Examining the impact Overturn of Roe v. Wade: Banning of Abortion on Infant Mortality Rates in the United States Using a Difference-in-Differences Approach*

The infant death rate increased by 0.285 deaths per 1,000 live births in states that became abortion-banned, compared to states where abortion remained legal.

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November 27, 2024

This study examines the impact of the Dobbs decision and subsequent abortion bans on infant mortality rates in the United States, focusing on data from 2021 to 2022. Using a Difference-in-Differences (DID) approach, we analyze trends in states where abortion remained legal compared to those where it became illegal after June 2022. Our results indicate that states enforcing abortion bans experienced an increase of 0.285 infant deaths per 1,000 live births, with compounded effects observed during the post-injunction period. Maternal age and race also emerged as significant predictors, with Black mothers facing disproportionately higher infant mortality rates. These findings underscore the compounded public health implications of restrictive abortion policies and the urgent need for targeted interventions to address racial and demographic disparities. By utilizing recent, high-quality data and rigorous modeling, this study provides critical insights into the intersection of reproductive rights and infant health outcomes.

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*Code and data are available at: [https://github.com/DianaShen1224/Relationship-between-infant-mortality-rate-and-prohibited-abortion).

1 Introduction

The overturning of Roe v. Wade on June 24, 2022, through the Supreme Court's decision in Dobbs v. Jackson Women's Health Organization, ended nearly five decades of constitutional protection for abortion rights. This landmark ruling shifted authority over abortion regulations to individual states, creating a patchwork of laws nationwide. The decision reignited debates about reproductive rights and public health, highlighting disparities in access to abortion services and their effects on health outcomes, especially in states with restrictive policies.

Banning abortion usually has been linked to a rise in maternal mortality rates, with Texas experiencing a 56% increase from 2019 to 2022 (Chuck 2024). However, restrictive abortion laws can also impact infant mortality, as they often lead to more unintended or high-risk pregnancies among disadvantaged populations with limited access to healthcare. These pregnancies are associated with higher rates of preterm births, low birth weights, and delivery complications, all of which elevate infant mortality rates. Even before Roe v. Wade was overturned, researchers highlighted the impacts of restrictive abortion laws on mortality rates. Burdick et al. (2024) found that states with 11–12 restrictive laws during 2014–2018 had a 16% higher infant mortality rate, particularly in counties with higher proportions of Black populations, inadequate prenatal care, and maternal smoking. Similarly, Harper et al. (2023) showed that restrictive laws are linked to higher maternal, fetal, and infant mortality, states with moderate abortion legislation had significantly lower maternal mortality (25.79 per 100,000 live births) and infant mortality (20.56 per 1,000 live births) compared to restrictive states, underscoring the health benefits of less restrictive policies.

The estimand of our analysis is the change in the difference in infant death rates between states that banned abortion and states where abortion remained legal after June 24, 2022.

The object of the estimation is to estimate the change in the difference in the infant death rate between the treatment and control groups based on observational data in the United States.

Instead of examining the impact of abortion laws over a broader time periods like prior research, our study focuses on the effect of abortion bans on infant mortality rates in the United States specifically from 2021 to 2022, with an emphasis on changes following the 2022 Dobbs decision. Using a Difference-in-Differences (DID) approach, we assess the interaction between abortion legality in states and the timing of the injunction implemented to understand its influence on infant health outcomes. The study utilizes observational data from the Centers for Disease Control and Prevention's WONDER database, captures infant mortality trends across states with varying levels of abortion restrictiveness. Key predictors include the mother's state of residence, race, age, and the year of infant death, enabling a nuanced examination of the effects of restrictive abortion laws on public health.

Our Results show that the overturning of Roe v. Wade and the implementation of abortion bans are linked to a rise in infant mortality rates in states where abortion became illegal. Through a Difference-in-Differences (DID) approach, we estimate that states enforcing abortion bans after the injunction saw an increase of 0.285 deaths per 1,000 live births compared to states where abortion remained legal. Furthermore, we find that maternal age and race are key determinants of infant mortality, with older maternal age groups associated with lower mortality rates and Black mothers experiencing significantly higher rates. These results emphasize the public health consequences of restrictive abortion laws and the urgent need for policies that mitigate these disparities.

This study is important as we highlight the public health implications of abortion bans, particularly their role in increasing infant mortality rates. By focusing on the 2022 Dobbs decision, we provide timely evidence on how restrictive abortion policies disproportionately affect vulnerable populations, emphasizing the need for data-driven policies to mitigate these adverse outcomes.

The structure of this paper is organized as follows: Section 2 provides details on the data sources and variables used in our analysis. Section 3 explains the modeling approach, including the assumptions and specifications of our linear regression framework. In Section 4, we present our findings, emphasizing the key predictors of Harris's support. Finally, Section 5 explores the implications of our results and suggests potential directions for future research. Appendix- A provides external data detail, Appendix- B provides model details, and Appendix- C provides a detailed introduction to surveys, sampling, and observational data in our paper.

2 Data

2.1 Overview

We conduct our infant death rate observational data analysis using the R programming language (R Core Team 2023). Our dataset, obtained from the CDC Wonder(Disease Control and Prevention 2024), based on data as of December 2022, provides a detailed overview of the Infant Death Rate across the USA. CDC WONDER (Wide-ranging ONline Data for Epidemiologic Research) is an online system providing public health professionals and the public with access to a wide range of the Centers for Disease Control and Prevention (CDC) epidemiologic data and resources. Following the guidelines outlined in Alexander (2023), we analyze the impact of abortion injunctions on infant death rates using the Difference-in-Difference method. This approach utilizes the interaction between the legality of abortion in the mother's state of residence and the timing of the infant's death as the predictor variable. Additionally, we include control variables such as infant year of death, the mother's state of residence, race, and age to account for potential confounding factors.

In this study, we utilized several R packages to streamline data manipulation, modeling, and visualization. The `tidyverse` package Wickham et al. (2019) was central to our workflow, providing tools for data wrangling and analysis, while `arrow` Richardson et al. (2024) efficiently managed parquet files for larger datasets. We used `modelsummary` package Arel-Bundock (2022) to generate clean and interpretable summaries of our regression models.We used `knitr` Xie (2014) and `kableExtra` Zhu (2024) to generate clean tables and reproducible reports, and `usmap` for geographical visualizations. We use `here` Müller (2020) package simplifies the management of file paths, ensuring a reproducible workflow by creating a consistent point of reference for file locations, regardless of the operating system or working directory. Data cleaning was facilitated by `janitor` Firke (2023), while `lubridate` Grolemund and Wickham (2011) handled date-time variables. Visualization tasks were enhanced with `ggplot2` Wickham (2016), and Bayesian regression modeling was conducted using `rstanarm` Goodrich et al. (2022). Together, these packages supported an efficient, reproducible workflow for analyzing and presenting our findings.

2.2 Measurement

The process of translating real-world events into our dataset requires a systematic approach to measurement and data gathering. In this research, we analyze infant mortality rates in the United States to understand the impact of abortion policies and demographic factors. The CDC's Linked Birth/Infant Death Records database provides comprehensive data, including maternal and infant characteristics, to support this study. Variables such as maternal age, race, education, birth weight, gestational age, and prenatal care are included to ensure a detailed examination of factors influencing infant health outcomes.

The data, sourced from birth and death certificates, undergoes a thorough cleaning and validation process to address inconsistencies and missing information, ensuring accuracy. Infant mortality rates are calculated per 1,000 live births, with additional indicators such as reliability labels for rates based on fewer than 20 deaths. To further enhance data accuracy, weights are applied to adjust for unlinked infant death records, ensuring that all deaths—linked and unlinked—are proportionally represented. Weights are calculated for each state and infant age-at-death cohort (<7 days, 7-27 days, and 28 days to 1 year) using the formula: Weight $= \frac{\text{Linked deaths+Unlinked deaths}}{\text{Linked deaths}}$ This adjustment means areas with complete linkages have a weight of 1.0, while areas with incomplete linkages are adjusted proportionally. Additionally, imputation techniques are employed to handle missing birthweight data, assigning values based on gestational period, race, sex, and plurality, further reducing potential bias in the analysis.

Once cleaned, the data is stratified by maternal and infant attributes, providing insights into trends and disparities across demographic groups. Statistical models are employed to estimate associations between state-level abortion policies and infant mortality, controlling for confounders such as maternal characteristics. This structured approach transforms complex datasets into actionable insights, shedding light on the health implications of varying abortion laws across the U.S. By utilizing comprehensive datasets and robust statistical techniques, this study offers a nuanced understanding of the intersection between policy, demographics, and infant health outcomes, informing the public health strategies and legislative decisions.

2.3 Outcome variables

2.3.1 Death Rate

The `death rate` refers to the number of deaths of infants under one year of age per 1,000 live births in a specified population during a given time period. It serves as a key indicator of a population's overall health and access to healthcare. Rates labeled as "Unreliable" occur when there are fewer than 20 deaths in the numerator, as these figures do not meet the National Center for Health Statistics (NCHS) standards for reliability or precision. After cleaning the dataset, the "Unreliable" label is converted into a separate variable named `reliable`.

