# *Abortion Policy Spillover*

## *When Policy Consequences Contradict the Intent*


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## Abstract

In a phenomenon known as policy spillover, one state's policies may affect outcomes in other states. Well-documented cases of policy spillover exist in many domains, including but not limited to gun restrictions, environmental legislation, and liquor taxation [17, 60, 89, 91]. Interstate variation in abortion policies creates a need for the exploration of abortion policy spillover. This thesis addresses the gap in the literature and provides a systematic look at abortion policy spillover in the United States from the years 2010 to 2019. Using linear mixed-effects models, this thesis finds that the effects of abortion restrictions transcend state lines. Restrictive policies from surrounding states have the desired effect of reducing overall abortion rates, earlier-term abortion rates, and resident abortion rates, but these policies have the undesired effect of increasing nonresident abortion rates and the later-term share of abortions. These findings demonstrate that state abortion restrictions increase certain types of abortions in other states, which contradicts the intent of lawmakers who wish to reduce abortions of all types. With the Supreme Court's reversal of Roe v. Wade in June 2022, this thesis will pave the way for the study of abortion spillover in a world without constitutional protections for abortions.[1]


[1] Roe v. Wade, 410 U.S. 113 (1973); Dobbs v. Jackson Women's Health Organization, 597 U.S. ____ (2022).

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*For every action, there is an equal and opposite reaction.*

Newton's Third Law of Motion

# 1 Introduction

## 1.1 Motivation

Unrestricted state borders allow people and goods to flow freely within the United States. When paired with state-level policy variation, these open borders can result in policy spillover, where a policy in one state affects outcomes in neighboring states. Well-documented cases of policy spillover exist in several domains, including but not limited to gun restrictions, environmental legislation, and liquor taxation [17, 60, 89, 91]. While policy spillover exists in many legislative areas, the current body of literature lacks a systematic study of the spillover effects of abortion policies. Recent changes to the abortion policy landscape create a need to understand the impact of state-level policies on nearby areas.

## 1.2 Problem

State-level variation in abortion policies incentivizes individuals from states with strict abortion regulations to seek abortion care in neighboring states.[1]

[1] In fact, the court argument for the landmark case Roe v. Wade alluded to interstate travel for abortions in the 1970s. Sarah Weddington – the attorney representing Norma

If interstate travel occurs on a large enough scale, the policy environment of surrounding states could impact abortion metrics within a given state. Assuming pro-life lawmakers oppose abortions everywhere and not just in their home state, policy spillover leading to higher abortion rates in nearby states would contradict the principles of pro-life legislators.

The possibility of this contradiction raises the question: do state abortion restrictions produce policy spillover in neighboring states? To address this question, this thesis will draw from state-level abortion and policy data to model abortion outcomes as a function of nearby states' policies.

## 1.3 Roadmap

This thesis proceeds as follows. Chapter 2 reviews the existing literature on policy spillover in other domains and motivates the study of abortion policy spillover. Chapter 3 explores the data and variables relevant to this analysis, and Chapter 4 outlines the methodology used for modeling the outcomes.[2] Then, Chapter 5 presents and interprets the results of the chosen models. Finally, Chapter 6 concludes with a discussion of the results and the future of policy spillover after the Supreme Court's ruling in Dobbs v. Jackson Women's Health Organization.

McCorvey under the anonymous name Roe – noted that Texas's strict abortion law, which prohibited abortions except when necessary to save a woman's life, had forced more than 1,600 women to travel out of state to obtain the procedure [74, p. 31].

[2]The GitHub repository posted at https://github.com/kayla-manning/state-abortions contains all code used to produce this analysis.

# 2
# Literature Review

In this chapter, I synthesize previous policy spillover research to highlight the need to study abortion policy spillover. First, I discuss studies of policy spillover in other domains. Then, I motivate the study of abortion policy spillover. Finally, I conclude with a discussion of how this thesis will fill the gaps left by previous research and contribute to future studies of abortion policy and policy spillover.

## 2.1 Spillover in Other Policy Domains

Unrestricted state borders in the United States can lead to policy spillover, where policies in one jurisdiction impact outcomes in neighboring jurisdictions. For this thesis, I define two types of policy spillover: undesired spillover and desired spillover. A policy exhibits desired spillover if it fulfills its goals beyond its original jurisdiction, and it exhibits undesired spillover if its outcomes in other jurisdictions contradict its original intent. Because policymakers enact legislation in an attempt to legislate or control a specific issue, policy spillover from neighboring jurisdictions can limit legislators' abilities to regulate issues they wish to address. The regulatory challenges posed by spillover have inspired previous research about spillover in numerous policy areas, including but not limited to environmental policy, liquor laws, and gun control legislation.

### 2.1.1 Environmental Spillover

One branch of research explores the spillover of environmental policies. For example, the status of clean water policies impacts the water quality of downstream jurisdictions. States and countries that fail to monitor or control water quality contribute to the downstream degradation of water quality in states and countries that do monitor water quality [90, 91]. Similarly, local and neighboring regulatory environments for clean air have an impact on the air pollution of a given jurisdiction [35].

### 2.1.2 Spillover of Goods and Services

While flowing air and water can cross even the most secure borders, the spillover of people and goods requires permeable borders like those within the United States. Previous research explores policy spillover of liquor sales, manufacturing facilities, firearm sales, and more. In general, strict regulations push people or goods out of a state. For example, state-level liquor taxes and bans drive people to purchase liquor in other states, with 20 to 40 percent of price elasticity for spirits coming from the resulting displacement of sales across state borders [93]. In addition, emissions regulations encourage companies to outsource production to less-developed regions, thus reducing emissions and water consumption in their home jurisdiction while increasing the burden on neighboring regions [33]. Similarly, strict state gun control laws create a shift in the market for guns to states where purchasing is easier [28].

As more restrictive policies push people away, more welcoming policies attract new crowds. States with lower sales taxes incentivize consumers to cross state lines to make purchases [17]. Similarly, generous redistributive government policies tend to attract the poor to cities [40].

## 2.2 Motivating the Study of Abortion Policy Spillover

Across all examples, people tend to leave states with strict regulations to obtain a good or service in states with more generous policies. This idea could extend to abortion restrictions: strict home-state abortion laws may push individuals to seek abortion care in neighboring states. Abortion laws vary between states, and recent evidence, though limited, suggests that individuals seeking abortions will cross state lines to obtain an abortion under certain policy conditions [85, 95].[1]

### 2.2.1 State-Level Policy Variation

Individuals seeking abortions will face different obstacles depending on their geographic location.[2] In 1973, Roe v. Wade established a broad trimester framework to prioritize a patient's right to privacy in the first trimester, protect a patient's health in the second trimester, and protect "the potentiality of human life" in the third trimester.[3] These loose guidelines have resulted in state-level policy variation [102, p. 15]. As of March 2022, 58% of women ages 18-44 in the United States lived in states with "hostile" or "extremely hostile" policies toward abortion, according to the Guttmacher Institute. On the other hand, 38% of women in the same age group live in states with "supportive" policy environments [73].[4] This variation allows people to exploit more favorable policy conditions by crossing state lines.

In June 2022, the Supreme Court overturned Roe v. Wade and created dramatic variation in state abortion policies. This thesis uses data from 2010 to 2019 and therefore operates under the rules handed down by Roe. However, the findings of this analysis may preview more dramatic results for a policy landscape without constitutional protections for abortion. Chapter 6 discusses the implications of the Dobbs v. Jackson Women's Health Organization ruling in greater detail.

### 2.2.2 Willingness to Travel

Recent evidence from Texas suggests that, when faced with heightened restrictions, individuals will seek abortion care in surrounding states. In

[1] In addition to these more recent accounts, previous research suggests that having a large number of abortion providers appears to encourage the geographic displacement of abortions from more restrictive states to these more welcoming states [18].

[2] Figure 3.1.3 in Chapter 3 maps the relative restrictiveness of the states' policy environments in 2010 and 2019.

[3] Roe v. Wade, 410 U.S. 113 (1973).

[4] Since not all individuals seeking abortion care identify as women, I use gender-neutral terms wherever possible [55]. However, some sources use gender-specific terms. To preserve accuracy when describing previous literature, I use the language adopted by the source.

September 2021, Texas Senate Bill 8 (TX SB 8) banned abortions after six weeks. After the law went into effect, the number of legal abortions in Texas decreased by half, but the total number of abortions obtained by Texas women only fell by around 10 percent [85]. Most Texas women denied abortions under SB 8 received abortion care in a nearby state.[5] In total, Texas women sought out-of-state abortions at a rate 12 times more than typical in the three months following the passage of the law [85].[6] Nearby states felt this impact most strongly, with clinics in states like Oklahoma and Louisiana experiencing large spikes in the number of patients from Texas [85, 95]. The Texas example indicates that when confronted with policy restrictions, women cross state lines to obtain an abortion.[7] This thesis expands upon these findings from Texas and analyzes the nationwide patterns of interstate travel for abortion care.

## 2.3 Previous Studies of Abortion Spillover

Continuing with the TX SB 8 example, reports from clinics in surrounding states support the presence of undesired spillover in later-term abortions. Following the passage of the September 2021 law, the clinic administrator of Hope Medical – an abortion clinic in Shreveport, Louisiana – reported that women from both Texas and Louisiana had to carry their pregnancies further along than they otherwise would due to longer wait times [85].[8] Moreover, Texas women seeking out-of-state care also described wait times of over two

[5]In addition, news reports also discuss women from Texas and neighboring states opting to order abortion pills online rather than seeking care in crowded clinics [85].

[6]For example, at least 110 patients at the Trust Women clinic in Oklahoma – one of only four clinics in the state – hailed from Texas in September 2021, compared to only 11 patients from Texas in August [95]. Intuitively, this would make it more difficult for women both from Oklahoma and Texas to obtain an abortion, causing an increase in wait times [96].

[7]A survey of women in an Atlanta, GA abortion clinic also supports the notion that women will seek care in nearby states when confronted with home-state restrictions. When confronted with a hypothetical law outlawing abortion in the state, 81.9% of women in an Atlanta, GA abortion clinic considered at least one way to end their pregnancy, with 66.1% of study participants considering travel to another state [27]. Of course, this study examines reactions to a hypothetical law, while the data from Texas describes the real-life travel patterns of individuals.

[8]As of March 2022, two-thirds of patients at Hope Medical in Shreveport, LA hailed from Texas, relative to only one-fifth before the passage of the September 2021 law. While the clinic used to perform most abortions before nine weeks, the longer wait times now force most patients to wait until they are in their late first or early second trimester.

weeks in neighboring states [103].[9] In states not equipped to handle the new crowds, this influx of patients could very likely increase wait times, which could then force individuals to carry their pregnancies longer and increase the share and rate of later-term abortions.[10]

Moving away from Texas, a limited body of literature examines the spillover effects of specific types of abortion policies. For example, researchers found that restrictions on Medicaid funding led to increased abortion rates in nearby states [18]. Similarly, a past Massachusetts parental consent law failed to discourage minors from obtaining an abortion and instead pushed them to seek care across state lines [26].

## 2.4 Gaps in Previous Research

Despite substantial research on spillover in other domains and case-specific reports of abortion policy spillover, the literature lacks a rigorous and comprehensive study of abortion spillover.[11] Recent examinations of abortion spillover rely on journalistic accounts, and the academic literature on abortion spillover largely comes from the twentieth century [18, 26, 85, 103]. The outdated research fails to capture the gradual weakening of abortion protections over the past couple of decades [15]. Moreover, the existing academic research focuses on individual policy types rather than overall policy environments [18, 26].

This thesis fills the gaps left by the previous literature and provides a systematic look at abortion spillover on a nationwide scale from 2010 to 2019. The findings of this thesis will have the power to inspire a broad range of future work in the field. Evidence of undesired spillover would raise questions about the true value of these policies and whether pro-life policymakers view their risks as worth the outcomes.[12] In addition, findings

[9] These descriptions of wait times from Texas women came from interviews conducted by the Texas Policy Research Center between October 2021 and February 2022. They conducted 65 interviews with Texas residents who received out-of-state abortions in Arkansas, Colorado, Kansas, Louisiana, Mississippi, New Mexico, and Oklahoma [103].

[10] In addition to the logistical barrier posed by increased wait times, women surrounded by states with restrictive policy environments may face a psychological barrier that could lead them to delay the decision to obtain an abortion until later in pregnancy.

[11] Previous work supports the intuitive result that restrictive state-level abortion legislation leads to decreases in in-state abortion occurrence, but it fails to examine the effect of such policies in surrounding states [20, 41, 44, 71].

[12] For example, is a modest reduction of in-state abortions worth an increase in later-term abortions in nearby states? When asked about his views on policy spillover, Texas

of undesired spillover in later-term abortions could inform the study of spillover in secondary outcomes in other policy realms.[13] Perhaps most importantly, knowing the impact of within-state and surrounding-state policy environments will inform our thinking as we navigate the post-Dobbs era.

State Representative Brad Buckley stated that "if [increased abortion restrictions] create the…unintended consequences of late-term abortions or more late-term abortions in adjacent states or other places, that to me would be a horrible unintended consequence" [21]. Evidence of undesired spillover could prompt lawmakers to reconsider the impact of their legislative actions.

[13]The same framework could extend to state-level variation in firearm legislation or sales taxes. Do residents of states with relaxed gun laws struggle to obtain firearms as a result of increases in out-of-state demand? Residents may struggle to obtain firearms as a result of either a decrease in supply or an increase in cost. Similarly, New Hampshire attracts out-of-state shoppers due to its relatively lower sales taxes [104]. Do Massachusetts shoppers cause an increase in prices in New Hampshire border towns?

# 3
# Data

To define desired and undesired spillover of abortion policies, I assume that pro-life legislators oppose abortions everywhere.[1] Despite only having the ability to enact legislation within their state, I assume that pro-life legislators seek to reduce abortion rates of all types across all jurisdictions when enacting policies. In addition, I assume they strongly oppose nonresident abortions since interstate travel enables people to flee the restrictions they impose on their state. Finally, I assume that they seek to reduce both the later-term abortion rate and the later-term share of abortions, which implies they express the strongest desire to reduce later-term abortions.[2] Table 5.2.2 in Chapter 5 summarizes these assumed policy intentions alongside the model results.

Table 3.0.1 provides a high-level overview of the data used to conduct this analysis. Each observation in the combined dataset corresponds to a

[1] To respect the labels assigned by members of each movement, I refer to individuals who wish to restrict abortion access as "pro-life" and individuals who wish to expand abortion access as "pro-choice."

[2] A desire to decrease the later-term share of abortions while also lowering the earlier-term abortion rate means that lawmakers wish to reduce later-term abortions by more than earlier-term abortions. The Later-Term Share of Abortions section at the end of this chapter elaborates on this idea.

**Table 3.0.1:** Sources for Modeling Dataset

| | Source | Years Available |
|---|---|---|
| Abortions by residence and location | US Centers for Disease Control and Prevention [36] | 2010-2019 |
| Abortions by known weeks gestation | US Centers for Disease Control and Prevention [51–53, 63–65, 76–78] | pre-2006-2019 |
| State-level abortion policies | Guttmacher Institute via the Internet Archive [5–14] | 2006-2022 |
| Controls | US Census Bureau [23, 24], National Science Foundation [38], MIT Elections Project [66] | — |

state-year pairing for the 48 contiguous states from 2010 to 2019. For each state-year observation, I consider two policy metrics: the within-state policies and the surrounding-state policies. Under the assumptions described above, surrounding-state policies exhibit desired spillover if they reduce abortion rates in a given state. On the other hand, surrounding-state policies exhibit undesired spillover if they increase abortion rates in that state.

I test whether abortion restrictions produce policy spillover across six variables: overall abortion rates, nonresident abortion rates, resident abortion rates, later-term abortion rates, earlier-term abortion rates, and the later-term share of abortions. To measure spillover in these outcomes, I model the various abortion rates as a function of within-state and surrounding-state abortion policies alongside numerous control variables. The remainder of this chapter describes the data and variables used in my models of policy spillover.

## 3.1 Policy Data

To measure policy spillover, I must quantify the relative restrictiveness of abortion policies. Previous studies of abortion policies use historical policy data from the Guttmacher Institute, a research and policy organization specializing in sexual and reproductive health and rights [20]. The Guttmacher Institute displays current state-level abortion restrictions on their website, but they do not aggregate this into a publicly available historical dataset [2].[3]

To construct a longitudinal dataset of state-level abortion restrictions, I recovered previous versions of the Guttmacher Institute's state policy tables from the Internet Archive [5–14].[4] The resulting policy dataset contains state policies across fifteen types of abortion restrictions from 2006 to 2022. The fifteen policies include various forms of legislation on physician and hospital requirements, gestational limits, public funding, coverage by private insurance, provider or institutional refusal, state-mandated counseling, waiting periods, parental involvement, and "partial-birth" abortions. Table A.1.2 in Appendix A describes the exact policies contained in the dataset.[5]

### 3.1.1 Quantifying Policy Environments

With this underlying policy dataset, I constructed within-state and surrounding-state policy scores to quantify the restrictiveness of policy environments. The literature on abortion does not use a standard policy index or scoring system,[6] so I adapted my own within-state policy scores from the approaches of previous policy studies [28, 46, 82, 100]. Then, I used the methodology of Kaufman et al. to compute a state's surrounding-state policy score as a population-weighted and distance-decayed average of the within-state scores [60]. The Within-State Policy Scores and Surrounding-State Policy Scores sections of this chapter describe the

[3] The State Policy team at the Guttmacher Institute declined to provide their archived data for this thesis.

[4] The Scraping from the Internet Archive section of Appendix A describes how I scraped the Guttmacher datasets from the Internet Archive.

[5] In addition, Table A.1.1 in Appendix A displays the dates I scraped each year's policies from the Internet Archive. I can provide the exact link for the Internet Archive policy webpages upon request.

[6] The literature on gun control typically uses scores derived from the Brady Center scorecard [54].

construction of the two scores in greater detail. In a model of abortion outcomes as a function of these policy scores, the model coefficient of the within-state score term captures the effectiveness of abortion restrictions in their respective state. When controlling for the within-state scores, the model coefficient of the surrounding-state score term measures policy spillover from a state's surroundings.[7]

The construction of the within-state and surrounding-state scores relies on small decisions that, in sum, could impact the results of the analysis. The Alternative Scoring System section in Appendix B describes an alternative scoring system, and the section includes models of the outcomes as a function of these new scores. Instead of assigning equal weight to each of the fifteen policies, this scoring system assigns unequal weights based on the burden imposed by different types of policies. Across the two scoring systems, the models yield the same conclusions and therefore support the robustness of results to different score definitions. Because the alternative scoring system relied on more subjective decisions when assigning weights to the policies, the main analysis uses the original scores with equal weights for each policy.

### Within-State Policy Scores

To construct within-state policy scores, I assign points to each policy in the Guttmacher dataset and sum the points across the fifteen policies. Fourteen of the policies describe abortion restrictions, and one policy describes an abortion protection. Restrictive policies receive between 0 and 1 points, with 0 representing the absence of a restriction and 1 representing the highest observed level of a restriction. The "public funding of all or most abortions" variable describes a protective policy and receives point values between 0 and -1.[8] Enjoined policies, or policies blocked by courts, receive 0 points.[9]

Each of the fifteen policies can take on varying levels of restrictiveness. Before assigning points to policies, I group policy levels into bins of similar

[7] In Chapter 5, the Exporting Resident Abortions to Other States section discusses another way to define and measure spillover in future models.

[8] This public funding variable differs from the variable that indicates if a state limits public funding to cases of rape or incest. If a state only allows public funding in the case of rape or incest, it receives a 1-point addition to the overall policy score, since that restricts one's ability to obtain an abortion. Otherwise, a state receives 0 points for the public funding policy variable.

[9] The Enjoined Policies section of Appendix A discusses the reason behind this decision and the limitations of this method.

**Table 3.1.1:** Assigning Points to Hospital Requirements

| Bins | Points |
|---|---|
| 12 weeks, 90 days | 1.00 |
| 14 weeks, 2nd trimester | 0.75 |
| Viability, 24 weeks | 0.50 |
| 3rd trimester | 0.25 |
| None | 0.00 |

severity and rank these bins by relative restrictiveness. Then, I assign points at evenly spaced intervals based on the ranked bins. Table A.1.3 in Appendix A displays the points assigned to the levels of each policy.

As an example, consider the `hospital_if` policy variable, which denotes the threshold at which states require an abortion to be performed in a hospital. Across all state-year observations, this variable takes on seven unique levels of restriction. Several of these levels have negligible differences, so I bin the policy levels into groups of comparable severity before assigning points. Table 3.1.1 lists the resulting five bins with varying degrees of restrictiveness.

After assigning point values to each of the fifteen policy variables for a state-year observation, I sum the points across the fifteen policies. The resulting sum represents the within-state score for that state-year observation, and it can take on values from -1 to 14, inclusive.[10] In reality, the lowest observed within-state score of -1 occurs in Vermont from 2010 to 2019, while the highest observed within-state score of 11.6 occurs in Oklahoma from 2016 to 2019. Figure 3.1.1 displays the distribution of the within-state scores of the 48 contiguous states from 2010 to 2019.

In general, within-state policy environments grew more polarized from 2010 to 2019. States such as Colorado and California grew less restrictive over the ten-year period, while states such as Arizona and Kansas grew more restrictive. Figure 3.1.3 in this chapter displays the geographic distribution of within-state policy scores for the years 2010 and 2019, and Figure A.1.1 in

[10] A state could have all fourteen restrictive policies in place, which results in a score of 14. On the other hand, a state could have zero restrictive policies in place while offering public funding for all or most medically necessary abortions, which would yield a within-state score of -1.

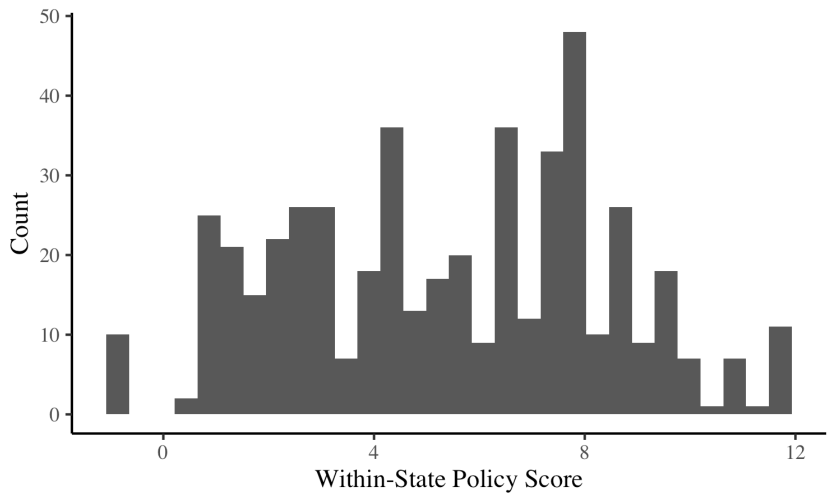


**Figure 3.1.1:** Within-State Policy Score Distribution

Counts correspond to state-year observations for the 48 contiguous states from 2010-2019.

