# Impact of Roe v. Wade's Overturn: Abortion Restrictions and Infant Mortality in the U.S. Using a Difference-in-Differences Analysis*

**Infant death rates rose by 0.285 per 1,000 live births in abortion-restricted states compared to protected states.**

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November 29, 2024

This study investigates the impact of the Dobbs decision and abortion bans on U.S. infant mortality rates using 2021–2022 data. A Difference-in-Differences (DID) analysis shows a 0.285 increase in infant deaths per 1,000 live births in states enforcing bans, with amplified effects post-injunction. Maternal age and race are key factors, with Black mothers experiencing higher mortality rates. These findings highlight the public health impact of restrictive abortion policies and the need for targeted interventions to address disparities. This study uses the latest available data and rigorous modeling to explore the link between reproductive rights and infant health.

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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 in the United States. 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 detailed 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 evidence-based policies to mitigate these adverse outcomes.

The structure of this paper is as follows: Section 2 details the data sources and variables used in the analysis. Section 3 outlines the modeling approach, including assumptions and specifications of the Bayesian DID framework. In Section 4, we present the findings, emphasizing key observations. In Section 4, we present findings on the impact of abortion bans and the post-injunction period, highlighting their association with increased infant mortality. Key disparities by maternal age and race are discussed, along with model validation metrics like RMSE and $R^2$. Finally, Section 5 explores the implications of the results and suggests potential directions for future research. Additional details are provided in the appendices: Appendix- A elaborates on external data sources, Appendix- B provides an in-depth explanation of the model, and Appendix- C introduces the idealized methodology for related qualitative analysis.

# 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). We use `fixest` (Bergé 2018) to conduct the event study. We use `caret` (Kuhn and Max 2008) to conduct the cross-validation of the model. 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 detailed 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 $= \frac{\text{Linked deaths}+\text{Unlinked deaths}}{\text{Linked deaths}}$ 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 an understanding of 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 understanding, highlighting on the health implications of varying abortion laws across the U.S. By utilizing detailed datasets and robust statistical techniques, this study offers a detailed 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.

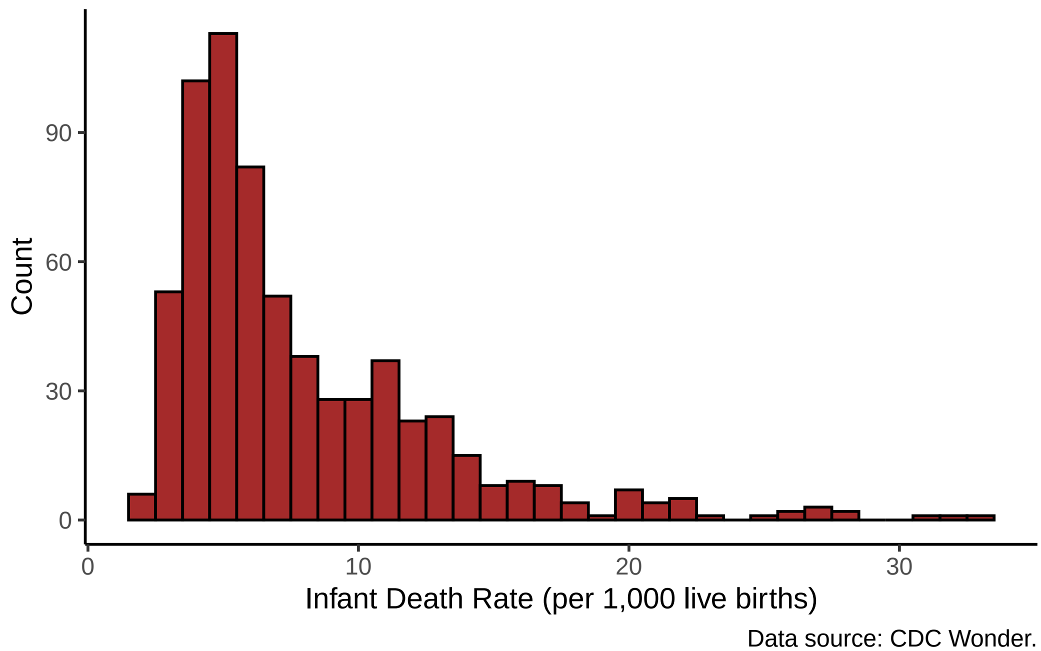



Figure 1: Distribution of Infant Death Rates: The infant death rate (per 1,000 live births) shows a peak between 5 and 10 deaths per 1,000 infants, with a right-skewed distribution.

## 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.

Figure 2 illustrates the legality of abortion across U.S. states. Based on Reproductive Rights (2024), after June 2022, 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.

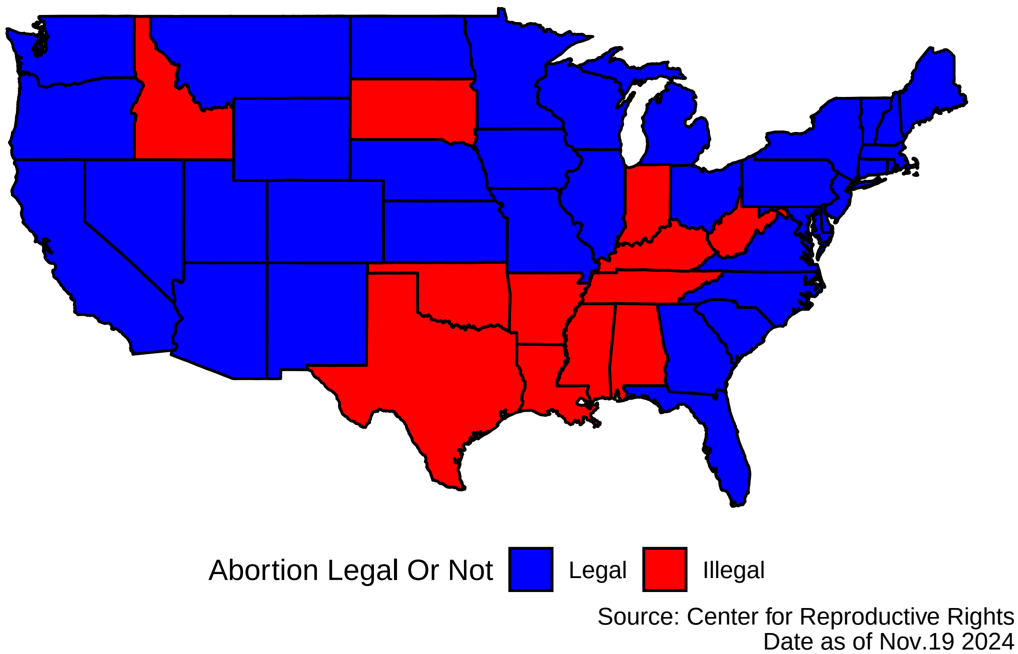



Figure 2: Abortion Legality by State: After June 2022, abortion is prohibited in the following states: Alabama, Arkansas, Idaho, Indiana, Kentucky, Louisiana, Mississippi, Missouri, North Dakota, Oklahoma, South Dakota, Tennessee, Texas, West Virginia, and Wisconsin.