Figure 1 illustrates the distribution of infant death rates (per 1,000 live births) based on the available data. The majority of infant death rates cluster around lower values, with a peak observed between 5 and 10 deaths per 1,000 infants. As the death rate increases, the frequency of occurrences decreases, indicating that higher infant death rates are relatively rare. There are few instances where the rate exceeds 20 deaths per 1,000 infants, suggesting these are outliers. Overall, the distribution is right-skewed, highlighting the predominance of lower infant death rates in the dataset.

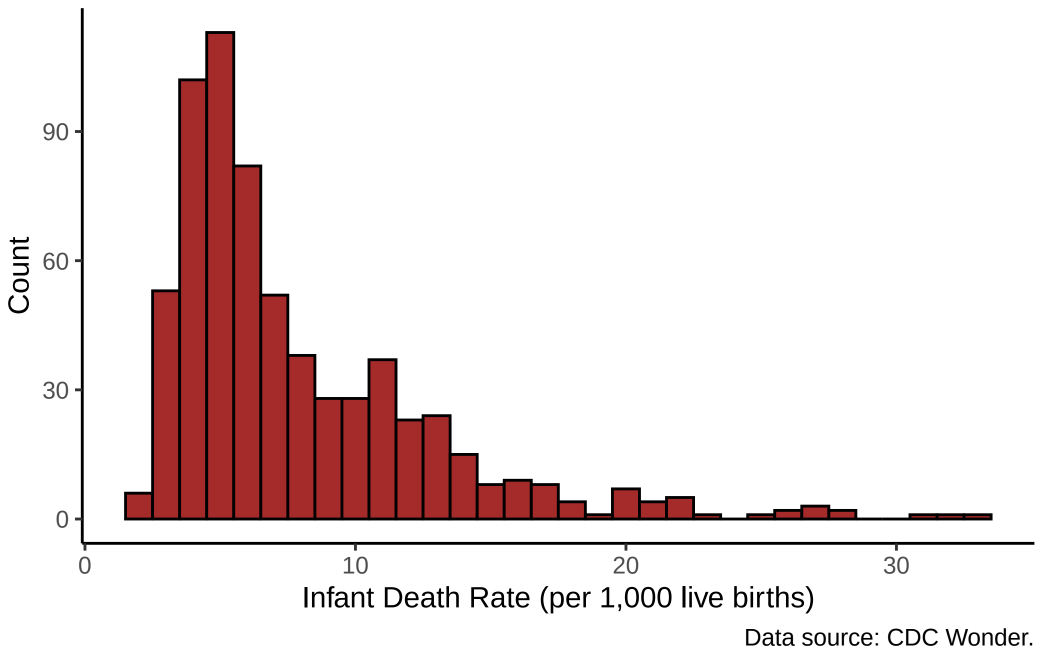


Figure 1: The distribution of infant death rate (per 1,000 live births), with a peak observed between 5 and 10 deaths per 1,000 infants. The distribution is right-skewed, highlighting the predominance of lower infant death rates in the dataset.

2.4 Predictor variables

2.4.1 Interaction Term: Abortion Legality and After Injunction

Abortion legality (named `abortion_illegal` in the dataset) is a newly created variable in our dataset, which refers to the legal status of abortion within a given state. It is represented as a binary variable, where 1 indicates that abortion is illegal in the state, and 0 indicates that abortion is legal. This classification reflects the policies and laws governing abortion access in each state.

Another created variable `after_injunction` indicates whether the date of infants' death falls after the implementation of the abortion injunctions following the overturn of Roe v. Wade in June 2022. It is coded as a binary variable, where 1 represents dates after June 2022, signifying the post-injunction period, and 0 represents dates before June 2022, indicating the pre-injunction period.

To evaluate the impact of abortion injunctions on infant death rates, we utilize the Difference-in-Difference (DID) method. As part of this approach, we construct an interaction term defined as the product of `abortion_illegal` and `after_injunction`. The resulting interaction term equals 1 when abortion is illegal the time is after the injunction, and 0 otherwise. This term is included in the analysis to evaluate the joint impact of these factors on infant death rates.

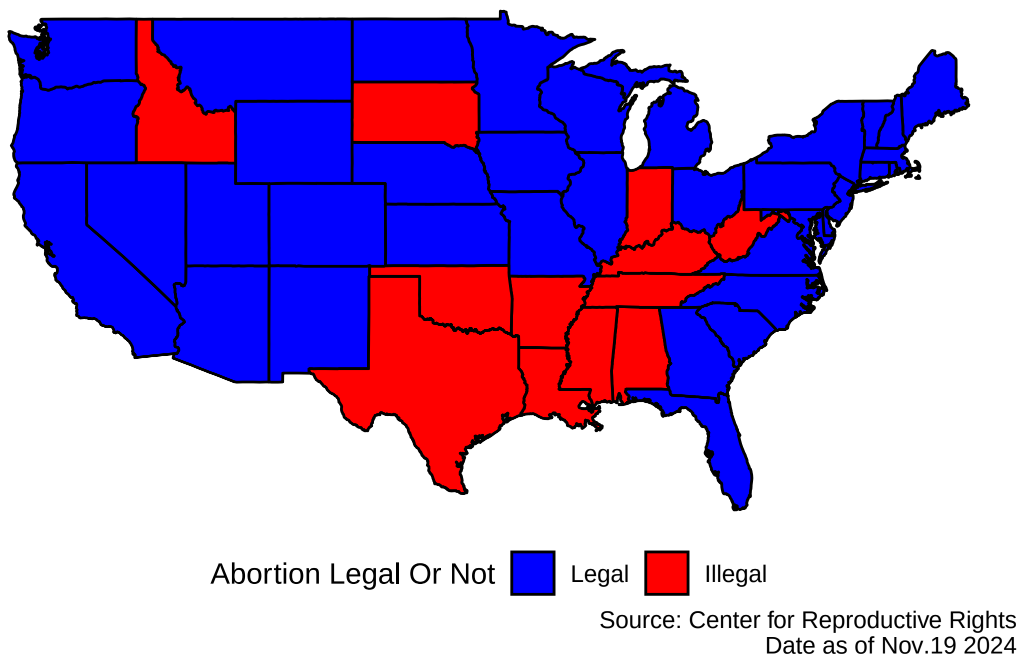


Figure 2: Abortion Legality by State. As of November 2024, abortion is illegal in Alabama, Arkansas, Idaho, Indiana, Kentucky, Louisiana, Mississippi, Missouri, North Dakota, Oklahoma, South Dakota, Tennessee, Texas, West Virginia, and Wisconsin.

Figure 2 illustrates the legality of abortion across U.S. states. Based on Reproductive Rights (2024), as of November 2024, abortion has been illegal in Alabama, Arkansas, Idaho, Indiana, Kentucky, Louisiana, Mississippi, Missouri, North Dakota, Oklahoma, South Dakota, Tennessee, Texas, West Virginia, and Wisconsin following the June 2022 decision.

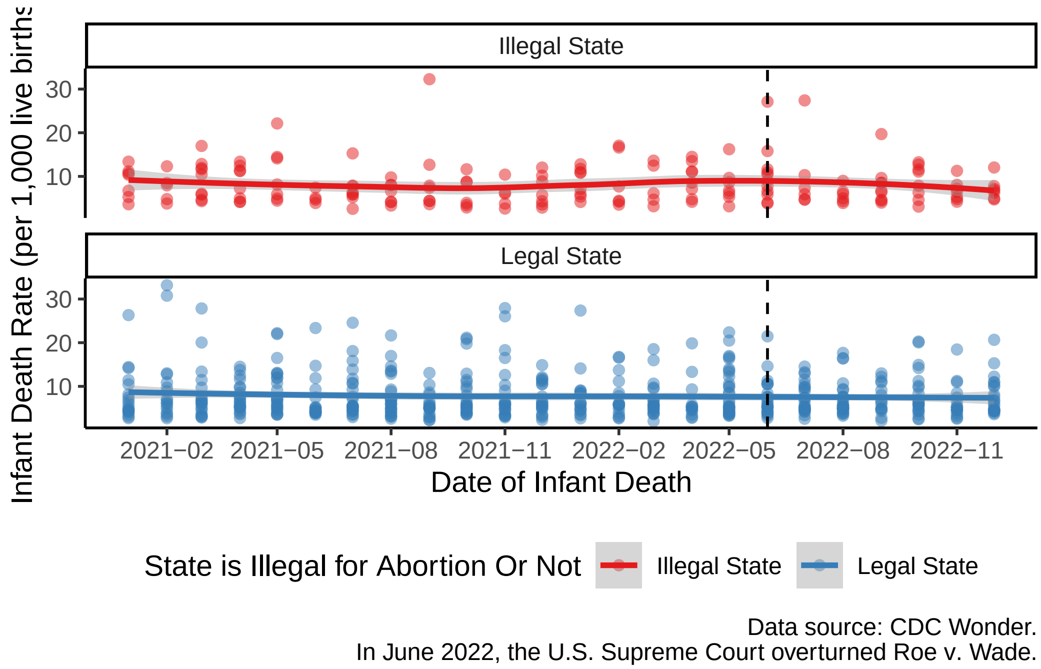


Figure 3: Infant death rates (per 1,000 live births) over time, with a slight increase after June 2022 in states where abortion is illegal, while rates remain stable in states where abortion is legal.

