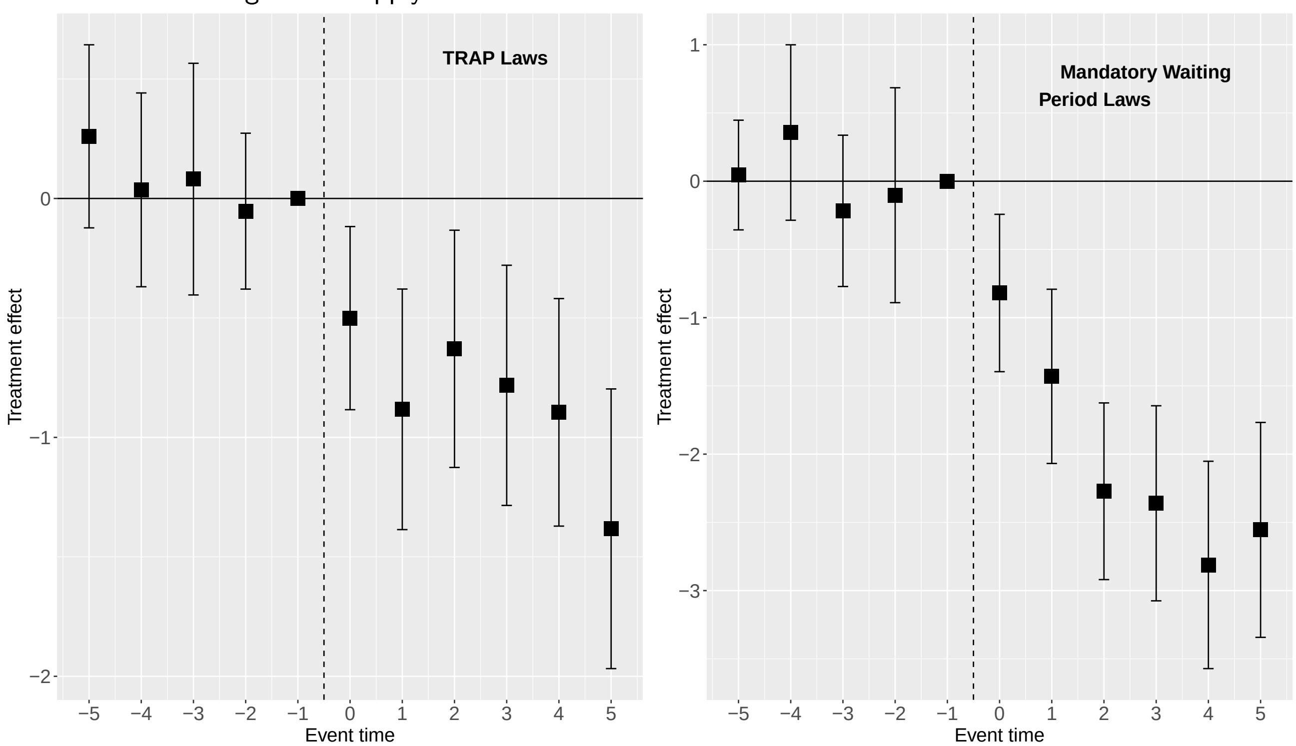
Notes: This figure shows the trends in the abortion rate from 2000-2020 for each region of the U.S., as well as the national trend. Aggregate trends are calculating by averaging across counties for each region, weighted by total population. Florida and Nebraska are omitted due to their late entry into the data sample. Source: Author's construction using county-level abortion data from various state-specific sources and Census data.

Figure 5: Abortion Restrictions Event Study



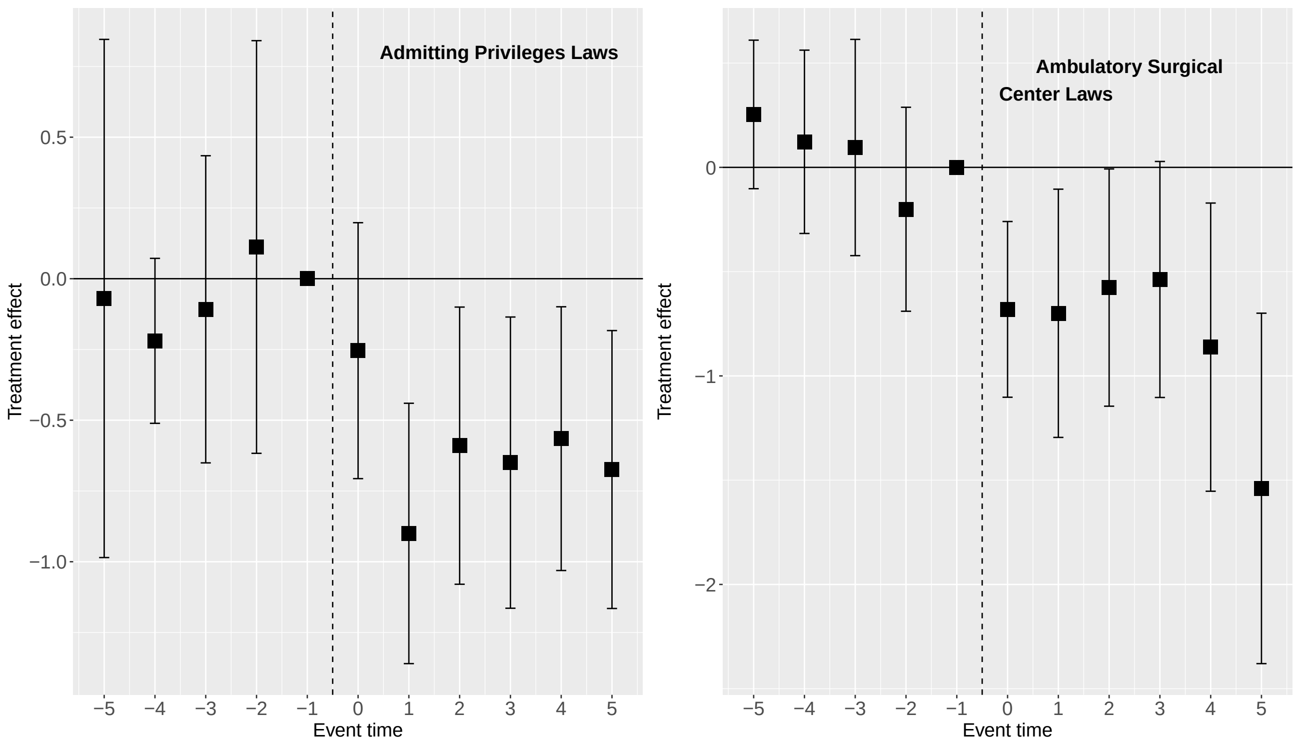
Notes: This figure shows the stacked difference-in-differences event study results of the effect of abortion restrictions on abortion rates. Included in the restrictions are Admitting Privileges laws, Ambulatory Surgical Center laws, and Mandatory Waiting Period laws. Standard error bars clustered at the county-level are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Austin and Harper (2019a), and Myers (2021a) data.

Figure 6: Supply-side and Demand-side Restrictions Event Studies



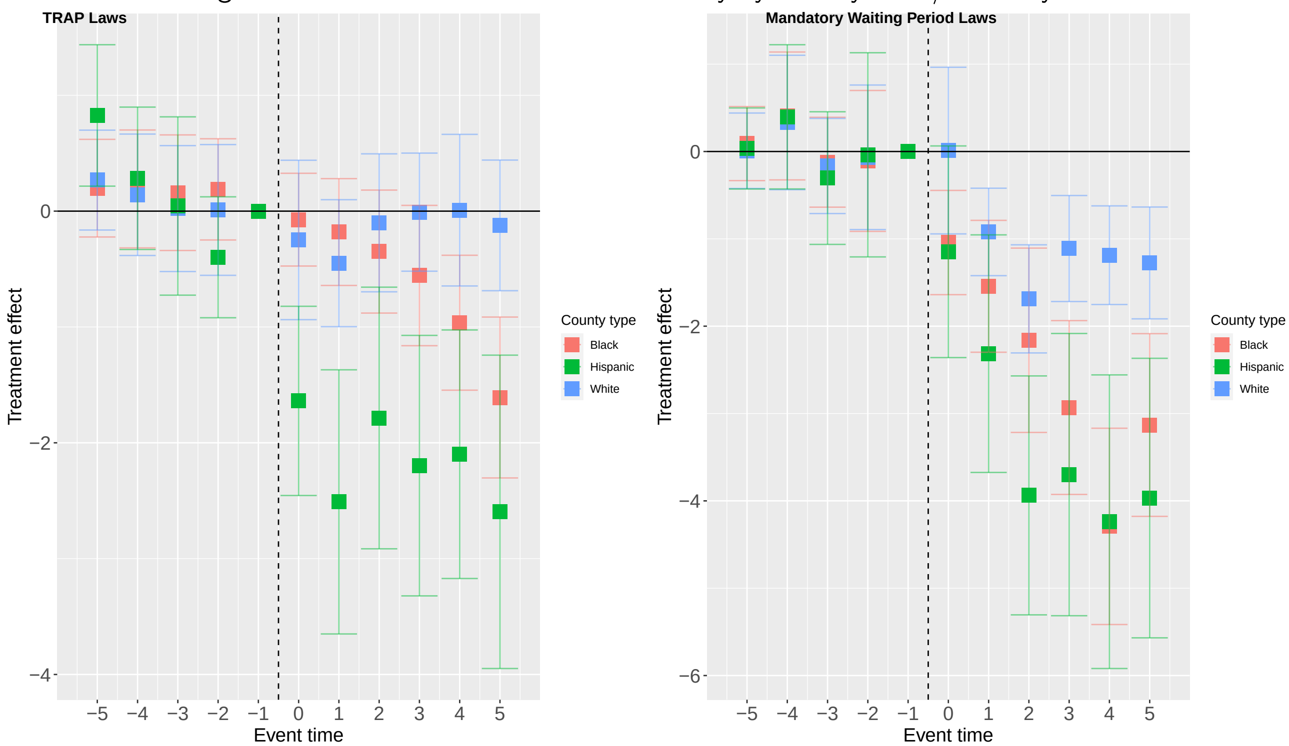
Notes: This figure shows the stacked difference-in-differences event study results of the effect of abortion restrictions on abortion rates, disaggregated by type of law. The left panel shows the effect of Targeted Regulations of Abortion Providers (TRAP) laws on abortion rates, and the right panel shows the effect of Mandatory Waiting Period laws. Included in the TRAP law restrictions are Admitting Privileges laws, Ambulatory Surgical Center laws. Standard error bars clustered at the county-level are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Austin and Harper (2019a), and Myers (2021a) data.