Appendix A displays maps for every year from 2010 to 2019.

### Surrounding-State Policy Scores

Adapted from studies of firearm spillover, the surrounding-state score takes a population-weighted and distance-decayed average of all within-state policy scores in a given year [60]. In constructing the surrounding-state score for a given state, the remaining 47 contiguous states receive unscaled weights equal to their populations divided by the squared distance between the two states' population centers.[11] With these weights, more populous states have a greater weight in surrounding-state scores because their restrictions have the potential to displace larger populations of abortion seekers.[12] In addition, nearby states receive a greater weight in surrounding-state scores to account for the inverse relationship between travel distances and abortion rates [80].[13]

Since the surrounding-state scores draw from within-state scores, this

[11] I follow the approach of Kaufman et al. when using the squared distance [60]. They consider squared distances and untransformed distances; their results demonstrate robustness to the different weight specifications. Since I conduct numerous sensitivity analyses across different scoring systems and model specifications, I left the distance as squared across all models.

[12] The scoring mechanism constructs weights with American Community Survey (ACS) population estimates for each state-year observation [23].

[13] The scoring system assigns weights based on the distances between states' population centers as of the 2020 Census [22]. Due to data availability, I calculate the surrounding-state scores with the population centers as of 2020 for all state-year observations.

approach ignores abortion restrictions in nearby countries such as Canada and Mexico. I do this for simplicity, but a more complex analysis would consider the proximity, policy environments, and abortion outcomes in other North American countries.[14] The Increasing Importance of Mexico section in Appendix C discusses the inclusion of Mexico in future studies of abortion spillover.

To illustrate the relationship between within-state scores and surrounding-state scores, the following paragraphs describe how to compute the surrounding-state policy score for state $i$ in year $y$. Let $J$ represent the set of the 48 contiguous states. Since I derive a state's surrounding-state score from a weighted average of the within-state scores of all states in $J$, I derive weights for every state $j \in J$.

Let $p_j^{(y)}$ represent the population of state $j$ in year $y$, and let $d_{ij}$ represent the distance between the population centers of state $i$ and state $j$ in the 2020 Census [22]. I define $w_{ij}^{(y)}$ as the unscaled weight assigned to state $j$, which divides the population by the squared distance.[15]

$$w_{ij}^{(y)} = \begin{cases} \frac{p_j^{(y)}}{d_{ij}^2}, & i \neq j \\ 0, & i = j \end{cases}$$

After computing the unscaled $w_{ij}^{(y)}$ for all $j \in J$, I rescale the weights so that all weights for state $i$ in year $y$ sum to 1.

$$q_{ij}^{(y)} = \frac{w_{ij}^{(y)}}{\sum_{j \in J} w_{ij}^{(y)}}$$

Then, I write the surrounding-state policy score for state $i$ in year $y$ as $s_i^{(y)}$. Denoting the within-state policy score of state $j$ in year $y$ as $x_j^{(y)}$, I compute $s_i^{(y)}$ as the sum of the products of the within-state scores and their

[14] Data for other countries would require the use of sources outside of the Guttmacher Institute's state policy dataset and the CDC's abortion surveillance program. On the policy side, other countries may restrict abortions with policies different from those observed in the United States. Because the within-state scores sum points across the fifteen policies in the Guttmacher state policy dataset, using data from other countries would require the creation of a new within-state scoring system. For abortion metrics, other countries do not report their abortion counts to the CDC. As a result, the numbers may not be held to the same standards as in the United States and would likely differ in their level of aggregation.

[15] To isolate the effect of a state's surroundings, I do not consider a state's own policy environment in its surrounding-state score, so I assign a weight of 0 to state $i$'s within-state score. Regression models will include a control term for the within-state score of each state-year observation.

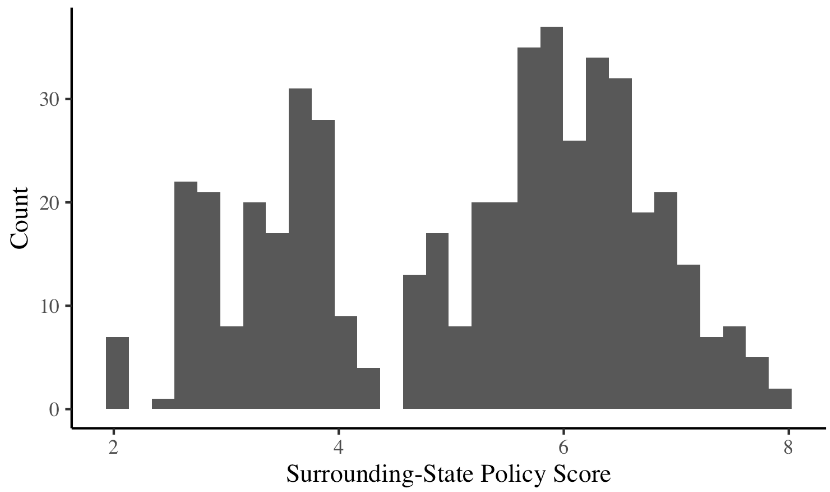


**Figure 3.1.2:** Surrounding-State Policy Score Distribution

Counts correspond to state-year observations in the 48 contiguous states from 2010 to 2019.

rescaled weights.

$$s_i^{(y)} = \sum_{j \in J} q_{ij}^{(y)} x_j^{(y)}$$

The resulting score measures the restrictiveness of a state's surroundings in the same units as the within-state scores. Across the policy dataset from 2010 to 2019, the lowest surrounding-state score of 2.04 occurred in Nevada in 2013, and the highest surrounding-state score of 7.93 occurred in Oklahoma in 2019.[16] Figure 3.1.2 displays the distribution of the surrounding-state scores of the 48 contiguous states from 2010 to 2019.

To visualize the geographic distribution of the two scores, Figure 3.1.3 displays maps of the within-state scores and surrounding-state scores in the first and last year of study. These maps display temporal trends in the two scores, and they highlight the relationship between the within-state scores and the surrounding-state scores.

First, the maps reveal changes in the policy landscape between the

[16] These values make sense with the surrounding geographic and policy environments of the two states. Oklahoma lies between the South and the Midwest, two regions notorious for their restrictive abortion policies. The population and distance-based weights mean that nearby states like Texas make large contributions to Oklahoma's surrounding-state score. On the other hand, Nevada's proximity to the West Coast means that nearby and populous California carries a large weight in determining Nevada's surrounding-state score.

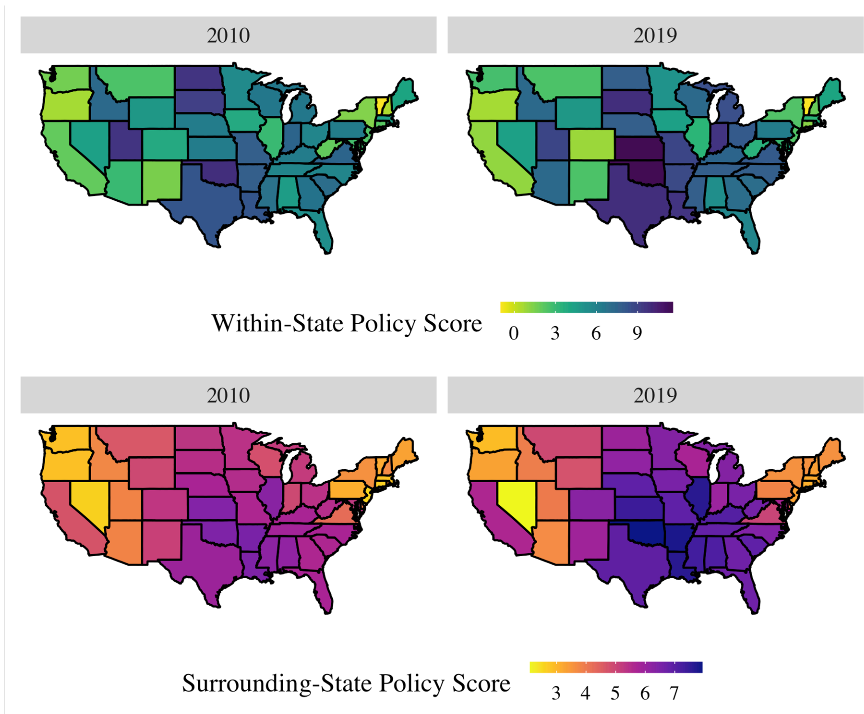


**Figure 3.1.3:** National Within-State and Surrounding-State Policy Landscapes

The maps display the first and the last years of the studied time frame. Figures A.1.1 and A.1.2 in Appendix A map within-state and surrounding-states for every year from 2010 to 2019.

beginning and the end of the studied time frame. Within-state policy scores generally gravitated toward extremes. While states such as Colorado and California grew less restrictive, most states grew more restrictive from 2010 to 2019.[17] Since I aggregate the within-state scores to compute the surrounding-state scores, the higher within-state scores also led to higher surrounding-state scores. Surrounding-state policy environments grew more restrictive from 2010 to 2019 in all states except Nevada, New Hampshire, and Rhode Island.

In addition to the temporal trends, Figure 3.1.3 also reveals states may have lower within-state restrictions but higher surrounding-state restrictions. This results if a state has abortion policies much less restrictive than its neighbors; for example, Illinois lies at the heart of the relatively restrictive Midwest but has relatively low levels of restriction itself. States like Colorado, New Mexico, California, and New Jersey find themselves in similar situations. These differences in within-state and surrounding-state restrictions make these states attractive to nonresidents from surrounding areas seeking care within the less restrictive states. As a result of the contrasting policy environments, these states present themselves as ideal grounds for policy spillover.

### 3.1.2 Standardizing Policy Scores

When fitting my models of spillover, I use standardized versions of the within-state and surrounding-state scores. Broadly, the within-state and surrounding-state scores grew more restrictive over the studied time frame. To control for these temporal trends, I group the data by year when standardizing the scores. Standardizing the policy scores centers the values around zero and changes the units to standard deviations from the national average of that year. For someone less familiar with the point system used to craft the policy scores, interpreting the policy terms as standard deviations from the national average emphasizes the relative restrictiveness of a state's policy environment.

For example, Minnesota's standardized within-state score of approximately 0 in 2015 indicates that the state had average levels of in-state restrictions in 2015. On the other hand, Virginia's standardized within-state score of

[17] California, Colorado, Connecticut, Massachusetts, Minnesota, North Dakota, and Utah are the only states that grew less restrictive from 2010 to 2019.

approximately 1 in 2011 indicates that its policies were one standard deviation more restrictive than the national average in 2011. Meanwhile, Montana's standardized within-state score of approximately -1 in 2012 indicates that its policies were one standard deviation less restrictive than the national average in 2012. In the most extreme cases, Kansas's score of 2 in 2014 and Vermont's score of -2 in 2017 indicate that the within-state scores of those states were two standard deviations more or less restrictive than the national average for their respective years. Figure A.1.3 in Appendix A displays the distributions of the standardized within-state and surrounding-state scores.

## 3.2 Abortion Data

As part of its Abortion Surveillance System, the United States Centers for Disease Control and Prevention (CDC) aggregates abortion count data by state of occurrence, state of residence, and known gestational age.[18] The CDC collects abortion data from states on a voluntary basis. I discuss the implications of nonreporting bias in the Voluntary Reporting section later in this chapter. For this analysis, I use CDC abortion data from two sources: a publicly released dataset with abortions by state of residence and state of occurrence, and a dataset with abortions by known weeks of gestation.[19]

The two data sources span different timelines. The CDC only releases abortion counts by the state of occurrence and the state of residence for the years from 2010 to 2019 [36].[20] However, the CDC releases abortion counts by known weeks of gestation for every year in the annual Abortion Surveillance reports. These reports date back to more than a decade before 2010, but they do not contain abortion counts by the state of residence and state of occurrence. As a result, I cannot use the reports to expand the timeline beyond the 2010 to 2019 time frame. For consistency, all models draw from the same combined dataset for the years from 2010 to 2019.

[18] In this data, the CDC defines a legal induced abortion as an intervention performed by a licensed clinician with the intent to terminate a suspected or ongoing pregnancy. To fall under this definition, abortion must not result in a live birth. Abortions may occur during surgery or as a result of medication.

[19] I created the gestational age dataset with information from the CDC's annual Abortion Surveillance reports.

[20] The CDC declined to provide abortion counts by the state of residence and occurrence for years outside of the window from 2010 to 2019.

### 3.2.1 Outcome Variables

This analysis measures policy spillover across six different outcome variables: overall abortion rates, nonresident abortion rates, resident abortion rates, later-term abortion rates, earlier-term abortion rates, and later-term share of abortions. All abortion rate metrics consider abortions as a rate of 1000 live births. I define earlier-term abortions as those occurring in the first thirteen weeks of known gestation, and I define later-term abortions as those that occur at or after fourteen weeks of known gestation. The following sections describe the data and substantive meaning behind each outcome variable.[21]

#### Overall Abortion Rates

The overall abortion rates provide a high-level view of abortion frequency in a state. I represent abortions as a rate of 1000 live births to normalize the number of abortions by the size of the child-bearing population, changes in the count of births, and other latent variables related to childbirth.[22] The highest abortion rate of about 380 abortions per 1000 live births occurred in Rhode Island in 2011, and the lowest rate of approximately 20 abortions per 1000 live births occurred in Missouri in 2019. Figure 3.2.1 displays the geographic distribution of abortion rates for reporting areas.

#### Resident Status

In addition to studying overall abortion rates, I consider abortion rates by resident status. As with overall abortion rates, both of these rate metrics consider abortions as a rate of 1000 live births.

[21] Any summary statistics in the below sections describe the observations in my final modeling dataset. For all models, I exclude any state-year observations that fail to report data in either of the two CDC data sources. In other words, any state-year observation that fails to report at least one of the six outcome variables is excluded from the analysis. In addition, I dropped Wyoming from the analysis because I could not distinguish between resident and nonresident abortions in their reported data.

[22] Abortion rates could use several values as the denominator, including but not limited to live births, the female population, the female population of childbearing age, and the overall population. Of the listed possibilities, the largest substantive difference exists between the number of births and the overall population size. However, even those two variables display a strong bivariate correlation of approximately 0.96 and nearly identical distributions, so I feel comfortable making the decision to consider abortion rates as a function of births on substantive grounds.

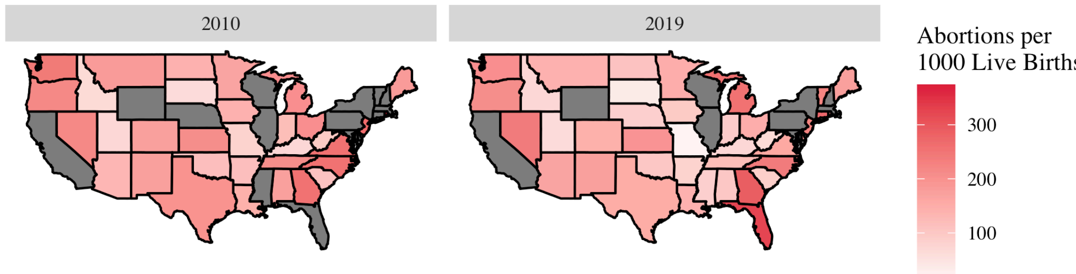


**Figure 3.2.1:** Mapping Overall Abortion Rates, 2010 & 2019

The above maps display overall abortion rates for the first and last years of the studied time frame. Abortion rates are defined as abortions per 1000 live births. States with dark gray shading fail to report at least one of the selected outcome variables.

Nonresident Abortion Rates Under the assumption that pro-life policymakers wish to reduce all abortions, abortion restrictions fail to fulfill their goals if the policies simply displace abortions elsewhere. To measure this aspect of undesired spillover, I consider the rate at which nonresidents obtain abortions within a given state.

An increase in nonresident abortion rates suggests that the increased levels of restriction in surrounding states pushed people to seek care in the nearby state.[23] This indicates that nonresidents view the state as a more attractive place to obtain an abortion relative to their home state. Not only would an increase in nonresident abortions provide evidence of policy spillover in nonresident abortion rates, but it could have secondary outcomes on resident and later-term abortion rates if crowds of nonresidents make it difficult for residents of a state to access care.

Figure 3.2.2 displays the geographic distribution of nonresident abortion rates for reporting areas. In the studied time frame, Kansas had the highest nonresident abortion rate of about 102 abortions per 1000 live births in 2010, while Arizona also had the lowest nonresident abortion rate of approximately 1 abortion per 1000 live births in 2018.[24]

[23]This assumes that the nonresidents travel from the states whose restrictions contribute to the higher surrounding-state score.

[24]Missing data from California may bias the nonresident abortion rate for Arizona, making the number appear lower than in reality. When compared to its surroundings, however, Arizona has a much more restrictive within-state policy environment, making it a relatively unattractive place to seek an out-of-state abortion. Because of this, I do not believe the missingness from nonreporting in California creates a cause for concern when interpreting

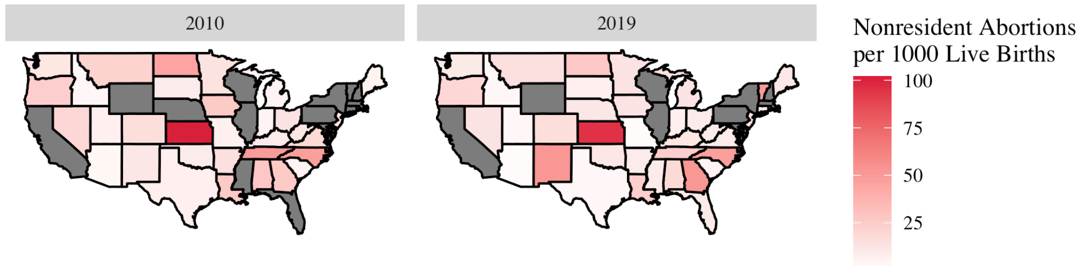


**Figure 3.2.2:** Mapping Nonresident Abortion Rates, 2010 & 2019

The above maps display nonresident abortion rates for the first and last years of the studied time frame. Nonresident abortions are the number of abortions obtained by people seeking out-of-state care in a given state, and nonresident abortion rates are defined as nonresident abortions per 1000 live births. States with dark gray shading fail to report at least one of the selected outcome variables.

Resident Abortion Rates In addition to nonresident abortion rates, I also examine resident abortion rates. The resident abortion rate measures the rate at which residents obtain abortions in their home state.[25] As alluded to in the Nonresident Abortion Rates section above, crowds of nonresidents seeking abortions may make it more difficult for residents to obtain an abortion in their home state. This could result in a decrease in resident abortions by pushing people to seek nonresident abortions in another state, encouraging people to self-manage medication abortions, or preventing people from seeking abortions altogether.[26]

Figure 3.2.3 displays the geographic distribution of resident abortion rates in reporting areas over the studied time frame. Missouri had the lowest observed resident abortion rate of approximately 19 abortions per 1000 live births in 2019, and Florida had the highest resident abortion rate of about 317 abortions per 1000 live births in 2019.

Arizona data.

[25] This measure does not include a state's residents that obtain abortions in other states.

[26] Longer wait times and difficulty accessing care could discourage people from seeking abortion care in their home state. In addition, pro-life activists from nearby states with already restrictive policies may focus their protests on the less restrictive nearby states, which could deter residents from seeking care altogether.

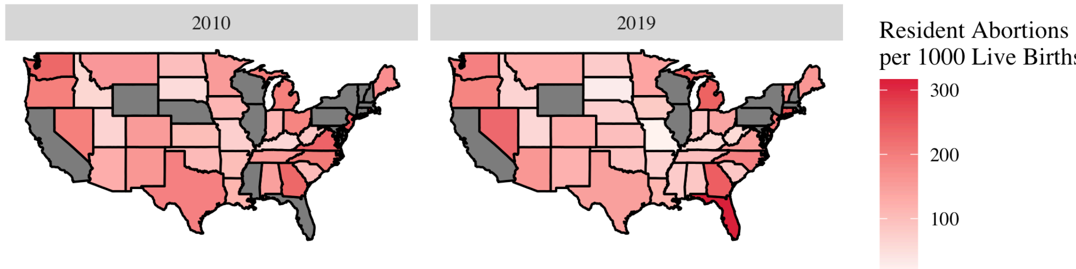


**Figure 3.2.3:** Mapping Resident Abortion Rates, 2010 & 2019

The above maps display resident abortion rates for the first and last years of the studied time frame. Resident abortions are the number of abortions obtained by a state's residents in their home state, and resident abortion rates are defined as resident abortions per 1000 live births. States with dark gray shading fail to report at least one of the selected outcome variables.

### Abortion Timing

In my study of policy spillover, I also consider the impact of abortion restrictions on the timing of abortions. Many abortion restrictions aim to limit the gestational age of abortions, so I assume that pro-life policymakers strongly oppose increases in the rate and share of later-term abortions.[27]

I refer to earlier-term abortions as those that occur up to thirteen weeks of known gestation, and I refer to later-term abortions as those that occur at fourteen weeks of known gestation or thereafter. In their Annual Abortion Surveillance reports, the CDC divides abortions into gestational age windows, but the gestational age windows vary across the studied time frame.[28] Fortunately, every report from 2010 to 2019 contains a threshold between thirteen and fourteen weeks of known gestation, which also marks the transition from the first and second trimesters of pregnancy [75]. As a result, I use the threshold between thirteen and fourteen weeks to distinguish between earlier-term and later-term abortions.[29]

[27] Later-term abortions terminate the pregnancy closer to viability, or the point around 24 weeks known gestation where a fetus can survive outside of the womb [19]. Under this reasoning, the assumed opposition of pro-*life* policymakers to later-term abortions makes sense in both a literal and medical sense.

[28] For example, the 2016 report displays abortion counts at 0-8, 9–13, 14–15, 16–17, 18–20, and 21 or more weeks of known gestation. Meanwhile, the 2019 report considers abortion counts at 0-6, 7–9, 10–13, 14–15, 16–17, 18–20, $\geq$ 21 weeks of known gestation.

[29] The data estimates gestational age based on the first day of the last menstrual cycle. Rather than reporting gestational age estimates to the CDC, some areas began reporting gestational age in terms of "probable post-fertilization age" in 2014. To make these measurements consistent with gestational age metrics, the CDC added 2 weeks to the probable

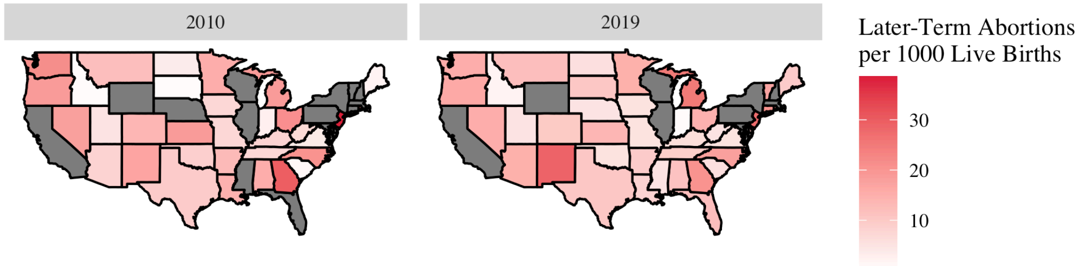


**Figure 3.2.4:** Mapping Later-Term Abortion Rates, 2010 & 2019

The above maps display later-term abortion rates for the first and last years of the studied time frame. Later-term abortions are abortions that occur at or after fourteen weeks of known gestation, and later-term abortion rates are defined as later-term abortions per 1000 live births. States with dark gray shading fail to report at least one of the selected outcome variables.