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

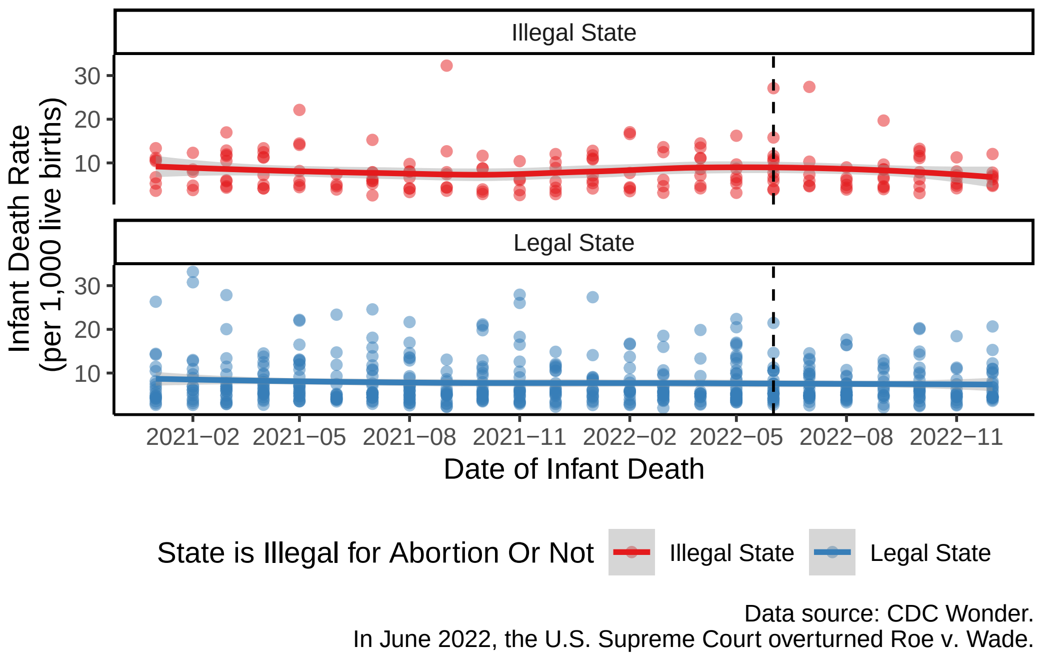



Figure 3: Infant Death Rates Over Time: Infant death rates (per 1,000 live births) show a slight increase in states where abortion became illegal following June 2022, whereas rates in states with legal abortion remained relatively stable.

a potential link between abortion bans and rising infant mortality rates, warranting further investigation.

Table 1: Average Infant Death Rate by Abortion Legality and Injunction Timing: States categorized as “Illegal Abortion and After Injunction” (‘1’) exhibit a higher average infant death rate (per 1,000 live births) compared to states in other categories, including “Legal Abortion and Before/After Injunction” or “Illegal Abortion and Before Injunction” (‘0’).

| Abortion Restriction Post-Overturn | Average Infant Death Rate (per 1,000 live births) |
|---|---|
| 0 | 7.9 |
| 1 | 8.3 |

*Note:*

Data Source: CDC Wonder

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.

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

Our analysis includes three key control variables: maternal age (`age_of_mother`), race (`mothers_single_race`), and year of death (`year_of_death`), to account for demographic and temporal differences.

Table 2 shows that 50.7% of infant deaths occurred in 2022, slightly higher than in 2021 (49.3%). The majority of cases were among mothers aged 25–29 (37.8%), followed by those

Table 2: Demographic Distribution of Infant Mortality Cases by Year, Maternal Age, and Race (2021–2022): The data highlights the proportional representation of cases across different years, maternal age groups, and racial categories. Younger mothers and Black or African American mothers show higher proportions of cases compared to other groups.

| | | N | % |
|---|---|---|---|
| Year of Death | 2021 | 325 | 49.3 |
| | 2022 | 334 | 50.7 |
| Age of Mother | 15-19 | 17 | 2.6 |
| | 20-24 | 179 | 27.2 |
| | 25-29 | 249 | 37.8 |
| | 30-34 | 214 | 32.5 |
| Mother's Single Race | Asian | 2 | 0.3 |
| | Black or African American | 158 | 24.0 |
| | White | 499 | 75.7 |

aged 30–34 (32.5%), and 20–24 (27.2%), with the lowest occurrence in mothers aged 15–19 (2.6%). By race, White mothers accounted for the highest percentage (75.7%), followed by Black or African American mothers (24.0%), and Asian mothers (0.3%).

### 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 essential 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 3 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 3: Average Infant Death Rate by Maternal Age Group: Infant mortality rates (per 1,000 live births) vary significantly by maternal age, with younger mothers experiencing higher rates. Mothers aged 20–24 exhibit the highest infant death rate at 10.0, while the lowest rate of 6.6 is observed among mothers 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 4: Average Infant Death Rate by Mother's Single Race: Infant mortality rates (per 1,000 live births) vary significantly by race, with Black or African American mothers experiencing the highest rate at 14.5, compared to 5.8 for White mothers and 5.4 for Asian mothers.

| 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.

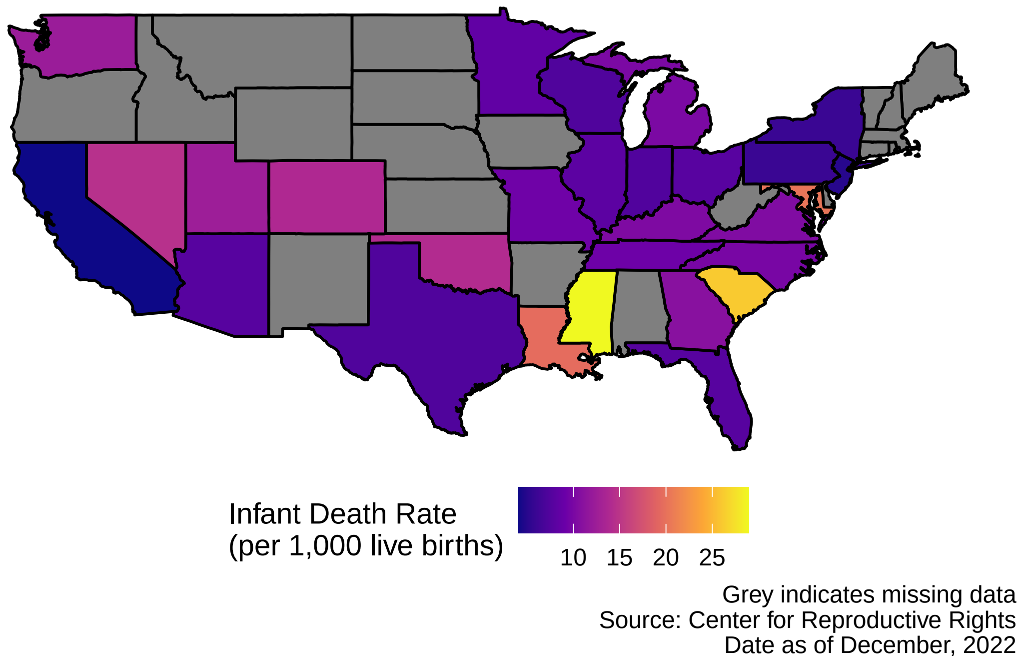



Figure 4: Infant Death Rates Across U.S. States (per 1,000 Live Births): The infant mortality rate is significantly higher in the Southeastern states, with Alabama and Mississippi reporting the highest rates. In contrast, states like California and New York exhibit notably lower rates.