Figure 7: Targeted Regulation of Abortion Provider Laws Event Studies



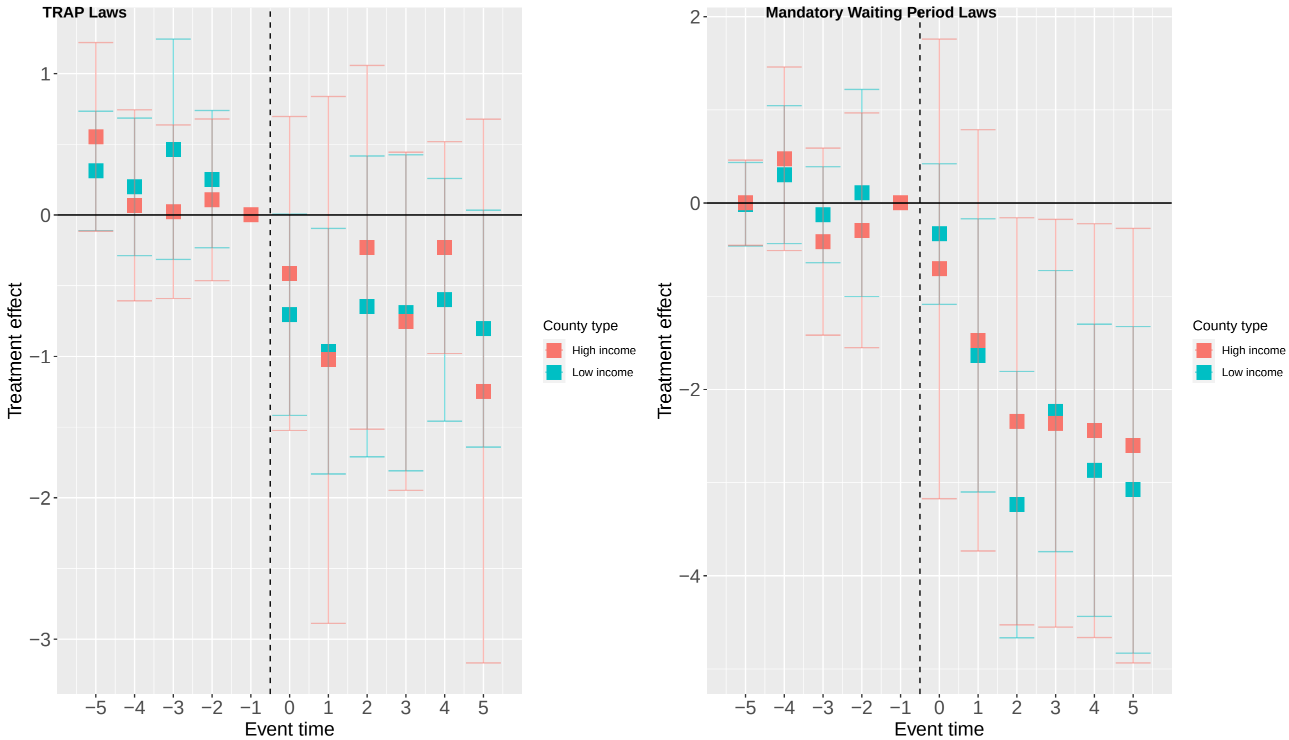
Notes: This figure shows the stacked difference-in-differences event study results of the effect of Targeted Regulation of Abortion Providers (TRAP) laws on abortion rates, disaggregated by type of law. The left panel shows the effect of Admitting Privileges laws on abortion rates, and the right panel shows the effect of Ambulatory Surgical Center laws. Standard error bars clustered at the county-level are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, and Austin and Harper (2019a) data.

Figure 8: Abortion Restrictions Event Study by County Race/Ethnicity



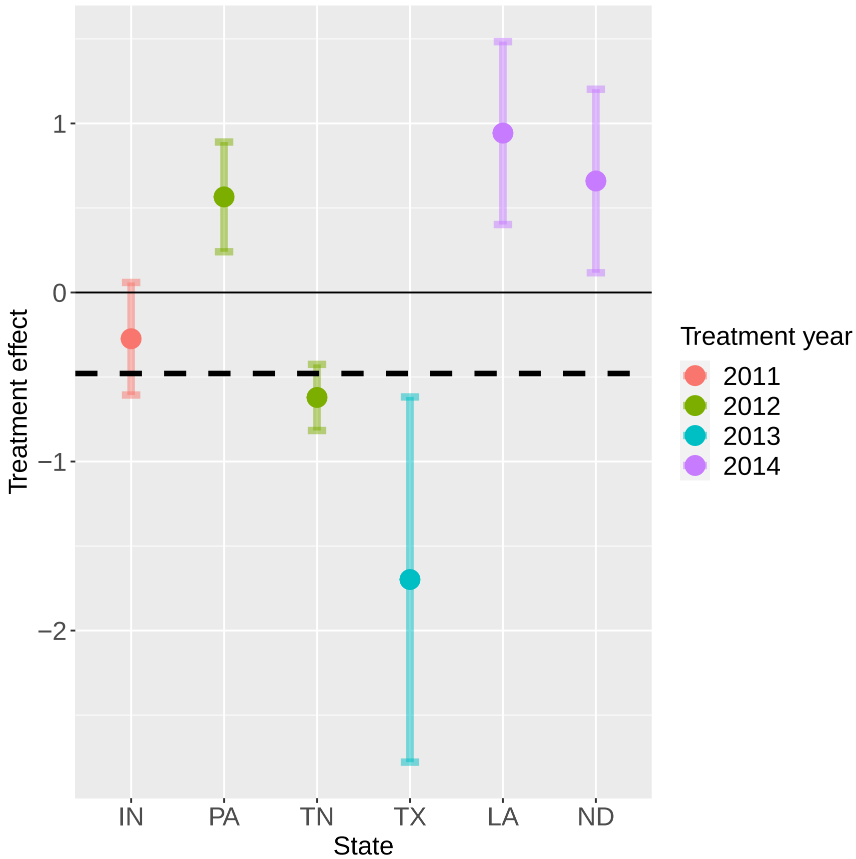
Notes: This figure shows the stacked difference-in-differences event study results of the effect of abortion restrictions on abortion rates, disaggregated by type of law and predominant racial or ethnic group of the county. The left panel shows the effect of Targeted Regulations of Abortion Providers (TRAP) laws on abortion rates, and the right panel shows the effect of Mandatory Waiting Period laws. Included in the TRAP law restrictions are Admitting Privileges laws, Ambulatory Surgical Center laws. The treatment effect for counties in the top quartile of total Black population share is shown in red, for counties in the top quartile of Hispanic population share in green, and for counties in the top quartile of white population share in blue. Standard error bars clustered at the county-level are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Austin and Harper (2019a), and Myers (2021a) data.

Figure 9: Abortion Restrictions Event Study by County Income



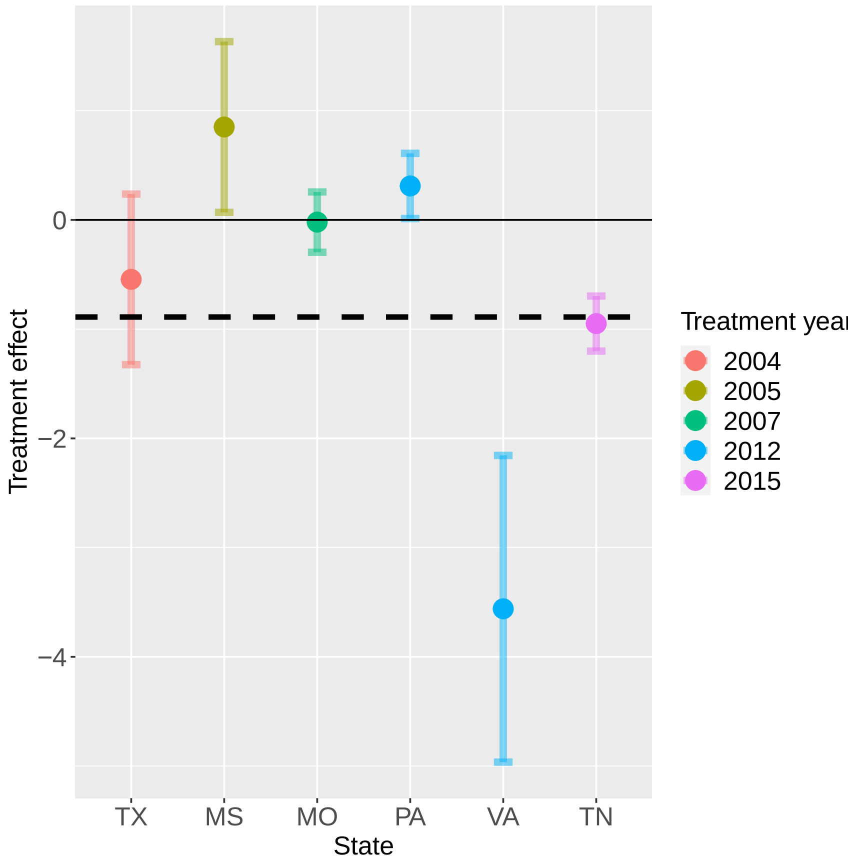
Notes: This figure shows the stacked difference-in-differences event study results of the effect of abortion restrictions on abortion rates, disaggregated by type of law and income county group. The left panel shows the effect of Targeted Regulations of Abortion Providers (TRAP) laws on abortion rates, and the right panel shows the effect of Mandatory Waiting Period laws. Included in the TRAP law restrictions are Admitting Privileges laws, Ambulatory Surgical Center laws. The treatment effect for counties in the top quartile of median household income are in red, and low median household income counties are in blue. Virginia is excluded from these estimates. Standard error bars clustered at the county-level are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Austin and Harper (2019a), and Myers (2021a) data.

Figure 10: Admitting Privileges Law Event-By-Event Study



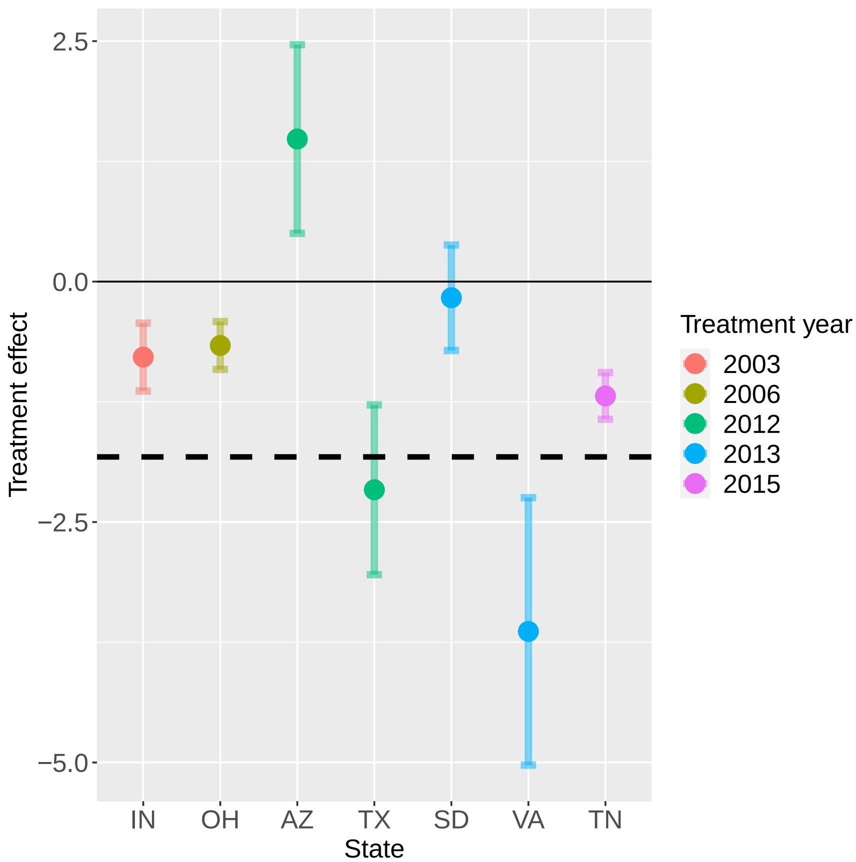
Notes: This figure presents the separate pooled DiD estimate with controls for each state which enacted an Admitting Privileges law over the sample period, where each color is a different year a law is enforced. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Standard error bars clustered at the county-level are reported at the 95% level. The dashed line shows the estimated coefficient value for the pooled effect of AP laws across all states as estimated by equation 2. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, and Austin and Harper (2019a) data.