Later-Term Abortion Rates To address whether undesired spillover occurs in later-term abortions, I examine the count of later-term abortions as a rate of 1000 live births. Figure 3.2.4 displays the geographic distribution of later-term abortion rates for reporting areas. Indiana observed the lowest later-term abortion rate of 0.238 abortions per 1000 live births in 2015, while New Jersey observed the highest later-term abortion rate of about 39 abortions per 1000 live births in 2011.

Earlier-Term Abortion Rates In addition to later-term abortion rates, I also consider how earlier-term abortion rates may change in response to more restrictive policies. Decreases in earlier-term abortion rates and increases in later-term abortion rates could suggest that more restrictive surrounding-state policies led people to carry their pregnancies closer to term.[30] On the other hand, movement of the same direction and magnitude in earlier-term and later-term abortion rates would suggest that surrounding-state policies have no unique impact on the timing of abortions.

Figure 3.2.5 displays the geographic distribution of earlier-term abortion rates for reporting areas. Missouri observed the lowest earlier-term abortion rate of 15 abortions per 1000 live births in 2019, while Rhode Island observed

post-fertilization age estimates [65]. I do not make any further adjustments to the data provided by the CDC.

[30] This delay could result from a logistical obstacle such as long wait times or an emotional barrier that would lead someone to delay the decision to obtain an abortion.

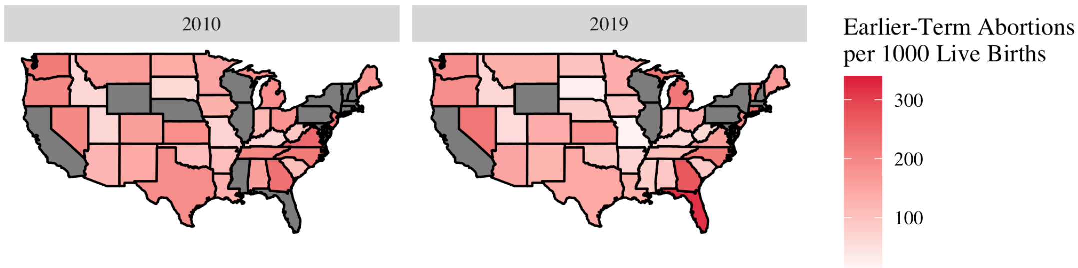


**Figure 3.2.5:** Mapping Earlier-Term Abortion Rates, 2010 & 2019

The above maps display earlier-term abortion rates for the first and last years of the studied time frame. Earlier-term abortions are abortions in a state that occur from zero to thirteen weeks known gestation, and earlier-term abortion rates are defined as earlier-term abortions per 1000 live births. States with dark gray shading fail to report at least one of the selected outcome variables.

the highest earlier-term abortion rate of roughly 348 abortions per 1000 live births in 2011.

Later-Term Share of Abortions While the earlier-term and later-term abortion rates measure abortions as a rate of 1000 live births, the later-term share of abortions captures the relative timing of the abortions that occur within a state. I calculate the later-term share of abortions as the proportion of abortions that occur at fourteen weeks of known gestation or thereafter. Mathematically, the later-term share of abortions may increase even if later-term abortion rates decrease.[31] A significant increase in the later-term share of abortions would indicate that the pro-life lawmakers' efforts disproportionately reduce earlier-term abortions while having a weaker or opposite effect on later-term abortions.

Figure 3.2.6 displays the geographic distribution of the later-term share of abortions for reporting areas. Indiana experienced the lowest later-term share of abortions of 0.0025 in 2013 and 2015. On the other hand, South Dakota observed the highest later-term share of abortions of 0.285 in 2019.[32]

[31] This simultaneous decrease in later-term abortion rates and increase in later-term abortion share would require that earlier-term abortion rates decrease by a larger magnitude than later-term abortion rates.

[32] This relatively large value likely results from having comparatively few total abortions; this proportion of abortions occurring later in pregnancy then appears much larger because a certain number of abortions after the 14-week mark likely resulted from medical necessity.

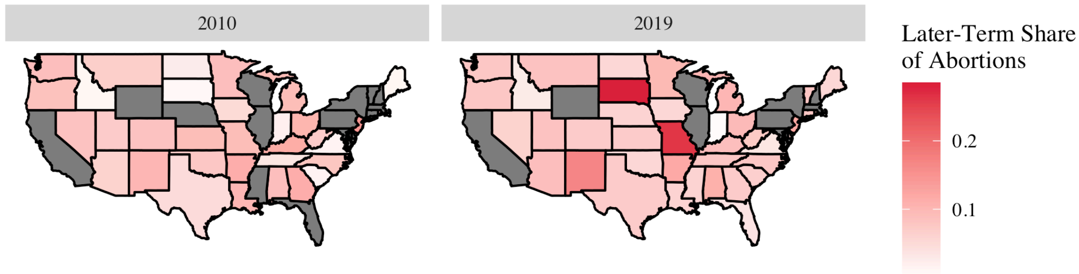


**Figure 3.2.6:** Mapping the Later-Term Share of Abortions, 2010 & 2019

The above maps display the later-term share of abortions for the first and last years of the studied time frame. The later-term share of abortions is defined as the proportion of total abortions that occur at or after fourteen weeks of known gestation. States with dark gray shading fail to report at least one of the selected outcome variables.

## 3.3 Data Limitations

A perfect model of policy spillover would draw from individual-level abortion data from all 48 contiguous states. Unfortunately, states voluntarily report their aggregated abortion counts to the CDC. The aggregated and voluntary nature of the abortion dataset limits my study of abortion spillover.

### CDC Aggregation

This thesis relies on previously collected and aggregated data, and the high level of aggregation in the CDC data limits the granularity of the analysis. For example, the CDC data does not contain the gestational age breakdown of resident and nonresident abortions. As a result, I must consider the gestational timing and resident status of individuals seeking abortions as separate outcomes.

### Voluntary Reporting

The CDC collects data from states on a voluntary basis, which means that states may choose to report none or only some of their abortion data. Consequently, I do not have abortion data for all 48 contiguous states across the studied time frame. For consistency across models, my modeling dataset excludes any state-year observation that fails to report at least one of the six

**Table 3.3.1:** States Missing CDC Data

| State | Years Missing |
|---|---|
| **Missing Some Years** | |
| Connecticut | 6 |
| Delaware | 1 |
| Florida | 7 |
| Maine | 1 |
| Mississippi | 9 |
| Nebraska | 3 |
| Rhode Island | 1 |
| Vermont | 2 |
| Wyoming | 9 |

| State |
|---|
| **Missing Every Year** |
| California |
| Illinois |
| Maryland |
| Massachusetts |
| New Hampshire |
| New York |
| Pennsylvania |
| Wisconsin |

outcome variables.[33] Table 3.3.1 lists states that fail to report data to the CDC for some or all of the years from 2010 to 2019.

Poor reporting of state vital statistics often results in biases, and missing abortion data will likely bias the results of this analysis [20, 57]. The potential for nonreporting bias exists alongside the potential for reporting errors among the states that do report data to the CDC. Among other states, my dataset does not include any observations from California, New York, or Illinois. These states contain the three largest cities in the country, so the dataset fails to capture massive portions of the United States population [25]. Not only that, but the states that fail to report data tend to vote more Democratic, exhibit higher levels of education, have larger Hispanic and non-white shares of the population, and have higher levels of household income, as demonstrated by Table 3.3.2.[34]

Perhaps most relevant to the analysis, nonreporting states tend to have lower levels of within-state and surrounding-state restrictions. Not only will the smaller sample sizes from nonreporting reduce the precision of my analysis, but this bias away from less restrictive policy environments will likely reduce the effect size of spillover in the models.[35]

[33] The Further Discussion of CDC Nonreporting section of Appendix A discusses the decision to exclude observations missing any of the outcome variables from all models.

[34] In Appendix A, I elaborate on patterns in missingness and implications for this analysis in the Further Discussion of CDC Nonreporting section.

[35] This suggestion assumes that states with less restrictive policies present themselves as prime targets for spillover.

**Table 3.3.2:** Two-Sided T-Tests for Differences in Means of Independent Variables

| | CDC Reporting Status | | |
|---|---|---|---|
| | Reporting | Nonreporting | p-value |
| **Policy Scores** | | | |
| Within-State Score | 5.947 | 3.397 | 0.000 |
| Surrounding-State Score | 5.309 | 4.476 | 0.000 |
| **Control Variables** | | | |
| Democratic Vote Share | 0.464 | 0.565 | 0.024 |
| Household Income | 54,879 | 61,809 | 0.001 |
| Bachelors Proportion | 0.319 | 0.378 | 0.000 |
| Hispanic Proportion | 0.114 | 0.148 | 0.000 |
| Non-White Proportion | 0.166 | 0.189 | 0.000 |
| Total Population | 5,278,318 | 11,991,698 | 0.000 |

The Reporting and Nonreporting columns display the mean value of the respective variable for each reporting group. The Model Specification section of Chapter 4 describes the control variables in greater detail.

Missingness only occurs in the outcome variables. Imputing the missing outcomes based on the predictors would not obtain any new information relative to dropping missing outcomes. In fact, imputing the missing outcome variables would only introduce additional uncertainty in my estimates [50]. Because of this, I exclude nonreporting states and acknowledge the limitations when analyzing model results.

# 4
# Methodology

While the previous chapter described the data used to quantify policy spillover, this chapter describes the structure of the models fit with the data. First, I describe the terms included in the model formula. Then, I consider a class of spatial models to account for spatial structure in the outcome variables. Finally, I perform likelihood ratio tests between the spatial and nonspatial models to determine which specification best fits the data.

## 4.1 Model Specification

With the appropriate transformations, I can approximate all six outcome variables as Gaussian distributions, as demonstrated in Figure 4.1.1. This allows for the use of standard linear models rather than their generalized linear counterparts.[1]

[1]Each year has a relatively limited sample size in my dataset, with observation counts ranging from $n = 32$ to $n = 37$. As a result, mixed-effects models present themselves as an attractive option for this analysis since they can control for longitudinal effects while preventing overfitting. Since I can approximate the outcome variables as a Gaussian distribution, I can use the `nlme` package to fit spatial linear mixed-effects models. Current R packages do not allow for spatial *generalized* linear mixed-effects models, but the Gaussian

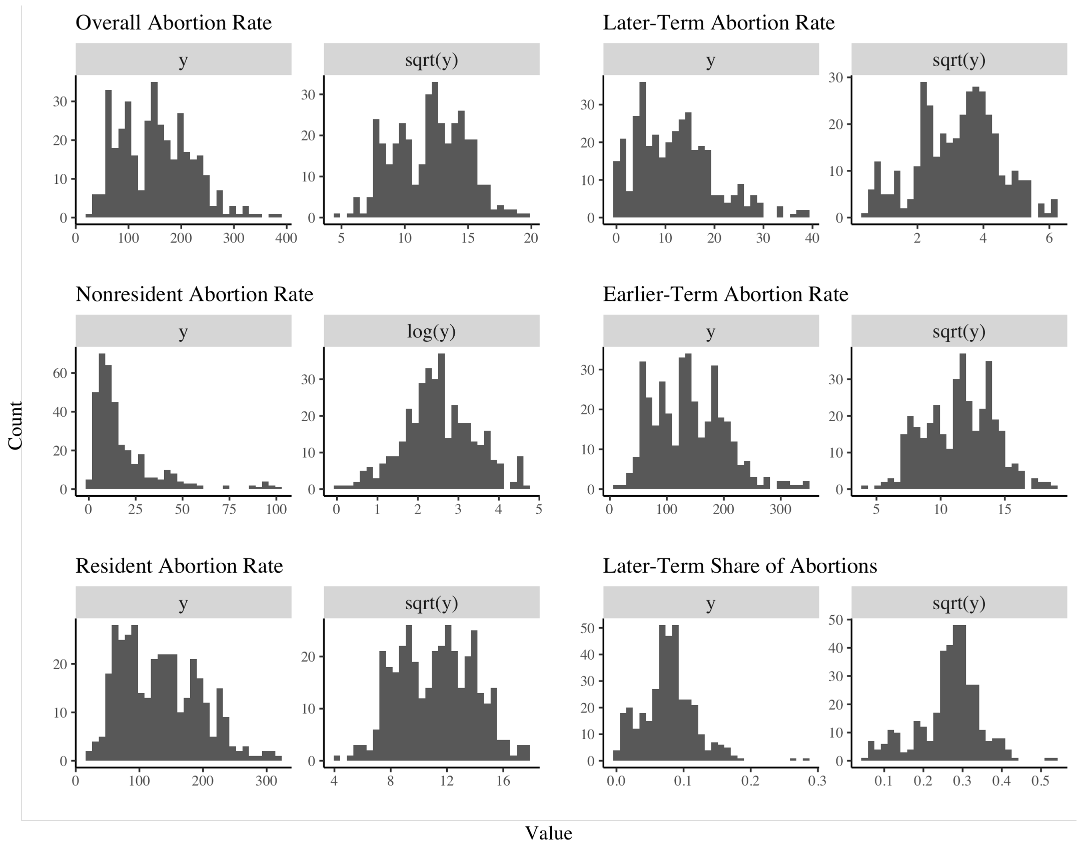


**Figure 4.1.1:** Gaussian-Transformed Outcome Variables

The graphs display the distributions of the outcome variables alongside their respective transformations for Gaussian approximation. The counts on the y-axis correspond to the number of state-year observations. Across all variables, these transformations shifted the center of the distributions to create a more symmetric shape.

Each of the fitted models includes terms for the within-state score, the surrounding-state score, and the interaction between the two policy scores. Substantively, the interaction term measures how abortion spillover varies at different levels of within-state restrictions. By including the main-effects terms and the interaction term, the models capture the individual and combined influence of within-state and surrounding-state policy environments.

To control for possible confounding between abortion outcomes and a state's population, the models include control terms for the proportion of the population with a bachelor's degree, the median household income, the Hispanic proportion of the population, the non-white proportion of the population, the Democratic two-party vote share in the most recent presidential election,[2] and the total population size.[3] In addition to using standardized versions of the policy scores, the models also use standardized versions of the control terms. By standardizing the control terms, I center the values around zero and change the units to standard deviations from the mean value for that year.[4] Lastly, the models include a year-based random intercept term.[5]

Using the framework described above, I fit a spatial and a nonspatial model for each outcome variable. The two models have identical formulas except for the inclusion of a Gaussian correlation structure in the spatial model. The following section motivates and describes this spatial structure in greater detail.

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approximations allow me to bypass the need for generalized linear models.

[2] A state with a moderate but left-leaning electorate will likely have an atmosphere less socially accepting of abortions than a state with a very liberal electorate, even if they have comparable state abortion policies.

[3] I considered an additional control variable for the percentage of counties without an abortion facility. The term did not change the magnitude or direction of the policy coefficients, and a likelihood ratio test of the overall abortion rate models indicated that the additional variable did not significantly improve the fit of the model ($p = 0.26$). As such, I opted for the more parsimonious model.

[4] As described in the Standardizing Policy Scores section of Chapter 3, I perform standardization while grouping the observations by year.

[5] By including random intercepts for the year, a mixed-effects model combats overfitting by shrinking the year-based intercepts toward the mean.

## 4.2 Spatial Structure in Outcomes

Just as unrestricted state borders motivate the study of policy spillover, they also introduce complications not accounted for in standard linear models. The maps of the outcome variables in Figures 3.2.1, 3.2.2, 3.2.3, 3.2.4, 3.2.5, and 3.2.6 reveal that groups of nearby states tend to exhibit similar levels of the measured outcomes.[6] Figure 3.2.1 demonstrates positive correlation in overall abortion rates, with particular regions having similar levels of abortion occurrence. For example, the Southeast and West appear to have relatively high overall abortion rates. On the other hand, Figure 3.2.2 reveals a possible negative correlation between nonresident abortions, with clusters of states like Kansas, Missouri, and Oklahoma exhibiting inverse relationships in their nonresident abortion rates.[7]

While the control variables may capture some of the spatial correlation between states, regional similarities may persist even after accounting for the demographic control variables. To ensure that my selected models control for spatial autocorrelation, I consider standard nonspatial models alongside spatial models that adjust for any remaining spatial structure.

The spatial models supplement the mixed-effects structure described in the Model Specification section with a Gaussian spatial correlation structure. I used the `corGaus` function from the `nlme` package in R to compute spatial weights as an exponentially weighted function of the distances between states.[8] The correlation structure groups observations by year and considers the distance between the two states' population centers as of the 2020 Census [22]. Using $d$ to represent the range and $r$ to represent the distance between two observations, the correlation function calculates the within-group correlation between two observations as $\exp(-(r/d)^2)$ [79].

[6] The Spatial Autocorrelation in Raw Outcome Variables section of Appendix A includes the results of Moran's I-tests for spatial correlation in the raw outcome variables.

[7] This negative correlation signals that people seeking nonresident care in a particular region flock to the same state. For example, Missouri had a more restrictive policy environment than Kansas in 2010, so Missouri residents likely sought abortion care in nearby Kansas when they could not receive care in their home state. In this example, Missouri residents contributed to Kansas's nonresident rate of abortions while Kansas residents have little incentive to travel to Missouri to obtain an abortion.

[8] In the Alternative Spatial Model Specification with `spatialreg` section of Appendix B, I consider models with different spatial weighting schemes. The model coefficients in Tables 5.2.1 and B.3.1 demonstrate robustness to the different spatial weights.

## 4.3 Model Selection

To assess the fit of the spatial versus nonspatial models, I conducted likelihood ratio tests between the two model specifications for each of the six outcome variables. Table 4.3.1 displays the results of the tests.

Across all outcomes, the likelihood ratio tests indicate that the selected covariates control for spatial dependencies. This implies that the Gaussian correlation structure failed to significantly improve the fit of the nonspatial models.[9] Because the spatial and nonspatial models fit the data equally well, Chapter 5 presents the results from the simpler, nonspatial models.

[9]Notice that the AIC, BIC, and log-likelihood change by very similar amounts when switching between spatial and nonspatial specifications for each variable. For example, the rounded AIC values all increase by approximately 2 units when moving from nonspatial to spatial specifications. This results from near-zero estimates of the spatial $\lambda$ parameter fit through maximum-likelihood regression. These near-zero $\lambda$ parameters indicate that the maximum-likelihood models attribute little to no value to the addition of the neighborhood weight matrices. AICs use the formula $AIC = -2\log(L(\theta)) + 2k$, where $L(\theta)$ represents the model's likelihood function and $k$ represents the number of parameters. The addition of the zero-weighted spatial structure yields little to no improvement in the model likelihood, but it introduces one additional parameter, which then increases the AIC values by 2.

**Table 4.3.1:** Likelihood Ratio Tests do not support the use of spatial models.

| | df | AIC | BIC | logLik | Test | p |
|---|---|---|---|---|---|---|
| **Overall Abortion Rate** | | | | | | |
| Nonspatial | 12 | 1504.3 | 1550.9 | -740.2 | | NA |
| Spatial | 13 | 1506.3 | 1556.8 | -740.2 | 1 vs 2 | 1.000 |
| **Nonresident Abortion Rate** | | | | | | |
| Nonspatial | 12 | 856.0 | 902.6 | -416.0 | | NA |
| Spatial | 13 | 858.0 | 908.4 | -416.0 | 1 vs 2 | 0.931 |
| **Resident Abortion Rate** | | | | | | |
| Nonspatial | 12 | 1379.2 | 1425.8 | -677.6 | | NA |
| Spatial | 13 | 1381.2 | 1431.7 | -677.6 | 1 vs 2 | 1.000 |
| **Later-Term Abortion Rate** | | | | | | |
| Nonspatial | 12 | 1030.3 | 1076.8 | -503.1 | | NA |
| Spatial | 13 | 1032.2 | 1082.7 | -503.1 | 1 vs 2 | 0.929 |
| **Earlier-Term Abortion Rate** | | | | | | |
| Nonspatial | 12 | 1487.9 | 1534.5 | -732.0 | | NA |
| Spatial | 13 | 1489.9 | 1540.4 | -732.0 | 1 vs 2 | 1.000 |
| **Later-term Share of Abortions** | | | | | | |
| Nonspatial | 12 | -775.6 | -729.1 | 399.8 | | NA |
| Spatial | 13 | -773.6 | -723.2 | 399.8 | 1 vs 2 | 0.974 |

# 5

# Model Results

This chapter focuses on the relationship between the outcome variables and the policy-related terms in the model. First, I describe the relationship between within-state policies and abortion outcomes when holding the surrounding-state scores at the mean.[1] Second, I describe the relationship between surrounding-state policies and abortion outcomes when holding the within-state scores at the mean. Next, I discuss the combined effect of within-state and surrounding-state scores on abortion outcomes. Then, I provide a quantitative example of how policy changes correspond to changes in the original units of the outcome. Finally, I summarize the results and consider reasons behind the described relationships. The Interpreting Control Terms section of Appendix B discusses the coefficients of the control terms.

Table 5.2.1 displays the coefficients of the fitted models. For the remainder of this thesis, any reference to *significant* findings refers to statistically significant results at the $\alpha = 0.05$ level. I consider both significant and insignificant model estimates in my model interpretations due to the limited

[1]When including an interaction term between two quantitative predictors, each of the main-effects terms hold the other predictor at zero. In this case, a standardized policy score of zero corresponds to the mean.

sample size.[2] In addition, any discussion of spillover *effects* refers to policy spillover in the colloquial sense rather than attempting to make a causal argument. The models include control terms to isolate the relationship between abortion outcomes and within-state and surrounding-state policies. Despite my efforts to preserve the internal validity of this study, missing data and unidentified control variables limit my ability to establish a causal relationship.[3]

## 5.1 Within-State Policies

The main-effects term for the within-state policy scores measures the impact of the within-state policy environment when holding surrounding-state scores constant at the mean. Across all models, the within-state effects of abortion restrictions align with pro-life policymakers' intentions to reduce abortions within their state. The models indicate that more restrictive within-state environments correspond to reductions in all six outcome variables, with significant reductions in resident abortion rates, later-term abortion rates, and the later-term share of abortions.

## 5.2 Surrounding-State Policies

The surrounding-state coefficients capture policy spillover, or the impact of policies beyond their jurisdictions. Since I assume that pro-life policymakers seek to reduce abortions of all types, negative coefficients on the surrounding-score term correspond to desired spillover while positive coefficients correspond to undesired spillover.

[2] An insignificant coefficient means that the model cannot conclude that the outcome and the respective predictor have a non-zero relationship. I interpret insignificant coefficients as plausible relationships between the predictors and outcomes since the limited sample size may reduce the precision of the results and increase the likelihood of insignificant estimates.