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.

# 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` × `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 (`age_of_mother`)**: The age of the mother at the time of birth, represented as a continuous variable.
- **Mother's Single Race (`mothers_single_race`)**: Self-identified race of the mother, represented as a categorical variable.
- **Year of Death (`year_of_death`)**: The year in which the infant death occurred, represented as a continuous variable.

Finally, we include a random variable:

- **State (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, validation of model assumption, 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 $\gamma_j$ 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

#### 3.3.1.1 Analysis Framework

For our analysis, we employ Bayesian regression models to estimate infant death rates in states where abortion injunctions were implemented and states where abortion remains legal. The causal effect of the abortion injunction is measured using the interaction term between after_injunction and abortion_illegal. To ensure consistency and comparability, both models share the same predictors, capturing the determinants of infant mortality.

One model includes control variables — Age of Mother, Mother's Single Race, and Year of Death to adjust for confounders that may influence infant death rates. This adjustment addresses compositional differences assumed in the DID framework and ensures unbiased estimates of the intervention's effect. The second model excludes these controls to focus on the overall intervention impact, avoid overfitting, and prioritize simplicity where variability is adequately accounted for by design or random effects. By fitting two models, we compare outcomes to refine estimates and evaluate the direct impact of the intervention.

#### 3.3.1.2 Model Design and Rationale

Our models include state as a random effect to account for regional variations in infant mortality that might introduce bias. Using a random effect rather than a fixed effect captures variability across states without estimating individual effects, modeling unobserved heterogeneity—such as differences in healthcare systems and socioeconomic conditions—through a single variance term. This approach avoids overfitting, enhances efficiency, and ensures generalizability. By adjusting for unmeasured state-specific factors, the models strike a balance between parsimony and interpretability, making them well-suited for our analysis.

#### 3.3.1.3 Why DID Over Alternative Models?

We selected the Difference-in-Differences (DID) framework because randomization is infeasible given the pre-existing differences between states in healthcare systems, socioeconomic conditions, and cultural factors. DID utilizes time and group-level variations, controlling for unobserved, time-invariant confounders. The parallel trends assumption ensures that untreated states provide a valid counterfactual for treated states. Interaction terms, such as after_injunction and abortion_illegal, allow for direct measurement of policy effects, while random effects adjust for regional variability.

Alternative models, such as Fixed Effects, Propensity Score Matching (PSM), and Interrupted Time Series (ITS), were considered but deemed less suitable. Fixed Effects cannot estimate the effects of variables that do not vary over time within a unit. PSM balances observed covariates but does not account for temporal dynamics. ITS analyzes trends within a single group but lacks a comparison group. DID's ability to integrate temporal and group-level differences makes it the most robust and appropriate framework for estimating the impact of abortion bans on infant mortality.

#### 3.3.1.4 Bayesian Framework

We use a Bayesian approach to enhance the Difference-in-Differences (DID) method, which allows us to incorporate prior knowledge and better account for uncertainty. With the `rstanarm` package, we apply weakly informative priors—such as a Normal prior centered at zero with moderate spread ($\mu = 0$, $\sigma = 2.5$) for fixed effects and an Exponential prior (rate = 1) for variability parameters. These priors automatically adjust to the scale of the data, improving model stability and ensuring they complement rather than dominate the observed data. This approach helps us center estimates realistically, account for hidden differences between groups, and produce reliable results while assuming trends between treated and control groups are similar before treatment.

#### 3.3.1.5 Limitations and Applicability

Our Bayesian DID model offers a robust approach to examining the impact of abortion bans on infant mortality but has limitations. Misspecified priors, data imbalances, and violations of the parallel trends assumption could introduce biases. Despite these challenges, the model effectively integrates prior knowledge and addresses uncertainty, providing a valuable understanding of policy impacts.

# 4 Results

## 4.1 Model Results

The results from the two Bayesian models are summarized in Table 5. The interaction term between after_injunction and abortion_illegal is positive and statistically significant (0.111 in first model and 0.280 in the second model), 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 the first model and 1.400 in the second model. The post-injunction period alone is associated with coefficients of -0.525 in the first model and -0.940 in the second model, indicating a decrease in infant mortality during this time.

Demographic variables also exhibit some 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 the second model, relative to groups 15-19 respectively. The coefficient for Black mothers in the second model is 6.66 relative to Asia mothers, reflecting a higher infant mortality compared to other racial groups.

Table 5: 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

The model highlights key demographic and policy-driven influences on infant mortality rates. The interaction between abortion bans and the post-injunction period is associated with increased mortality, while states with abortion bans consistently exhibit higher rates. Younger mothers and Black mothers face significantly elevated risks, highlighting disparities likely driven by limited healthcare access and systemic inequities. Conversely, increasing maternal age correlates with lower infant mortality rates, reflecting improved access to resources, better prenatal care, and greater maternal stability. These results demonstrate the impact of policy and demographic factors on infant health outcomes.

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 notable patterns in infant mortality rates influenced by policy and demographic factors. For states where abortion remained legal, the post-injunction period (after_injunction1) is associated with reductions in infant mortality rates, with a decrease of 0.525 deaths per 1,000 live births in the first model and 0.947 in the second model, compared to the pre-injunction period. In contrast, states where abortion became illegal (abortion_illegal1) experienced significantly higher infant mortality rates, with increases of 3.365 deaths in the first model and 1.401 in the second model, relative to states where abortion remained legal.

The Difference-in-Differences (DID) interaction term (after_injunction1 $\times$ abortion_illegal1) indicates that abortion bans during the post-injunction period resulted in an additional increase of 0.111 deaths per 1,000 live births in the first model and 0.280 in the second model. These effects highlight the compounded impact of restrictive abortion policies on infant health outcomes.

Demographic factors also play a significant role. Compared to mothers aged 15–19 years (reference level), older maternal age groups (20–24, 25–29, and 30–34 years) are associated with progressively lower infant mortality rates, with reductions of 3.571, 5.732, and 6.155 deaths per 1,000 live births in the second model, respectively. Regarding maternal race, Black or African American mothers have a significantly higher infant mortality rate, with an increase of 6.604 deaths per 1,000 live births compared to Asian mothers (reference level). In contrast, White mothers exhibit a lower infant mortality rate, with a decrease of 2.562 deaths per 1,000 live births compared to Asian mothers.

These findings underscore the interplay of policy and demographic factors, emphasizing the disproportionate burden of restrictive abortion policies and systemic inequities on infant mortality rates.

## 5.2 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.

## 5.3 Addressing Public Health and Long-Term Implications of Restrictive Abortion Laws

Restrictive abortion policies significantly impact maternal and infant health, as evidenced by an increase of 0.285 infant deaths per 1,000 live births in states enforcing abortion bans during the post-injunction period. These policies exacerbate systemic issues such as inadequate prenatal care, gaps in healthcare access, and socioeconomic inequities, disproportionately affecting marginalized communities. Over time, the consequences may include higher rates of untreated maternal mental health issues, delayed or insufficient prenatal care, and elevated infant mortality, creating lasting health challenges for families and communities. Addressing these disparities requires targeted interventions, such as expanding maternal mental health services, improving prenatal and postnatal care in underserved areas, ensuring culturally competent healthcare, and advocating for equitable policies. Investments in community-based support systems, enhanced healthcare delivery, and robust data infrastructure are essential to monitor and mitigate the long-term impacts of these policies, fostering sustainable improvements in maternal and infant health outcomes.