Figure 11: Ambulatory Surgical Center Law Event-By-Event Study



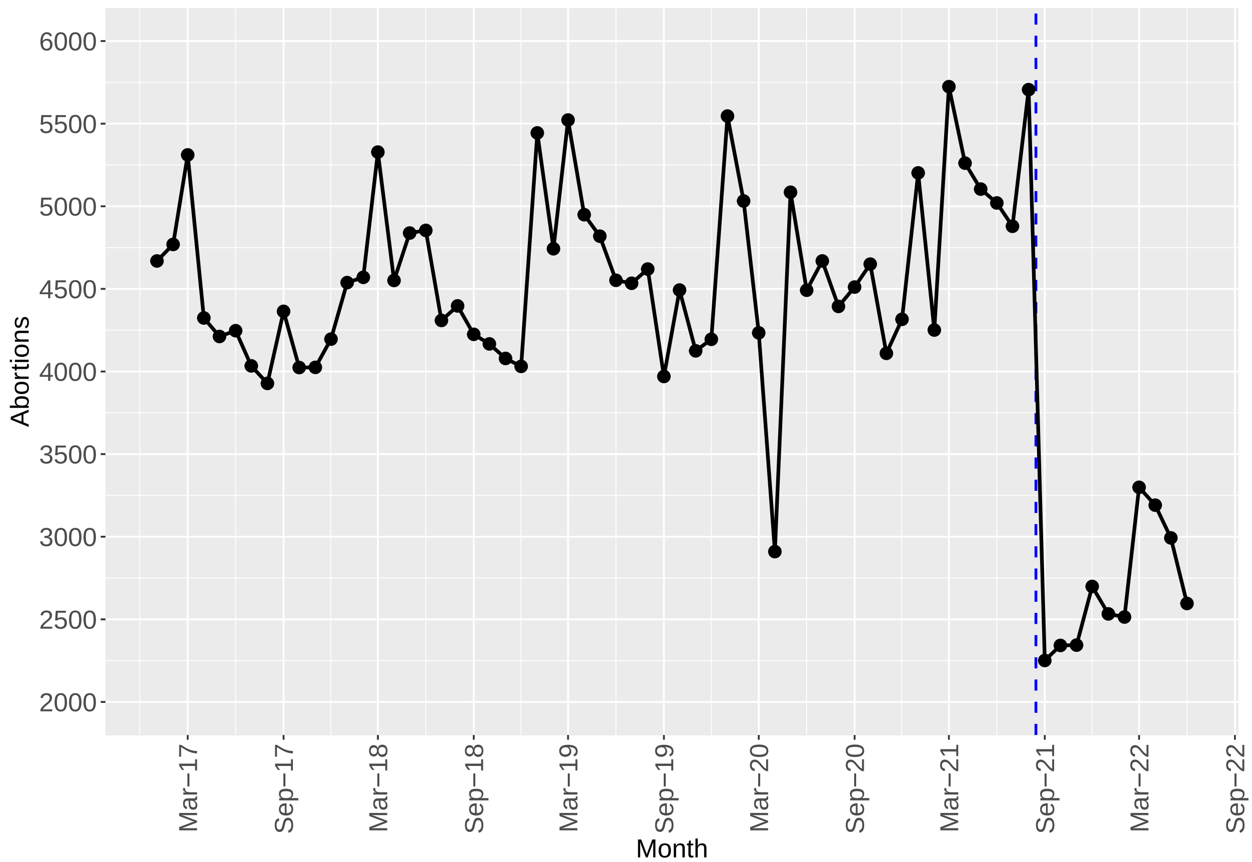
Notes: This figure presents the separate pooled DiD estimate with controls for each state which enacted an Ambulatory Surgical Center law over the sample period, where each color is a different year a law is enforced. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Standard error bars clustered at the county-level are reported at the 95% level. The dashed line shows the estimated coefficient value for the pooled effect of ASC laws across all states as estimated by equation 2. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, and Austin and Harper (2019a) data.

Figure 12: Mandatory Waiting Period Law Event-By-Event Study



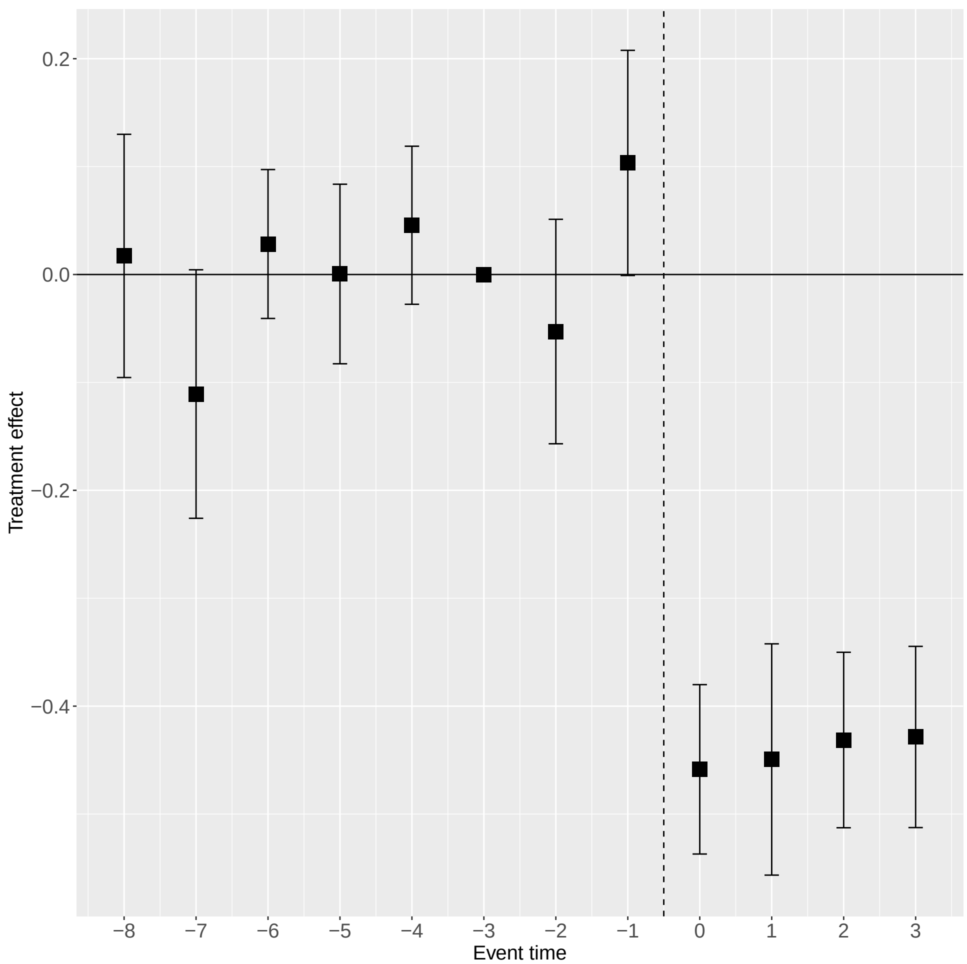
Notes: This figure presents the separate pooled DiD estimate with controls for each state which enacted an Mandatory Waiting Period law over the sample period, where each color is a different year a law is enforced. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Standard error bars clustered at the county-level are reported at the 95% level. The dashed line shows the estimated coefficient value for the pooled effect of MWP laws across all states as estimated by equation 2. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, and Myers (2021a) data.

Figure 13: Monthly Abortions in Texas Before and After a 6-Week Ban



Notes: This figure shows the number of monthly abortion is Texas before and after the enactment of S.B. 8. in September, 2021, shown by the dashed blue vertical line. The black line plots the time series of the number of abortions from January 2017 to June 2022. Source: Author's calculations using monthly abortion data from Texas Department of Health and Human Services.

Figure 14: Abortion Ban Event Study



Notes: The figure shows the event study of Texas's ban on abortion after six weeks of pregnancy. Standard error bars clustered at the county-level are reported at the 95% level. Source: Author's calculations using monthly abortion data from various state-specific sources and Census data.

Tables

Table 1: Abortion restrictions estimates

Dependent Variable:	Abortion rate					
	All laws		TRAP laws		MWP laws	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Restriction	-1.0923***	-1.0596***	-0.9003***	-0.8585***	-2.0275***	-1.8228***
	(0.2027)	(0.1684)	(0.1873)	(0.1518)	(0.2792)	(0.2117)
Pre-treatment controls	No	Yes	No	Yes	No	Yes
Fixed-effects						
County-cohort	Yes	Yes	Yes	Yes	Yes	Yes
Year-cohort	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	177,899	171,319	132,562	127,232	81,292	78,639
R^2	0.8559	0.8591	0.8427	0.8439	0.7991	0.8047

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

Notes: This table shows the pooled treatment effect of abortion restrictions overall, Targeted Regulation of Abortion Provider (TRAP) laws, or Mandatory Waiting Period (MWP) laws on abortion rates over the six year post-treatment period. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, Austin and Harper (2019a) data, and Myers (2021a) data.

Table 2: TRAP law estimates

Dependent Variable:	Abortion rate			
	AP law		ASC law	
Model:	(1)	(2)	(3)	(4)
Variables				
Restriction	-0.5488**	-0.4692**	-0.8291***	-0.8890***
	(0.2568)	(0.1990)	(0.2179)	(0.1983)
Pre-treatment controls	No	Yes	No	Yes
Fixed-effects				
County-cohort	Yes	Yes	Yes	Yes
Year-cohort	Yes	Yes	Yes	Yes
Fit statistics				
Observations	84,478	81,622	75,840	72,027
R^2	0.8038	0.8346	0.8563	0.8567

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

Notes: This table shows the pooled treatment effect of Admitting Privileges (AP) laws and Ambulatory Surgical Center (ASC) laws on abortion rates over the six year post-treatment period. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, Austin and Harper (2019a) data, and Myers (2021a) data.

Table 3: TRAP law race estimates

Dependent Variable:	Abortion rate					
	Black	Hispanic	White	Black	Hispanic	White
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
TRAP law	-0.7698***	-2.1966***	-0.2322	-0.8311***	-1.9354***	-0.5046***
	(0.2422)	(0.4532)	(0.1743)	(0.2365)	(0.4313)	(0.1638)
Pre-treatment controls	No	No	No	Yes	Yes	Yes
Fixed-effects						
County-cohort	Yes	Yes	Yes	Yes	Yes	Yes
Year-cohort	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	123,836	125,115	122,635	118,683	120,087	117,660
R^2	0.8859	0.8433	0.8857	0.8860	0.8438	0.8854

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

Notes: This table shows the pooled treatment effect of Targeted Regulation of Abortion Provider (TRAP) laws on abortion rates over the six year post-treatment period. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, Austin and Harper (2019a) data, and Myers (2021a) data.