[3] The Nonreporting Bias Affecting Model Results section of this chapter discusses threats posed to the internal validity of this study by missing data. In Chapter 6, the New Variables section discusses the inclusion of new control variables for future study. Unobserved variables, including those discussed in Chapter 6, could also limit my ability to draw causal conclusions for the 2010-2019 time frame.

**Table 5.2.1:** Fixed-Effects Coefficients for Linear Mixed-Effects Models of Transformed Outcomes

| Variable | Overall Rates | Nonresident Rates | Resident Rates | Later-Term Rates | Earlier-Term Rates | Later-Term Share |
|---|---|---|---|---|---|---|
| (Intercept) | 12.502* | 2.440* | 11.903* | 3.329* | 11.969* | 0.264* |
| **Policy Environment** | | | | | | |
| Surrounding-State Score | -0.539* | 0.353* | -0.809* | 0.017 | -0.568* | 0.019* |
| Within-State Score | -0.229 | -0.162* | -0.330* | -0.362* | -0.144 | -0.028* |
| Policy Interaction | 0.232* | 0.125* | 0.106 | 0.195* | 0.196 | 0.011* |
| **Control Variables** | | | | | | |
| Democratic Vote Share | 1.366* | 0.160* | 1.317* | 0.296* | 1.311* | -0.002 |
| Household Income | -0.907* | -0.349* | -0.522* | -0.360* | -0.801* | -0.009 |
| Non-White Proportion | 0.379* | 0.188* | 0.095 | 0.338* | 0.233* | 0.017* |
| Hispanic Proportion | 0.706* | 0.135* | 0.732* | 0.257* | 0.646* | 0.005 |
| Bachelors Proportion | 1.170* | 0.584* | 0.621* | 0.449* | 1.052* | 0.009 |
| Total Population | 0.672* | -0.506* | 1.175* | 0.143 | 0.712* | 0.000 |

* $p < 0.05$

Exact p-values are available upon request or by running the code at https://github.com/kayla-manning/state-abortions. Coefficient values correspond to changes in the square-root-transformed outcomes for all variables except for the log-transformed nonresident abortion rates. The Model Illustrations with Synthetic Data section of this chapter describes how policy changes correspond to changes in the original units of the outcomes.

**Table 5.2.2:** Summarizing Policy Intent and Detected Spillover

| Outcome | Assumed Policy Intent | Response to More Restrictive Surroundings |
|---|---|---|
| Overall Rates | Decrease | Decrease* |
| Nonresident Rates | Decrease | Increase* |
| Resident Rates | Decrease | Decrease* |
| Later-Term Rates | Decrease | Increase |
| Earlier-Term Rates | Decrease | Decrease* |
| Later-Term Share | Decrease | Increase* |

* $p < 0.05$
Green rows correspond to desired spillover, where policy outcomes align with policy desires, while red rows correspond to undesired spillover, where policy outcomes contradict policy desires.

The models provide evidence of desired spillover in overall, resident, and earlier-term abortions, but they detect undesired spillover in nonresident and later-term abortions. More specifically, more restrictive surrounding-state environments have the desired effect of significantly reducing the overall, resident, and earlier-term abortion rates in a state. However, these more restrictive surrounding-state policies have the undesired effect of increasing later-term abortion rates and significantly increasing the nonresident abortion rates and the later-term share of abortions in a given state. Later in this chapter, the Considering Mechanisms Behind Model Results section discusses possible roots of these findings. For now, Table 5.2.2 summarizes the spillover effects of surrounding-state environments.

## 5.3 Policy Interactions

The main-effects term for surrounding-state scores describes policy spillover when holding the within-state score constant at the mean, but the policy interaction term considers how spillover changes in response to different within-state environments. An interaction term in the same direction as the surrounding-state coefficient indicates that states with more restrictive in-state policies tend to experience stronger spillover. On the other hand, an

**Table 5.3.1:** Summarizing Detected Spillover and Interaction Effects

| Outcome | Assumed Policy Intent | Surrounding-State Effect | Interaction Effect | Change in Spillover |
|---|---|---|---|---|
| Overall Rates | Decrease | Decrease* | Increase* | Weaken |
| Nonresident Rates | Decrease | Increase* | Increase* | Strengthen |
| Resident Rates | Decrease | Decrease* | Increase | Weakens |
| Later-Term Rates | Decrease | Increase | Increase* | Strengthen |
| Earlier-Term Rates | Decrease | Decrease* | Increase | Weaken |
| Later-Term Share | Decrease | Increase* | Increase* | Strengthen |

* $p < 0.05$

Green rows correspond to desired spillover, where policy outcomes align with policy desires, while red rows correspond to undesired spillover, where policy outcomes contradict policy desires.

interaction term in the opposite direction of the surrounding-state score term indicates that spillover weakens as within-state environments grow more restrictive.

All models have positive interaction terms, and all outcomes have significant interaction effects except for resident and earlier-term abortion rates. This suggests that the undesired increases in the later-term share of abortions and the nonresident and later-term abortion rates grow larger with more restrictive within-state and surrounding-state environments. On the other hand, the models estimate that desired reductions in overall, resident, and earlier-term abortion rates shrink in magnitude in more restrictive environments.[4] Table 5.3.1 summarizes the interaction effects between surrounding-state and within-state policy environments, and Figure 5.4.1 illustrates how surrounding-state effects change at different levels of within-state restrictions.

[4]In the outcomes that demonstrated desired spillover, only overall abortion rates have a significant interaction term.

## 5.4 Model Illustrations with Synthetic Data

The model coefficients displayed in Table 5.2.1 represent changes in the square-root-transformed or log-transformed outcome variables. Ideally, I would interpret the coefficients in terms of their direct impact on abortion rates rather than their impact on the square root of abortion rates. Unfortunately, square-root-transformed outcomes do not allow for the transformation of individual coefficients. However, I can use the model coefficients to generate predictions of the transformed outcomes. Then, I can back-transform the outcomes to their original units. To do this, I utilize a synthetic dataset that varies the within-state and surrounding-state scores.

The synthetic dataset holds all of the standardized, non-policy predictors at their mean value of 0, fixes the year at 2019, and considers policy scores ranging from -1 to 1. While the actual scores fall into the approximate range from -2 to 2, states generally do not observe within-state scores of 2 alongside surrounding-state scores of -2 or vice versa. By restricting the range of these co-occurring scores between -1 and 1, I avoid extrapolating to within-state and surrounding-state pairings not observed in the actual dataset.[5]

Then, I generate predictions with the fitted models under the different policy conditions of the synthetic dataset. I exponentiate the predicted nonresident abortion rates and square all other predicted outcomes to obtain predictions in the original units of the variables.[6] Figure 5.4.1 displays the model predictions from this synthetic dataset.[7]

The different lines in Figure 5.4.1 represent within-state policy environments one standard deviation below the mean, at the mean, and one standard deviation above the mean. Earlier in this chapter, the Within-State Policies and Surrounding-State Policies sections described the effect of one score while holding the other score at the mean value of 0.[8] The results from

[5] For example, West Virginia had approximate within-state scores -1 and 1 across all years in the dataset.

[6] Recall from Figure 4.1.1 that I log-transformed nonresident abortion rates and square-root transformed the remaining outcome variables to approximate Gaussian distributions.

[7] Since I quantify policy spillover with the surrounding-state scores, Figure 5.4.1 displays how the outcomes change in response to different surrounding-state environments. If I wanted to examine the relationship between abortion outcomes and in-state policies, I could have put the within-state score on the x-axis and fit different lines for surrounding-state scores.

[8] When viewing Figure 5.4.1, the slopes of the lines with within-state scores of 0 correspond to the surrounding-state main-effects coefficients, and the gaps between the lines

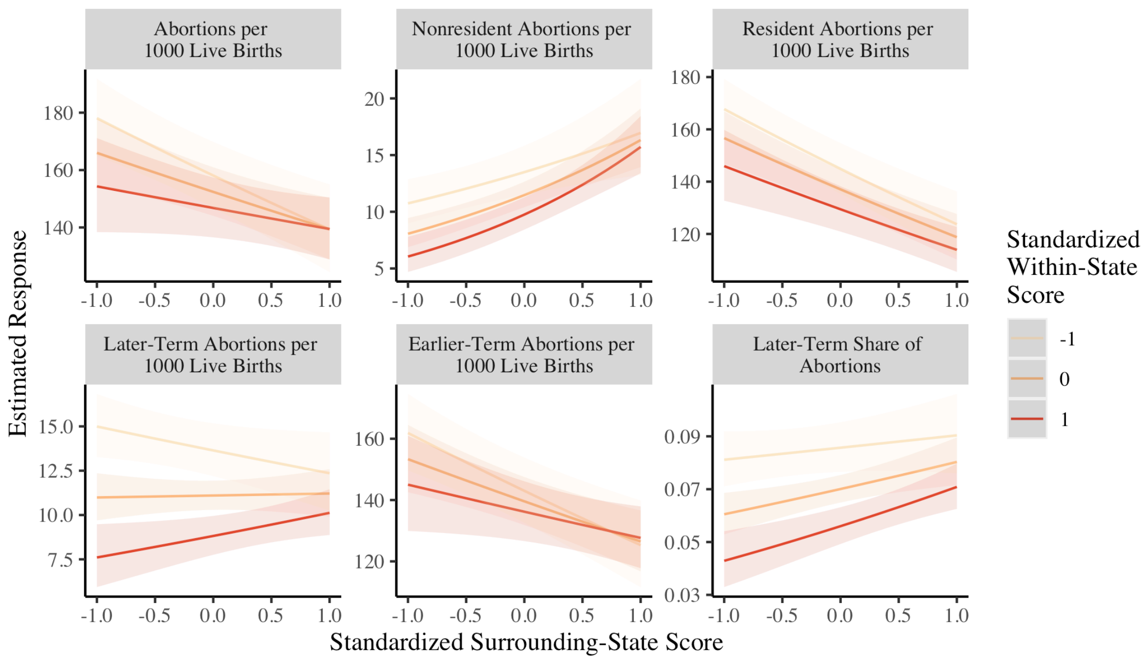


**Figure 5.4.1:** Modeling Outcomes with Synthetic Data

Each y-axis corresponds to the labeled outcome in its original units. The line colors correspond to within-state policy environments at the average level of restriction or one standard deviation above and below the average. For each of these within-state policy environments, the slopes of the lines show the change in the outcome in response to more restrictive surroundings. The shaded bands cover two standard errors above and below the predicted values, and they serve as approximate 95% confidence intervals.

the synthetic dataset illustrate the differential effects of surrounding-state scores in various within-state environments.

At the lowest levels of surrounding-state restrictions, restrictive within-state policy environments correspond to the lowest abortion rates. However, the abortion outcomes of different within-state environments converge at higher levels of surrounding-state restrictions. This demonstrates that within-state environments have a diminishing impact on abortion outcomes as surroundings grow more restrictive.

The slopes represent the effect of changing surrounding-state policy environments while holding the within-state environments constant. Graphically, the positive surrounding-state slopes increase at higher levels of restriction, while the negative surrounding-state slopes flatten at higher levels of restriction. The curvature of the lines in Figure 5.4.1 highlights how desired spillover weakens and undesired spillover strengthens in more restrictive environments.

To quantify policy spillover in terms of abortion counts, consider states with standardized within-state scores of 1, corresponding to the dark red lines in Figure 5.4.1.[9] The overall abortion rate model estimates a reduction of 14 abortions per 1000 lives births when changing the surrounding-state score from one standard deviation below the average for that year to one standard deviation above the average for that year. When considering abortion timing, this corresponds to about 3 more later-term abortions but 17 fewer earlier-term abortions per 1000 births. In terms of residency, this corresponds to about 10 more nonresident abortions but 31 fewer resident abortions per 1000 live births.

## 5.5 Discussion

### 5.5.1 Results

In this thesis, I sought to assess the impact of abortion restrictions beyond their original jurisdictions. The models found that restrictive surrounding-state policies have the desired effect of reducing the overall,

when the surrounding-state scores are 0 represent the within-state main-effects terms.

[9]This takes a different view of the discussion of the surrounding-state main effects in the Surrounding-State Policies section of this chapter. Since that section did not consider the interaction term, the trends discussed in that section apply to the lines that represent within-state scores of 0.

resident, and earlier-term abortion rates beyond state lines. However, these restrictive surroundings have the undesired effect of increasing the nonresident abortion rates, later-term abortion rates, and the later-term share of abortions.[10] Because state abortion restrictions lead to an increase in certain types of abortions in other states, these undesired spillover effects contradict the intent of pro-life lawmakers who wish to reduce abortions of all types. In stricter within-state and surrounding-state environments, the desired spillover effects weaken while the undesired spillover effects strengthen.

### 5.5.2 Considering Mechanisms Behind Model Results

By considering the rates of different types of abortions, the models reveal that decreases in resident and earlier-term abortions drive the desired spillover in overall abortion rates. These desired spillover effects in resident and earlier-term abortion rates are larger in magnitude than the undesired spillover effects in nonresident and later-term abortions, which means that overall abortion rates decrease in response to more restrictive surroundings.

In the following sections, I discuss four possible explanations for the observed spillover trends. The first section describes the actual occurrence of desired spillover, and the following three sections describe ways in which the models may incorrectly identify desired spillover. First, I consider how external pressure from more restrictive surroundings may lead to desired spillover. Then, I consider how the CDC dataset may underrepresent abortion counts by not including self-managed abortions. Next, I consider how missing abortion data may bias the undesired spillover results toward zero. Finally, I describe how my chosen outcomes and treatment variables contribute to the asymmetric changes in resident and nonresident abortions, and I discuss alternative specifications for future models.

**External Pressures Discouraging Abortions** The most straightforward explanation of the desired spillover in resident and earlier-term abortions is that, even if surrounding-state laws do not have legal power outside of their jurisdictions, restrictive surroundings create an environment that discourages abortions.

[10] The estimated increase in later-term abortion rates is not statistically significant.

More restrictive surroundings could discourage individuals from seeking abortion care by instilling subconscious fears of judgment or inflaming overt anti-abortion sentiments in the population. For example, if Missouri pro-life activists learn that residents of their state have been seeking care in Kansas clinics, they may travel to Kansas to protest the procedure in neighboring states. In addition, more restrictive surrounding-state environments may trigger pro-life Kansas residents to take a more active stand against the procedure in their home state. Even if people still wish to obtain an abortion in the face of more restrictive policy environments, abortion clinic closures resulting from anticipated policy changes or losses of revenue could also discourage people from seeking abortion care.

This reduction in abortions would contribute toward the observed desired spillover, and it would align well with the spoken goals of Texas lawmakers. In an interview for this thesis, Texas State Representative Brad Buckley described his hope to create "a culture of life in our society" that will change the "hearts and minds of people" so that "they'll decide [to no longer seek abortion]" [21]. Similar to the remarks of Representative Buckley, Texas Governor Greg Abbott has publicly cited SB 8's ability to save "the life of every unborn child with a heartbeat from the ravages of abortion" [85]. Even though the models revealed that more restrictive surroundings increase nonresident and later-share abortion rates, the desired spillover in overall, resident, and earlier-term rates could point toward this "culture of life" that Buckley described.

Self-Managed Abortions Outside the CDC's Periphery While more restrictive surroundings could discourage abortions, they might instead encourage people to seek resident or earlier-term abortions outside of the CDC's purview. The CDC data tracks legal induced abortions, but they cannot track abortions that occur outside of traditional medical settings. Individuals can self-manage their abortions by receiving misoprostol prescriptions for non-abortifacient purposes, seeking medication or surgical abortion in Mexico, or ordering abortion pills from Europe and elsewhere [56].[11] The Model Adjustments for Future Study section of Chapter 6 discusses how improved models could consider factors related to

[11] The Increasing Importance of Mexico and Turning to Abortion Pills sections in Appendix C describe details relating to Mexico and medication abortions at greater length.

self-managed abortions, but for now I focus on how self-managed abortions may impact the existing results.

To understand how self-administered abortions may reduce resident and earlier-term abortions in the CDC data, consider abortion pills. The two-drug, FDA-approved protocol enables people to terminate a pregnancy up to 10 weeks of known gestation.[12] Early in pregnancy, self-managing a medication abortion provides a quick and easy alternative to receiving care in a clinic. Individuals may obtain both pills in the two-drug protocol from overseas pharmacies without a prescription, or they can obtain misoprostol prescriptions in the United States for non-abortion purposes.[13] Because people can safely terminate their pregnancies via medication abortion up to 10 weeks of known gestation, the timing of medication abortions aligns with the reduction in earlier-term abortion rates. In addition to time-related factors, the convenience of self-managed abortions could contribute to the large reduction of resident abortions. If residents believe that nonresidents from surrounding states are filling clinics, they may opt to self-manage their abortions to avoid the inconvenience of seeking care in a clinical setting.

Studies indicate relatively widespread interest in self-managed abortions over the study period from 2010 to 2019. Between 2011 and 2017, Google searches for terms related to self-managed abortion surged from 119,000 to 700,000 [94]. Moreover, Women on Web documented 6,022 specific requests for self-managed medication abortion over a 10-month period between 2017 and 2018 [56].[14] While individuals demonstrate online interest in self-managed abortions, widespread interest may not translate to widespread action. In interviews of 32 individuals who sought out abortion pills online,

[12] Under the current protocol, individuals first take mifepristone, which blocks progesterone and makes the uterus unable to support a pregnancy. Then, 24 to 48 hours after taking mifepristone, an individual will take misoprostol, which causes the uterus to contract and expel the pregnancy. The Food and Drug Administration (FDA) approved mifepristone in 2000 and the current two-drug protocol in 2016. Both drugs in the current protocol require a prescription from a certified healthcare provider, though individuals may obtain misoprostol for purposes other than abortion and then attempt to self-manage an abortion [56].

[13] Aid Access, founded in 2018, allows users to order abortion pills from overseas pharmacies, even in states with abortion bans [3]. While Aid Access connects people to overseas pharmacies, people could have ordered abortion pills directly from these pharmacies before 2018.

[14] Women on Web is a website that facilitates access to contraception and safe abortion services. These requests appear tied to restrictive policy environments, with residents of states with the most restrictive abortion policies making these requests at the greatest rates [56].

researchers at the University of Texas found that none of them purchased pills and most sought out clinical abortion care instead [4]. In a 2017 survey of US women, only 1.4% of respondents reported attempting to end a pregnancy on their own, and only 28% of those individuals successfully ended their pregnancy [43].

Nonreporting Bias Affecting Model Results  As described in the in the Voluntary Reporting section of Chapter 2, some of the least restrictive states fail to report abortion data to the CDC.[15] States with low levels of in-state restrictions serve as prime locations for policy spillover since they have few limitations on abortions relative to their surroundings.[16] The exclusion of several of the least restrictive states likely biases the coefficient estimates toward zero.[17] This bias may explain why the models estimate insignificant spillover effects in later-term abortion rates. Moreover, the model results may not reflect the nationwide spillover trends since the dataset excludes several states that systematically differ from the rest of the country.[18]

Exporting Resident Abortions to Other States  The previous three sections unpack the model results through factors outside of the model's control: why desired spillover might actually occur, how the data might underrepresent abortions, and why nonreporting might lead the models to underestimate spillover effects. This final section describes how my selected variables contribute to the different magnitudes of the desired and undesired spillover results.

The current models reveal that restrictive surroundings lead to reductions in resident abortions, but the models do not track if these restrictive

[15] I also discuss nonreporting in the Further Discussion of CDC Nonreporting section of Appendix A.

[16] For example, Illinois fails to report gestational age data for all years in the time frame. As demonstrated in Figure 3.1.3, the state has relatively low levels of within-state restrictions but very high levels of surrounding-state restrictions. The same applies to California and New York.

[17] The Voluntary Reporting section of Chapter 2 considers the possibility of imputing the abortion metrics for these states. I opted not to impute the missing abortion data because the missingness is only in the outcome variable. If I imputed the data using the existing predictors, the models would not uncover any different trends from the existing models, but the imputed data points would increase the uncertainty of the model estimates.

[18] In addition, patterns in nonreporting may change in response to the drastic policy changes discussed in Chapter 6.

surroundings encourage residents to seek abortion care outside of their home region. In other words, the models do not track the number of resident abortions "exported" to other states.

As an illustrative example, consider the state of Oklahoma. The current models predict that more restrictive surroundings in states like Texas and Arkansas would result in fewer resident and earlier-term abortions in Oklahoma. However, the models say nothing about how many Oklahoma residents would leave Oklahoma to seek abortion care in more distant states like Colorado, Illinois, or New Mexico. More restrictive surroundings could motivate Oklahomans to seek out-of-state abortion care for several reasons. For one, Oklahomans may fear possible crowds of nonresidents seeking care in Oklahoma. In addition, increasingly restrictive surroundings could invigorate anti-abortion sentiments within the state of Oklahoma, as described in the External Pressures Discouraging Abortions section.

According to the current models, more restrictive surroundings result in larger decreases in resident abortion rates than nonresident abortion rates. The current model specification may inflate this actual effect. When residents seek care in other states, the resident rate model reflects the loss of all resident abortions from a state-year observation. However, each state-year observation in the nonresident model only absorbs a fraction of exported abortions from each state. Continuing with Oklahoma, the resident model would detect the loss of all Oklahomans who seek abortion care in states like Colorado, Illinois, Kansas, and more. However, each of these states would only absorb a fraction of Oklahomans in the nonresident model.

In theory, each state would absorb a fraction of exported abortions from several states. If this were the case, the aggregate effect of exported abortions would balance out between the resident and nonresident models. However, very few states had highly restrictive policies from 2010 to 2019 when compared to the present, which means fewer states exported abortions on a large scale. As a result, many states likely shared the burden of the exported abortions from a relatively small number of states.[19] This shared burden would inflate the effect size in the resident model relative to the nonresident model. Future iterations of this analysis should consider if the reductions in resident abortions result from exported abortions or true

[19] The states with the least restrictive policies likely absorbed the most abortions. However, many of these states fail to report data to the CDC, so I cannot test this hypothesis.

reductions in abortions.

More broadly, future studies of abortion spillover should expand the definition and direction of spillover. The current models measure how surrounding-state restrictions from many states spill into one state. Future work could also consider how the within-state restrictions of one state spill out to surrounding states.

# 6

# Importance of Policy Spillover in a Post-Dobbs World

Seven months into this thesis, the Supreme Court overturned Roe v. Wade and thus removed constitutional protections of abortions.[1] In the Dobbs v. Jackson Women's Health Organization ruling, the Supreme Court granted states the ability to ban abortions.[2] The ruling created a national policy landscape characterized by extremes: more restrictive states banned or severely limited abortion access, while less restrictive states protected the right to the procedure.[3]

Abortion spillover will grow more relevant as policy variation increases in the aftermath of Dobbs. From 2010 to 2019, this thesis found significant undesired spillover in the nonresident and later-term share of abortions for the years.[4] Under the post-Dobbs policy landscape, these findings raise questions about the future of undesired spillover.