## 5.4 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. As no publicly available dataset currently provides complete 2023 data or longer-term health outcomes, future research should incorporate more detailed and updated datasets to provide a clearer and more complete analysis of the long-term trends and implications of restrictive abortion policies.

### 5.5 Weaknesses and Future Directions

While this study provides meaningful 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 tables 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 correspond 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 in 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 Model Card

The model card, referenced from Ozoani, Gerchick, and Mitchell (2022), is included in the README under the section titled `Model Card for Infant Mortality and Abortion Policy Analysis Model` for detailed documentation.

## B.2 Parall Assumption: An Event Study Analysis

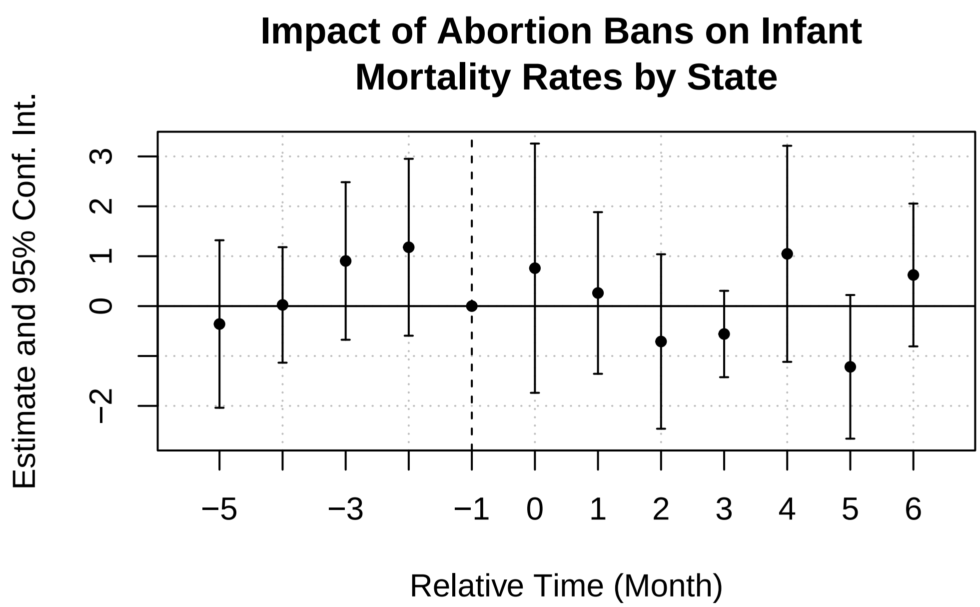



Figure 5: Event Study Analysis of the Impact of Abortion Bans on Infant Mortality Rates in the United States: Evidence Using June 2022 as the Treatment Date and Pre-Treatment (-1, May 2022) as the Reference Period.

Figure 5 depicts the estimated effects of abortion bans on infant mortality rates over time, with relative months on the x-axis and coefficient estimates with 95% confidence intervals on the y-axis. Before the implementation of abortion bans ($t < 0$), the coefficients are centered around zero, indicating no significant differences in infant mortality rates between treated and control states, supporting the parallel trends assumption. Post-ban ($t \geq 0$), the estimates show a slight upward trend, suggesting a potential increase in infant mortality rates in restricted states; however, the wide confidence intervals, which overlap with zero, indicate that these effects are not statistically significant. Overall, the results do not provide conclusive evidence of a causal relationship between abortion bans and changes in infant mortality rates, emphasizing the need for further analysis with more precise data or extended time frames.

### B.3 Posterior predictive check

In Figure 6a and Figure 6b we implement a posterior predictive check for the first model and second model. It represents posterior predictive checks for the first model and second model, illustrating how well each model captures the observed data. The posterior predictive checks for the first model (policy-focused) and the second model (policy and demographic factors) illustrate model fit. In Figure 6a, the observed ($y$) and replicated ($y_{rep}$) distributions align moderately, reflecting general trends but limited precision. Figure 6b shows improved alignment, indicating that adding demographic factors enhances predictive accuracy and better captures the complexities of infant mortality rates.

In Figure 7 and Figure 8 we compare the posterior with the prior. The posterior vs. prior plots for the first model and second model illustrate the role of data in informing the posterior estimates of the model parameters. In the first model Figure 7, which focuses on policy-related predictors (e.g., abortion restrictions), the data significantly shifts the posterior distributions for key variables, demonstrating their explanatory power. The second model Figure 8, 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 the second model provides better-informed parameter estimates, supporting the hypothesis that demographic factors play an essential role in understanding infant mortality in the context of restrictive abortion laws.

### B.4 Prior Summary for Models

Table 6: Prior Specifications for Bayesian Models

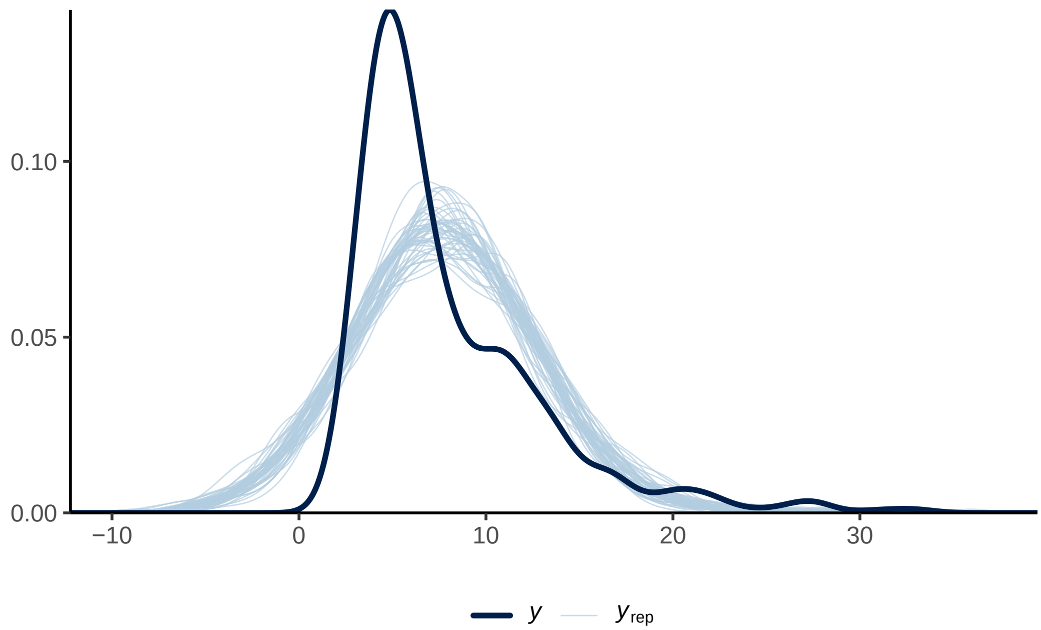
| **Model** | **Component** | **Specified Prior** | **Adjusted Prior** | **Description** |
|---|---|---|---|---|
| **First Model** | Intercept | Normal(0, 2.5) | Normal(0, 12) | Prior for intercept after centering predictors. |
| | Coefficients | Normal([0,0,0], [2.5,2.5,2.5]) | Normal([0,0,0], [26.84,28.43,45.17]) | Prior for coefficients, adjusted for predictor scaling. |
| | Auxiliary (sigma) | Exponential(1) | Exponential(0.2) | Prior for the standard deviation of residuals. |
| | Covariance | Decov(reg. = 1, conc. = 1, shape = 1, scale = 1) | Decov(reg. = 1, conc. = 1, shape = 1, scale = 1) | Regularizing prior for covariance. |