Table 4: Mandatory Waiting Period law race estimates

Dependent Variable:	Abortion rate					
	Black	Hispanic	White	Black	Hispanic	White
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Mandatory Waiting Period law	-2.5554***	-3.2296***	-1.0148***	-2.4166***	-2.7141***	-1.0705***
	(0.4013)	(0.6666)	(0.1823)	(0.3724)	(0.5514)	(0.1899)
Pre-treatment controls	No	No	No	Yes	Yes	Yes
Fixed-effects						
County-cohort	Yes	Yes	Yes	Yes	Yes	Yes
Year-cohort	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	75,870	77,087	75,626	73,305	74,522	73,021
R^2	0.8263	0.7971	0.8247	0.8259	0.8022	0.8236

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

Notes: This table shows the pooled treatment effect of Mandatory Waiting Period (MWP) laws on abortion rates over the six year post-treatment period. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, Austin and Harper (2019a) data, and Myers (2021a) data.

Table 5: TRAP law income estimates

Dependent Variable:	Abortion rate			
	Low income	High income	Low income	High income
Model:	(1)	(2)	(3)	(4)
Variables				
TRAP law	0.1307	0.4431***	-1.1855***	-1.4995***
	(0.3359)	(0.1709)	(0.3190)	(0.5272)
Pre-treatment controls	No	No	Yes	Yes
Fixed-effects				
County-cohort	Yes	Yes	Yes	Yes
Year-cohort	Yes	Yes	Yes	Yes
Fit statistics				
Observations	14,679	14,751	118,785	117,781
R^2	0.8694	0.8701	0.8710	0.8607

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

Notes: This table shows the pooled treatment effect of Targeted Regulation of Abortion Provider (TRAP) laws on abortion rates over the six year post-treatment period by county income controlling continuously for population density. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, Austin and Harper (2019a) data, and Myers (2021a) data.

Table 6: Mandatory Waiting Period law income estimates

Dependent Variable:	Abortion rate			
	Low income	High income	Low income	High income
Model:	(1)	(2)	(3)	(4)
Variables				
Mandatory Waiting Period law	-2.1607***	-2.9413***	-1.9005***	-2.8373***
	(0.5818)	(0.8438)	(0.5265)	(0.6777)
Pre-treatment controls	No	No	Yes	Yes
Fixed-effects				
County-cohort	Yes	Yes	Yes	Yes
Year-cohort	Yes	Yes	Yes	Yes
Fit statistics				
Observations	75,900	75,873	73,323	73,298
R^2	0.8182	0.8081	0.8175	0.8100

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

Notes: This table shows the pooled treatment effect of Mandatory Waiting Period (MWP) laws on abortion rates over the six year post-treatment period controlling continuously for population density. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, Austin and Harper (2019a) data, and Myers (2021a) data.

Table 7: TRAP law income estimates excluding VA

Dependent Variable:	Abortion rate			
	Low income	High income	Low income	High income
Model:	(1)	(2)	(3)	(4)
Variables				
TRAP law	-0.9867**	-0.7819	-1.0951***	-0.8919*
	(0.4063)	(0.5362)	(0.3434)	(0.5225)
Pre-treatment controls	No	No	Yes	Yes
Fixed-effects				
County-cohort	Yes	Yes	Yes	Yes
Year-cohort	Yes	Yes	Yes	Yes
Fit statistics				
Observations	123,544	122,185	118,522	117,209
R^2	0.8716	0.8649	0.8709	0.8630

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

Notes: This table shows the pooled treatment effect of Targeted Regulation of Abortion Provider (TRAP) laws on abortion rates over the six year post-treatment period by county income controlling continuously for population density and excluding Virginia. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, Austin and Harper (2019a) data, and Myers (2021a) data.

Table 8: Mandatory Waiting Period law income estimates excluding VA

Dependent Variable:	Abortion rate			
	Low income	High income	Low income	High income
Model:	(1)	(2)	(3)	(4)
Variables				
Mandatory Waiting Period law	-2.2294***	-1.8964**	-1.9436***	-1.9175***
	(0.6812)	(0.9498)	(0.6285)	(0.7328)
Pre-treatment controls	No	No	Yes	Yes
Fixed-effects				
County-cohort	Yes	Yes	Yes	Yes
Year-cohort	Yes	Yes	Yes	Yes
Fit statistics				
Observations	75,624	75,302	73,047	72,727
R^2	0.8177	0.8108	0.8170	0.8111

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

Notes: This table shows the pooled treatment effect of Mandatory Waiting Period (MWP) laws on abortion rates over the six year post-treatment period controlling continuously for population density and excluding Virginia. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, Austin and Harper (2019a) data, and Myers (2021a) data.

A Details on County-Level Abortion Data

The primary dataset constructed for this project contains abortion counts and rates by county of residence for most U.S. states. Existing datasets of abortion counts and rates, such as the CDC Abortion Surveillance Program.[16] and the Guttmacher Institute.[17] do not have county-level data available, despite the fact that variation at a finer geographic level than states may be useful to researchers, activists, policy-makers, and medical professionals for a wide array of reasons. This dataset is an attempt to fill this gap. Using archived state-level Vital Statistics reports as well as a number of other sources, it presents a panel dataset of county-level resident abortions and abortion rates for 35 states, with most states having data for 2000-2020, and a large proportion of these states with data starting in the 1990s. This data will be made available for public use in the replication package at https://doi.org/10.7910/DVN/ZWOPNX.

Figure 3 presents the states for which county-level abortion data is available. For most of these states, data is available for at least 2000-2019, with earlier and later years available for a substantial number of these states. Some states, such as Florida, have only started to collect this data recently. Other states, such as Oklahoma, stopped collecting these data after a certain year. Table A1 shows the years available for each state. Some counties may have missing data for some of these years.

As stated above, these abortion counts are for county residents, and not occurrences. Since many states have only a few abortion providers, resulting in large cross-county movement to access abortions, abortion counts by county of occurrence will be severely misstate the number of abortions by residence. It is important to note that while some states have data-sharing agreements with other states to keep track of their residents who get abortions out of states, in general these agreements are not widespread. Therefore, as a rule-of-thumb one should assume that abortions obtained out-of-state are not included in these figures.

The bulk of these data were gathered in the fall of 2021 and spring of 2022 using a combination of state Vital Statistics reports, state abortion reports, state health department databases, as well as direct and public records requests. These reports present counts of abortion by county of residence. The numbers were copied into a separate excel file, and then combined using an R script.

A summary of the primary data sources used for each state is presented in table A2. Some states report abortion statistics with some suppression. For example, Wisconsin does not give the abortion count in a county if the total number of abortions is less than 5. In general, suppression occurs only for very small numbers, but for Illinois, suppression is much larger at 50 counts. Some data is suppressed only for a subset of years.

The raw data and source files used to construct these data will be available for download in the replication package. The raw data contains both the reports themselves as well as links to the reports. Please note that some links may break overtime. If this is the case, the WayBack Machine may have

16. See https://www.cdc.gov/reproductivehealth/data_stats.
17. See https://www.guttmacher.org/public-use-dataset.

had the website archived.[18] If the data were obtained from a state database or a direct request, the raw version of those data downloaded from the database or sent by the state health department are contained in the raw data folder as well. The scripts used to combine the raw data are also available.

Abortion counts presented in the dataset are defined as the number of abortions by county of residence in a given county and year. Abortion rates are calculated as the number of abortions per 1,000 women aged 15-44 in a given county and year. Population data by gender and age is obtained from the United States Census Bureau County Intercensal datasets.[19] These data are also available in the raw data folder, along with links to the exact datasets on the Census website. Suppressed cells are marked as missing data.

For Massachusetts and North Dakota, abortion counts are only reported by health regions, which are groups of counties. In order to get a county-level count for these states, the total number of abortions in a health region is distributed to its consistent counties based on each counties share of women aged 15-44 First, region-county crosswalks were constructed based off maps of the health regions which show county boundaries. These crosswalks are available in the raw data, and maps of the health regions are typically shown in the state Vital Statistics reports. Second, the total number of women aged 15-44 are calculated using county-level data from the Census. Then, the share of women aged 15-44 relative to the health region total are calculated for each county. Lastly, the number of abortions for the health region is multiplied by this county share to distribute the abortions by population share of women aged 15-44.

18. See https://archive.org/web/.
19. See https://www.census.gov/programs-surveys/popest/data/data-sets.html.

Table A1: State county-level abortion data range

	State	Start Year	End Year
1	Alabama	1998	2019
2	Arizona	1990	2020
3	Colorado	2000	2020
4	Delaware	2000	2019
5	Florida	2017	2021
6	Georgia	1994	2020
7	Hawaii	1996	2019
8	Idaho	1992	2020
9	Illinois	1995	2020
10	Indiana	2000	2020
11	Kansas	1998	2020
12	Louisiana	2004	2021
13	Massachusetts	1999	2020
14	Michigan	1998	2020
15	Minnesota	1999	2020
16	Mississippi	1980	2020
17	Missouri	1999	2019
18	Montana	1998	2021
19	Nebraska	2013	2020
20	Nevada	2000	2020
21	New York	1997	2019
22	North Carolina	2000	2020
23	North Dakota	1998	2020
24	Ohio	1995	2020
25	Oklahoma	2002	2011
26	Oregon	1989	2020
27	Pennsylvania	1995	2020
28	South Carolina	1998	2019
29	South Dakota	1997	2020
30	Tennessee	2008	2019
31	Texas	2001	2020
32	Utah	1998	2019
33	Vermont	1998	2019
34	Virginia	1995	2020
35	Washington	1997	2020
36	Wisconsin	1994	2020

Source: Author's construction using a variety of state-specific sources. See text for details.

Table A2: State county-level abortion data sources

	State	Suppression	Primary Source	Notes
1	Alabama	None	State Vital Statistics Reports	
2	Arizona	None	State Abortion Reports	
3	Colorado	<4	Direct Request	
4	Delaware	None	State Vital Statistics Reports	
5	Florida	<20	State Abortion Reports	Abortion counts by county of residence not reported prior to 2017
6	Georgia	None	State Database	
7	Hawaii	None	State Abortion Reports	
8	Idaho	None	State Vital Statistics Reports	
9	Illinois	<50	State Database	
10	Indiana	<5	State Vital Statistics Reports	Data only suppressed prior to 2014
11	Kansas	None	State Vital Statistics Reports	
12	Louisiana	<5	Direct Request	
13	Massachusetts	None	Direct Request	Data reported only by Health Region; see documentation
14	Michigan	None	State Vital Statistics Reports	
15	Minnesota	<5	State Abortion Reports	
16	Mississippi	<5	State Database	
17	Missouri	None	State Vital Statistics Reports	
18	Montana	<5	Direct Request	
19	Nebraska	<5	State Vital Statistics Reports	Prior to 2013 county of residence rarely reported
20	Nevada	None	Direct Request	Prior to 2011, most counties only reported in an aggregate
21	New York	None	State Vital Statistics Reports	
22	North Carolina	None	State Vital Statistics Reports	
23	North Dakota	None	State Vital Statistics Reports	Data reported only by Health Region; see documentation
24	Ohio	None	State Vital Statistics Reports	
25	Oklahoma	<5	State Vital Statistics Reports	Data no longer reported after 2011
26	Oregon	None	State Vital Statistics Reports	
27	Pennsylvania	None	State Vital Statistics Reports	
28	South Carolina	None	State Vital Statistics Reports	
29	South Dakota	<10	State Vital Statistics Reports	
30	Tennesse	None	State Vital Statistics Reports	
31	Texas	None	State Vital Statistics Reports	
32	Utah	<5	State Vital Statistics Reports	
33	Vermont	None	State Vital Statistics Reports	
34	Virginia	None	State Vital Statistics Reports	
35	Washington	<10	State Database	
36	Wisconsin	<5	State Vital Statistics Reports	

Source: Author's construction using a variety of state-specific sources. See text for details.