[1] Roe v. Wade, 410 U.S. 113 (1973)

[2] Dobbs v. Jackson Women's Health Organization, 597 U.S. ____ (2022)

[3] The policy landscape of the nation remains in flux as court battles determine the legality of state and federal restrictions and protections for years to come.

[4] In addition, the model detected insignificant increases in the later-term abortion rate.

In the first section of this chapter, I provide an overview of the changes to the policy landscape after the Dobbs ruling. Then, I discuss how I would adjust my existing models to study abortion spillover in the post-Dobbs era. Next, I describe weaknesses introduced by Dobbs that pose difficulties for any models of spillover. Finally, I conclude with a discussion of the importance of abortion spillover in the past and present.

## 6.1 Changing Policy Landscape

### 6.1.1 State Actions

In May 2022, a month prior to the Dobbs ruling, thirteen states had trigger bans in place, or laws pre-emptively designed to prohibit or severely limit abortion if the Court overturned Roe. At least eight states banned abortions on the day of the June 24 ruling, while several other states had bans set to take effect after a set time period following the decision. In addition to states with trigger bans in place, other states had pre-Roe abortion bans that automatically went into effect after the Dobbs ruling. Indiana became the first state to pass a ban after the ruling, but the state supreme court blocked the ban shortly after it went into effect [62].[5] As of September 23, 2022, at least fourteen states banned abortions in almost all cases, while an additional nine states had abortion bans blocked by courts [98].

While many states pre-emptively or quickly banned abortion, many other states protected the procedure through legislation or court decisions [62]. As of August 2022, Colorado, New Jersey, Oregon, Vermont, and Washington DC protected the procedure over the entire course of pregnancy without state interference; in total, twenty states and DC will likely continue to protect the availability and legality of abortion [49]. In August 2022, Kansas voters directly voted to protect the right to abortion in their state by rejecting a proposed state constitutional amendment that would have eliminated the right to abortion within the state [70].[6] Figure 6.1.1 displays the national policy landscape as of October 1, 2022.

[5] Later in this chapter, the Policy Uncertainty and Volatility section discusses the sequence of events in Indiana in further detail.

[6] The Appendix C section titled The Kansas Vote, the Thermostatic Nature of Public Opinion, and the 2022 Midterms includes further discussion about the general dynamics of public opinion and what that may mean for abortions in the near-term future.

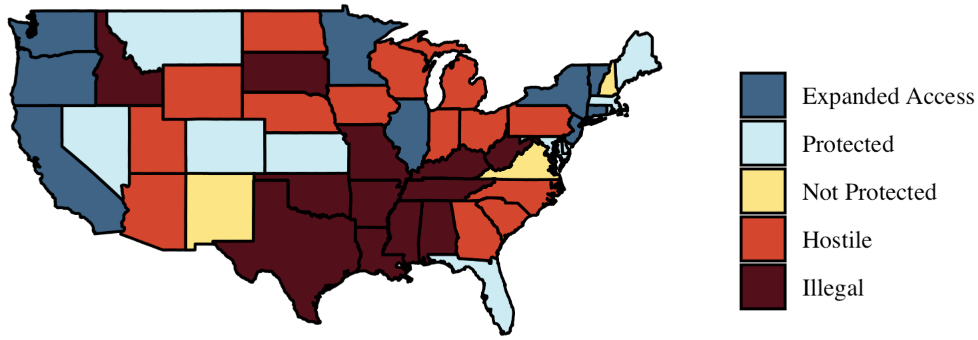


**Figure 6.1.1:** State Abortion Policies as of October 1, 2022 [37]

### 6.1.2 Federal Actions

In response to heightened state-level restrictions, pro-choice actors in the federal government have attempted to protect abortion access. Two weeks after the Dobbs ruling, President Biden signed the Executive Order Protecting Access to Reproductive Health Care Services. The executive order directed the Department of Health and Human Services, the White House Gender Policy Council, and other federal bodies to protect abortion access, safeguard the privacy of patients, promote the safety and security of patients and providers, and coordinate the implementation of these protections [48].

While President Biden's executive order emphasized his administration's support for abortion protections, Congress must restore the protections of Roe as federal law to guarantee the right to abortion. The House has made several attempts to protect abortion access, but the evenly split Senate has blocked these protections from going into law [86]. In one attempt to protect the procedure, the House passed the Women's Health Protection Act of 2022, which prohibited states from limiting abortions or making them more difficult or costly to obtain [59]. In addition, the House passed the Ensuring Access to Abortion Act, which prohibited states from criminalizing out-of-state abortions in places that allow the procedure, and it explicitly protected medication abortions by citing that states cannot prohibit the interstate commerce of FDA-approved drugs [32].[7] As legal protections for

[7] In recent months, state legislatures have attempted to mitigate interstate travel for abortions by criminalizing residents who attempt to obtain an out-of-state abortion elsewhere [61]. No state has successfully banned its citizens from obtaining an out-of-state abortion as of August 2022, but Texas's SB 8 takes an approach that could serve the same purpose. This legislation, passed pre-Dobbs and made into law in September 2021, allows

out-of-state abortions remain contested in courts and legislatures, private employers have worked to minimize the financial and travel-related barriers faced by employees seeking out-of-state abortions.[8]

Even without federal protections in place, federal agencies may try to circumvent state restrictions. In September 2022, the Department of Veterans Affairs (VA) announced that they will provide abortion services to beneficiaries whose lives or health lie in danger. This announcement marked the first time in the VA's history that they will provide abortion services, and they said they will provide the service in all states, irrespective of bans in place. The VA claims their federal status allows them to offer the service despite state restrictions [45]. In a similar vein, Attorney General Merrick Garland and President Joe Biden have cited the FDA's approval of mifepristone to argue that states may not ban the drug for use in medication abortions [31, 48].[9] Realistically, legal experts say that litigation will have to determine whether federal law preempts state law on the issue.[10]

## 6.2 Model Adjustments for Future Study

Any model forecasts based on the current policies would assume that previous patterns in the data generalize to the future. However, the reversal of a 49-year-old precedent creates a policy landscape unlike anything experienced by this generation.[11] That said, this thesis provides a foundation for a post-Dobbs analysis of abortion spillover. Changes to the abortion

private citizens to enforce abortion restrictions by bringing civil lawsuits against individuals who aid or abet an abortion. If strongly enforced, this type of legislation would likely prevent the occurrence of policy spillover since residents can no longer seek abortions in less restrictive states. Already, the Texas style of legislation has introduced ambiguity in the legality of abortion funds and employer policies that cover out-of-state travel for an abortion [68]. If other states follow Texas's lead, this vigilante-style policy could serve the same purpose as a ban on out-of-state abortions.

[8] As of August 2022, 35% of employers – including names such as Amazon, Target, and Walt Disney – offer benefits to cover abortion-related travel and lodging [39, 87].

[9] Misoprostol, the second drug in the two-pill protocol, also treats stomach ulcers and is still available in states with abortion bans.

[10] GenBioPro, the maker of mifepristone, challenged restrictions against medical abortion in a 2020 federal lawsuit. Currently underway, the case will likely determine whether states can ban the FDA-approved drug [92].

[11] For example, the significant model interaction terms suggest that undesired spillover worsens as policy landscapes grows more restrictive. Now, policies can grow so restrictive that states ban abortion altogether, and states that do not perform abortions cannot experience legal abortion spillover. While future models could account for abortion bans, my current models cannot accurately determine how outcomes might change.

access landscape will naturally impact the utility of the models presented in this analysis, so the following sections outline several considerations and adjustments for a post-Dobbs analysis.

Changing Spatial Structure Though the model selection process did not deem spatial models necessary for the time frame from 2010 to 2019, future models should consider potential changes to the spatial structure. Pre-Dobbs research estimated that the average driving distance for women in states without any abortion clinics would likely increase from 35 miles to 280 miles if the Supreme Court overturned Roe v. Wade [85]. With entire clusters of states in the South and Midwest banning or heavily restricting abortions following the Dobbs decision, individuals from certain regions will have to travel much further to receive care.

Individuals seeking abortion care will have to weigh increased travel distance against increased travel costs. Flights, hotels, rental cars, gas, and other potential expenses incurred by obtaining an out-of-state abortion have all risen dramatically over the past couple of years [84]. Though private corporations have begun to offer abortion travel reimbursement for employees, more time must pass before the data reflects the impact of increased travel distances and costs on the spatial structure of abortion outcomes [39, 87].

Updating Policy Scoring System Future models will also have to adopt a new policy scoring system to match the post-Dobbs policy environment. This updated scoring system would need to extend to much higher levels of restrictions, and it should have a separate level of coding for abortion bans.

The current scoring system assigns points based on the existing restrictions in the 2010-2019 dataset, with the maximum level of restriction for each policy receiving 1 point. However, policies have grown increasingly restrictive since 2019, and a new scoring system would need to account for higher levels of restriction. Even before the Dobbs ruling, states tested the limits of Roe v. Wade's protections beyond the levels observed in the 2010-2019 policy dataset, and these experimental policies would require adjustments to the scoring mechanism. For example, Texas's SB 8 went into law in September 2021 and banned abortions after 6 weeks. Though not as drastic as a total abortion ban, this type of restriction falls much earlier in pregnancy than the earliest abortion ban of 20 weeks in the 2010-2019 dataset.[12] Without constitutional protections for abortions, states will only continue to exceed previously observed levels of restrictions.

In addition to accounting for higher levels of restrictions, an updated scoring system must devise a separate level of coding for abortion bans. The existing scoring system sums points across fifteen different policies. When a state places an outright ban on the procedure, however, they no longer need parental notification laws, waiting periods, or other abortion-related restrictions.

New Variables Finally, the Dobbs ruling introduced several factors that will likely play an increasingly important role in abortion services moving forward. For example, the current model does not consider the distinction between surgical or medical abortion, nor does it clearly define variables for a state's proximity to Mexico or its social stigma surrounding abortion. These variables and others, such as the use and availability of contraception, may have an increasingly powerful effect on the outcome variables in a post-Dobbs world.[13]

## 6.3 Model Weaknesses Exacerbated by Dobbs

While I could adjust future models for the factors described above, the Dobbs ruling also introduced weaknesses beyond my control. The following sections discuss three model weaknesses introduced by Dobbs. First, I discuss how the increasing importance of "safe states" exacerbates issues arising from data missingness. Next, I describe how the rapidly changing policy landscape does not allow for stable predictions. Then, I close with a discussion of how the increased incentives to engage in self-managed abortions may cause more abortions to occur outside of the CDC's purview.

[12] Moreover, the vigilante-style law introduced a new type of abortion policy and enabled private citizens to sue anyone who helps to facilitate an abortion. The existing scoring system does not account for policies like this because they did not exist during the studied time frame. So, while Dobbs introduced additional flaws in the scoring mechanism, making quantitative predictions based on the policy environments observed from 2019 to 2022 would extrapolate beyond the policies used to fit the models.

[13] The sections titled Turning to Abortion Pills and Increasing Importance of Mexico in Appendix C discuss abortion pills and the importance of Mexico at greater lengths.

New Importance of "Safe" States As many states severely restrict abortion access, the post-Dobbs policy environment places a greater emphasis on new "safe" states. This increased emphasis on states with abortion protections highlights the gap created by nonreporting from some of the least restrictive states in the CDC dataset.[14]

For example, states like New Mexico and Kansas will take on new levels of prominence as places that offer abortion services. While the previous models include data from New Mexico and Kansas across all years in the time frame, abortion bans in neighboring states will likely direct larger patient populations to these states in the post-Dobbs landscape.[15] New Mexico now serves as Texas' only contiguous neighbor to allow the procedure,[16] and Kansas now serves as an access point for patients seeking abortion care in the Southeast and Midwest [70].[17]

Not only will new states take on roles as abortion access points, but states like California and New York – which already had low levels of restriction but were not included in this analysis due to nonreporting – will likely bear an even greater load of abortion spillover.[18] In September 2022, California Governor Gavin Newsom's midterm reelection campaign launched billboards in states like Texas, Oklahoma, South Dakota, Mississippi, and more to explain how individuals may access abortion care. For example, a billboard in Austin, TX has the tagline "Need an Abortion? California is Ready to Help." and directs readers to visit California's official abortion website, which contains information about the laws protecting abortion in the state and the

[14] See for a more in-depth description of nonreporting states.

[15] For example, the dataset never observed a time in which New Mexico served as Texas' sole contiguous neighbor to allow the procedure. In fact, the dataset concludes before Texas enacted its six-week abortion ban, so both New Mexico and Oklahoma took on a much greater level of importance between 2020 and the first half of 2022.

[16] Oklahoma and New Mexico absorbed many of the Texas individuals seeking abortions following the state's six-week abortion ban [103]. However, a trigger law banned abortions in Oklahoma after the Dobbs ruling; as a result, New Mexico will have to absorb an even greater amount of traffic from Texas, Oklahoma, and other surrounding states [97].

[17] In August 2022, a state referendum solidified abortion access in its state constitution. Recall from the Nonresident Abortion Rates section in Chapter 3 that Kansas already had the highest observed nonresident abortion rate in the dataset. The August 2022 vote in Kansas will likely place an even greater strain on its resources. The Kansas Vote, the Thermostatic Nature of Public Opinion, and the 2022 Midterms section in Appendix C discusses the Kansas vote at greater length in the context of public opinion dynamics in the country.

[18] This statement assumes that the trends detected by the models apply to California and New York.

logistics and financial costs of traveling to California for the procedure [42].

Policy Uncertainty and Volatility  With states and courts struggling to navigate the new policy environment, the Dobbs ruling created much more volatility in the policy landscape. Since policies can change overnight, model predictions and inferences will remain unstable for as long as policies remain in flux. For example, the state of Indiana did not have a trigger ban in place before the Dobbs ruling, but the state passed the first post-Dobbs abortion ban in early August 2022. One week after the law went into effect in September 2022, an Indiana judge blocked the law and restored abortion rights in the state [34]. Indiana is the only state to have switched from legal to illegal to legal abortions in the post-Dobbs era. However, reproductive rights activists and organizations have filed numerous lawsuits to challenge state abortion bans, which could lead to similar reversals of bans [47].

Turning to Self-Managed Abortions  As abortion clinics close in states with abortion bans, self-managed abortions will likely rise in popularity in the post-Dobbs world.[19] Following the Dobbs ruling, organizations that provide abortion pills from overseas pharmacies have expanded their networks in the United States. Aid Access, Las Libres, and other organizations offer abortion pills to Americans seeking to terminate their pregnancies, regardless of the legality of the procedure in their home state [16]. For individuals in areas with highly restrictive policies, the relative ease of self-managing abortions may encourage more abortions to occur outside of traditional clinical settings.

## 6.4 What Does This Mean for Policy Spillover?

While policy spillover posed issues in the pre-Dobbs world, the Dobbs ruling made this thesis even more relevant. For the years from 2010 to 2019, the models detected desired spillover in overall, resident, and earlier-term abortion rates, but they found undesired spillover in nonresident abortion rates, later-term abortion rates, and the later-term share of abortions.[20] As

[19] The Self-Managed Abortions Outside the CDC's Periphery section of Chapter 5 discussed the possibility of self-managed abortions in the 2010 to 2019 time frame.

[20] The estimated increase in later-term abortion rates is not statistically significant.

within-state and surrounding-state grew more restrictive, the model interaction terms revealed that desired spillover weakened while undesired spillover strengthened.

With the advent of abortion bans, the number of states allowing abortions will decrease while the demand for the service will likely remain the same. Several states will find themselves serving much larger patient populations than in a pre-Dobbs world [72].[21] States expecting new patient populations may try to mitigate the impact of undesired spillover, but these measures may not offset the surges in demand.[22] With a lower supply of abortion providers but a steady demand for the procedure, pre-existing undesired policy spillover could grow in magnitude as resources face further constraints.

[21]For example, the Kansas vote raises questions about the state's capacity to withstand the demand from nearby states with abortion bans. As of August 2022, only four Kansas clinics perform abortions, with all clinics located in the Wichita and Kansas City areas. This limits provider coverage to the southern and eastern regions of the state. Both Oklahoma and Missouri – which border Kansas to the south and east, respectively – have abortion bans in the wake of the Dobbs ruling [97, 101].

[22]For example, Illinois has prepared for an influx of patients from the Midwest and South by extending clinic hours, increasing staffing, and opening two new clinics opened in the wake of Dobbs [72]. These steps aim to combat the undesired spillover of later-term abortions but not the undesired spillover of nonresident abortions. Clinics are bracing themselves as they prepare to care for their existing resident populations in addition to the nonresidents coming as a result of undesired spillover.

# A

# Extended Exploratory Data Analysis

## A.1 Policy Data

### A.1.1 Scraping from the Internet Archive

The Guttmacher Institute has reconfigured its website over the years, so each of the archived state policy pages has slightly different formats. From 2017 to 2022, the Guttmacher webpages displayed the state policy landscape as HTML tables, which enabled me to scrape the data with the R package `rvest`. The Guttmacher Institute posted the pre-2017 state policies as embedded PDFs, which required the use of the `tabulizer` package in R to convert the PDF tables into dataframes.

Unfortunately, `tabulizer` read the entire table as a single column with no standard separator between values. As a result, I could not determine which entries corresponded to which column when reading in the entire tables at once. As a solution, I read the individual columns into R as separate dataframes. Then, I bound the single-column dataframes together into a single dataframe. To iterate through each column, I hard-coded a dataframe of coordinates for each corner of each column in the Guttmacher PDFs. Then, I referred to the appropriate coordinates when running the

**Table A.1.1:** Earliest Available Policy Data for Each Calendar Year

| Year | Policy Date |
|---|---|
| 2010 | April 1 |
| 2011 | January 1 |
| 2012 | January 1 |
| 2013 | January 1 |
| 2014 | February 1 |
| 2015 | January 1 |
| 2016 | January 1 |
| 2017 | February 1 |
| 2018 | January 1 |
| 2019 | January 1 |

`extract_tables` function on each of the columns.

### A.1.2 Inconsistent Policy Start Dates

The timing of policies in the dataset depends on when the Internet Archive scraped the Guttmacher Institute's state policy webpage. Because the Internet Archive does not visit the webpage on a regimented schedule, not all years have policies as of January 1 of that year. For consistency, I use policy data from the earliest available date in each calendar year from 2010 to 2019.[1]

### A.1.3 Policy Types and Levels

Table A.1.2 describes each of the fifteen policies included in the policy dataset. The dataset describes the level of restriction across fifteen abortion-related policies for each year in the time frame, and my scoring system assigned points based on the relative restrictiveness of each policy. Table A.1.3 displays the points awarded to the different levels of each policy in the dataset.

[1] Policy scores aggregate data across fifteen different policies, so a state's overall policy score should not change drastically in one to three months. The analysis included in the Visualizing Policies with Tercile-Based Categories section of Appendix A found that 26 states appeared in the same tercile-based category from 2010 to 2019. This indicates that a one-to-three-month delay in policy data collection will have negligible if any impact on the results of this analysis. Large-scale changes in a policy environment – if they occur at all – generally occur over an extended time frame.

**Table A.1.2:** Guttmacher Policy Variables and Meaning

| Variable | Description |
|---|---|
| fund_all_most | Public funding for all or most medically necessary abortions |
| fund_life_rape_incest | Public funding limited to life endangerment, rape, and incest |
| hospital_if | Must be performed in a hospital at [gestational age] |
| hr_wait_post_counseling | Waiting period (in hours) after counseling |
| indiv_prov_refuse | Individual providers may refuse to participate |
| instit_prov_refuse | Institutional providers may refuse to participate |
| licensed_physician | Must be performed by a licensed physician |
| mandate_breast_cancer | Mandated counseling includes information on breast cancer link |
| mandate_fetal_pain | Mandated counseling includes information on fetal pain |
| mandate_neg_psych | Mandated counseling includes information on negative psychological effects |
| parental_involv_minors | Parental involvement required for minors |
| partial_birth_ban | "Partial-birth" abortion banned |
| priv_insurance_limit | Private insurance coverage limited |
| prohibited_except_death_if | Prohibited in cases of life or health endangerment if at [gestational age] |
| second_physician_if | Second physician must participate if at [gestational age] |

**Table A.1.3:** Points Allotted to Each Policy Level

| Level | Points |
|---|---|
| **licensed_physician** | |
| X | 1.00 |
| **hospital_if** | |
| 12 weeks | 1.00 |
| 90 days | 1.00 |
| 14 weeks | 0.75 |
| 2nd trimester | 0.75 |
| Viability | 0.50 |
| 20 weeks | 0.50 |
| 24 weeks | 0.50 |
| 3rd trimester | 0.25 |
| **second_physician_if** | |
| 12 weeks | 1.00 |
| 20 weeks | 0.67 |
| Viability | 0.67 |
| 24 weeks | 0.67 |
| 3rd trimester | 0.333 |
| **partial_birth_ban** | |
| X | 1.00 |
| Entire Pregnancy | 1.00 |
| Postviability | 0.50 |
| **fund_all_most** | |
| X | -1.00 |
| **priv_insurance_limit** | |
| X | 1.00 |
| **fund_life_rape_incest** | |
| Life Only | 1.00 |
| X | 0.50 |

| Level | Points |
|---|---|
| **prohibited_except_death_if** | |
| 20 weeks | 1.00 |
| Viability | 0.67 |
| 24 weeks | 0.67 |
| 3rd trimester | 0.333 |
| **indiv_prov_refuse** | |
| X | 1.00 |
| **instit_prov_refuse** | |
| X | 1.00 |
| Private | 0.67 |
| Religious | 0.333 |
| **mandate_breast_cancer** | |
| X | 1.00 |
| **mandate_fetal_pain** | |
| X | 1.00 |
| **mandate_neg_psych** | |
| X | 1.00 |
| **hr_wait_post_counseling** | |
| 72 | 1.00 |
| 48 | 0.833 |
| 24 | 0.67 |
| 18 | 0.50 |
| Day Before | 0.33 |
| 1 | 0.167 |
| **parental_involv_minors** | |
| Consent and Notice | 1.00 |
| Consent | 0.67 |
| Notice | 0.33 |

Table A.1.2 defines each of the policy variables.
If a state does not have any restrictions in place for the specific policy, it receives 0 points.