| Model | Component | Specified Prior | Adjusted Prior | Description |
|---|---|---|---|---|
| **Second Model** | Intercept | Normal(0, 2.5) | Normal(0, 12) | Prior for intercept after centering predictors. |
| | Coefficients | Normal([0,0,0,...], [2.5,2.5,2.5,...]) | Normal([0,0,0,...], [26.84,28.43,24.78,...]) | Prior for coefficients, adjusted for predictor scaling. |
| | Auxiliary (sigma) | Exponential(1) | Exponential(0.2) | Prior for the standard deviation of residuals. |
| | Covariance | Decov(reg. = 1, conc. = 1, shape = 1, scale = 1) | Decov(reg. = 1, conc. = 1, shape = 1, scale = 1) | Regularizing prior for covariance. |

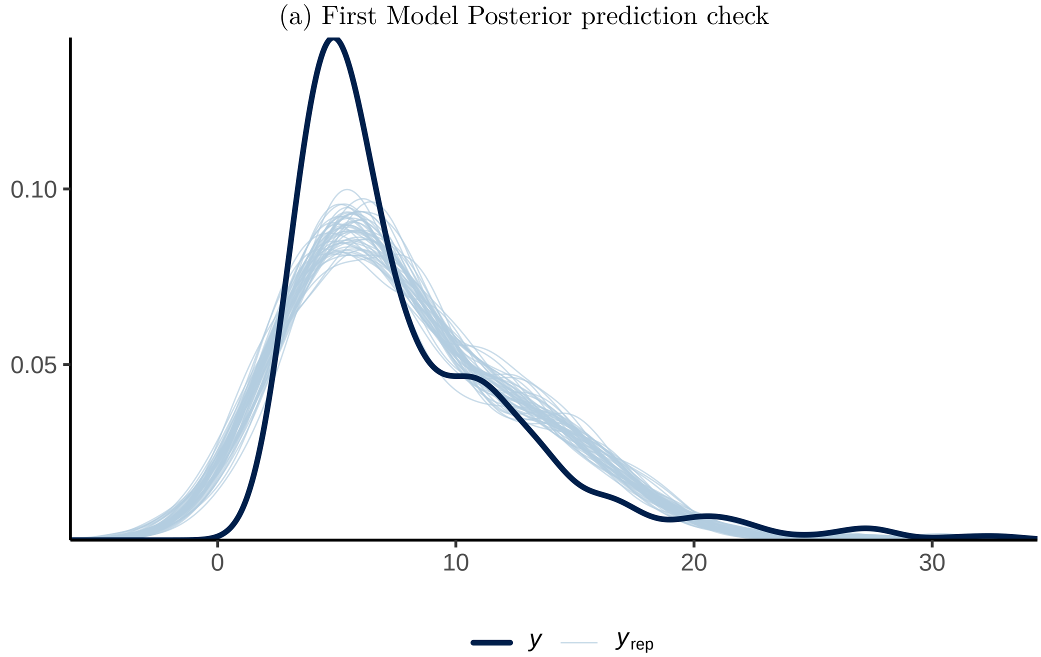
Table 6 shows the prior summaries for the two models, `first_model` and `second_model`, indicating that both use weakly informative priors. For the intercept, a normal prior with a mean of 0 and a standard deviation of 2.5 was specified, which adjusts to a scale of 12 after centering the predictors. 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.5 Distribution

Credibility intervals are the Bayesian equivalent of confidence intervals, offering an understanding of the range of probable values for a parameter Alexander (2023). Using Bayesian estimation, we derive a posterior distribution for each model coefficient. Figure 9a presents the 95% credibility intervals for coefficients in the first model, while Figure 9b illustrates the same for the second model. 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).




(a) First Model Posterior prediction check




(b) Second Model Posterior prediction check

Figure 6: Posterior Predictive Check: Examining how the model for infant death rate fits, and is affected by, the data

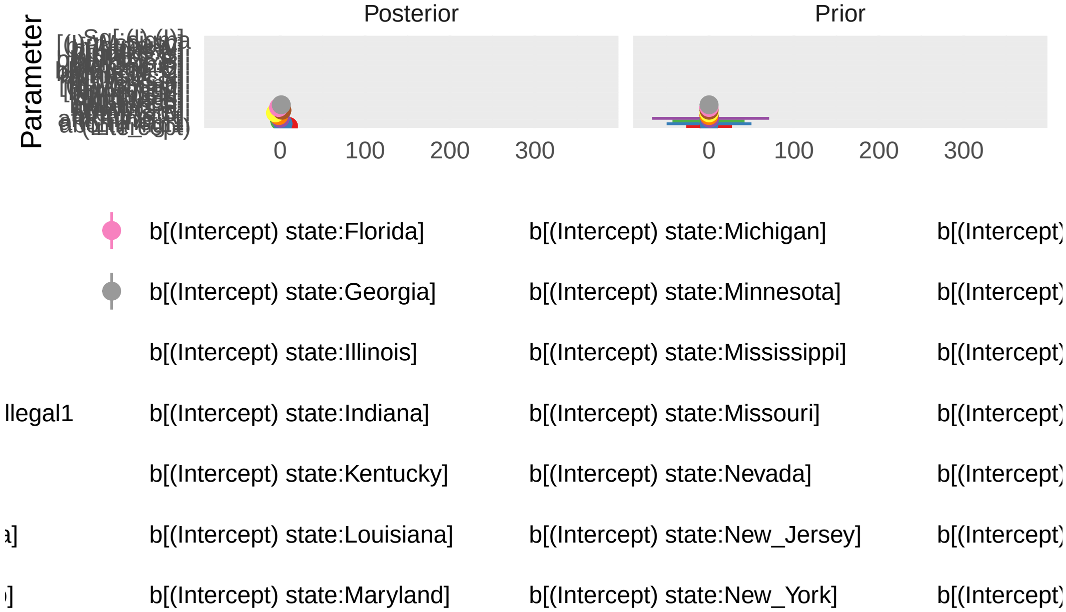



Figure 7: Comparing Prior and Posterior Distributions: Examining how the first model for infant death rate fits, and is affected by, the data