Figure 3 illustrates trends in infant death rates (per 1,000 live births) over time in states where abortion is illegal versus legal. In states with abortion bans, infant mortality shows a slight increase after June 2022, marked by the dashed line representing the overturn of Roe v. Wade. In contrast, states where abortion remains legal exhibit relatively stable trends. This suggests a potential link between abortion bans and rising infant mortality rates, warranting further investigation.

Table 1: Average Infant Death Rate (per 1,000 live births) by Interaction Between Abortion Legality and Injunction Timing. States with “Illegal Abortion and After Injunction” (denoted as ‘1’) have a higher average infant death rate compared to states with “Legal Abortion and Before/After Injunction or Illegal Abortion and Before Injunction” (denoted as ‘0’).

illegal_after_injunction	Average Infant Death Rate (per 1,000 live births)
0	7.9

1	8.3

Note:
Data Source: CDC Wonder

Table 1 highlights average infant death rates (per 1,000 live births) based on abortion legality and injunction timing. States categorized as '1', where abortion became illegal after the injunction, show a higher average infant death rate of 8.3 compared to 7.9 in '0' states, where abortion remained legal or abortion used to be legal before the injunction. This suggests that restrictive abortion policies and their enforcement may contribute to higher infant mortality, potentially due to increased unintended or high-risk pregnancies, reduced access to maternal healthcare, and exacerbated social or economic disparities.

2.5 Control Variables

2.5.1 Year of Death

The Year of Death variable represents the calendar year in which the infant death occurred, specifically focusing on the years 2021 and 2022 in this study. This variable is essential for analyzing temporal trends and identifying patterns or shifts in infant mortality rates over this critical period. By controlling the year of death, we can closely examine the impact of significant policy changes, such as the overturning of Roe v. Wade in 2022, as well as other temporal factors on infant health outcomes.

2.5.2 Age of Mother

The Age of the Mother (`age_of_mother`) refers to the age group of the mother at the time of childbirth. In our observational data, age is categorized into the brackets 15–19 years, 20–24 years, 25–29 years, and 30–34 years in the raw data, in compliance with privacy requirements.

Table 2 displays the average infant death rate (per 1,000 live births) by the age group of mothers. It shows a clear trend: younger mothers, particularly those aged 15–19 and 20–24, have higher infant death rates (9.0 and 10.0, respectively), while older mothers in the 25–29 and 30–34 age groups have lower rates (7.4 and 6.6, respectively). This suggests that maternal age may be a factor influencing infant mortality, with younger mothers experiencing higher risks.

Table 2: Average Infant Death Rate (per 1,000 live births) of different age groups of Mothers. It shows that infant death rates decrease with increasing maternal age, with the highest rate (10.0) among mothers aged 20–24 and the lowest (6.6) among those aged 30–34.

Age of Mother	Average Infant Death Rate (per 1,000 live births)
15-19	9.0
20-24	10.0
25-29	7.4
30-34	6.6

Note:
Data Source: CDC Wonder

2.5.3 Mother's Single Race

The self-identified race of the mother was recorded as a single race category. In this dataset, the available categories are: Asian, Black or African American, and White. This classification facilitates the analysis of maternal and infant health outcomes across these racial groups.

Table 3: Average Infant Death Rate (per 1,000 live births) of different age groups of Mothers. It shows that infant death rates decrease with increasing maternal age, with the highest rate (10.0) among mothers aged 20–24 and the lowest (6.6) among those aged 30–34.

Mother's Single Race	Average Infant Death Rate (per 1,000 live births)
Asian	5.4
Black or African American	14.5
White	5.8

Note:
Data Source: CDC Wonder

2.6 Random Variable

2.6.1 State

The state of the mother's legal residence at the time of birth. This data is categorized by the mother's state of residence and excludes territories.

Figure 4 is a choropleth map that visualizes the average infant death rate per 1,000 live births across U.S. states, with data categorized by color intensity. States with higher infant death rates are shown in lighter shades (yellow), while states with lower rates are represented in darker shades (purple). States with missing data are indicated in grey. The map highlights disparities in infant mortality rates, with some states, particularly in the southeastern U.S., exhibiting notably higher rates compared to others. States like Alabama and Mississippi show the highest rates, while states such as California and New York exhibit lower rates.

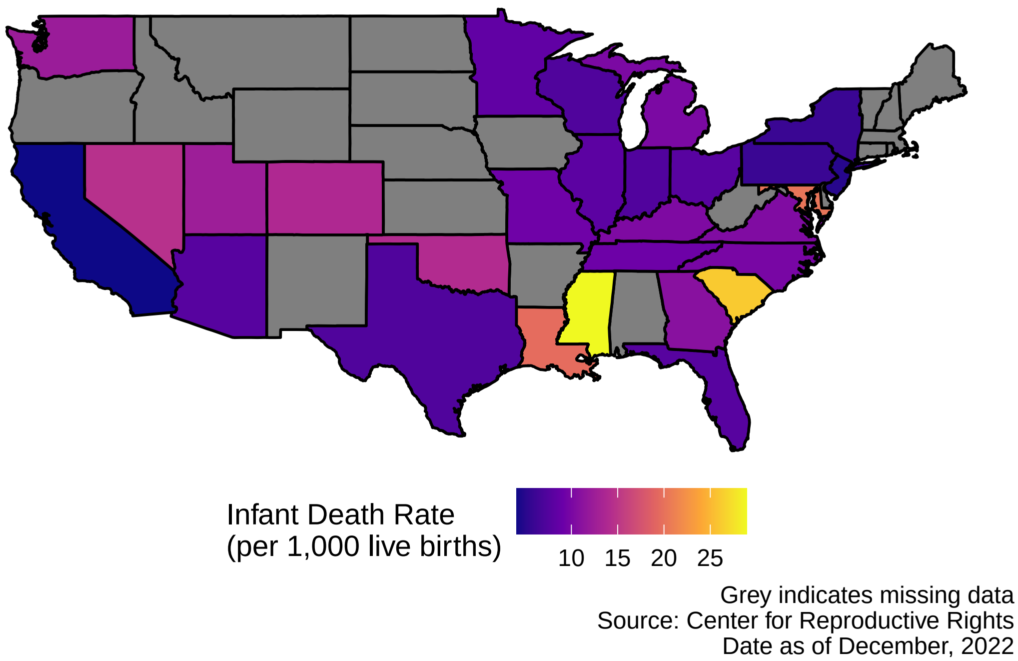


Figure 4: Infant Death Rates Across U.S. States (per 1,000 Live Births), December 2022. The infant Mortality Rate is much higher in Southeastern. Alabama and Mississippi show the highest rates, while California and New York exhibit lower rates.

3 Model

For our analysis, we use a Bayesian Difference-in-Differences (DID) model to quantify the impact of abortion injunctions on infant death rate across states in the USA. This method compares changes in infant death rates over time between a treatment group (states where abortion injunctions were implemented) and a control group (states where abortion remains legal), providing a robust framework for estimating causal effects.

3.1 Difference-In-Difference Approach (DID)

Difference-in-Differences (DID) is a causal inference method that estimates the impact of an intervention by comparing changes in outcomes over time between a treatment group and a control group. By assuming parallel trends in the absence of the intervention, the DID framework isolates the intervention's effect through **the interaction between time periods (pre- and post-intervention) and group membership**. This makes it a robust method for evaluating policy changes and other significant events.

3.1.1 Assumption

The validity of the Difference-in-Differences (DID) approach in our study relies on several key assumptions, which, if violated, could affect the robustness and reliability of our results (Cunningham 2021):

3.1.1.1 Parallel Trends Assumption

The model relies on the assumption that, without the abortion injunction, the treatment group (states where abortion became illegal) and the control group (states where abortion remained legal) would have followed similar trends in infant mortality rates. However, this assumption can be challenged by differences in healthcare systems, socioeconomic conditions, or pre-existing policy environments, which may cause deviations from parallel trends.

3.1.1.2 Compositional Differences

In addition to parallel trends, compositional changes in repeated cross-sectional data over time can influence results. For instance, shifts in demographic factors such as maternal age or racial makeup between pre-and post-intervention periods may confound the observed changes in infant mortality rates. Including control variables helps adjust for these confounders, ensuring that the estimated effect reflects the policy intervention rather than changes in the population composition.