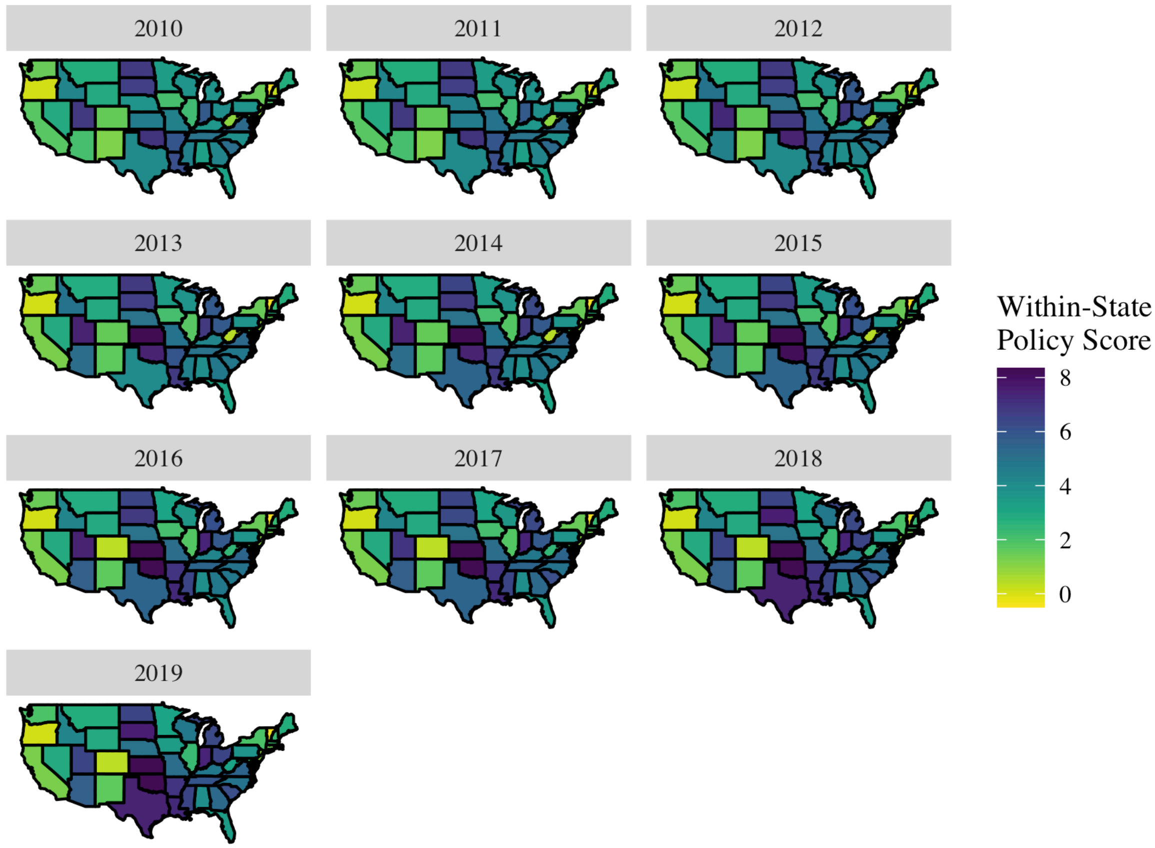


**Figure A.1.1:** National Within-State Policy Landscape, 2010-2019

### A.1.4 Full Policy Maps

Figures A.1.1 and A.1.2 map the within-state and surrounding-state policy scores for all years of study.

### A.1.5 Visualizing Standardized Policy Scores

The standardized score distributions maintain the same shape as previously, but the units change to standard deviations rather than the points derived in the scoring system. Standardized scores rarely exceed two standard deviations from the mean, as demonstrated by Figure A.1.3.

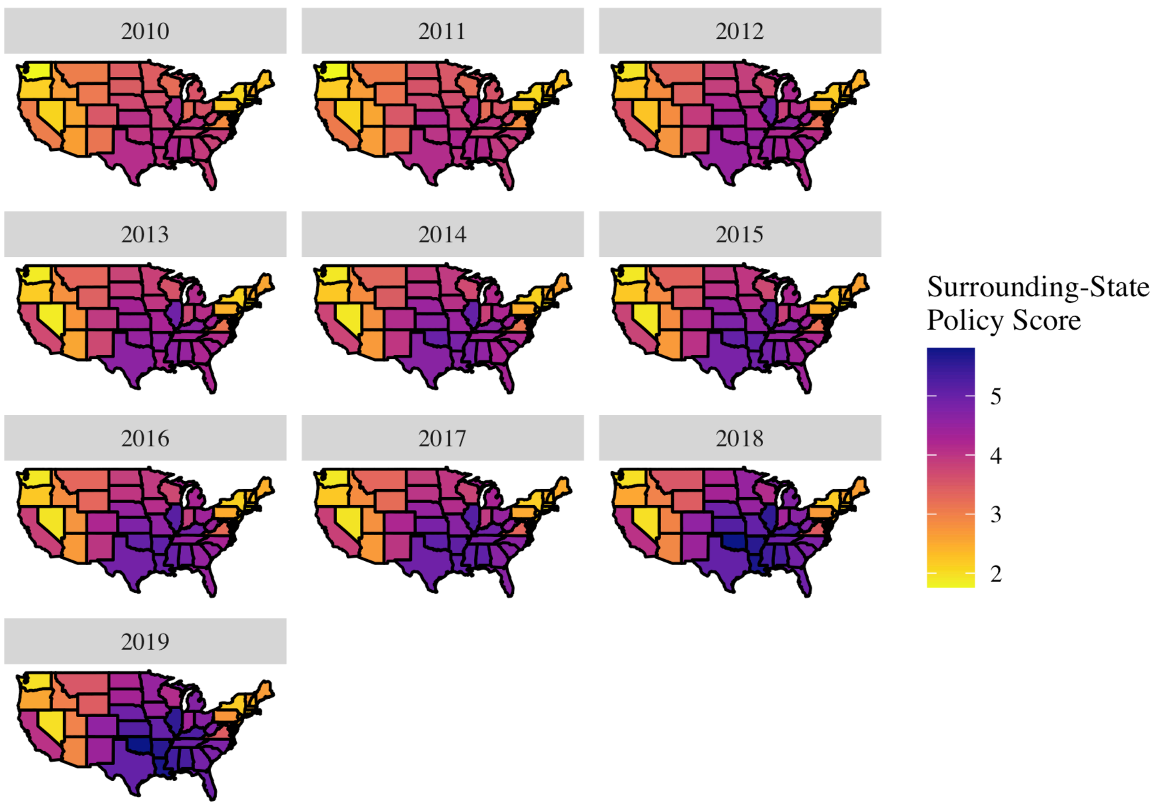


**Figure A.1.2:** National Surrounding-State Policy Landscape, 2010-2019

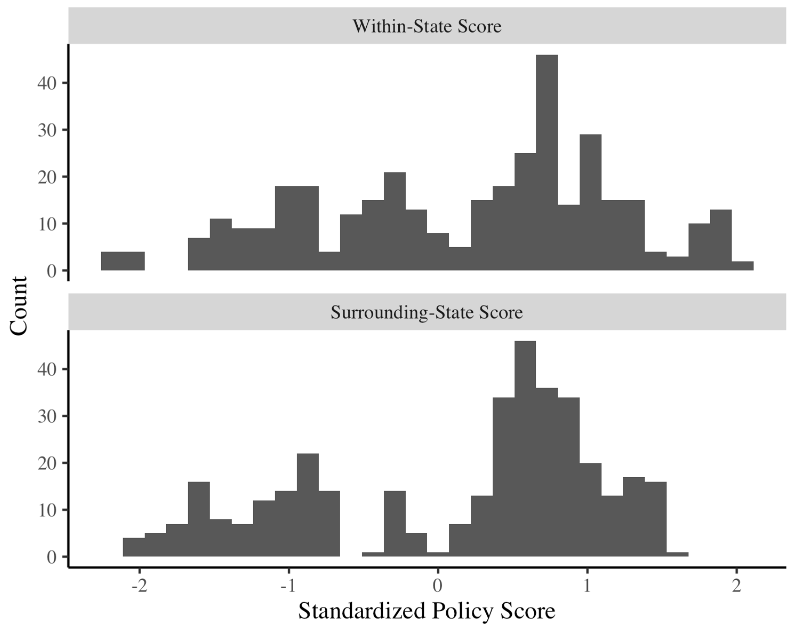


**Figure A.1.3:** Standardized Policy Score Distributions

### A.1.6 Visualizing Policies with Tercile-Based Categories

While the models use policy scores on continuous scales, binning state-year observations into discrete categories illustrates possible relationships between within-state and surrounding-state policy environments. To explore this, I divided within-state and surrounding-state scores into low, medium, and high categories based on the terciles of the overall distributions. When viewing both scores' category assignments together, I have nine total tercile-based policy categories with the naming convention [*within*]-[*surrounding*].

Recall that lower scores correspond to lower levels of restriction, while higher scores correspond to higher levels of restriction. Figure A.1.4 displays within-state and surrounding-state scores on a two-dimension plot, binning the scores into the tercile-based categories.

The top left region of Figure A.1.4 corresponds to low-high observations, or those with low levels of restrictions within the state but high levels of restriction surrounding the state. These low-high states present themselves as prime targets for policy spillover since individuals with restrictive surroundings may have to travel to the less restrictive state to obtain an abortion.


**Figure A.1.4:** Tercile-Based Policy Grid

The two-dimensional grid illustrates possible within-state and surrounding-state policy categories. The grid determines whether a state has low, medium, or high levels of restriction based on the terciles of the policy score distributions.

Few Policy Extremes, Exacerbated by Missing Data The tercile-based categories illustrate how within-state and surrounding-state environments relate to one another. Certain policy categories appear much more frequently in the data than others, and the two categories with opposing extremes – high-low and low-high – have the fewest observations in the dataset. This indicates that states tend to have policies similar to their surroundings.

The number of low-high observations shrinks even further when excluding states that do not report abortion data to the CDC. Illinois presents itself as an optimal location for policy spillover since it has very restrictive surroundings but relatively low levels of restriction within the state. Unfortunately, the state does not report any gestational age data to the CDC from 2010 to 2019. As a result, the model cannot illustrate the potential spillover of later-term abortions in the state.

As touched on in the Voluntary Reporting section of Chapter 3 and the Further Discussion of CDC Nonreporting section of Appendix A, the states that fail to report data to the CDC tend to have lower levels of within-state and surrounding-state restrictions. This lowers the sample size of state-year observations operating in the least extreme policy environments. Because of this imbalance in the policies used for model construction, I caution against

**Table A.1.4:** Policy Terciles of Reporting vs. Nonreporting States

| | Count of Observations by CDC Reporting Status | | |
|---|---|---|---|
| Tercile Category | Reporting | Nonreporting | Total |
| low-low | 54 | 40 | 94 |
| low-med | 35 | 20 | 55 |
| low-high | 13 | 10 | 23 |
| med-low | 43 | 17 | 60 |
| med-med | 27 | 23 | 50 |
| med-high | 47 | 7 | 54 |
| high-low | 12 | 0 | 12 |
| high-med | 55 | 0 | 55 |
| high-high | 82 | 1 | 83 |

the extrapolation of model inferences to policy extremes. This becomes increasingly relevant when I consider the post-Dobbs implications of my model in Chapter 6.

Policies Grow More Restrictive with Time The policy categories also highlight changes in restrictiveness over time. Changes in the overall policy environment tend to happen gradually. Of the ten years in the data, 26 states appeared in the same category across the entire time frame. In general, the country shifted to more restrictive categories, with the distribution of category counts shifting toward the high-high category with time. Figure A.1.5 illustrates these trends in the tercile-based policy categories, and this supports the spatial trends demonstrated in Figures A.1.1 and A.1.2.

### A.1.7 Policy Scoring Limitations

A single metric for something as nuanced as abortion policies will naturally have its weaknesses. As described in the Chapter 3 section Quantifying Policy Environments, I drew from previous literature to limit subjective decisions where possible [28, 46, 60, 82, 100]. Despite my best efforts, different policy timelines and levels of enforcement limit my ability to perfectly capture abortion restrictions with a single score. The following

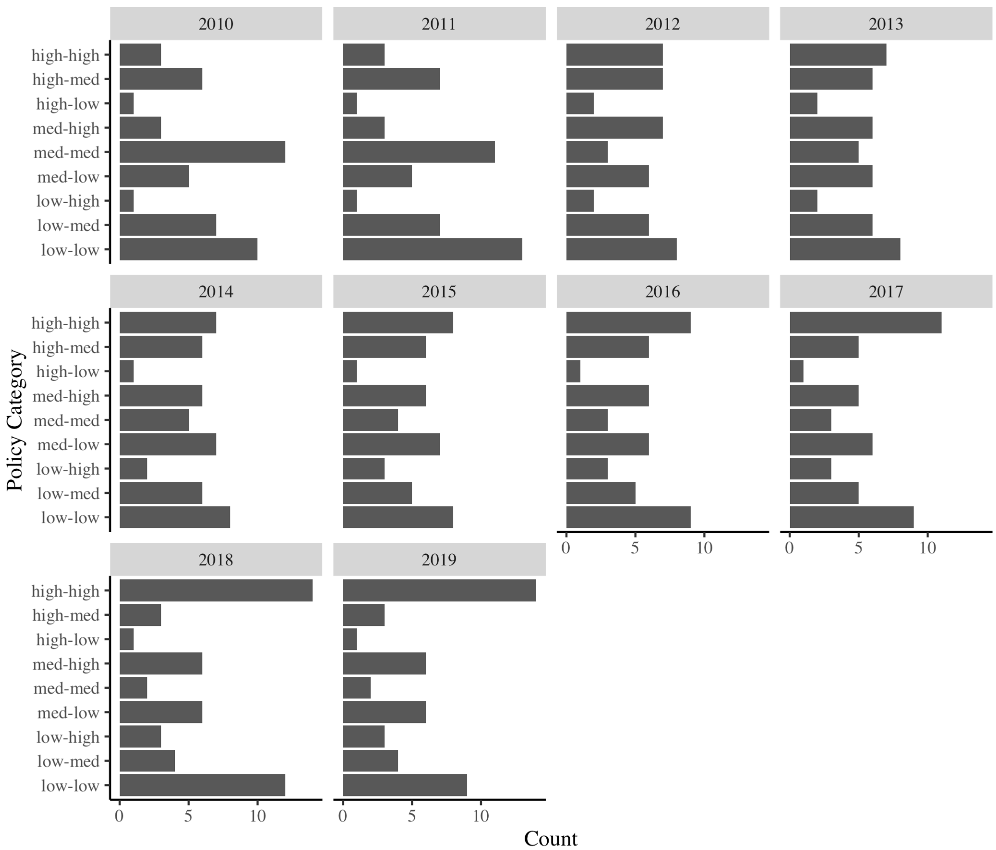


**Figure A.1.5:** Tercile-Based Categories Over Time, 2010-2019

Policies gravitated toward extremes over the 10-year time frame.

sections describe limitations of my current scoring system.

#### Time Under Law

The existing scoring system does not consider the time under law of a particular policy. A more fine-tuned scoring system could scale each policy's point values to the proportion of the previous year that the policy was in place. This approach would require data over much more frequent intervals since I would need to know when policies changed to their current status. Because the Internet Archive's scraping schedule controls the available policy dates, a more granular policy dataset is not feasible for every year in the data.[2] As an alternative approach, I considered including lagged score terms in the model. However, the inclusion of these terms raised issues with model collinearity and failed to improve the fit of the models in terms of AIC, BIC, and log-likelihood. Ultimately, I opted to only include the terms for that year's policies.

#### Enjoined Policies

The court system may enjoin or block the enforcement of abortion policies, which can introduce ambiguity about the legality of abortion. Table A.1.5 displays the count of observed injunctions for each policy in the dataset. While an unenforced policy may affect patients and providers for psychological reasons, restrictions blocked by courts do not have the legal power to restrict abortion access [82]. Since I aim to measure the impact of active abortion policies, I assign zero points to enjoined policies. An alternative method could assign a fraction of the usual points to enjoined policies.

## A.2 Abortion Data

### A.2.1 Spatial Autocorrelation in Raw Outcome Variables

I performed permutation-based Moran's I-tests to establish a baseline understanding of the spatial relationships of the outcome variables. Using

[2] The Internet Archive did not scrape the Guttmacher Institute's website on a consistent schedule, so the lack of data availability would not allow for data collection of policies from the same dates within smaller time intervals across all years.

**Table A.1.5:** State-Year Observations with Injunctions for Each Policy

| Policy | Count |
|---|---|
| partial_birth_ban | 238 |
| parental_involv_minors | 95 |
| hr_wait_post_counseling | 66 |
| prohibited_except_death_if | 20 |
| priv_insurance_limit | 14 |
| second_physician_if | 10 |
| fund_life_rape_incest | 3 |
| hospital_if | 3 |
| mandate_neg_psych | 2 |
| licensed_physician | 1 |

Table A.1.2 defines each of the policy variables.

the same spatial weight matrices described in the Model Specification section of Chapter 4, these tests use weights calculated from an exponentially-weighted function of the inverse distance between states.

Confirming the observations from Figures 3.2.1, 3.2.2, 3.2.3, 3.2.4, 3.2.5, and 3.2.6 in the Abortion Data section of Chapter 3, permutation-based Moran's I-tests demonstrate spatial autocorrelation at an $\alpha = 0.05$ significance level in overall abortion rates and resident abortion rates across most years. However, the tests do not detect significant autocorrelation in nonresident abortion rates, later-term abortion rates, earlier-term abortion rates, and the later-term share of abortions. Table A.2.1 displays these results.

In a Moran's test, a positive I-statistic serves as a sign of positive autocorrelation between neighbors, while a negative I-statistic indicates the presence of negative autocorrelation. Across all outcomes, the Moran's I-statistics estimate some degree of positive autocorrelation, but most tests yield insignificant results. Overall abortion rates and resident abortion rates exhibit significant positive autocorrelation at the greatest rate. To account for the potential need for additional spatial controls, I considered nonspatial and spatial linear mixed-effects models in the Model Selection section of Chapter 4.

**Table A.2.1:** Moran's I-Tests on Outcome Variables

| Year | I-statistic | p-value | Year | I-statistic | p-value |
|---|---|---|---|---|---|
| **Overall Abortion Rate** | | | **Later-Term Abortion Rate** | | |
| 2010 | 0.997 | 0.204 | 2010 | 0.997 | 0.248 |
| 2011 | 1.006* | 0.026 | 2011 | 0.996 | 0.384 |
| 2012 | 1.005* | 0.017 | 2012 | 1.002 | 0.059 |
| 2013 | 1.003* | 0.045 | 2013 | 0.992 | 0.478 |
| 2014 | 1.006* | 0.016 | 2014 | 0.992 | 0.499 |
| 2015 | 1.004* | 0.045 | 2015 | 0.999 | 0.167 |
| 2016 | 1.014* | 0.001 | 2016 | 0.993 | 0.283 |
| 2017 | 1.013* | 0.003 | 2017 | 1.003* | 0.046 |
| 2018 | 0.996 | 0.330 | 2018 | 0.997 | 0.183 |
| 2019 | 0.998 | 0.102 | 2019 | 0.996 | 0.130 |
| **Nonresident Abortion Rate** | | | **Earlier-Term Abortion Rate** | | |
| 2010 | 0.997 | 0.136 | 2010 | 0.997 | 0.242 |
| 2011 | 0.989 | 0.230 | 2011 | 1.003* | 0.036 |
| 2012 | 0.989 | 0.199 | 2012 | 1.001 | 0.089 |
| 2013 | 0.991 | 0.239 | 2013 | 1.000 | 0.114 |
| 2014 | 0.991 | 0.298 | 2014 | 1.004* | 0.036 |
| 2015 | 0.991 | 0.310 | 2015 | 1.003 | 0.069 |
| 2016 | 0.982 | 0.394 | 2016 | 1.013* | 0.001 |
| 2017 | 0.980 | 0.224 | 2017 | 1.011* | 0.006 |
| 2018 | 0.991 | 0.482 | 2018 | 0.995 | 0.393 |
| 2019 | 0.984 | 0.523 | 2019 | 0.996 | 0.135 |
| **Resident Abortion Rate** | | | **Later-Term Abortion Rate** | | |
| 2010 | 0.998 | 0.523 | 2010 | 0.997 | 0.262 |
| 2011 | 1.008* | 0.015 | 2011 | 0.984 | 0.078 |
| 2012 | 1.007* | 0.008 | 2012 | 0.986 | 0.108 |
| 2013 | 1.005* | 0.027 | 2013 | 0.982* | 0.041 |
| 2014 | 1.006* | 0.018 | 2014 | 0.985 | 0.082 |
| 2015 | 1.005* | 0.015 | 2015 | 0.99 | 0.225 |
| 2016 | 1.017* | 0.001 | 2016 | 0.978 | 0.229 |
| 2017 | 1.015* | 0.005 | 2017 | 0.983 | 0.482 |
| 2018 | 0.997 | 0.225 | 2018 | 0.992 | 0.665 |
| 2019 | 1.000 | 0.061 | 2019 | 0.984 | 0.427 |

* $p<0.05$

**Table A.2.2:** State-Year Observations Missing Abortion Count Data

| State | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|---|
| California | X | X | X | X | X | X | X | X | X | X |
| Florida | X | X | X | X | X | X | X | | | |
| Maryland | X | | X | X | X | X | X | X | X | X |
| New Hampshire | X | X | X | X | X | X | X | X | X | X |

"X" denotes missing data.

### A.2.2 Further Discussion of CDC Nonreporting

The Voluntary Reporting section of Chapter 3 discusses nonreporting of CDC abortion count data at a high level. The following sections consider missingness at a more granular level, examining missing observations in the abortion counts by occurrence and residence, examining missing observations in the abortion counts by known weeks gestation, and comparing missingness with more detail than in Chapter 3.

#### Nonreporting of Abortion Counts by State of Occurrence and Residence

Table A.2.2 displays the state-year observations missing overall abortion count data. Some states may not report abortions that occur within the state, but they may have residents accounted for in the data that obtain abortions in other states. The CDC advises readers to interpret these numbers with caution.

#### Nonreporting of Abortion Counts by Known Weeks of Gestation

Table A.2.3 displays the state-year observations that do not report gestational age data to the CDC. Note that some states may report their abortion counts by residence and occurrence but fail to report their abortion counts by known weeks of gestation. As described in the Voluntary Reporting section of Chapter 3, the modeling dataset excludes state-year observations that fail to report any of the outcome variables. This means that the modeling dataset will not include a state-year observation if it reports its abortions by residence and occurrence but fails to report its abortions by known weeks gestation. Since my study of spillover compares

**Table A.2.3:** State-Year Observations Missing Gestational Age Data

| State | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|---|
| California | X | X | X | X | X | X | X | X | X | X |
| Connecticut | X | X | X | X | X | X | | | | |
| Delaware | X | | | | | | | | | |
| Florida | X | X | X | X | X | X | X | | | |
| Illinois | X | X | X | X | X | X | X | X | X | X |
| Maine | | X | X | | | | | | | |
| Maryland | X | X | X | X | X | X | X | X | X | X |
| Massachusetts | X | X | X | X | X | X | X | X | X | X |
| Mississippi | X | | | | | | | | | |
| Nebraska | X | X | X | | | | | | | |
| New Hampshire | X | X | X | X | X | X | X | X | X | X |
| New York | X | X | X | X | X | X | X | X | | X |
| Pennsylvania | X | X | X | X | X | X | X | X | X | X |
| Rhode Island | | | | | | | | | X | |
| Vermont | X | | | | | | | | | |
| Wisconsin | X | X | X | X | X | X | X | X | X | X |
| Wyoming | X | X | X | X | X | X | X | X | X | |

"X" denotes missing data.