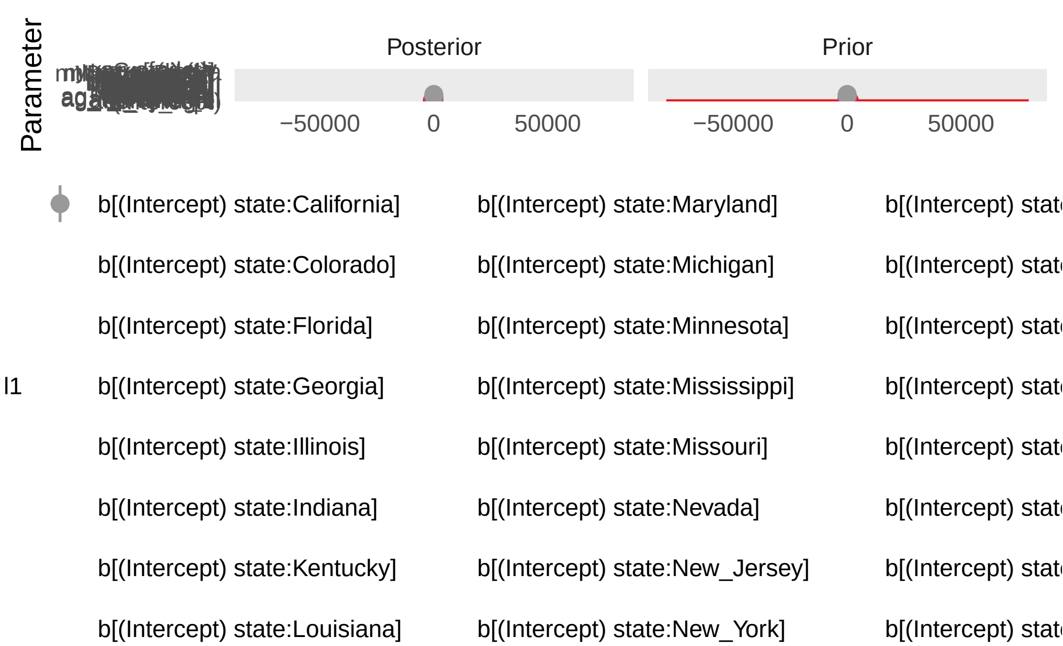
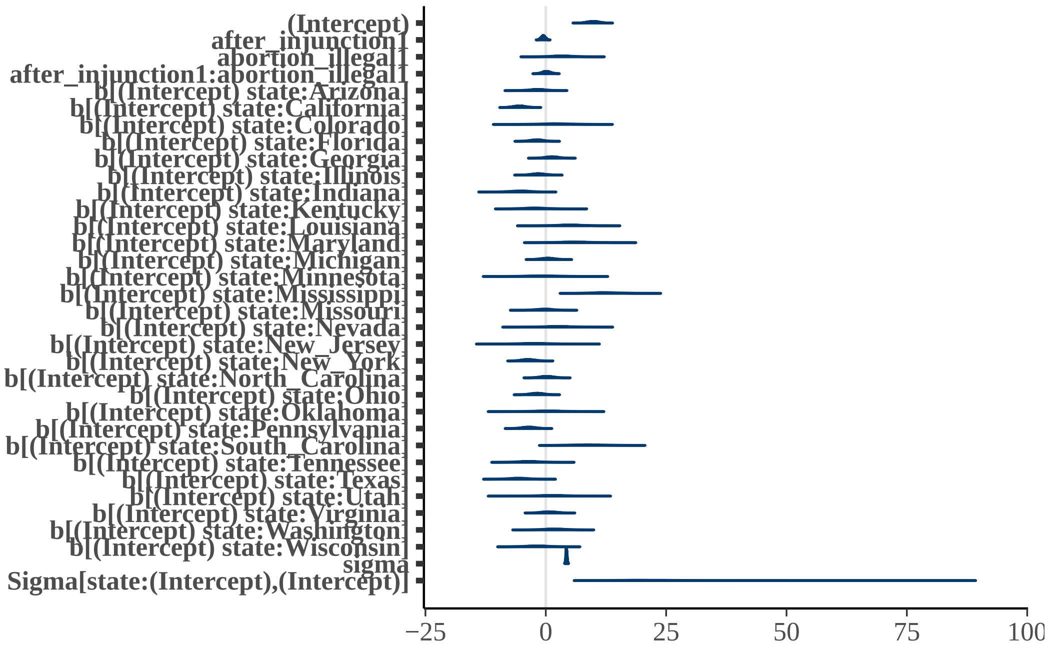
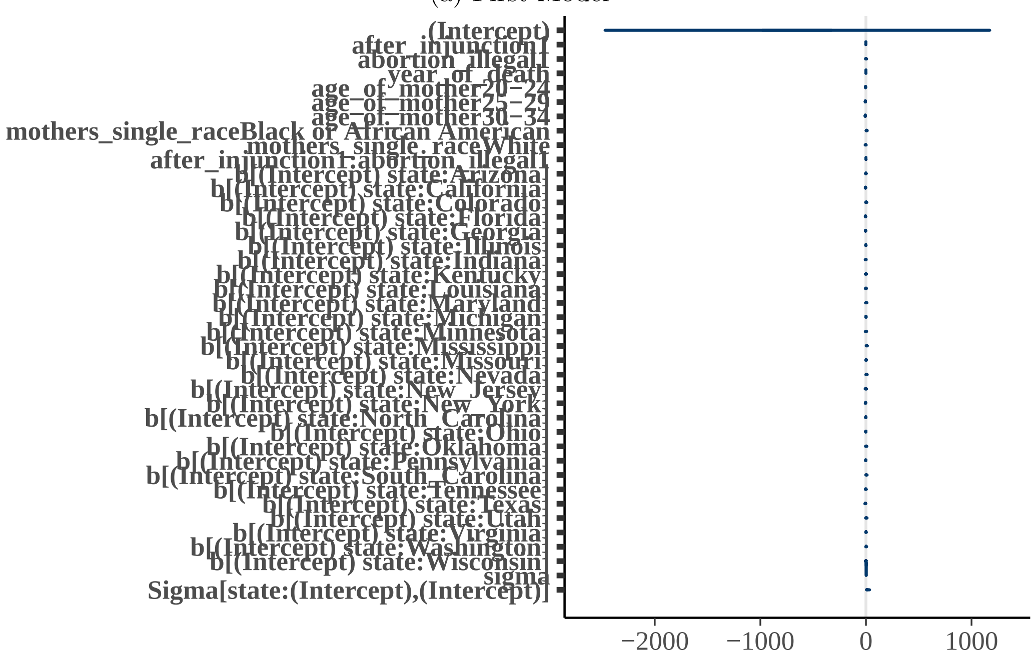



Figure 8: Comparing Prior and Posterior Distributions: Examining how the second model for infant death rate fits, and is affected by, the data