3.1.1.3 Long-term Effects vs. Reliability

The length of the analysis period further complicates the reliability of the results. While longer periods allow for capturing long-term effects, they also increase the likelihood of unrelated factors, such as new policies or healthcare advancements, influencing the outcome. Over time, some states in the control group may also implement similar abortion policies, diluting the treatment effect. Conversely, shorter analysis periods

3.1.1.4 Functional Form Dependence

Finally, the model assumes that the functional relationship between predictors and outcomes is correctly specified. If this assumption is violated, differences in outcomes between treatment and control groups may stem from misspecified relationships rather than the intervention itself. This highlights the importance of carefully assessing the model's structure and assumptions to ensure valid results.

3.2 Model Parameters

The model focuses on the infant death rate per 1,000 live births as the dependent variable and includes the following independent variables:

- **Treatment Group Indicator `abortion_illegal`**: A binary variable indicating the group: 1 if abortion is illegal in the state. 0 if abortion remains legal.
- **Time Indicator `after_injunction`**: A binary variable indicating the time period: 0 for the period before the injunction was implemented. 1 for the period after the injunction was implemented.
- **Interaction Term`after_injunction` $\times$ `abortion_illegal`**: The interaction term captures the additional change in the outcome (e.g., percentage of support, behavior, or health-related metrics) for regions where abortion is illegal after the injunction implemented, beyond any changes observed in regions where abortion remains legal.

Additionally, we include these control variables to adjust for demographic and temporal factors that could influence infant mortality rates, ensuring that the estimated effects are not confounded by these characteristics:

- **`age_of_mother`**: The age of the mother at the time of birth, represented as a continuous variable.
- **`mothers_single_race`**: Self-identified race of the mother, represented as a categorical variable.
- **`year_of_death`**: The year in which the infant death occurred, represented as a continuous variable.

Finally, we include a random variable:

- **state**: Mother's residence state when the infant was born as a random effect in the model.

By isolating the impact of the abortion injunction through this interaction term after_injunction×abortion_illegal, our model identifies changes in infant death rates that can be attributed to the policy intervention. Additional details and diagnostics supporting the model's implementation is provided in Appendix- B.

3.3 Model set-up

In our analysis, we employ two models. The first model includes only the predictor variables and the random effect for the state. The second model builds on the first by incorporating additional control variables to account for potential confounding factors.

Define y_i as as the infant death rate per 1,000 live births, and γ_j as the random state effect.

$$
\begin{aligned}
y_i|\mu_i, \sigma &\sim \text{Normal}(\mu_i, \sigma) \\
\text{First Model}: \mu_i &= \beta_0 + \beta_1 \cdot \text{After Injunction} + \beta_2 \cdot \text{Abortion Illegal} \\
&+ \beta_3 \cdot \text{After Injunction} \cdot \text{Abortion Illegal}_i + \gamma_j \\
\text{Second Model}: \mu_i &= \beta_0 + \beta_1 \cdot \text{After Injunction}_i + \beta_2 \cdot \text{Abortion Illegal}_i \\
&+ \beta_3 \cdot \text{After Injunction}_i \cdot \text{Abortion Illegal}_i \\
&+ \beta_4 \cdot \text{Year of Death}_i + \beta_5 \cdot \text{Age of Mother}_i + \beta_6 \cdot \text{Mother's Single Race}_i + \gamma_j \\
\beta_0 &\sim \text{Normal}(0, 2.5) \\
\beta_1 &\sim \text{Normal}(0, 2.5) \\
\beta_2 &\sim \text{Normal}(0, 2.5) \\
\beta_3 &\sim \text{Normal}(0, 2.5) \\
\beta_4 &\sim \text{Normal}(0, 2.5) \\
\beta_5 &\sim \text{Normal}(0, 2.5) \\
\beta_6 &\sim \text{Normal}(0, 2.5) \\
\gamma_j &\sim \text{Normal}(0, \sigma_j^2) \\
\sigma &\sim \text{Exponential}(1)
\end{aligned}
$$

The models are run in R (R Core Team 2023) using the rstanarm package of Goodrich et al. (2022). The default priors from rstanarm are used for both GLM Bayesian models. We run the model in R (R Core Team 2023) using the rstanarm package of Goodrich et al. (2022). We use the default priors from rstanarm used for both Gaussian Bayesian models.

3.3.1 Model justification

For our analysis, we use separate Bayesian regression models to estimate the infant death rates in states where abortion injunctions were implemented and in states where abortion remains legal. We use the interaction term between after_injunction and abortion_illegal to measure the causal effect of the abortion injunction. Both models share the same predictors to ensure consistency and comparability in capturing the determinants of infant mortality.

For one of our models, we include control variables (`age_of_mother`, `mothers_single_race`, and `year_of_death`) to adjust for confounders that could influence infant death rates, addressing the assumption of compositional differences in the DID approach and ensuring unbiased estimates of the intervention's effect. In the other model, we exclude these controls focus on the overall intervention impact, and avoid overfitting, and prioritize simplicity when variability is adequately accounted for by the design or random effects. Thus, our decision to fit two models to compare the outcomes: one adjusts for confounders to refine the estimates, while the other focuses on the direct effect of the intervention.

Our model includes `state` as a random effect to account for regional variations in infant mortality that could introduce bias. We use a random effect rather than a fixed effect to capture variability across states without estimating specific effects for each one. This approach models unobserved heterogeneity, such as differences in healthcare systems and socioeconomic conditions, using a single variance term, which avoids overfitting and ensures efficiency and generalizability. By adjusting for unmeasured state-specific factors, the model provides robust and reliable findings while balancing parsimony and interpretability, making it well-suited for our analysis.

We choose the Bayesian framework since it enhances the DID approach by incorporating prior information and quantifying uncertainty in a probabilistic manner. In our Bayesian models, we use weakly informative priors from the `rstanarm` package, including a Normal prior ($\mu = 0$ and $\sigma = 2.5$) for fixed effects and an Exponential prior (rate $= 1$) for the auxiliary parameter, with `autoscale=TRUE` to dynamically adjust priors based on the data scale. This enhances convergence and ensures priors are calibrated to predictor ranges without dominating the data. The model assumes plausible parameter centering, random effects capture unobserved heterogeneity, and the DID framework relies on parallel trends between groups. However, limitations include potential bias from misspecified priors, computational challenges for hierarchical models, and sensitivity to data sparsity or imbalances. This model may not be suitable if group-level effects are negligible, parallel trends are violated, or data is insufficient, but when applied appropriately, it provides robust and interpretable causal estimates.

4 Results

The results from the two Bayesian models are summarized in Table 4. The interaction term between after_injunction and abortion_illegal is positive and statistically significant (0.111 in

Table 4: Summary of Bayesian Regression Model Examining the Impact of Abortion Bans on Infant Mortality Rates in the United States: A Difference-in-Differences Approach Using 2021-2022 Infant Mortality Data

	(1)	(2)
(Intercept)	9.850	−650.671
after_injunction1	−0.525	−0.947
abortion_illegal1	3.365	1.401
after_injunction1 × abortion_illegal1	0.111	0.285
year_of_death		0.330
age_of_mother20-24		−3.571
age_of_mother25-29		−5.732
age_of_mother30-34		−6.155
mothers_single_raceBlack or African American		6.604
mothers_single_raceWhite		−2.562
Num.Obs.	659	659
R2	0.256	0.793
R2 Adj.	0.213	0.778
R2 Marg.	0.081	0.631
ICC	0.6	0.7
Log.Lik.	−1885.342	−1460.443
ELPD	−1911.4	−1496.7
ELPD s.e.	33.8	45.9
LOOIC	3822.9	2993.5
LOOIC s.e.	67.7	91.7
WAIC	3820.7	2989.5
RMSE	4.21	2.36
r2.adjusted.marginal	0.213273523198565	0.778118665191066

Note. All models include a random variable for the state. The reference level of age_of_mother is 15-19. The reference level of monthers_single_race is Asian. Source: CDC Wonder

Model 1 and 0.280 in Model 2), indicating a change in infant mortality rates associated with the combination of abortion bans and the post-injunction period.

For the independent effects, states where abortion is illegal show higher infant mortality rates, with coefficients of 3.365 in Model 1 and 1.400 in Model 2. The post-injunction period alone is associated with coefficients of -0.525 in Model 1 and -0.940 in Model 2, indicating a decrease in infant mortality during this time.

Demographic variables also exhibit notable associations. Maternal age is negatively associated with infant mortality, with coefficients for age groups 25–29 and 30–34 of -5.73 and -6.15 in Model 2, respectively. The the coefficient for Black mothers in Model 2 is 6.66, reflecting a higher infant mortality compared to other racial groups.

The models performed well, with low RMSE values and high R^2 values, indicating that the predictors account for a substantial portion of the variance in infant mortality rates.