**Table A.2.4:** Number of Observations in Each Missingness Category

| Missing CDC data | Number of observations |
|---|---|
| No | 368 |
| Yes | 112 |

results across models, I used the same underlying dataset for all outcome variables and dropped observations missing any of the six outcomes.

### Comparing Missingness

The modeling dataset includes 368 state-year observations, and the dataset excludes the 112 state-year observations that failed to report data on abortion counts, gestational age, or both.[3]

[3] Note that 368 and 112 sums to 480 total possible state-year observations, which corresponds to the total number of state-year observations across the 48 contiguous United States over a 10-year period.

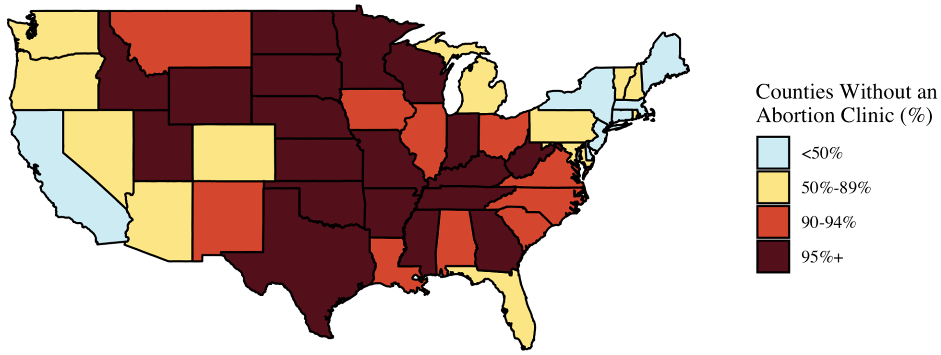


**Figure A.2.1:** Mapping Abortion Access Across the Country, 2017

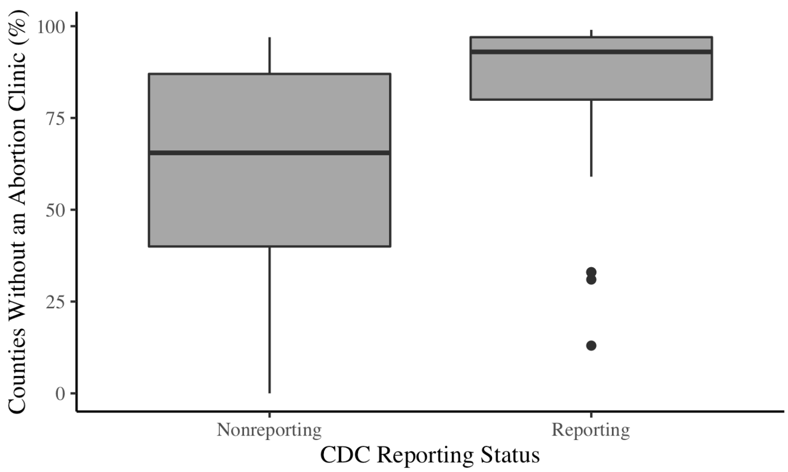


**Figure A.2.2:** Abortion Access in Reporting vs. Nonreporting States

Any patterns in missingness would have negative implications for model inference and generalizability. The differences between reporting and nonreporting states make sense when considering how states such as California, Massachusetts, Illinois, and New York fail to report abortion occurrence or gestation data for most or all years in the dataset. In addition to having less restrictive policy environments, Figures A.2.1 and A.2.2 reveal that nonreporting states have much greater rates of abortion access than the remaining reporting states.[4]

Missing abortion data from states as populous and Democratic as

[4]I quantify abortion access with the percentage of counties without a known abortion clinic in 2017 [1].

California and New York will likely lower any effect size in this analysis. As a largely Democratic state, California's nonrestrictive abortion policies make it an obvious safe haven for individuals seeking abortions. Its long borders make it prime for cross-border traffic, and it has numerous abortion clinics with the capacity to cater to large populations [1].

Even though California will not have abortion counts associated with it, it will play a role in other states' surrounding-state policy scores. For example, California will not have the counts of Arizona residents obtaining an abortion within California, but the surrounding-state policy score of Arizona will reflect the presence of the very populous and nonrestrictive state nearby. Then, corresponding decreases in abortion counts in Arizona could be attributed to the relatively low surrounding-state score, even if the effect size would be stronger with the counts of residents seeking care in California.

# B

# Model Diagnostics

## B.1 Selected Model Residuals

### B.1.1 Linear Regression Assumptions

Figures B.1.1, B.1.2, B.1.3, B.1.4, B.1.5, and B.1.6 display the model residuals of linear mixed-effect nonspatial models for each of the outcome variables. None of the plots display clear patterns in the model residuals, so they support the use of linear models.

### B.1.2 Spatial Structure in Nonspatial Residuals

The residuals of the selected nonspatial models exhibit little to no spatial structure. Moran's I-tests require the use of a spatial weight matrix, so I extracted the spatial weight matrices created in the model-fitting process for the spatial models. The mixed-effects models grouped observations by year,

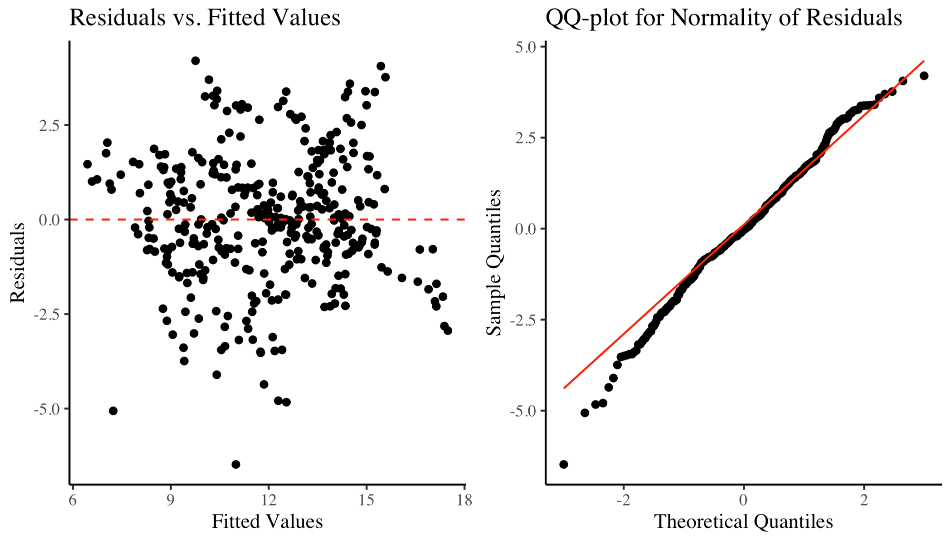


**Figure B.1.1:** Overall Abortion Rate Model Residuals

The overall abortion rate model residuals display no clear patterns.

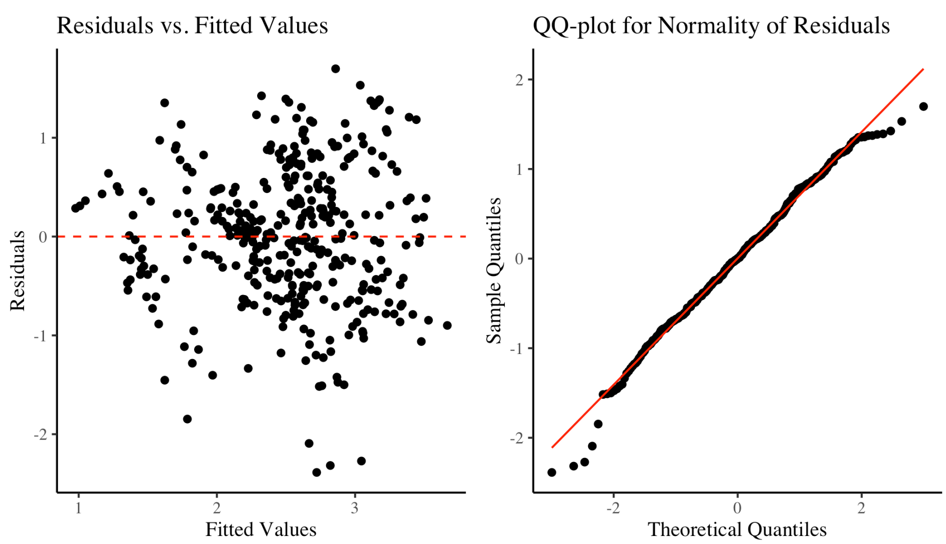


**Figure B.1.2:** Nonresident Abortion Rate Model Residuals

The nonresident abortion rate model residuals display no clear patterns.

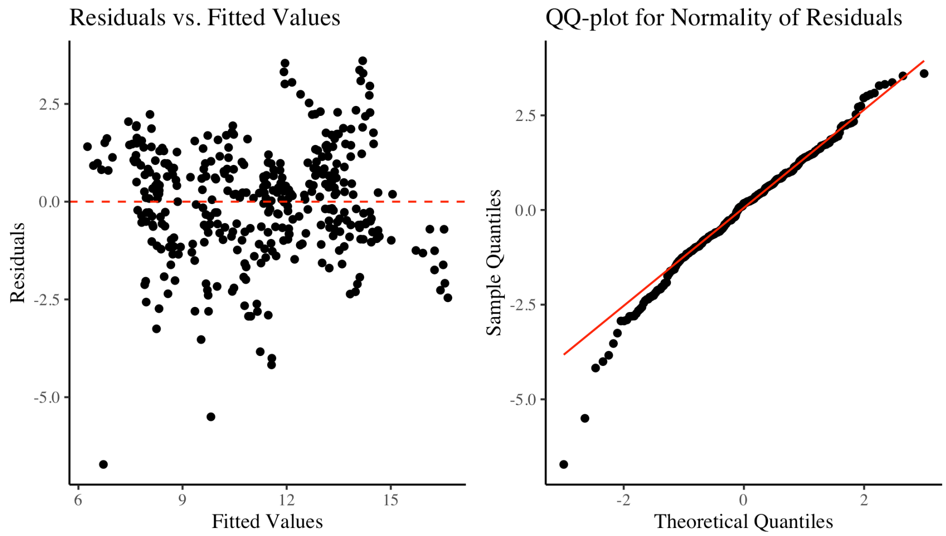


**Figure B.1.3:** Resident Abortion Rate Model Residuals

The resident abortion rate model residuals display no clear patterns.

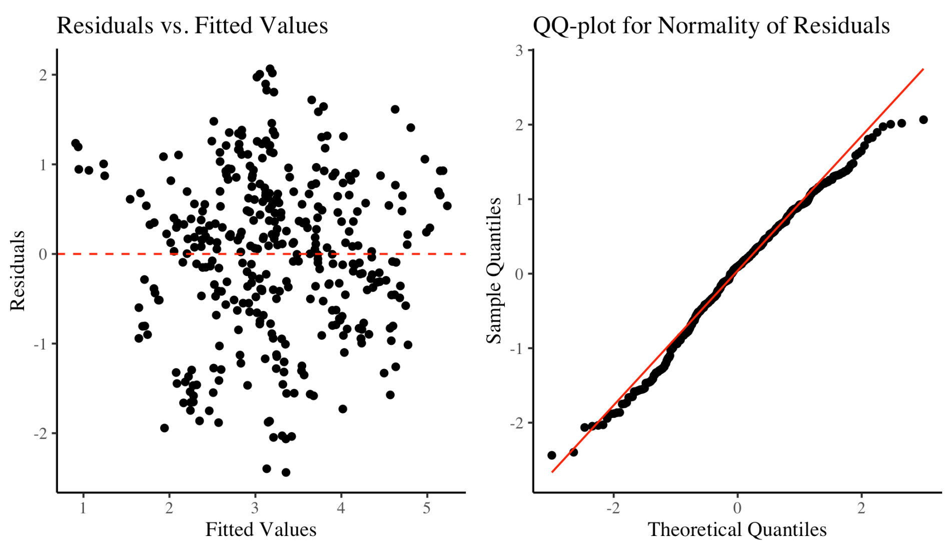


**Figure B.1.4:** Later-Term Abortion Rate Model Residuals

The later-term abortion rate model residuals display no clear patterns.

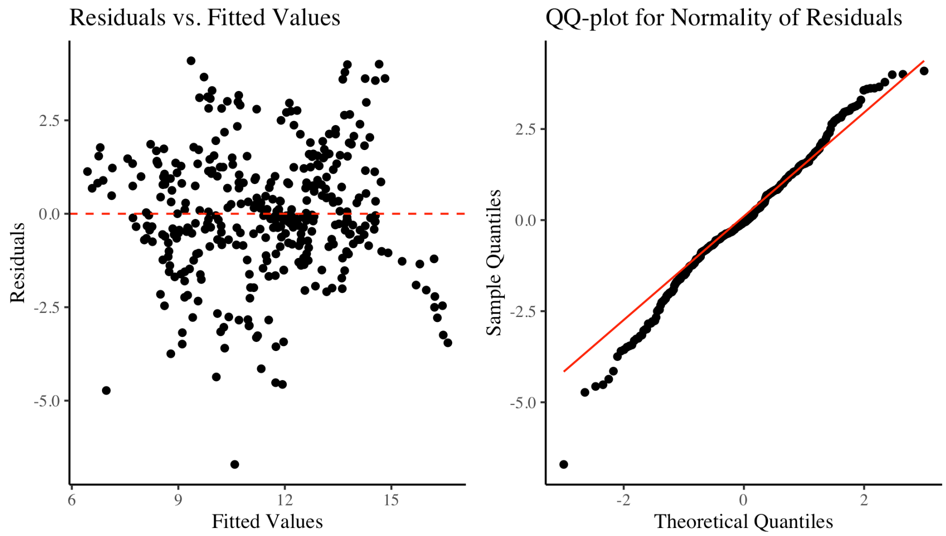


**Figure B.1.5:** Earlier-Term Abortion Rate Model Residuals

The earlier-term abortion rate model residuals display no clear patterns.

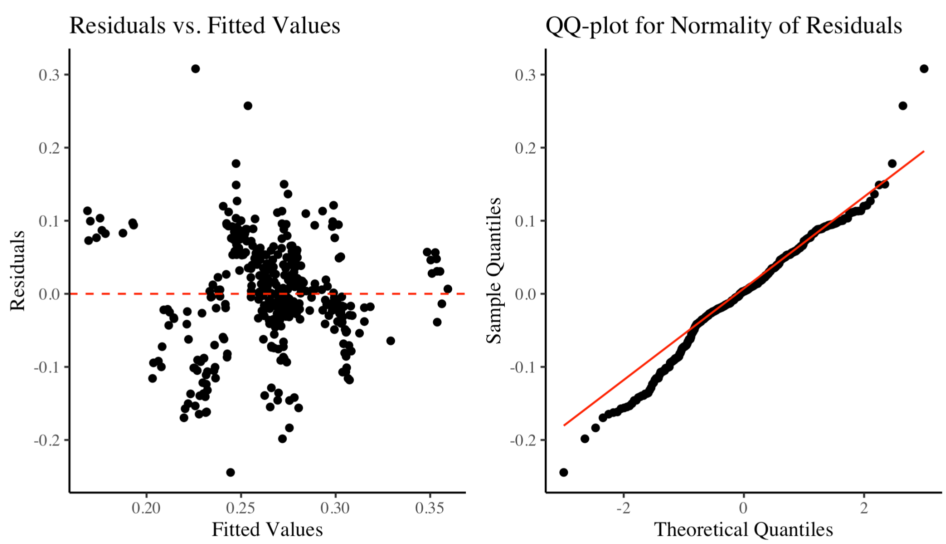


**Figure B.1.6:** Later-Term Share Model Residuals

The later-term share model residuals display no clear patterns.

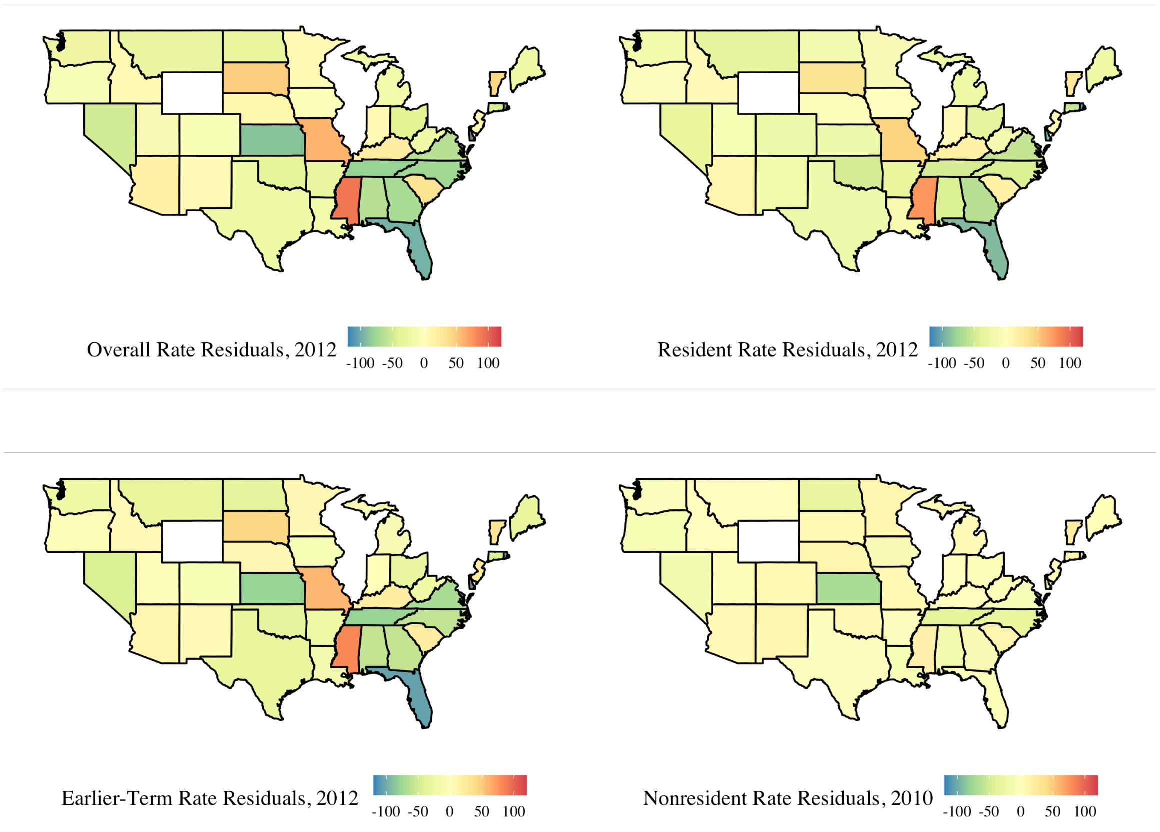


**Figure B.1.7:** Mapping Model Residuals for Selected Years

The maps display the model residuals in units of abortions per 1000 live births.

and spatial models calculated separate weight matrices based on the observations that reported data for that year. Since different subsets of states reported data each year, I had to run separate Moran's I-tests for each year in the dataset. For all six outcome variables, permutation-based Moran's I-tests of the model residuals produced insignificant results at the $\alpha = 0.05$ significance level across nearly every year. Table B.1.1 displays the Moran test outputs for each of my chosen models.

The maps in Figure B.1.7 display a subset of the years and outcomes with significant spatial autocorrelation in model residuals. Notably, the three outcome variables that exhibit desired spillover – overall abortion rates, resident abortion rates, and earlier-term abortion rates – exhibit very similar spatial structure in the model residuals. For the selected years, the models

**Table B.1.1:** Moran's I-Tests on Model Residuals

| Year | I-statistic | p-value |
|---|---|---|
| **Overall Rate** | | |
| 2010 | 0.996 | 0.070 |
| 2011 | 0.987 | 0.133 |
| 2012 | 0.982* | 0.042 |
| 2013 | 0.985 | 0.073 |
| 2014 | 0.987 | 0.126 |
| 2015 | 0.986 | 0.078 |
| 2016 | 0.985 | 0.831 |
| 2017 | 0.992 | 0.356 |
| 2018 | 0.992 | 0.873 |
| 2019 | 0.984 | 0.481 |
| **Nonresident Rate** | | |
| 2010 | 0.995* | 0.013 |
| 2011 | 0.988 | 0.176 |
| 2012 | 0.988 | 0.187 |
| 2013 | 0.989 | 0.182 |
| 2014 | 0.988 | 0.147 |
| 2015 | 0.987 | 0.117 |
| 2016 | 0.979 | 0.324 |
| 2017 | 0.970* | 0.046 |
| 2018 | 0.988 | 0.254 |
| 2019 | 0.981 | 0.290 |
| **Resident Rate** | | |
| 2010 | 0.997 | 0.152 |
| 2011 | 0.987 | 0.168 |
| 2012 | 0.980* | 0.025 |
| 2013 | 0.986 | 0.088 |
| 2014 | 0.989 | 0.186 |
| 2015 | 0.988 | 0.137 |
| 2016 | 0.989 | 0.642 |
| 2017 | 0.998 | 0.101 |
| 2018 | 0.993 | 0.715 |
| 2019 | 0.985 | 0.642 |

| Year | I-statistic | p-value |
|---|---|---|
| **Later-Term Rate** | | |
| 2010 | 0.996 | 0.107 |
| 2011 | 0.99 | 0.395 |
| 2012 | 0.994 | 0.959 |
| 2013 | 0.990 | 0.328 |
| 2014 | 0.991 | 0.398 |
| 2015 | 0.992 | 0.521 |
| 2016 | 0.981 | 0.423 |
| 2017 | 0.985 | 0.829 |
| 2018 | 0.992 | 0.874 |
| 2019 | 0.985 | 0.817 |
| **Earlier-Term Rate** | | |
| 2010 | 0.997 | 0.114 |
| 2011 | 0.984 | 0.070 |
| 2012 | 0.978* | 0.017 |
| 2013 | 0.981* | 0.028 |
| 2014 | 0.984* | 0.048 |
| 2015 | 0.983* | 0.047 |
| 2016 | 0.983 | 0.560 |
| 2017 | 0.991 | 0.411 |
| 2018 | 0.992 | 0.867 |
| 2019 | 0.984 | 0.445 |
| **Later-Term Share** | | |
| 2010 | 0.997 | 0.283 |
| 2011 | 0.986 | 0.150 |
| 2012 | 0.989 | 0.230 |
| 2013 | 0.985 | 0.099 |
| 2014 | 0.988 | 0.207 |
| 2015 | 0.992 | 0.364 |
| 2016 | 0.980 | 0.311 |
| 2017 | 0.985 | 0.748 |
| 2018 | 0.992 | 0.962 |
| 2019 | 0.985 | 0.539 |

* $p<0.05$

underestimate the actual abortion rates in the southeastern region of the United States. These trends indicate that the models overestimate the desired spillover in these outcome variables in the Southeast.

On the other hand, the variables experiencing undesired spillover – nonresident abortion rates, later-term abortion rates, and the later-term share of abortion – exhibit little to no spatial correlation in the model residuals. None of the Moran's I-tests yielded significant results for the models of the later-term rate and share, and the nonresident abortion rate only yielded significant results in 2010 and 2017. While nonresident abortions also exhibit higher model residuals in the Southeast, the models underestimate the nonresident abortion rates by a much smaller amount than the desired spillover variables.