(a) First Model




(b) Second Model

Figure 9: 95% credibility intervals for fitted models

### B.6 Cross Validation

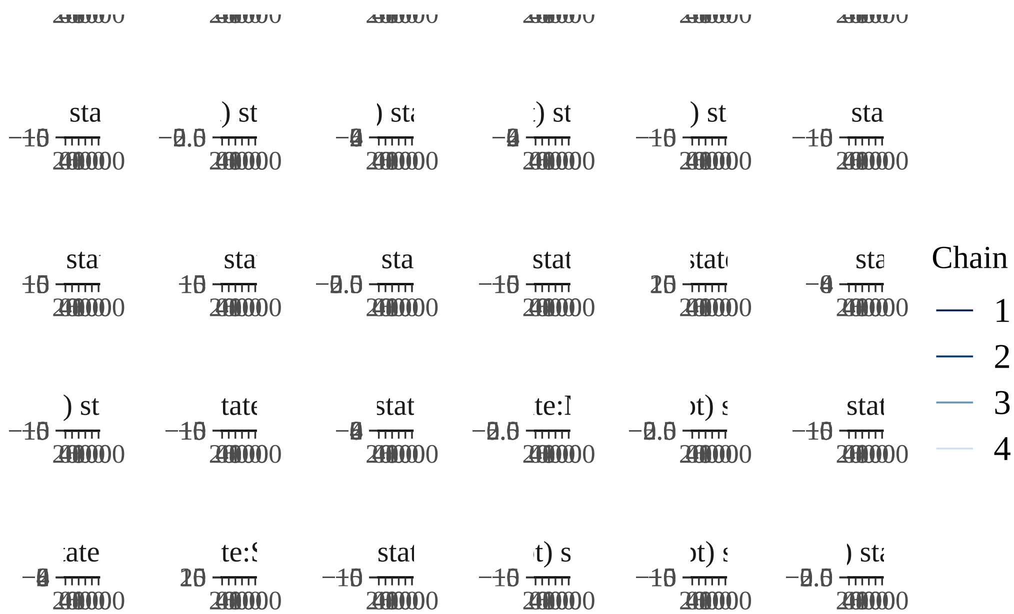
The RMSE values from cross-validation indicate that the first model and the second model perform similarly in predicting infant mortality rates, with RMSE values of 5.07 and 5.06, respectively. This similarity suggests that adding demographic factors such as maternal age and race in the second model has only a marginal impact on predictive accuracy compared to the first model, which primarily relies on policy-related variables like abortion legality and timing of the injunction. An average error of approximately 5 deaths per 1,000 live births indicates the magnitude of prediction errors, which may or may not be acceptable depending on the variability in the dataset. While the second model slightly reduces the error, its added complexity may not justify the trade-off if simplicity is a priority. However, if a nuanced understanding of demographic influences is essential, the second model provides a modest improvement in accuracy while offering more detailed insights into maternal and infant health disparities. The cross-validation process reinforces the reliability of these models by confirming their performance across multiple data splits, reducing the risk of overfitting.

### B.7 Diagnostics

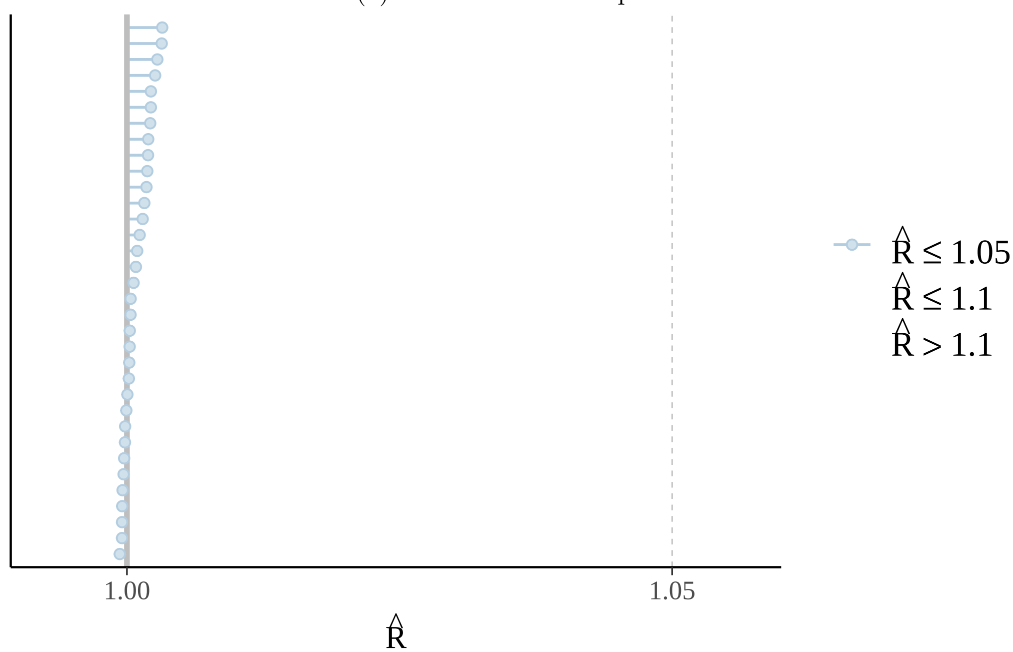
The trace plot in Figure 10a shows the sampling chains for the first model, indicating good mixing and convergence as the chains overlap and appear stable throughout. This suggests that the model has achieved convergence during sampling. The Rhat plot in Figure 10b demonstrates that all Rhat values are below 1.05, further confirming convergence and indicating that the model's posterior samples are reliable. Figure 11a represents the trace plots for the second model, 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 11b is the Rhat diagnostic plot for the second model. All Rhat values are close to 1.00, confirming that the Markov chains have converged, and the posterior estimates are reliable. This supports the validity of the second model's Bayesian estimation process.

## C Idealized Methodology for A Survey-Based Qualitative Studies

Our study examines the impact of abortion bans on infant mortality rates in the U.S. following the Dobbs decision, combining observational Difference-in-Differences (DID) analysis with qualitative surveys. While the DID analysis quantifies policy impacts, qualitative surveys provide a context-specific understanding of how restrictive abortion policies affect maternal mental health, healthcare access, and pregnancy decisions. These lived experiences help interpret quantitative findings, offering a fuller understanding of the systemic and psychological factors driving observed trends, and supporting evidence-based policy recommendations.