5 Discussion

5.1 Key Findings and Implications

The analysis reveals distinct patterns in infant mortality rates across various policy and demographic factors. In states where abortion remained legal, the post-injunction period (after_injunction1) is linked to reductions in infant mortality rates by 0.525 and 0.940 deaths per 1,000 live births in Models 1 and 2, respectively. However, states with abortion bans (abortion_illegal1) exhibit significantly higher infant mortality rates, with increases of 3.365 deaths in Model 1 and 1.400 deaths in Model 2. The DID interaction term (after_injunction1 × abortion_illegal1) reveals that abortion bans during the post-injunction period results in an additional increase of 0.111 deaths in Model 1 and 0.280 deaths in Model 2. Demographic factors also play a critical role, with older maternal age (25–34 years) reducing infant mortality rates, while younger mothers (15–19 years) face elevated risks. Black mothers experience disproportionately higher infant mortality rates, with an increase of 6.660 deaths per 1,000 live births compared to Asian mothers. These findings collectively emphasize the compounded effects of policy and demographic disparities on infant health outcomes.

5.2 Public Health Implications of Restrictive Abortion Laws

The findings highlight the significant public health consequences of abortion bans in the United States. The observed increase of 0.285 infant deaths per 1,000 live births in states enforcing abortion bans after the Dobbs decision underscores the detrimental impact of restrictive abortion policies. These increases often reflect systemic issues such as inadequate prenatal care, gaps in healthcare access, and underlying socioeconomic inequities. States with pre-existing healthcare challenges may experience amplified effects, suggesting an urgent need for comprehensive policy interventions to address these disparities. Tackling the root causes of these health disparities—such as improving prenatal care, expanding healthcare access, and addressing socioeconomic inequalities—will be essential for mitigating the unintended consequences of restrictive abortion legislation.

5.3 Racial and Socioeconomic Disparities

The results reveal stark racial disparities in infant mortality rates, with Black mothers experiencing significantly higher rates compared to other racial groups. These disparities are exacerbated by restrictive abortion policies, which disproportionately affect already vulnerable populations. The intersection of systemic healthcare inequities, socioeconomic challenges, and restrictive legislation creates compounded risks for marginalized communities, leading to worse health outcomes. Addressing these inequities requires targeted policies that ensure equitable access to maternal and infant healthcare, particularly in communities most impacted by these disparities. Such policies should prioritize investments in healthcare infrastructure, culturally competent care, and programs that support at-risk populations.

5.4 Integration of Policy and Healthcare Systems

The significant interaction between abortion legality and the post-injunction period illustrates the compounded impact of restrictive abortion policies on infant mortality rates. These findings underscore the need for integrated healthcare systems that can address the consequences of high-risk pregnancies, improve prenatal care and ensure equitable access to medical services. Policymakers must consider the broader public health implications of abortion bans and implement strategies that safeguard maternal and infant health. This includes enhancing healthcare delivery in underserved areas, investing in community-based interventions, and ensuring that restrictive policies are accompanied by measures to mitigate their public health impact.

5.5 Data and Temporal Limitations

A key limitation of our analysis is the temporal and demographic scope of the dataset. The data includes only infant deaths under 1 year of age occurring within the United States to U.S. residents during 2021–2022. This timeframe does not capture the full year of infant mortality outcomes following the Dobbs decision, as infants who died in 2023 are not included. Furthermore, the dataset's focus on infants under 1 year of age may exclude cases that reflect longer-term health impacts. These limitations could lead to an underestimation of the full effects of abortion bans. Future research should incorporate more comprehensive and updated datasets to provide a clearer and more complete analysis of the long-term trends and implications of restrictive abortion policies.

5.6 Weaknesses and Future Directions

While this study provides valuable findings, several limitations should be addressed in future research. The analysis relies on aggregate state-level data, which may obscure localized effects and intra-state disparities. Unmeasured confounders, such as economic conditions, healthcare infrastructure differences, or state-specific policies, could also influence the results. Moreover, the short timeframe of the dataset limits the ability to assess the long-term effects of abortion policies. Future research should integrate more granular data, such as county-level analyses, and extend the study period to capture longer-term impacts. Qualitative studies focusing on the lived experiences of affected populations can complement quantitative analyses, offering a deeper understanding of the broader implications of restrictive abortion laws. These efforts will support the development of evidence-based policies aimed at reducing disparities and improving maternal and infant health outcomes.

Appendix

A Additional data details

A.1 Dataset and Graph Sketches

Sketches depicting both the desired dataset and the graphs generated in this analysis is available in the GitHub Repository `other/sketches`.

A.2 Data Cleaning

The raw dataset, consisting of U.S. infant mortality records from 2021 and 2022, was cleaned and pre-processed to ensure its suitability for analysis. The dataset was first imported from a tab-separated file, with irregular lines handled appropriately. Variables were standardized using `janitor::clean_names()` to ensure consistent naming conventions. Key variables such as state, maternal age, maternal race, year of death, month, and infant death rates were selected for analysis, and missing values were removed.

Additional variables were created to facilitate analysis: `after_injunction`, indicating whether the data corresponded to the period after June 2022 (post-Dobbs decision), and `abortion_illegal`, denoting whether the state had restrictive abortion laws. Death rate reliability was assessed, and unreliable rates were flagged for transparency. The death rate column was cleaned to remove annotations and converted to numeric format for analysis. A date variable was created by combining the year and month columns, providing a timeline for analysis. Finally, a date variable was created by combining the year and month variables. The cleaned dataset was saved in CSV and Parquet formats to ensure compatibility with analytical workflows.

A.3 Attribution Statement

The data utilized in this study was sourced from the CDC WONDER Online Database. Access to the data and its use complies with the terms outlined on the CDC WONDER Data Use Agreement. Specifically, the data was used for academic research purposes, with acknowledgment of the Centers for Disease Control and Prevention (CDC) as the original data provider. The CDC, however, does not assume responsibility for any analyses, interpretations, or conclusions drawn from the data by the authors of this study.

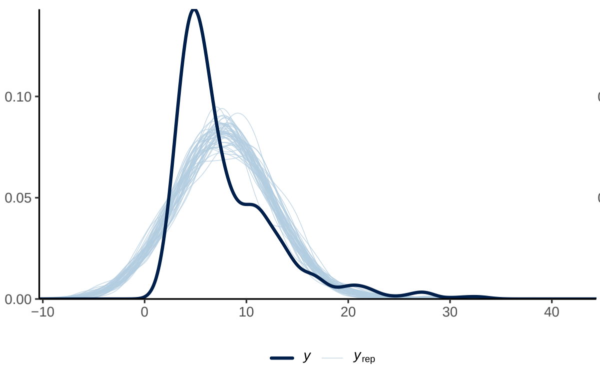
B Model details

B.1 Posterior predictive check

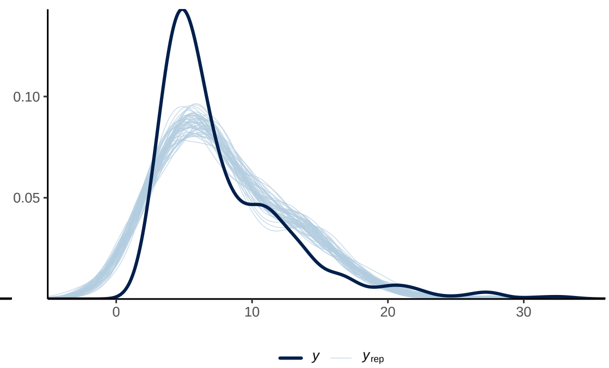
In Figure 5a and Figure 5b we implement a posterior predictive check for the first model and second model. It represents posterior predictive checks for Model 1 and Model 2, illustrating how well each model captures the observed data. The posterior predictive checks for Model 1 (policy-focused) and Model 2 (policy and demographic factors) illustrate model fit. In Figure 5a, the observed (y) and replicated (y_{rep}) distributions align moderately, reflecting general trends but limited precision. Figure 5b shows improved alignment, indicating that adding demographic factors enhances predictive accuracy and better captures the complexities of infant mortality rates.

In Figure 5c and Figure 5d we compare the posterior with the prior. The posterior vs. prior plots for Model 1 and Model 2 illustrate the role of data in informing the posterior estimates of the model parameters. In Model 1 Figure 5c, which focuses on policy-related predictors (e.g., abortion restrictions), the data significantly shift the posterior distributions for key variables, demonstrating their explanatory power. Model 2 Figure 5d, incorporating additional demographic factors such as maternal age and race, shows a more refined and concentrated posterior distribution, emphasizing the added predictive utility of demographic variables. The comparison indicates that Model 2 provides better-informed parameter estimates, supporting the hypothesis that demographic factors play a crucial role in understanding infant mortality in the context of restrictive abortion laws.