B Details on Abortion Restrictions Data

This section describes the additional details of the abortion restrictions data. This paper focuses on three types of restrictions: Admitting Privilege (AP), Ambulatory Surgical Centers (ASC), and ''two-period'' Mandatory Waiting Periods (MWP). To a lesser extent, it also examines Texas's Ban on abortions after approximately six weeks.

The data for MWP laws are taken from Myers (2021a). Myers (2021a) reports monthly dates, so to assign monthly start dates to years, if the law was enacted before July 1, then the first period of treatment is the year in which the law was enacted. If the law was enacted after this date, then the first period of treatment is the year after which the law was enacted.

Information about Texas's ''Heartbeat Bill'', most importantly its start date, is from Center for Reproductive Rights (2021).

Data for AP and ASC laws are primarily from Austin and Harper (2019a) with additional years of data derived from Policy Surveillance Program and Advancing New Standards in Reproductive Health Care (2021a, 2021c, 2021a). Since legal coding can sometimes be subjective, I evaluate the compatibility of the Austin and Harper (2019a) data and the Policy Surveillance Program data by identifying differences in legal coding in 2017, a year covered by both datasets. Then, I incorporate the data from 2018-2020 from the Policy Surveillance Program data. For AP and ASC laws, this mostly means noting when laws have been blocked. However, since the effect of AP and ASC laws has been to close clinics and cause congestion, the empirical approach taken in this paper is not to ''turn-off'' the treatment once the law is repealed, since the damage in terms of closed clinics has already been done. Further, any recovery relative to the baseline if the law is repealed in the six-year period after it is first enacted would appear in the event study coefficients.

For ASC laws, the Austin and Harper (2019a) and Policy Surveillance Program data disagreed in 2017 about three states: Maryland, Missouri, and Ohio. For Missouri, Austin and Harper (2019a) codes the state has having a law in 2017 while the Policy Surveillance Program does not. This is because the law was blocked in the later half of 2017 as a result of *Whole Woman's Health v. Hellerstedt* (2016), so Missouri is coded as as blocked in 2017 (State of Missouri 2017). For Ohio, Austin and Harper (2019a) codes an ASC law as being enacted in 1999, while the Policy Surveillance Program data has no law for Ohio. However, according to State of Ohio (2019), the ASC law remains in place as of 2021. Therefore, the state is coded as having the law. Regarding Maryland, Austin and Harper (2019a) codes the States as having an ASC law, while Policy Surveillance Program data records no law. There is no clear evidence of an ASC law in Ohio's Legislative records as of 2021. Also, Austin and Harper (2019a) does not include any source for Maryland's law in the Supplemental Materials section of the article, and the Guttmacher Institute also does not record Maryland as having an ASC law. Therefore, I code Maryland as not having an ASC law. The remaining ASC data agree in 2017, and any changes from 2017-2020 are from the Policy Surveillance Program data. Indiana repealed its ASC law in 2021, Tennessee repealed it in 2017, Illinois and and Virginia repealed it in 2019, and Texas repealed the ASC requirements for first trimester abortions in 2016.

The disagreements for AP laws are more numerous. This is because the distinction between an Admitting Procedure, and a law which just requires formal or informal transfer agreements is hard to distinguish. Further, there are differences in AP laws, some of which require individual physicians to have admitting privileges, and others which require facilities to have such procedures.

The following states disagree in 2017: Alaska, Michigan, Missouri, Mississippi, Rhode Island, Texas, and Virginia. While Alaska and Michigan are reported as having AP laws in 2017 in the Policy Surveillance Program data, the additional details reported in the same dataset suggest these are transfer agreements, so these remain coded as having no law. For Missouri, the AP law was blocked in 2017, so the law is coded as being blocked then (*Comprehensive Health of Planned Parenthood Great Plains v. Williams* 2017). Mississippi blocked the law in 2014 according to both datasets. According to the documentation cited in the Policy Surveillance Program data, Rhode Island's AP law only requires a plan, not formal agreements, so this state is coded as not having an AP law. For Texas, the AP law was blocked in 2016 (*Whole Woman's Health v. Hellerstedt* 2016). Lastly, Virginia's law is closer to a transfer agreement according to Policy Surveillance Program, so this state is kept coded as having no law.

Table B1 shows if and when a state ever enforced a MWP, ASC, or AP law, and if relevant, when it was blocked or repealed. Years that are reported as zeros indicate when states passed an ASC or AP law, but it was never enforced due to legal challenges.

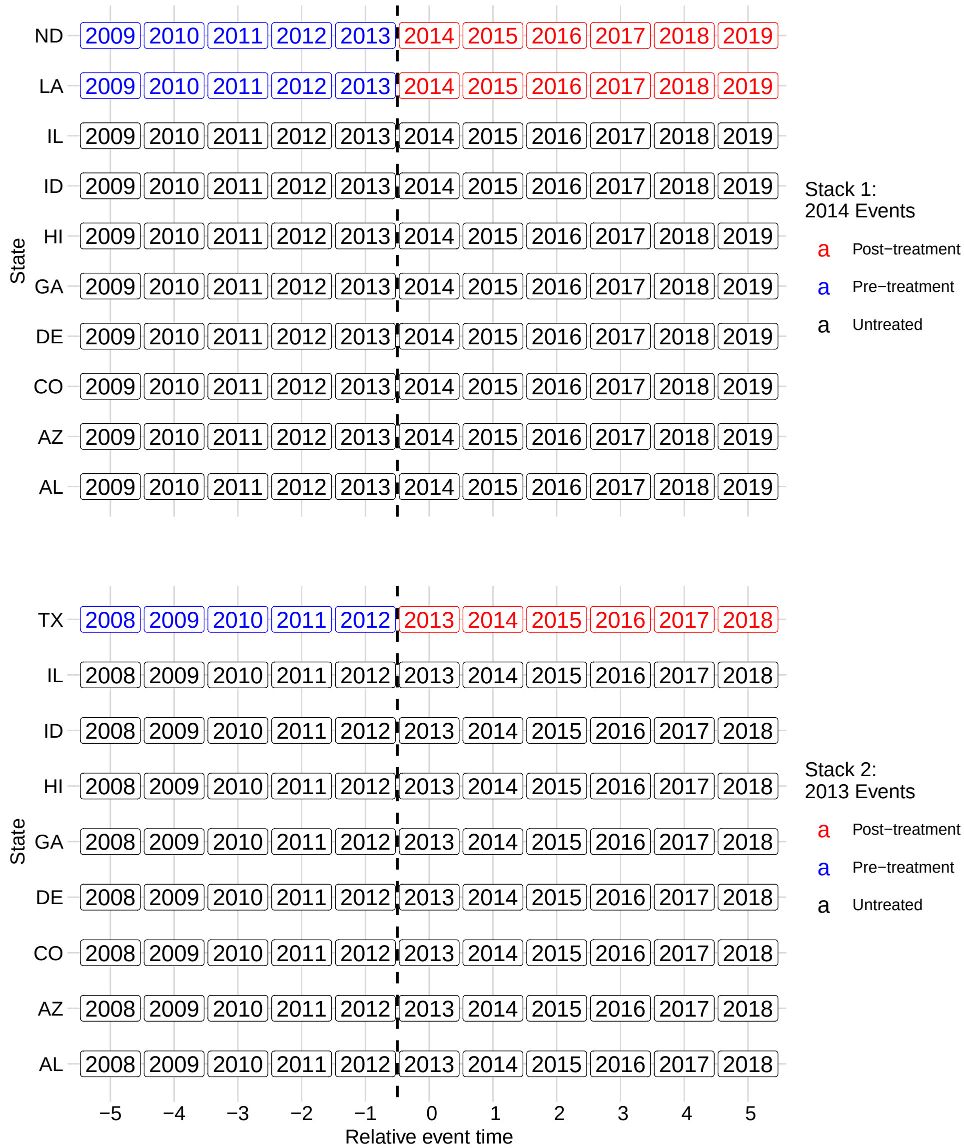
Table B1: Abortion Restrictions Enforcement and Repeal

	State	MWP Enforcement	MWP Repeal	ASC Enforcement	ASC Repeal	AP Enforcement	AP Repeal
1	Alabama					0	2014
2	Alaska			1970			
3	Arizona	2012					
4	Arkansas	2015				0	2015
5	Florida					2016	
6	Georgia			1974		1974	
7	Illinois			1973	2019	1973	2019
8	Indiana	2003		1973		2011	
9	Kansas			0	2011	0	2011
10	Louisiana	1996				2014	2016
11	Michigan			1999			
12	Mississippi	1993		2005	2017	2013	2013
13	Missouri			2007	2017	1988	2017
14	North Dakota					2014	
15	Ohio	2006		1999			
16	Oklahoma					0	2014
17	Pennsylvania			2012		2012	
18	Rhode Island			1973			
19	South Carolina			1996		1996	
20	South Dakota	2013					
21	Tennessee	2015	2021	2015	2017	2012	2017
22	Texas	2012		2004		2013	2016
23	Utah	1994				1998	2017
24	Virginia	2013	2020	2012	2019		
25	Wisconsin	1998				0	2015

Source: Author's construction using Austin and Harper (2019a) data, Policy Surveillance Program data, and Myers (2021a) data.