## B.2 Interpreting Control Terms

While this thesis focuses on policy spillover, the control variables enhance the internal validity of the policy-related results. With the exception of the later-term share model, the models detect significant relationships between nearly all of the control variables and the outcomes. In many cases, the effect size of the control variables exceeds the effect size of the policy variables. The chosen controls highlight the relationship between abortion outcomes and population characteristics.

For one, higher Democratic two-party vote shares correspond to higher abortion rates. While I would expect Democratic vote share to correspond to more lenient state-level abortion policies, the regression controls for within-state and surrounding-state policy environments. With these policy controls, the two-party Democratic vote share serves as a proxy for the liberalness of a state's population. The strong effect of Democratic vote share likely results from Democratic sentiments contributing to social environments more supportive of abortion, regardless of the policies in place.

Larger non-white and Hispanic populations correspond to higher abortion rates of all types. In addition, higher levels of household income correspond to decreases in abortion rates while higher levels of education correspond to increases in abortion rates. In these cases, higher levels of income may correspond to people with health insurance, contraception access, and other variables that may prevent unintended pregnancies. Finally, larger populations tend to correspond to increased abortion rates in all cases except nonresident abortions. This relationship between population size and abortion rates may result from greater tax revenue to support more hospitals and clinics.

## B.3 Verifying Robustness of Results

### B.3.1 Alternative Spatial Model Specification with `spatialreg`

The main analysis described nonspatial and spatial mixed-effect models fit with the `nlme` package in R. Early in the model-fitting process, I also considered spatial models fit with the `spatialreg` package. I considered four `spatialreg` models for each variable. The first model – a standard linear regression – ignored spatial dependence.[1] Following the standard linear regression, I considered three spatial models: a conditional autoregressive (CAR) model, an error-based simultaneous autoregressive (SAR) model, and a lagged SAR model.

These models differ slightly in their definitions of spatial relationships between variables. A CAR model specifies the spatial component in terms of the independent variables, assuming that the outcome variable in a given state is a function of a neighbor's predictors. This contrasts with the lagged SAR model, which specifies the spatial dependence in terms of the outcome variables of neighbors. Lastly, an error-based SAR model attributes any autocorrelation to missing spatial covariates in the data.

Table B.3.1 contains the AIC, BIC, and log-likelihood for each of the `spatialreg` models, under each neighborhood specification.

[1] This model differs slightly from the `nlme` nonspatial model due to its inclusion of fixed effects rather than random effects for the year.

**Table B.3.1:** Assessing Fit of `spatialreg` Models

| Method | AIC | | | BIC | | | Log-Likelihood | | |
|---|---|---|---|---|---|---|---|---|---|
| | Inverse distance | Inverse distance squared | Contiguous | Inverse distance | Inverse distance squared | Contiguous | Inverse distance | Inverse distance squared | Contiguous |
| **Overall Rate** | | | | | | | | | |
| raw_errorsar | 1394.0 | 1425.2 | 1461.6 | 1440.9 | 1472.1 | 1508.5 | -685.0 | -700.6 | -718.8 |
| raw_lagsar | 1486.7 | 1485.0 | 1466.5 | 1533.6 | 1531.9 | 1513.4 | -731.3 | -730.5 | -721.3 |
| raw_lm | 1485.7 | 1485.7 | 1485.7 | 1528.7 | 1528.7 | 1528.7 | -731.8 | -731.8 | -731.8 |
| raw_car | 1487.0 | 1486.6 | 1484.2 | 1533.9 | 1533.5 | 1531.1 | -731.5 | -731.3 | -730.1 |
| **Nonresident Rate** | | | | | | | | | |
| raw_errorsar | 632.0 | 642.4 | 813.3 | 678.9 | 689.3 | 860.2 | -304.0 | -309.2 | -394.6 |
| raw_lagsar | 671.9 | 670.3 | 813.8 | 718.8 | 717.2 | 860.7 | -324.0 | -323.1 | -394.9 |
| raw_car | 808.1 | 801.6 | 814.2 | 855.0 | 848.5 | 861.1 | -392.1 | -388.8 | -395.1 |
| raw_lm | 812.2 | 812.2 | 812.2 | 855.2 | 855.2 | 855.2 | -395.1 | -395.1 | -395.1 |
| **Resident Rate** | | | | | | | | | |
| raw_errorsar | 1299.2 | 1328.9 | 1332.7 | 1346.1 | 1375.8 | 1379.6 | -637.6 | -652.4 | -654.3 |
| raw_lm | 1362.2 | 1362.2 | 1362.2 | 1405.2 | 1405.2 | 1405.2 | -670.1 | -670.1 | -670.1 |
| raw_car | 1363.9 | 1363.9 | 1360.8 | 1410.8 | 1410.8 | 1407.7 | -670.0 | -669.9 | -668.4 |

**Table B.3.1:** Assessing Fit of `spatialreg` Models

| Method | AIC | | | BIC | | | Log-Likelihood | | |
|---|---|---|---|---|---|---|---|---|---|
| | Inverse distance | Inverse distance squared | Contiguous | Inverse distance | Inverse distance squared | Contiguous | Inverse distance | Inverse distance squared | Contiguous |
| raw_lagsar | 1363.6 | 1364.1 | 1339.6 | 1410.5 | 1411.0 | 1386.5 | -669.8 | -670.1 | -657.8 |
| **Later-Term Rate** | | | | | | | | | |
| raw_errorsar | 874.5 | 924.8 | 983.9 | 921.4 | 971.7 | 1030.8 | -425.3 | -450.4 | -479.9 |
| raw_lagsar | 930.5 | 948.0 | 992.8 | 977.4 | 994.9 | 1039.7 | -453.3 | -462.0 | -484.4 |
| raw_car | 990.6 | 989.8 | 990.3 | 1037.5 | 1036.7 | 1037.2 | -483.3 | -482.9 | -483.1 |
| raw_lm | 991.4 | 991.4 | 991.4 | 1034.4 | 1034.4 | 1034.4 | -484.7 | -484.7 | -484.7 |
| **Earlier-Term Rate** | | | | | | | | | |
| raw_errorsar | 1376.3 | 1407.9 | 1446.2 | 1423.2 | 1454.7 | 1493.1 | -676.1 | -691.9 | -711.1 |
| raw_lm | 1468.4 | 1468.4 | 1468.4 | 1511.4 | 1511.4 | 1511.4 | -723.2 | -723.2 | -723.2 |
| raw_lagsar | 1469.7 | 1468.4 | 1448.1 | 1516.6 | 1515.3 | 1495.0 | -722.8 | -722.2 | -712.0 |
| raw_car | 1469.7 | 1469.3 | 1467.0 | 1516.6 | 1516.2 | 1513.9 | -722.8 | -722.7 | -721.5 |
| **Later-Term Share** | | | | | | | | | |
| raw_errorsar | -922.2 | -880.9 | -869.5 | -875.3 | -834.0 | -822.6 | 473.1 | 452.5 | 446.7 |
| raw_lagsar | -910.8 | -875.2 | -863.5 | -863.9 | -828.3 | -816.6 | 467.4 | 449.6 | 443.8 |
| raw_lm | -865.0 | -865.0 | -865.0 | -822.0 | -822.0 | -822.0 | 443.5 | 443.5 | 443.5 |

**Table B.3.1:** Assessing Fit of `spatialreg` Models

| Method | AIC | | | BIC | | | Log-Likelihood | | |
|---|---|---|---|---|---|---|---|---|---|
| | Inverse distance | Inverse distance squared | Contiguous | Inverse distance | Inverse distance squared | Contiguous | Inverse distance | Inverse distance squared | Contiguous |
| raw_car | -863.8 | -863.4 | -865.1 | -816.9 | -816.5 | -818.2 | 443.9 | 443.7 | 444.6 |

In all cases, the error-based SAR model with the inverse distance weights minimized the AIC, minimized the BIC, and maximized the log-likelihood. Collectively, these results suggest an error-based SAR framework with inverse-distance weights most accurately captures the earlier observed spatial autocorrelation in the dependent variables. The error-based SAR framework further minimizes the AIC and BIC from the mixed-effect nonspatial model.[2]

Ultimately, this analysis used `nlme` for its capability to fit spatial models with mixed effects, which `spatialreg` lacks. As previously described, the relatively small sample size within yearly groups makes mixed-effects modeling attractive. The `spatialreg` models control for the longitudinal nature of the data by including a categorical fixed-effect term for year.[3] In addition, the `spatialreg` models require the definition of a neighborhood weight matrix. While `nlme` considered an exponentially weighted function of the distances between states, the `spatialreg` models considered three different neighborhood specifications: contiguity,[4] inverse distance,[5] and inverse squared distance. Aside from the temporal and spatial effects, all other terms in the `spatialreg` model formulas remained the same as the `nlme` models.

Despite differences in longitudinal controls and spatial structure between the `nlme` and `spatialreg` models, the models demonstrate robust results across the two model classes. Table B.3.2 considers the policy coefficients for the "best" models under the `nlme` and `spatialreg` specifications. When looking at the direction and significance of the surrounding-state score coefficients, the mixed-effect nonspatial model and the fixed-effect SAR

[2]Despite the improvements in AIC and BIC in the fixed-effect SAR model from the mixed-effect nonspatial model, this thesis included the mixed-effect nonspatial model in the analysis. Due to the relatively small sample size of observations per year, including year as random-effects with shrinkage to the mean makes the mixed-effect model more attractive for generalizability.

[3]This creates intercept terms relative to the reference category of `year` = 2010.

[4]States that share borders serve as a very straightforward definition of neighborhood. This approach operates under the assumption that states that share borders are most likely to share spatial characteristics not captured by the predictors included in the model. In the case of abortion spillover, it makes sense that women will cross as few state lines as possible to obtain an abortion and contiguity-based neighborhoods capture this in the simplest sense.

[5]In addition to contiguity-based neighborhoods, I also considered distance-based neighborhoods. The contiguity approach assumes zero spatial relationships between states that do not share borders. As a result, contiguity-based models would fail to capture spatial relations in regions such as New England where many states exist in relatively close proximity without shared borders. However, distance-based approaches should detect these broader spatial relations.

**Table B.3.2:** Robustness Check of Policy Coefficients

| | Mixed-Effect Nonspatial Model (`nlme`) | Fixed-Effect SAR Model (`spatialreg`) |
|---|---|---|
| **Overall Rate** | | |
| surrounding_score | -0.516* | -0.755* |
| within_score | -0.189 | -0.379* |
| surrounding_score:within_score | 0.226* | 0.252* |
| **Nonresident Rate** | | |
| surrounding_score | 0.354* | 0.227* |
| within_score | -0.161* | -0.236* |
| surrounding_score:within_score | 0.124* | 0.13* |
| **Resident Rate** | | |
| surrounding_score | -0.779* | -0.03* |
| within_score | -0.277* | -0.012* |
| surrounding_score:within_score | 0.097 | 0.004* |
| **Later-Term Rate** | | |
| surrounding_score | 0.026 | 0.003 |
| within_score | -0.346* | -0.008* |
| surrounding_score:within_score | 0.192* | 0.006* |
| **Earlier-Term Rate** | | |
| surrounding_score | -0.546* | -0.024* |
| within_score | -0.107 | -0.009* |
| surrounding_score:within_score | 0.19 | 0.007* |
| **Later-Term Share** | | |
| surrounding_score | 0.02* | 0.028* |
| within_score | -0.026* | -0.017* |
| surrounding_score:within_score | 0.011* | 0.012* |

model yield identical conclusions regarding policy spillover.

### B.3.2 Alternative Scoring System

Under the current scoring system, the within-state policy scores sum the points assigned to each of the fifteen policies. Instead of assigning equal weight to each of the fifteen policies in the Guttmacher dataset, a more nuanced scoring system could vary the weights for different types of policies. For example, the Guttmacher dataset has three separate variables for mandatory counseling on different topics: the link between abortion and breast cancer, the ability of a fetus to feel pain, and the long-term mental health consequences for the woman. At the same time, the dataset only has one variable for banning abortions past a certain gestational age. Under the scoring mechanism described in the Within-State Policy Scores section of Chapter 3, a state could receive up to 3 points for mandating counseling of different types. In contrast, a state could only receive up to 1 point if it has the earliest observed abortion ban of 20 weeks.

To test the sensitivity of the models to different scoring systems, I crafted an alternative scoring system that assigns greater weight to policies that have more of a direct impact on abortion access. Table B.3.3 lists the groupings of the policy variables into five categories and their respective weights. To compute the alternative within-state scores, I assign between zero and one point to each of the fifteen policies as outlined in the Within-State Policy Scores section of Chapter 3 and in Table A.1.3 in Appendix A. Once each of the fifteen policies has its own point value, I find the average point value of each category listed in Table B.3.3. Once each policy category has a numeric value between 0 and 1, I multiply that category's average score by the relative weight.

I considered two main factors when assigning these weights to the different policy categories: the power of the policy category to limit an individual from obtaining an abortion, and the number of variables within each category. For example, the policy category for banning the procedure receives four total points for two total policies. This category receives the greatest weight because it prohibits individuals from seeking any sort of care under the specified restrictions, and each policy within this category carries a maximum weight of two points in this updated system. Meanwhile, the category for counseling-related policies only receives a weight of one point, which means that each of the four restrictions only receives a maximum of 0.25 points in the updated scoring system. The updated within-state scores sum the reweighted category scores. I calculate the updated surrounding-state scores from the updated within-state scores, using the same methods described in the Surrounding-State Policy Scores section of Chapter 3.

Table B.3.4 displays the model coefficients with these alternative scores. This thesis aims to measure policy spillover, so the analysis relies on the direction and significance of the surrounding-state coefficients. The

**Table B.3.3:** Categories and Weights for Alternative Scoring System

| |
|---|
| **Banning the Procedure (4 points)** |
| prohibited_except_death_if |
| partial_birth_ban |
| **Restricting the Setting (2 points)** |
| licensed_physician |
| hospital_if |
| second_physician_if |
| priv_insurance_limit |
| **Counseling-Related Policies (1 point)** |
| mandate_breast_cancer |
| mandate_fetal_pain |
| mandate_neg_psych |
| hr_wait_post_counseling |
| **Third-Party Refusal of Care (1 point)** |
| indiv_prov_refuse |
| instit_prov_refuse |
| parental_involv_minors |
| **Funding Restrictions (1 point)** |
| fund_all_most |
| fund_life_rape_incest |

Table A.1.2 defines each of the policy variables.

surrounding-state terms in these updated models yield the same conclusions about policy spillover: more restrictive surroundings create desired spillover in overall, resident, and earlier-term abortion rates, but these more restrictive surroundings create undesired spillover in nonresident abortion rates, later-term abortion rates, and the later-term share of abortions. In this model and the main model presented in Table 5.2.1 of Chapter 5, the surrounding-state coefficients indicate significant spillover in all outcomes except for the later-term abortion rate. Just as the model results demonstrated robustness to the different spatial weights in Table B.3.2, the model results also demonstrate robustness to the different scoring systems in Table B.3.4.

**Table B.3.4:** Fixed-Effects Coefficients for Linear Mixed-Effects Models of Transformed Outcomes, Using Alternative Policy Scores

| Variable | Overall Rates | Nonresident Rates | Resident Rates | Later-Term Rates | Earlier-Term Rates | Later-Term Share |
|---|---|---|---|---|---|---|
| (Intercept) | 12.505* | 2.404* | 11.925* | 3.292* | 11.986* | 0.262* |
| **Policy Environment** | | | | | | |
| surrounding_score | -0.719* | 0.343* | -1.006* | 0.062 | -0.770* | 0.026* |
| within_score | 0.038 | -0.081 | -0.106 | -0.317* | 0.120 | -0.031* |
| surrounding_score:within_score | 0.229* | 0.151* | 0.084 | 0.235* | 0.178 | 0.013* |
| **Control Variables** | | | | | | |
| dem_2party | 1.498* | 0.196* | 1.427* | 0.341* | 1.435* | -0.002 |
| hh_income | -1.089* | -0.373* | -0.714* | -0.347* | -0.996* | -0.004 |
| prop_hisp | 0.401* | 0.203* | 0.095 | 0.346* | 0.253* | 0.017* |
| prop_nonwhite | 0.635* | 0.116* | 0.683* | 0.236* | 0.579* | 0.006 |
| prop_bachelors | 1.242* | 0.615* | 0.67* | 0.432* | 1.133* | 0.006 |
| total_population | 0.718* | -0.557* | 1.243* | 0.091 | 0.775* | -0.006 |

* $p < 0.05$

Exact p-values are available upon request. All outcome variables required a square-root transformation for Gaussian approximation except for nonresident abortion rates, which used a log transformation. As such, the coefficient values do not correspond to changes in the original units of the data and instead correspond to changes in the transformed abortion rates. However, the sign of the coefficients still represents an increase or a decrease in the original units of the quantity.

# C

# Additional Post-Dobbs Reflections

## C.1 The Kansas Vote, the Thermostatic Nature of Public Opinion, and the 2022 Midterms

In August 2022, Kansas voters rejected a proposed state constitutional amendment that would have eliminated the right to abortion within the state [70]. As a reliably Republican state, the Kansas vote demonstrated that the pre-Dobbs understanding of public opinion on abortion may no longer hold in a post-Dobbs future. Polling before the August 2022 vote suggested that 48 percent of Kansas voters agreed that abortion should be mostly legal, while 47 percent of Kansas voters believed the procedure should be mostly illegal [29]. However, the numbers from the actual election told a much different story: the proposed amendment fell at a 59-41 margin [29]. This clear victory defied the previous polling that would suggest a close race, and experts estimate that the Kansas vote implies that around 40 of the 50 states would reject a similar initiative to restrict abortion rights [29].

While the Kansas vote defied expectations of what would happen in a traditionally conservative state, the results of the referendum support the thermostatic theory of public opinion. This theory suggests that as policies move in one direction, public opinion moves in the other direction out of fear of radical change. Based on historical polling, public opinion of abortion tends to follow this pattern. After two Supreme Court decisions increased states' abilities to restrict abortion in the 1980s and 1990s, support for abortion increased [67]. More recently, the May 2022 WSJ-NORC poll found that 57% of Americans favored legal abortion for any reason. This number increased from 44% in 2016 and 54% in 2021 [69].

If voters bring this enthusiasm to the polls, this shift in public opinion may present hope to those opposed to highly restrictive abortion policies. Democratic governors in states like Pennsylvania and Michigan have blocked anti-abortion legislation passed by Republican state legislatures [62]. The 2022 midterm elections will give voters the opportunity to elect more lawmakers and executives that would protect abortion access.

That said, the midterm elections will have several issues on the ballot. Unlike the single-issue Kansas referendum, midterm voters will have to weigh the desire for abortion access against high inflation numbers and low approval ratings for Joe Biden [69]. Present issues aside, the president's party tends to fare poorly in midterm elections: the president's party lost an average of 28 House seats and 4 Senate seats in the 22 midterm elections from 1934 to 2018 [105]. With the odds stacked against Democrats in the midterm elections, the abortion issue may provide the energy and enthusiasm needed to unite the party ahead of midterms to either prevent losses or make gains.[1]

## C.2 Increasing Importance of Mexico

As demonstrated in Figure 6.1.1, most states in the southern United States banned or severely restricted abortion access following the Dobbs ruling. In contrast to traveling cross-country to seek abortion care in the United States, Mexico presents itself as a nearby neighbor with easy access to abortion care.[2] As the United States has restricted abortion access in recent years, Mexico has expanded access to the service [88].

Due to data constraints, this thesis did not include Mexico in its study of

[1] Historically, registered Republicans exhibit greater turnout than registered Democrats, but this imbalance flipped in the Kansas referendum [29].

[2] Similarly, the increasing levels of restriction in the Midwest make Canada a possible place for Americans to seek abortion care. However, obstacles to abortion access in Canada make the country an unlikely destination for Americans seeking abortion care [30].

abortion spillover from 2010 to 2019. In the increasingly restrictive post-Dobbs world, however, Americans may seek abortions in Mexico at greater rates. Future models could consider variables such as a state's proximity to the Mexican border, abortion rates in Mexican states, or surrounding-state scores that incorporate Mexican state policies.

Mexico offers several paths for Americans to seek both medication and surgical abortions. Mexican pharmacies do not require a prescription for abortion pills, so people can manage their abortions without ever visiting a clinic. Mexican advocacy groups have facilitated this process across Mexico for years, but these Mexican volunteer networks have expanded into the United States in recent years to help facilitate at-home medication abortions for Americans [99]. In addition to at-home medication abortions with pills from Mexico, American patients may also receive surgical abortions in Mexican clinics. Even before the Roe reversal, Mexican abortion clinics saw some patients from the United States, with a Tijuana clinic estimating that 25% of its patients in May 2022 came from the US [88]. These numbers will likely grow as abortion access in the United States grows more limited.

## C.3 Turning to Abortion Pills

Future analyses of abortion spillover should consider medication abortion apart from surgical abortion, perhaps by modeling medication abortion rates and surgical abortion rates as separate outcome variables. According to the Guttmacher Institute, more than half of abortions in the United States in 2020 used abortion pills, and demand will likely continue to rise following the Dobbs ruling as pro-life lawmakers restrict abortion access [58].[3]

In pre-pandemic years, individuals had to pick up mifepristone at hospitals, clinics, or medical offices. But, in December 2021, the FDA lifted the requirement and allowed telehealth appointments to prescribe mifepristone so that patients could receive the prescription in the mail in states that permitted the drug [58]. Following the Dobbs decision, health experts anticipate surges in telehealth consultations for medical abortions, online purchases of the pills, and self-managed medication abortions [92].

With the heightened restrictions of a post-Dobbs world, people have found

[3] States have a much harder time regulating medication abortion, as demonstrated by unsuccessful attempts from Texas to restrict access to abortion pills [106].

ways to circumvent restrictions on abortion pills. For a provider to legally prescribe abortion pills, the patient must provide a shipping address in a state that allows abortions. Patients may exploit state-level policy variation by receiving telehealth care from providers in states that allow abortion. Then, patients can use mail-forwarding accounts to ship their prescriptions to states with legal abortions before forwarding the pills to their actual addresses [83]. Since the delivery of abortion pills happens through private mail, restrictions against medication abortions are hard to enforce.[4] As discussed in the Self-Managed Abortions Outside the CDC's Periphery section of Chapter 5, individuals can also self-manage medication abortions with pills from overseas pharmacies or with prescriptions obtained for non-abortifacient purposes.[5] When paired with the heightened restrictions of the post-Dobbs era, the ease of these methods will likely lead to a rise in medication abortions.

[4] As discussed in the Federal Actions section of Chapter 6, individuals within the federal government have tried to safeguard access to abortion drugs.

[5] Even if an individual needs medical attention after ending a pregnancy with misoprostol and mifepristone, they will exhibit the same symptoms and require the same treatment as individuals experiencing a miscarriage. As a result, a self-managed abortion using a non-abortion misoprostol prescription would remain undetected and undocumented [81].

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