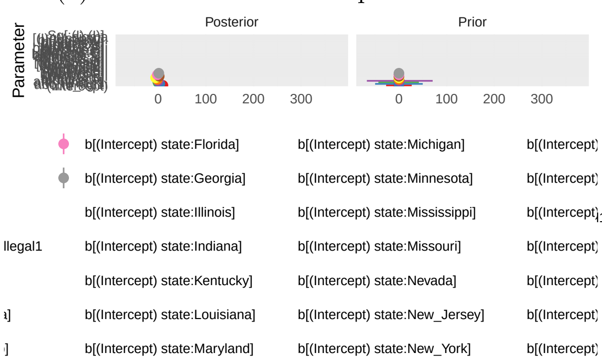
```
Priors for model 'first_model'
------
Intercept (after predictors centered)
  Specified prior:
    ~ normal(location = 0, scale = 2.5)
  Adjusted prior:
    ~ normal(location = 0, scale = 12)

Coefficients
  Specified prior:
    ~ normal(location = [0,0,0], scale = [2.5,2.5,2.5])
  Adjusted prior:
    ~ normal(location = [0,0,0], scale = [26.84,28.43,45.17])

Auxiliary (sigma)
  Specified prior:
    ~ exponential(rate = 1)
  Adjusted prior:
```



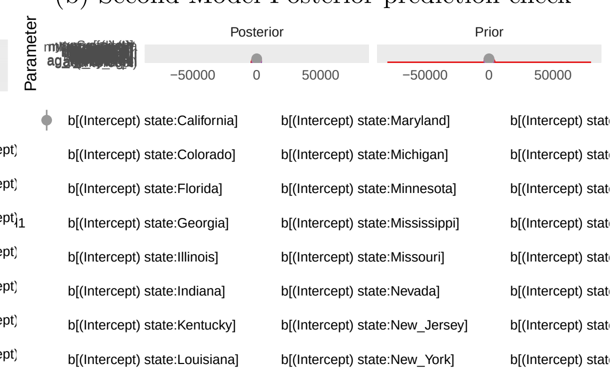
(a) First Model Posterior prediction check



(b) Second Model Posterior prediction check



(c) First Model Comparing the posterior with the prior



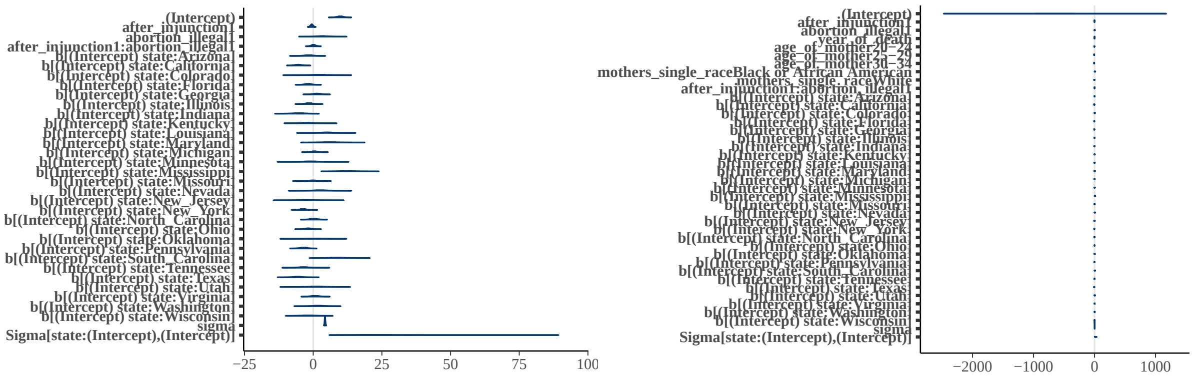
(d) Second Model Comparing the posterior with the prior

Figure 5: Examining how the model for infant death rate fits, and is affected by, the data

```
    ~ exponential(rate = 0.2)

Covariance
 ~ decov(reg. = 1, conc. = 1, shape = 1, scale = 1)
------
See help('prior_summary.stanreg') for more details

Priors for model 'second_model'
------
Intercept (after predictors centered)
  Specified prior:
    ~ normal(location = 0, scale = 2.5)
  Adjusted prior:
    ~ normal(location = 0, scale = 12)

Coefficients
  Specified prior:
    ~ normal(location = [0,0,0,...], scale = [2.5,2.5,2.5,...])
  Adjusted prior:
    ~ normal(location = [0,0,0,...], scale = [26.84,28.43,24.78,...])

Auxiliary (sigma)
  Specified prior:
    ~ exponential(rate = 1)
  Adjusted prior:
    ~ exponential(rate = 0.2)

Covariance
 ~ decov(reg. = 1, conc. = 1, shape = 1, scale = 1)
------
See help('prior_summary.stanreg') for more details
```

The prior summaries for the two models, `first_model` and `second_model`, indicate that both use weakly informative priors. For the intercept, a normal prior with a mean of 0 and a standard deviation of 2.5 was specified, which adjusts to a scale of 12 after centering the predictors. The coefficients for both models are also assigned normal priors with a mean of 0 and a scale of 2.5, which are adjusted based on the predictors, resulting in scales such as [26.84, 28.43, 45.17] for the first model and [26.84, 28.43, 24.78,...] for the second model. The auxiliary parameter (sigma) follows an exponential prior with a rate of 1, adjusted to 0.2, while a decov prior regularizes the covariance structure in both models. Although the prior structure is similar, the second model incorporates more predictors, leading to a larger number of coefficients with slightly adjusted scales. These priors are designed to be weakly informative, allowing the data to primarily guide the posterior estimates while avoiding extreme parameter values.

B.2 Distribution



(a) First Model

(b) Second Model

Figure 6: 95% credibility intervals for fitted models

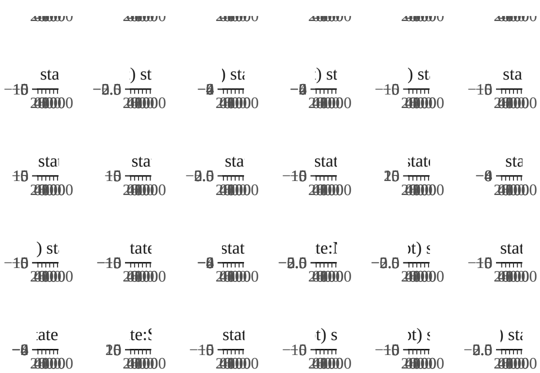
Credibility intervals are the Bayesian equivalent of confidence intervals, offering insight into the range of probable values for a parameter Alexander (2023). Using Bayesian estimation, we derive a posterior distribution for each model coefficient. Figure 6a presents the 95% credibility intervals for coefficients in Model 1, while Figure 6b illustrates the same for Model 2. These intervals represent the range within which 95% of the posterior probability mass falls, offering a robust understanding of parameter uncertainty and the influence of predictors under the Bayesian framework Alexander (2023).

B.3 Diagnostics

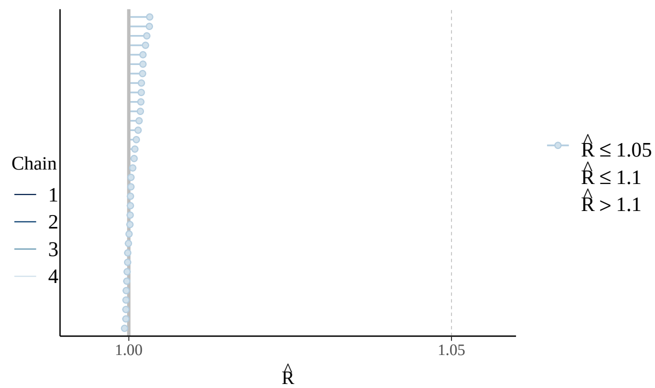
Figure 7a is a trace plot for model 1. It shows… This suggests…

Figure 7b is a Rhat plot. It shows… This suggests…

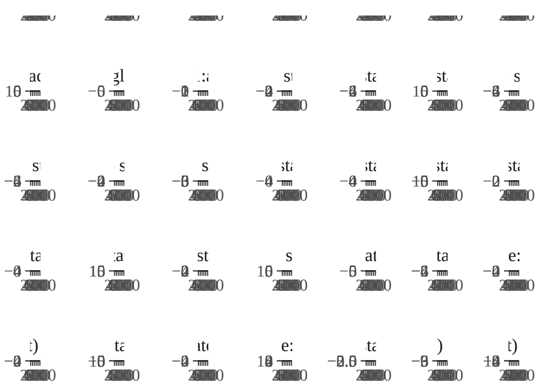
The trace plot in Figure 7a shows the sampling chains for model 1, indicating good mixing and convergence as the chains overlap and appear stable throughout. This suggests that the model has achieved convergence during sampling. The Rhat plot in Figure 7b demonstrates that all Rhat values are below 1.05, further confirming convergence and indicating that the model's posterior samples are reliable. Figure 7c represents the trace plots for Model 2, showing the posterior samples across four chains. The plots indicate good mixing, as the chains overlap well and stabilize around the same region, suggesting convergence. Figure 7d is the Rhat diagnostic plot for Model 2. All Rhat values are close to 1.00, confirming that the Markov



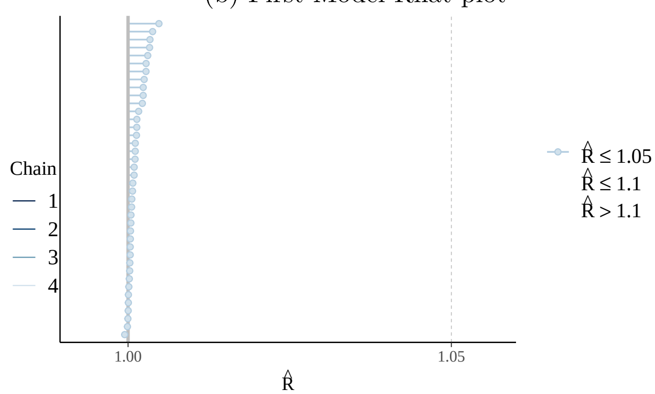
(a) First Model Trace plot



(b) First Model Rhat plot



(c) Second Model Trace plot



(d) Second Model Rhat plot

Figure 7: Checking the convergence of the MCMC algorithm for the infant death rate model

chains have converged, and the posterior estimates are reliable. This supports the validity of Model 2's Bayesian estimation process.