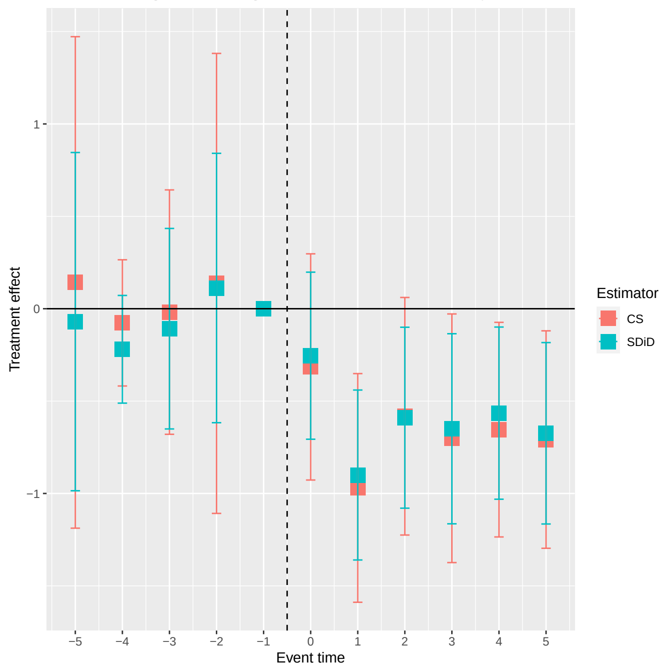
C Additional Figures and Tables

Figure C1: Stacked Event Study Visualization



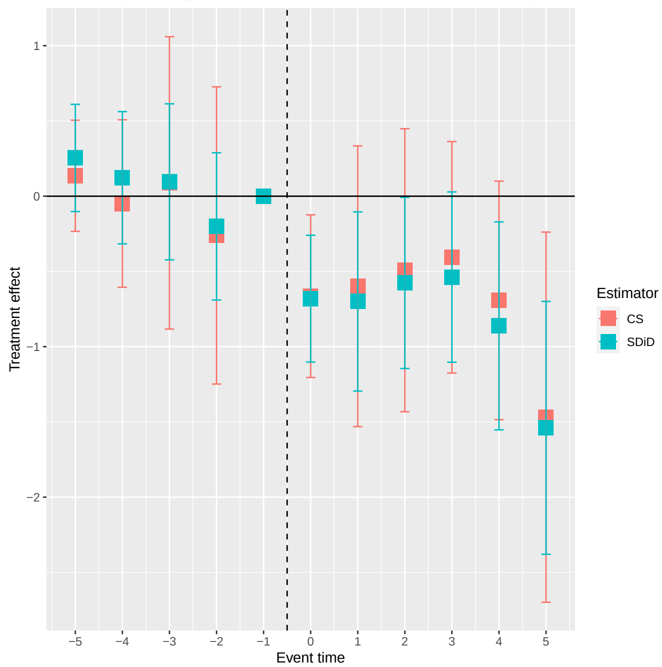
Notes: The figure presents a visualization of the shape of the data needed for a stacked difference-in-differences model. In this example, states are treated either in 2014 or 2013, with two states being treated in 2014 (ND and LA) and one state being treated in 2013 (TX). There are 8 control states which are untreated. Each square represents a unique data-year for each state, with the blue squares showing the pre-treatment years for the treated state, and the red squares showing the post-treatment years. To create the stacked data, a subset of the data containing all the states initially treated in the same year, as well as all the control states, is selected for the data-years which comprise an 11 year window around the event. In this example, this first stack comprises the states treated in 2014 (ND and LA) and the 8 control states. States which are treated at earlier or later times in the event window are omitted. The second stack is created by selecting those states which are initially treated in 2013 (only TX in this example), as well as the control states, but omitting the states which are initially treated in 2014. These individual stacks are then "stacked" on top of each other so that the relative event times are aligned. The control states will appear once in each stack, but the treated states only appear in their individual stack. Source: Author's construction using data from Austin and Harper (2019a).

Figure C2: Admitting Privilege Law Event Study Estimator Comparison



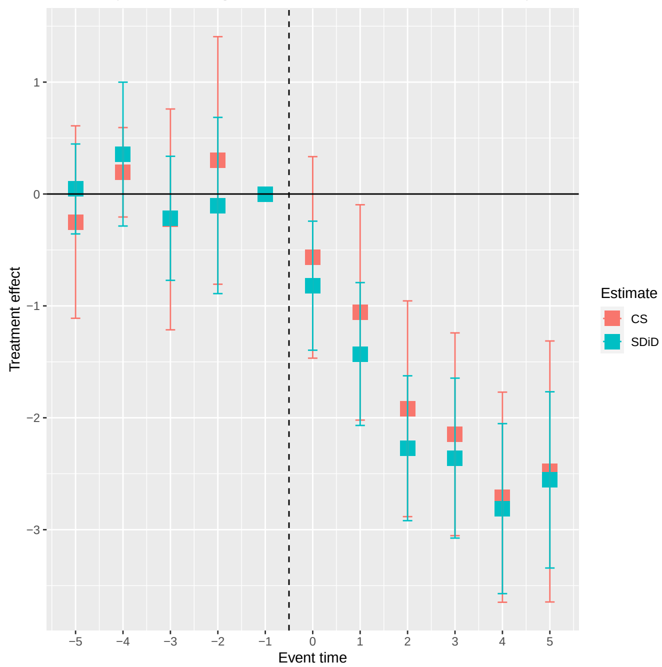
Notes: This figure compares the results between the CS estimator and the stacked DiD estimator. Standard error bars clustered at the county-level are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, and Austin and Harper (2019a) data.

Figure C3: Ambulatory Surgical Center Law Event Study Estimator Comparison



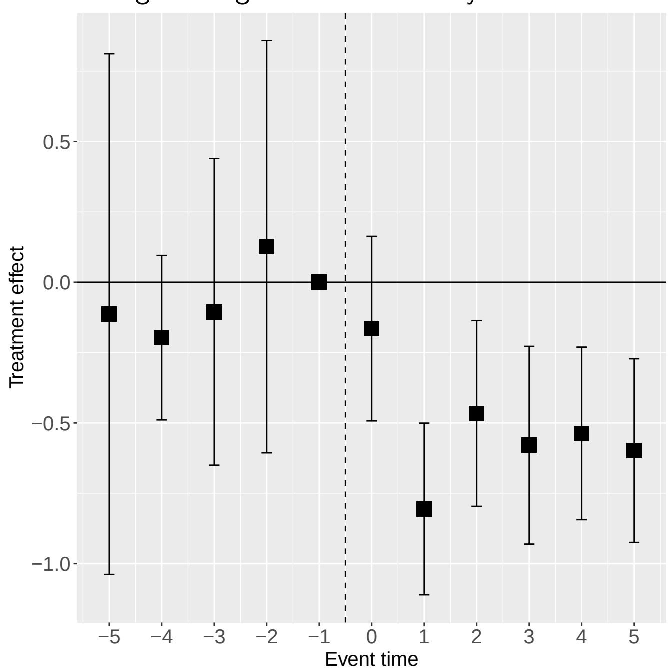
Notes: This figure compares the results between the CS estimator and the stacked DiD estimator. Standard error bars clustered at the county-level are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, and Austin and Harper (2019a) data.

Figure C4: Mandatory Waiting Period Law Event Study Estimator Comparison



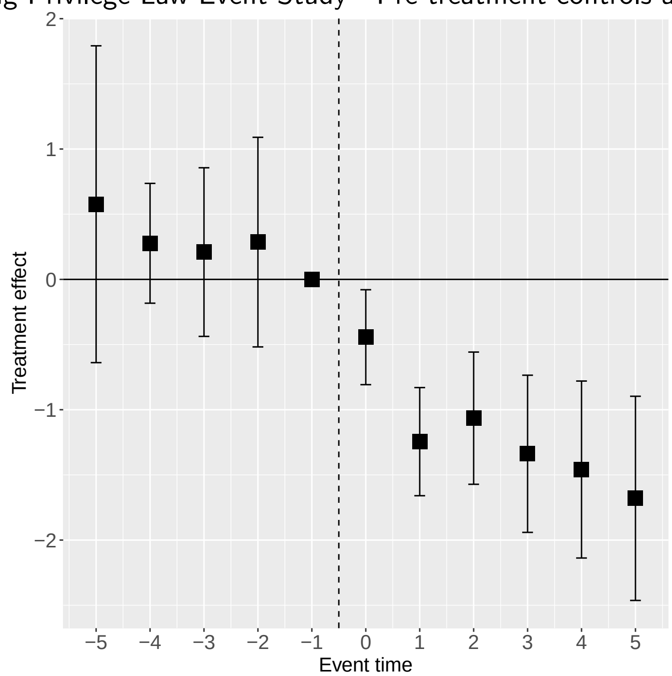
Notes: This figure compares the results between the CS estimator and the stacked DiD estimator. Standard error bars clustered at the county-level are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, and Myers (2021a) data.

Figure C5: Admitting Privilege Law Event Study - Pre-treatment controls



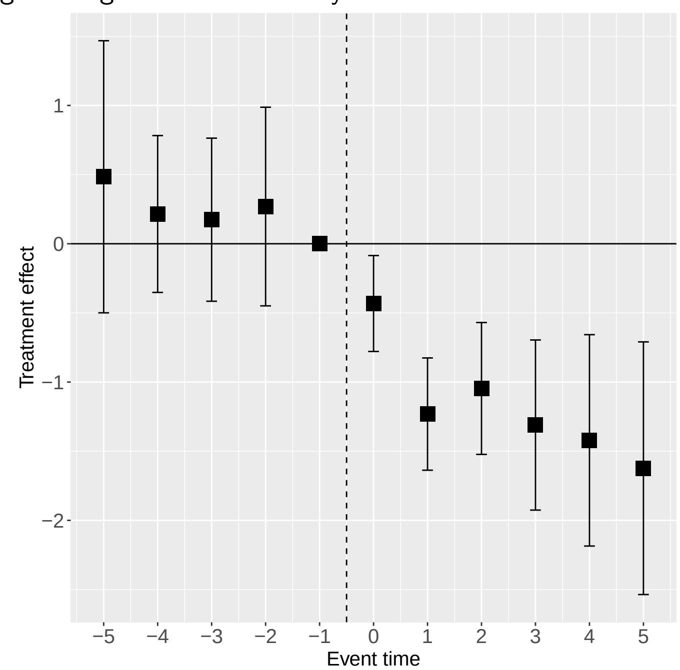
Notes: This figure shows the stacked DiD event study results for the Admitting Privilege law estimates with pre-treatment controls. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Standard error bars clustered at the county-level are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, and Austin and Harper (2019a) data

Figure C6: Admitting Privilege Law Event Study - Pre-treatment controls and state time trends



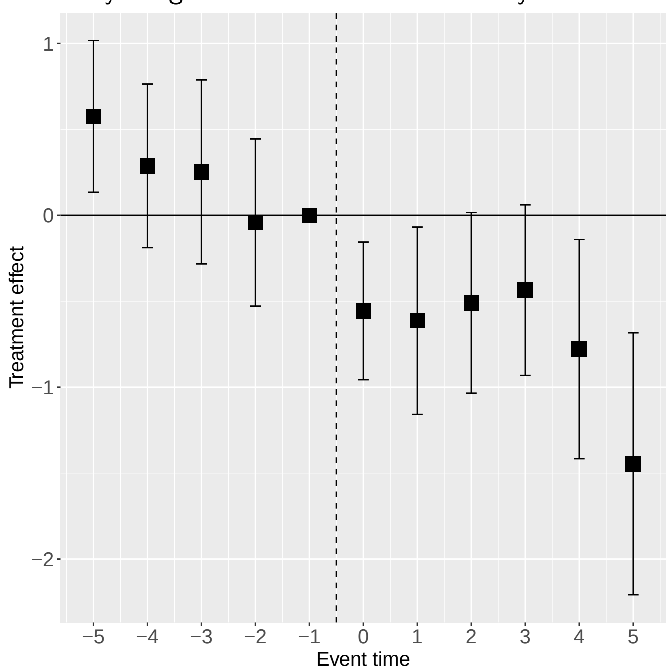
Notes: This figure shows the stacked DiD event study results for the Admitting Privilege law estimates with pre-treatment controls and state linear time trends. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Standard error bars clustered at the county-level are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, and Austin and Harper (2019a) data.