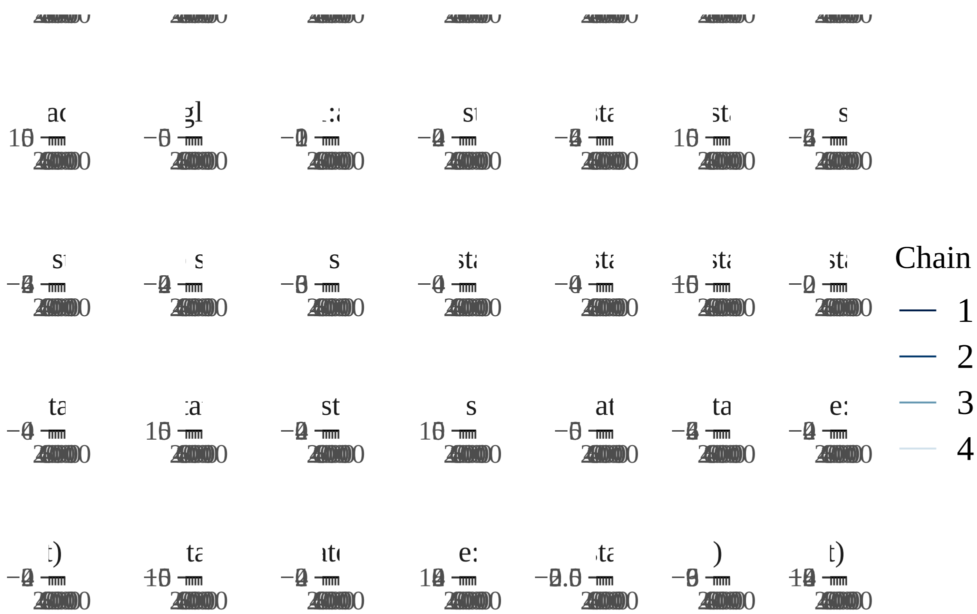



(a) First Model Trace plot

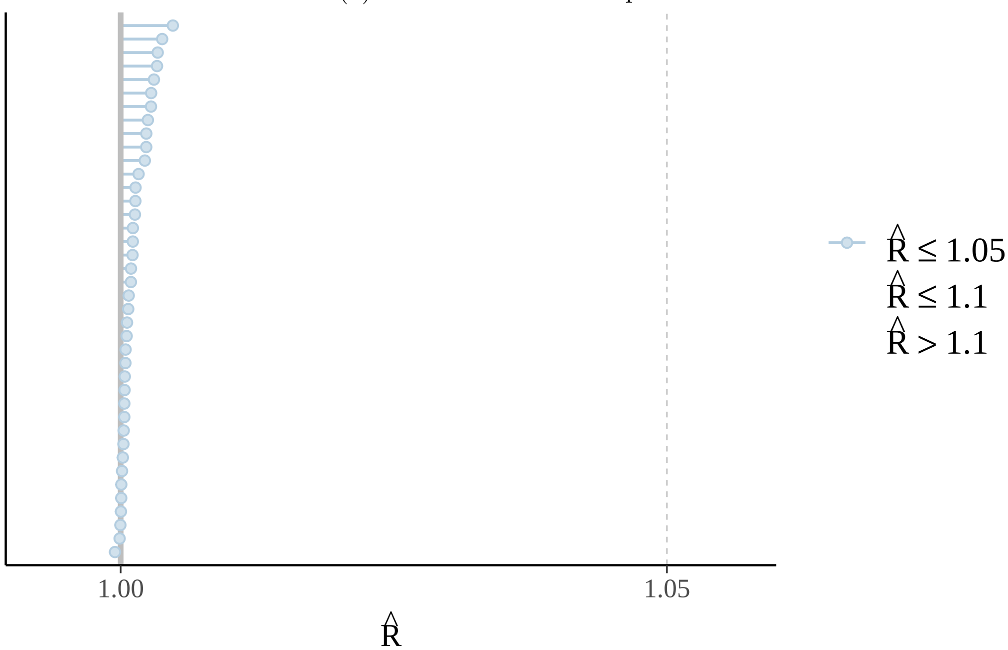



(b) First Model Rhat plot

Figure 10: First Model: Checking the convergence of the MCMC algorithm for the infant death rate model




(a) Second Model Trace plot




(b) Second Model Rhat plot

Figure 11: Second Model: Checking the convergence of the MCMC algorithm for the infant death rate model

## C.1 Introduction

Restrictive abortion laws can heighten maternal stress, anxiety, or depression—particularly in unintended or high-risk pregnancies—compromising maternal health and prenatal care. Research Crugnola and Ierardi (2022) highlights maternal mental health as a key determinant of infant health outcomes, with conditions like chronic stress and depression adversely affecting prenatal behaviors, healthcare access, and overall well-being. These compounded challenges, driven by societal and systemic barriers, can significantly increase risks of adverse infant outcomes, including mortality.

Our survey focuses on mothers unable to access abortion services who later experienced the death of their infant, documenting their experiences to better understand these interconnected factors. By integrating quantitative data with qualitative perspectives, this study aims to inform evidence-based interventions, addressing maternal psychological and healthcare needs, and mitigating the adverse effects of restrictive abortion policies.

## 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 and explore the role of maternal stress and healthcare barriers in adverse outcomes. 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 use non-probability Respondent-Driven Sampling (RDS), developed by Heckathorn (1997), is a recruitment method designed for hidden populations lacking a sampling frame, where participants recruit others through their social networks, with dual compensation for participation and recruitment, ensuring confidentiality and mitigating biases. RDS enables peer-to-peer recruitment with dual compensation for participation and recruitment, fostering trust within communities. This method maintains confidentiality, reduces bias through statistical adjustments, and is particularly effective for sensitive topics like abortion.

We use Respondent-Driven Sampling (RDS) for our survey as it is effective for accessing hidden or stigmatized populations, such as mothers unable to access abortion services and who experienced the death of their infant. RDS utilizes peer networks for recruitment, fostering trust and participation in sensitive contexts while maintaining confidentiality and reducing social stigma. Its statistical adjustments mitigate biases in network-based recruitment, enhancing sample representativeness. These strengths make RDS an ethical and effective method for examining 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 this study, identifying and reaching participants presents a significant challenge. To address this, we will collaborate with support groups and advocacy organizations, such as Abortion Rights Advocacy Groups, which can connect researchers with individuals otherwise difficult to reach. These organizations are essential for engaging with populations affected by restrictive abortion laws, particularly concerning maternal and infant health.

Thus, the sample frame for our study comprises mothers who reside in areas where abortion services are inaccessible due to restrictive laws, have experienced the death of their infant within the first year of life, and are reachable through advocacy organizations following the Dobbs decision.

## C.6 Sample

We aim to survey 20 respondents who meet our defined sample criteria: mothers unable to access abortion services due to restrictive laws, who experienced the death of their infant within the first year of life, and who are reachable through Abortion Rights Advocacy Groups. Participation will be voluntary, and respondents must be willing to answer the survey questions, ensuring the quality and depth of the data collected.

## C.7 Recruitment of Respondents

To recruit participants for this sensitive study, we will employ a Respondent-Driven Sampling (RDS) approach in collaboration with Abortion Rights Advocacy Groups, leveraging their established connections with our target population. This organization will act as initial "seeds" to identify mothers affected by restrictive abortion laws who meet our study criteria. Participants may also invite others from their network with similar experiences, allowing the sample to grow while maintaining confidentiality. Outreach materials emphasizing anonymity and the study's significance will be shared through trusted channels. Interested participants will undergo a screening process and provide informed consent, with the option to complete the survey online for safety and privacy. To ensure participant well-being, mental health resources will be offered throughout the process, fostering trust and encouraging meaningful engagement.

### 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 data credibility, we implement a robust respondent validation process. Participants will first undergo screening to confirm eligibility, including inability to access abortion services due to restrictive laws and experiencing infant loss within the first year of life. Responses will be assessed for completeness and consistency, and duplicate entries will be removed to maintain integrity. Partnering with trusted support groups and advocacy organizations enhances reliability, ensuring the findings accurately represent the target population's experiences.

### C.10 Ethical Concerns

This study addresses sensitive and emotionally charged topics, requiring an ethical approach to safeguard participants' well-being. Recognizing the potential psychological distress associated with discussing unintended pregnancies, restrictive abortion laws, and infant loss, the survey will include trigger warnings and allow participants to skip questions or withdraw at any time without penalty. Strict confidentiality protocols will protect participants' identities, and responses will be securely stored. Recruitment through trusted advocacy groups will foster a safe and supportive environment, while mental health resources will be provided to those who experience discomfort during the study. This framework reflects our commitment to ethical, respectful, and responsible research practices.

### 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 meaningful guidelines 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 detailed understanding, 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 detailed 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): The survey design addresses social desirability bias (SDB) by emphasizing anonymity and confidentiality throughout. A clear introduction outlines the survey’s purpose—academic research on the impact of restrictive abortion laws—and reassures participants that their responses will remain confidential and solely used for research. The anonymous online format creates a safe environment

for participants to share their experiences without fear of judgment or stigma. A feedback section at the end encourages participants to express concerns or share additional thoughts, fostering trust and enhancing data quality.

### 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 understanding 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 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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