C Idealized Methodology for A Survey-Based Qualitative Studies

In our study, we examine the impact of abortion bans on infant mortality rates in the United States following the Dobbs decision, employing both observational data and survey-based research. Observational data provide quantitative insights, revealing trends and associations across large populations. However, they often fall short in addressing underlying mechanisms due to limitations such as confounding factors and challenges in establishing causality.

To address these gaps, in this appendix we propose incorporating surveys to gather qualitative data, which provide rich, detailed accounts of individual experiences and contextual factors. Qualitative methods allow for a deeper understanding of how restrictive abortion policies affect maternal health, access to healthcare, and infant outcomes capturing nuances that quantitative analysis alone cannot.

By combining quantitative and qualitative approaches, this study utilizes the strengths of both methods. Quantitative data offer generalizable findings and statistical rigor, while qualitative data provide depth and context to interpret those findings. Together, they create a more comprehensive framework for understanding the complex relationship between restrictive abortion policies, maternal health, and infant outcomes, enabling the development of nuanced, evidence-based interventions and policy recommendations.

C.1 Introduction

Restrictive abortion laws may exacerbate maternal stress, anxiety, or depression—especially in cases of unintended or high-risk pregnancies—potentially undermining maternal health and prenatal care. Research indicates that maternal mental health is a critical determinant of infant health outcomes, as conditions such as chronic stress, depression, or anxiety during pregnancy can negatively impact prenatal behaviors, access to healthcare, and overall maternal well-being. These psychological challenges, compounded by societal pressures and systemic barriers can significantly increase the risk of adverse infant outcomes, including infant mortality. The survey will focus on mothers unable to access abortion services who subsequently experienced the death of their infant, documenting their experiences to better understand these interconnected factors.

To provide a comprehensive perspective, the study will also involve healthcare providers and support organizations, capturing insights into systemic challenges and the broader impacts of abortion bans on family healthcare. By combining these perspectives with mothers' lived experiences, the survey aims to inform evidence-based interventions addressing maternal psychological and healthcare needs and mitigating the negative consequences of restrictive abortion policies.

This dual approach, integrating quantitative and qualitative methods, seeks to uncover the complex relationship between restrictive abortion laws, maternal mental health, and infant outcomes, forming the basis for effective policy recommendations.

C.2 Objective

The objective of this study is to investigate the psychological, social, and systemic impacts of restrictive abortion laws on maternal health and infant outcomes. By focusing on mothers unable to access abortion services who experienced the death of their infant, the study aims to document lived experiences, explore the role of maternal stress and healthcare barriers in adverse outcomes, and gather perspectives from healthcare providers and support organizations. Understanding how maternal mental health directly affects prenatal care decisions, access to healthcare, and overall maternal behavior is essential to addressing the systemic factors contributing to higher infant mortality rates. The findings will guide the development of evidence-based strategies to improve maternal mental health, enhance healthcare access and shape policy responses to restrictive abortion laws.

C.3 Sampling Approach

In this analysis, we will use non-probability Respondent-driven sampling to find respondents. Respondent-driven sampling (RDS), developed by Heckathorn (1997), is ideal for studying hidden populations lacking a sampling frame and facing potential stigma or harm. Unlike snowball sampling, RDS offers dual compensation for participation and recruitment, with recruitment occurring peer-to-peer via social networks. This method maintains confidentiality, reduces bias through statistical adjustments, and is particularly effective for sensitive topics, such as abortion, by utilizing trust within communities.

We use Respondent-Driven Sampling (RDS) for our survey because it is well-suited for reaching hidden or stigmatized populations, such as mothers who were unable to access abortion services and experienced the death of their infant. These individuals may be difficult to identify through conventional methods due to the sensitive nature of the topic and the lack of a clear sampling frame.

RDS utilizes peer networks, allowing participants to recruit others they trust, and fostering higher participation rates in populations that may distrust external researchers. This approach helps maintain confidentiality and reduces the risk of social stigma. Additionally, RDS provides a structured framework for statistical adjustments, mitigating biases inherent in network-based recruitment, and improving the representativeness of the sample. These advantages make RDS an effective and ethical choice for gathering insights into the psychological, social, and systemic impacts of restrictive abortion laws.

C.4 Target Population

Our target population is mothers who sought but were unable to access abortion services due to restrictive laws and experienced the death of their infant within the first year of life in states with abortion bans following the Dobbs decision.

C.5 Sample frame

Given the sensitive nature of our study, identifying and reaching the initial participants poses a significant challenge. To address this, we aim to collaborate with support groups and advocacy organizations like Abortion Rights Advocacy Groups. These groups play a critical role in connecting researchers with individuals who are otherwise difficult to reach, particularly for sensitive topics like the impact of restrictive abortion laws on maternal and infant health.

Therefore, the sample frame of our study will be mothers who live in areas where they are unable to access abortion services due to restrictive laws and have experienced the death of their infant within the first year of life in states with abortion bans following the Dobbs decision and are reachable and can be contacted by Abortion Rights Advocacy Groups.

C.6 Sample

We plan to survey 20 respondents for this study. Our sample will consist of mothers who fit the defined sample frame—those who were unable to access abortion services due to restrictive laws, experience death of their infant within the first year of life, and are reachable through Abortion Rights Advocacy Groups. These mothers must also be willing to participate in and answer our survey questions, ensuring the reliability and depth of the collected data.

C.7 Recruitment of Respondents

To recruit participants for this sensitive study, we will use a Respondent-Driven Sampling (RDS) approach in collaboration with Abortion Rights Advocacy Groups, that have established relationships with our target population. These organizations will serve as initial “seeds” to identify and reach mothers affected by restrictive abortion laws who meet our study criteria. Outreach materials emphasizing confidentiality and the study’s importance will be shared through trusted channels. As part of the RDS methodology, participants may also invite others from their network who share similar experiences, ensuring the sample expands while maintaining anonymity. Interested participants will undergo a screening process and provide informed consent, with the option to complete the survey anonymously online, ensuring safety and confidentiality. To support participant well-being, we will provide access to mental health resources throughout the process, fostering trust and encouraging meaningful participation.

C.8 Handling Non-response bias

Non-response bias is a concern as it can distort survey results and lead to unrepresentative conclusions about the target population. Since our survey addresses a sensitive topic and takes approximately 10–15 minutes to complete, there is a risk of participant dropout or refusal. To minimize this, we provide a clear overview of the survey's purpose, confidentiality measures, and estimated completion time, fostering trust and encouraging participation.

C.9 Respondent Validation

To ensure the credibility of our data, we implement a respondent validation process. Participants will undergo an initial screening to confirm they meet the study criteria, such as being unable to access abortion services due to restrictive laws and experiencing the loss of an infant within the first year of life. Responses will be reviewed for completeness and consistency, and duplicate entries will be removed to maintain data integrity. Collaboration with trusted support groups and advocacy organizations further enhances respondent reliability, ensuring that our findings accurately reflect the experiences of the target population.

C.10 Ethical Concerns

This study addresses sensitive and emotionally charged topics, necessitating a careful and ethical approach to protect participants' well-being. We acknowledge the potential psychological distress that discussing experiences of unintended pregnancies, restrictive abortion laws, and infant loss may cause. To mitigate this, the survey will include trigger warnings, and participants will have the option to skip questions or withdraw at any time without penalty. All data collection will adhere to strict confidentiality protocols, ensuring that participants' identities remain anonymous and their responses are securely stored. Recruitment through trusted advocacy groups will ensure that participants feel safe and supported throughout the process. Additionally, we will provide resources for mental health support to any participant who may experience discomfort as a result of participating in the study. This approach underscores our commitment to conducting ethical, respectful, and responsible research.