Figure C7: Admitting Privilege Law Event Study - Pre-treatment controls and county time trends



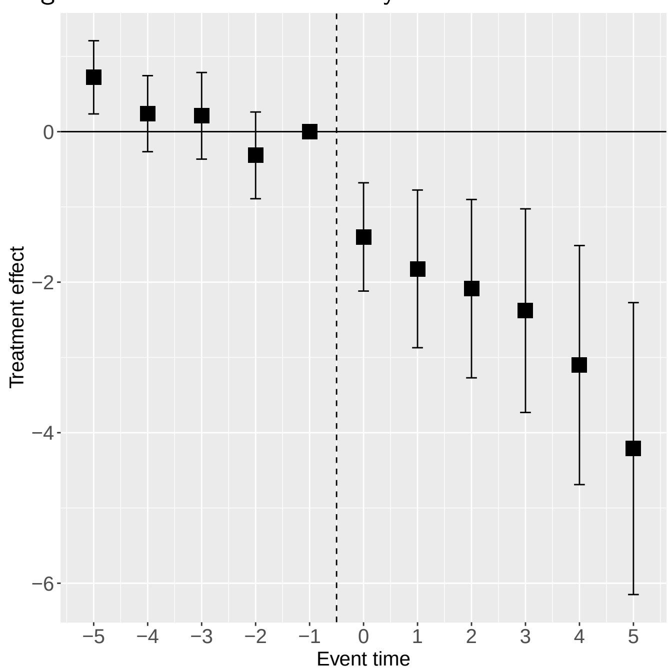
Notes: This figure shows the stacked DiD event study results for the Admitting Privilege law estimates with pre-treatment controls and county linear time trends. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Standard error bars clustered at the county-level are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, and Austin and Harper (2019a) data.

Figure C8: Ambulatory Surgical Center Law Event Study - Pre-treatment controls



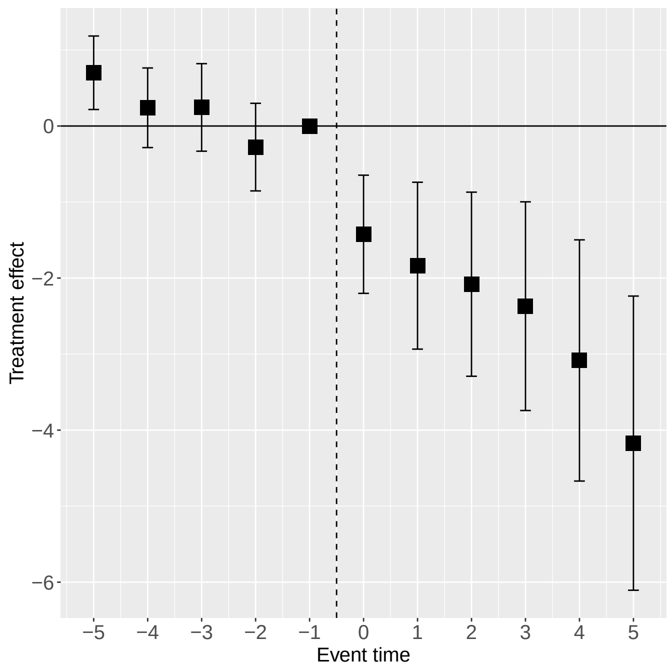
Notes: This figure shows the stacked DiD event study results for the Ambulatory Surgical Center law estimates with pre-treatment controls. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Standard error bars clustered at the county-level are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, and Austin and Harper (2019a) data.

Figure C9: Ambulatory Surgical Center Law Event Study - Pre-treatment controls and state time trends



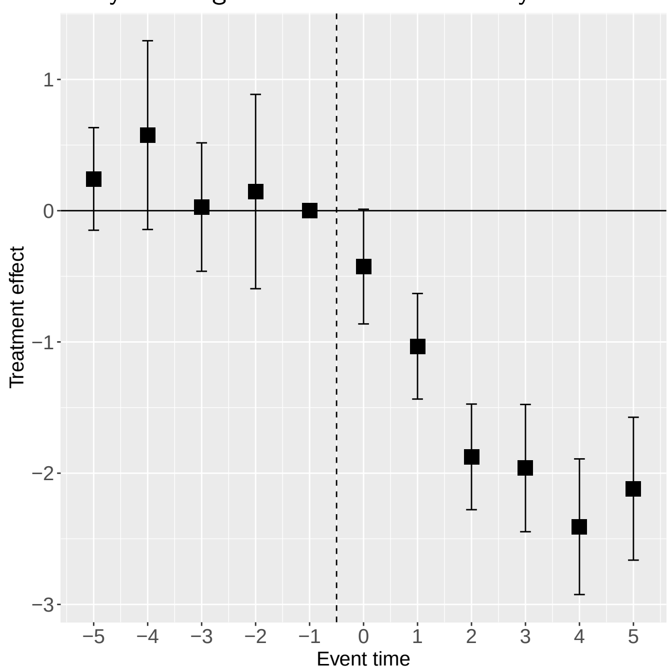
Notes: This figure shows the stacked DiD event study results for the Ambulatory Surgical Center law estimates with pre-treatment controls and state linear time trends. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Standard error bars clustered at the county-level are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, and Austin and Harper (2019a) data.

Figure C10: Ambulatory Surgical Center Law Event Study - Pre-treatment controls and county time trends



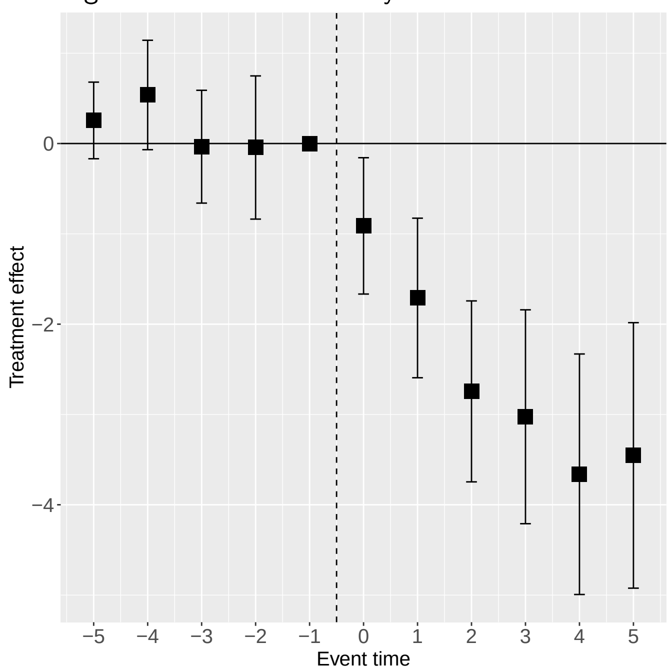
Notes: This figure shows the stacked DiD event study results for the Ambulatory Surgical Center law estimates with pre-treatment controls and county linear time trends. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Standard error bars clustered at the county-level are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, and Austin and Harper (2019a) data.

Figure C11: Mandatory Waiting Period Law Event Study - Pre-treatment controls



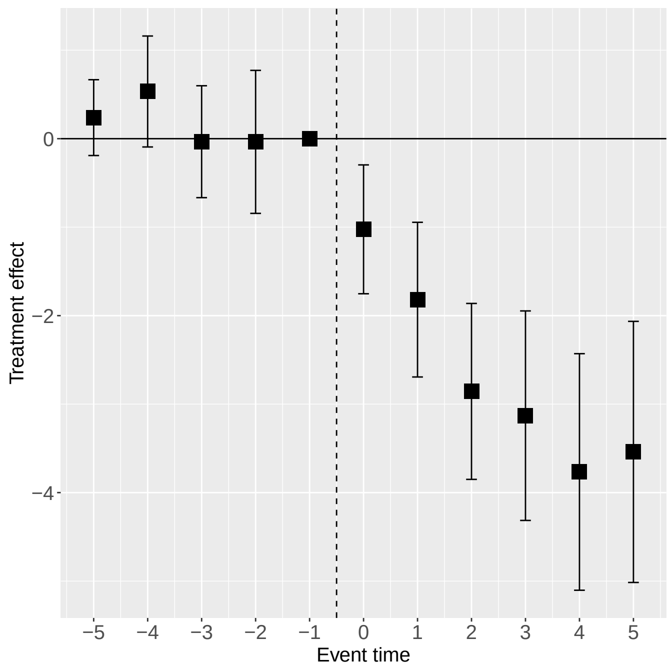
Notes: This figure shows the stacked DiD event study results for the Mandatory Waiting Period law estimates with pre-treatment controls. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Standard error bars clustered at the county-level are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, and Myers (2021a) data.

Figure C12: Mandatory Waiting Period Law Event Study - Pre-treatment controls and state time trends



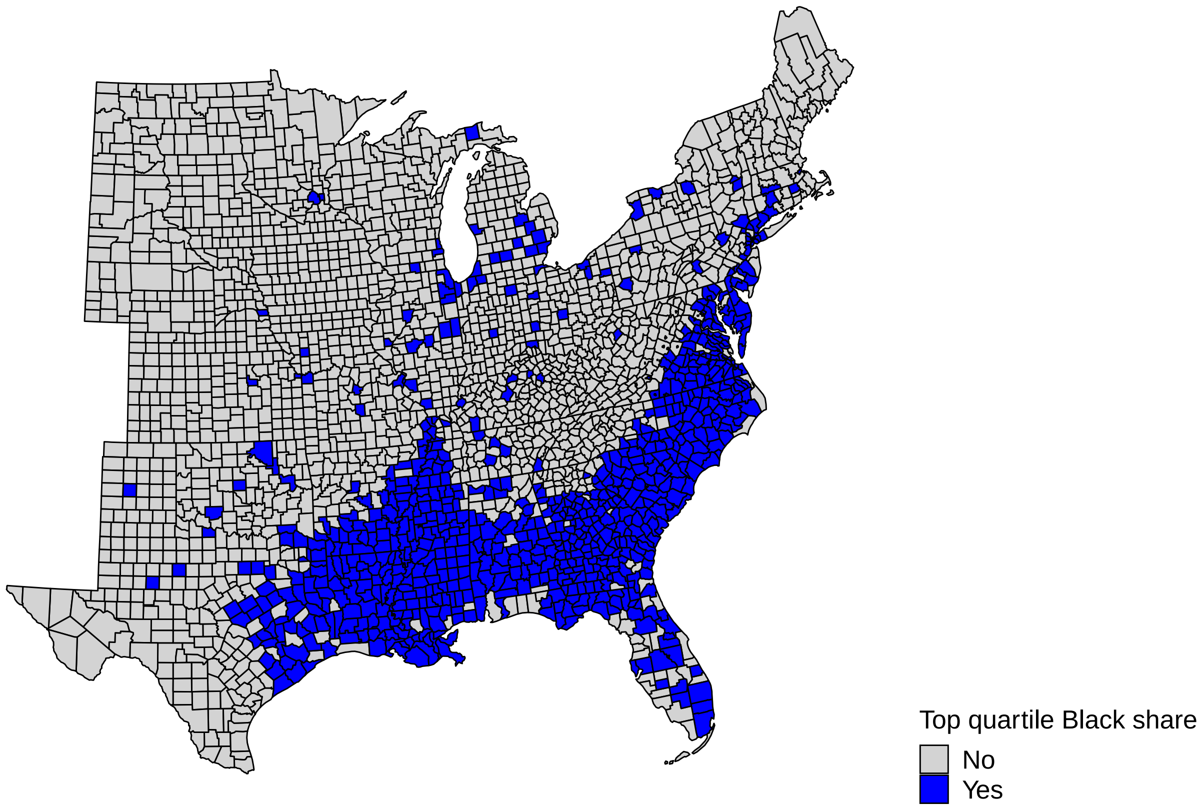
Notes: This figure shows the stacked DiD event study results for the Mandatory Waiting Period law estimates with pre-treatment controls and state linear time trends. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Standard error bars clustered at the county-level are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, and Myers (2021a) data.

Figure C13: Mandatory Waiting Period Law Event Study - Pre-treatment controls and county time trends



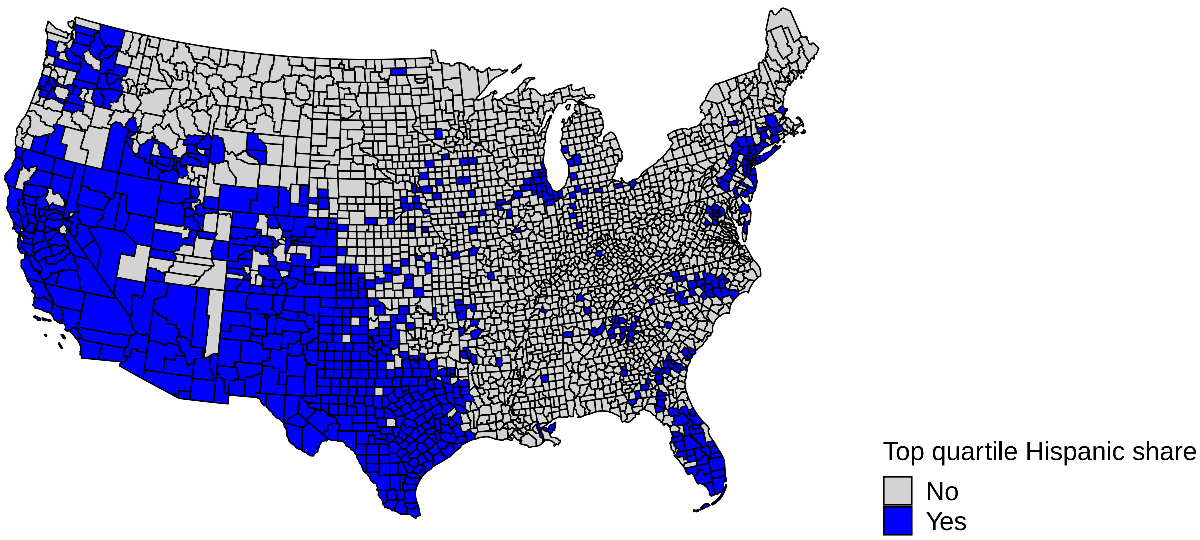
Notes: This figure shows the stacked DiD event study results for the Mandatory Waiting Period law estimates with pre-treatment controls and county linear time trends. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Standard error bars clustered at the county-level are reported at the 95% level. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, and Myers (2021a) data.

Figure C14: Counties With Top Quartile Black Population Share



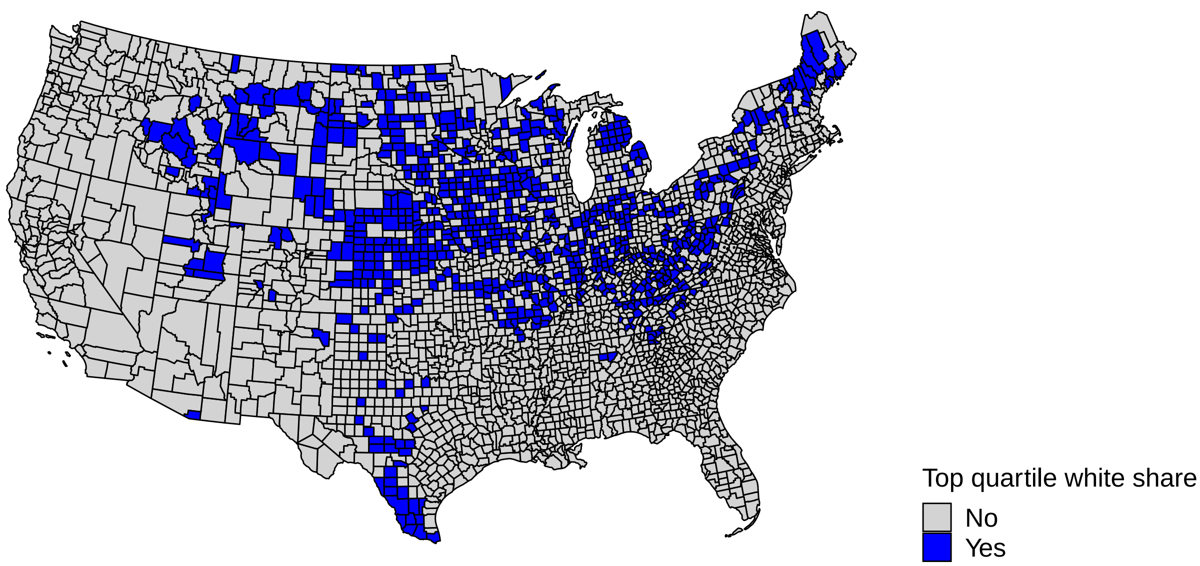
Notes: This figure shows the counties which are in the top quartile of all U.S. counties' Black population share. Western states are omitted due to the very few number of top quartile Black population share counties in that region. Population shares are computed based on the U.S. Census Bureau 2010 county-level population data. Source: Author's calculations using U.S. Census data.

Figure C15: Counties With Top Quartile Hispanic Population Share



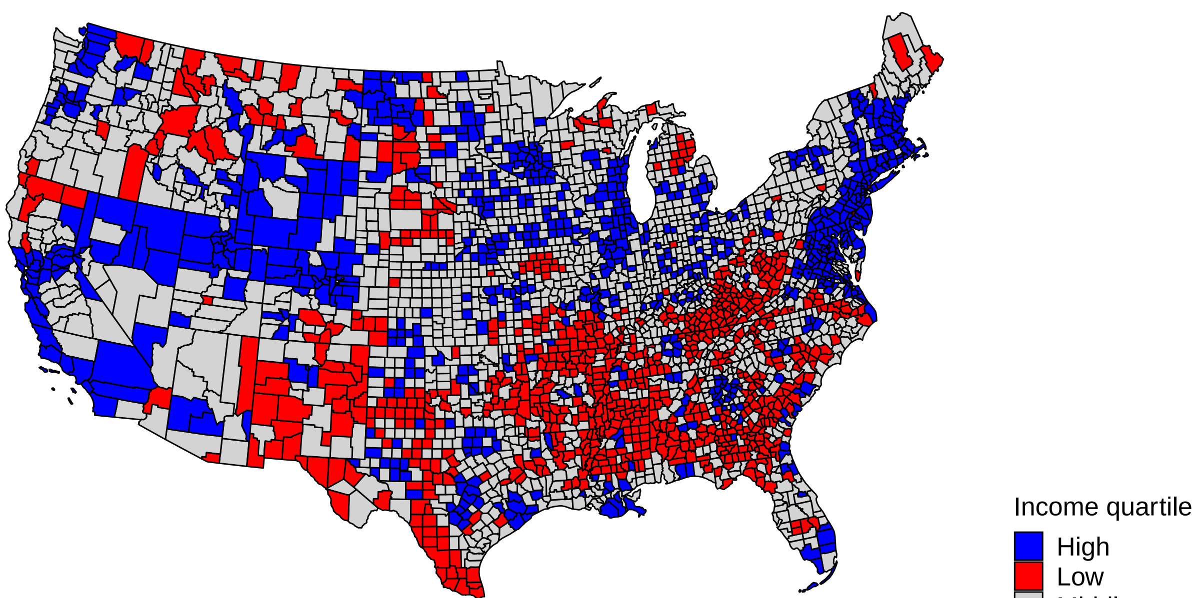
Notes: This figure shows the counties which are in the top quartile of all U.S. counties' Hispanic population share. Population shares are computed based on the U.S. Census Bureau 2010 county-level population data. Source: Author's calculations using U.S. Census data.

Figure C16: Counties With Top Quartile White Population Share



Notes: This figure shows the counties which are in the top quartile of all U.S. counties' white population share. Population shares are computed based on the U.S. Census Bureau 2010 county-level population data. Source: Author's calculations using U.S. Census data.

Figure C17: Counties in the Top and Bottom Income Quartiles



Notes: This figure shows the counties which are in the top and bottom quartile of median household income for all U.S. counties. Median household income is from the U.S. Census Bureau's SAIPE 2010 data. Source: Author's calculations using U.S. Census Bureau data.

Table C1: Admitting Privilege law baseline estimates

Dependent Variable:	Abortion rate			
Model:	(1)	(2)	(3)	(4)
Variables				
Admitting Privileges law	-0.5488**	-0.4692**	-0.5336***	-0.5401***
	(0.2568)	(0.1990)	(0.1845)	(0.1996)
Pre-treatment controls	No	Yes	Yes	Yes
State time trend	No	No	Yes	No
County time trend	No	No	No	Yes
Fixed-effects				
County-cohort	Yes	Yes	Yes	Yes
Year-cohort	Yes	Yes	Yes	Yes
Fit statistics				
Observations	84,478	81,622	81,622	81,622
R^2	0.8038	0.8346	0.8400	0.8902

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

Notes: This table shows the pooled treatment effect of Admitting Privileges (AP) laws on abortion rates over the six year post-treatment period. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, and Austin and Harper (2019a) data.

Table C2: Ambulatory Surgical Center law baseline estimates

Dependent Variable:	Abortion rate			
Model:	(1)	(2)	(3)	(4)
Variables				
Ambulatory Surgical Center law	-0.8291***	-0.8890***	-1.5534***	-1.6090***
	(0.2179)	(0.1983)	(0.3421)	(0.3732)
Pre-treatment controls	No	Yes	Yes	Yes
State time trend	No	No	Yes	No
County time trend	No	No	No	Yes
Fixed-effects				
County-cohort	Yes	Yes	Yes	Yes
Year-cohort	Yes	Yes	Yes	Yes
Fit statistics				
Observations	75,840	72,027	72,027	72,027
R^2	0.8563	0.8567	0.8583	0.8719

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

Notes: This table shows the pooled treatment effect of Ambulatory Surgical Center (ASC) laws on abortion rates over the six year post-treatment period. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, and Austin and Harper (2019a) data.

Table C3: Mandatory Waiting Period law baseline estimates

Dependent Variable:	Abortion rate			
Model:	(1)	(2)	(3)	(4)
Variables				
Mandatory Waiting Period law	-2.0275***	-1.8228***	-2.0910***	-2.2061***
	(0.2792)	(0.2117)	(0.3992)	(0.3932)
Pre-treatment controls	No	Yes	Yes	Yes
State time trend	No	No	Yes	No
County time trend	No	No	No	Yes
Fixed-effects				
County-cohort	Yes	Yes	Yes	Yes
Year-cohort	Yes	Yes	Yes	Yes
Fit statistics				
Observations	81,292	78,639	78,639	78,639
R^2	0.7991	0.8047	0.8057	0.8193

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

Notes: This table shows the pooled treatment effect of Mandatory Waiting Period (MWP) laws on abortion rates over the six year post-treatment period. Pre-treatment controls include the county-level unemployment rate, poverty rate, median household income, total population, black, asian, and hispanic population shares, the female reproductive age population share, the abortion rate, and the state-level minimum wage in the year prior to treatment for a given cohort. Source: Author's calculations using county-level abortion data from various state-specific sources, Census data, Bureau of Labor Statistics data, Vaghul and Zipperer (2021) data, and Myers (2021a) data.