C.11 Proposed Survey Design

Abortion, or even considering abortion, carries significant social stigma. Therefore, our survey requires extremely careful phrasing and design to minimize this stigma's impact on the study of abortion, pregnancy, fertility, and related demographic and health outcomes. In Lindberg et al. (2022), researchers tested innovative methods in a national survey to address persistent underreporting of abortion in the U.S., focusing on question design and placement to reduce sensitivity, social desirability bias, and perceived intrusiveness. Although none of their experimental approaches significantly improved abortion reporting compared to the control condition, their study offers valuable insights for improving abortion measurement. We aim to adapt our survey design based on their methodologies to enhance data accuracy and respondent comfort.

This survey explores the impacts of restrictive abortion laws on maternal mental health and infant outcomes, emphasizing neutral, carefully crafted questions to ensure participant comfort and minimize social desirability bias. Inspired by Lindberg et al. (2022), it employs strategies like thoughtful question placement, phrasing, and opt-out options (e.g., "Prefer not to say") to address underreporting in sensitive topics. Combining multiple-choice and open-ended formats, the survey aims to balance structured data collection with nuanced insights, fostering trust and enhancing data accuracy. Also, based on Lindberg et al. (2022) findings that respondents preferred introductions emphasizing how sharing their abortion experiences could help improve health services for other women, we adopted a "helping" framework in each section of our survey introductions to encourage accurate reporting and increase participants' motivation to contribute.

C.12 Solution to the response bias in our survey

We draw on recommendations from Stantcheva (2023) to minimize response biases. Common response biases identified in survey design include moderacy bias, extreme response bias, ordering bias, acquiescence bias, experimenter demand effect(EDE), and social desirability bias (SDB). Our survey primarily focuses on strategies to reduce moderacy bias, extreme response bias, ordering bias, and SDB. The detailed definitions of these biases are provided in Appendix- C.14.

To mitigate bias, we enhance our survey in the following ways, drawing on recommendations from Stantcheva (2023):

- Addressing Extreme/Moderacy Bias: We use a minimum of five response options for scale questions to provide more nuanced choices, reducing the likelihood of respondents defaulting to extreme or middle answers.
- Mitigating Response Order Bias: For nominal questions, we randomize response options.

- Minimizing Social Desirability Bias (SDB): Our online survey is carefully designed to minimize social desirability bias (SDB) while addressing the sensitivity of the topic. The survey begins with a clear introduction explaining its purpose—academic research on the impact of restrictive abortion laws—while emphasizing respondent anonymity and confidentiality. Before sensitive questions, participants are reassured that their responses are entirely confidential and will only be used for research purposes. The anonymous online format provides a safe space for participants to share their experiences without fear of judgment or stigma. Additionally, a feedback section at the end invites respondents to voice any concerns or share additional thoughts, fostering trust and enhancing the quality of the data collected.

C.12.1 Survey Link

The survey has been implemented using Google Forms. You can access it here: Survey Link.

C.13 Copy of Survey on Restrictive Abortion Laws and Maternal Health

Welcome Section

Introduction: Welcome to our study on the impact of restrictive abortion laws on maternal and infant health. Your participation in this survey will help us understand the psychological, social, and systemic impacts of these laws. Rest assured that your responses are anonymous and will only be used for academic research purposes.

This survey is conducted by nonpartisan researchers in public health and social sciences. It consists of 17 carefully designed questions and should take approximately 10–15 minutes to complete.

Please answer the questions honestly. If you experience any discomfort while completing the survey, you may stop at any time. For support, we provide a list of mental health resources at the end of the survey.

Contact Information: Diana Shen Email: diana.shen@mail.utoronto.ca

Section 1: Demographics and Background Information

1. What is your age?
    - Under 18
    - 18–24
    - 25–34
    - 35–44
    - 45–54
    - 55+

- Prefer not to say

2. What is your highest level of education?
   - Less than high school
   - High school graduate or equivalent
   - Some college
   - Bachelor's degree
   - Graduate or professional degree
   - Prefer not to say

3. What is your marital status? - Single - Married - Divorced - Widowed - Prefer not to say

Section 2: Understanding Abortion Experiences

Introduction: This section focuses on understanding abortion experiences, including the circumstances and decisions surrounding them. Your responses are invaluable in helping researchers and policymakers improve health services and support for women and families. Please know that your answers are entirely confidential and will only be used for research purposes. If you are comfortable, we encourage you to answer as honestly as possible. If you prefer not to answer, you are welcome to skip this section.

1. Are you willing to answer this part?
   - Yes
   - No [Jump to Section 3]

2. Did you seek abortion services during your pregnancy?
   - Yes
   - No
   - Prefer not to say

3. If yes, were you unable to access abortion services due to legal restrictions in your state?
   - Yes
   - No
   - Prefer not to say

4. How did the inability to access abortion services impact your mental health during pregnancy?
   - No impact
   - Mild impact
   - Moderate impact
   - Severe impact
   - Prefer not to say

5. Did you receive any support from healthcare providers or community organizations during your pregnancy?
    - Yes
    - No
6. If you were unable to access abortion services, what barriers did you encounter? (Select all that apply)
    - Legal restrictions
    - Financial constraints
    - Lack of healthcare providers
    - Distance to clinic
    - Fear of stigma or judgment
    - Prefer not to say
7. If you sought an abortion but were unable to access one, how did this affect your mental health during pregnancy?
    - Increased stress
    - Anxiety
    - Depression
    - Anger or frustration
    - Feeling of helplessness
    - Prefer not to say

Section 3: Experiences and Support for Women Facing Pregnancy Challenges

Introduction: This section seeks to understand the experiences and outcomes of women who, due to restrictive abortion laws, were unable to access abortion services and subsequently faced the loss of their child. We recognize that discussing past pregnancies can be sensitive, especially those involving circumstances such as abortion or the loss of a child. Your insights are invaluable in identifying areas where healthcare and support services can be improved. If you prefer not to answer, you are welcome to skip this section.

1. Are you willing to answer this part?
    - Yes
    - No [Jump to Section 4]
2. Did you experience the loss of your child within the first year of life?
    - Yes
    - No [Jump to Section 4]
    - Prefer not to say
3. What was the primary cause of your child's death as communicated by healthcare providers?

- Premature birth or related complications
- Congenital abnormalities or genetic conditions
- Sudden Infant Death Syndrome (SIDS)
- Infections (e.g., pneumonia, sepsis)
- Birth trauma or delivery complications
- Lack of access to timely medical care
- Other (please specify)

4. To what extent do you believe the instances during your pregnancy where mental health challenges prevented you from seeking or receiving adequate medical care?
    - 1 (No impact)
    - 2
    - 3
    - 4
    - 5 (Significantly)

5. To what extent do you believe the mental health challenges caused by the inability to access abortion services contributed to health complications for your child?
    - Not at all – I don't believe my mental health challenges had any impact on my child's health.
    - Slightly – I think there may have been a minor impact on my child's health.
    - Moderately – I feel my mental health challenges had a noticeable impact on my child's health.
    - Significantly – I believe my mental health challenges had a considerable impact on my child's health.
    - Completely – I think my mental health challenges were the primary factor in my child's health complications.
    - Prefer not to say

6. Looking back, do you believe access to abortion services could have positively affected your mental and physical health during pregnancy?
    - Yes
    - No
    - Maybe
    - Prefer not to say

Section 4: Perspectives and Support

If you feel distressed or need support after completing this survey, the following resources are available to provide assistance:

1. Postpartum Support International (PSI)
    - Website: www.postpartum.net

- Helpline: 1-800-944-4773 (Text "Help" to 800-944-4773)
- Services: Support for mental health during and after pregnancy, including peer support and counseling.

2. Mental Health America (MHA)
   - Website: www.mhanational.org
   - Services: Online screening tools, support networks, and educational materials.
3. SAMHSA National Helpline
   - Website: www.samhsa.gov
   - Hotline: 1-800-662-HELP (4357)
   - Services: Free, confidential referrals for mental health and substance use disorders.

Section 5: Feedback

1. Do you have any concerns or feedback regarding the survey, surveyor, or entity?
   - Your feedback is important to us and will help ensure transparency and trust in the research process.

Section 6: Thank You

Thank you for taking the time to complete this survey. Your honest feedback is invaluable and will help us better understand and address the experiences of women who have faced similar circumstances. We deeply appreciate your participation and the courage it takes to share your experiences.

C.14 Response bias definition

In the design of the questionnaire, there will be some common biases that may occur when running the questionnaire.

Stantcheva (2023) defines these biases as:

- **Moderacy response bias**: The tendency to choose mid-scale responses.
- **Extreme response bias**: The inclination to select extreme values on the scale.
- **Response order bias**: Occurs when the position of options influences responses, with the **primacy effect** (favoring early options in written surveys) and **recency effect** (favoring later options in oral surveys) as common forms.
- **Social desirability bias**: Respondents may hide true views to present a socially favorable image, influenced by topic and social context.
- **Acquiescence bias**: The habit of giving positive responses, such as consistently choosing "agree" or "yes."

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