LIFE AFTER DOBBS: EXPLORING THE IMPACT OF TRIGGER ABORTION BANS ON INTIMATE PARTNER VIOLENCE

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ABSTRACT

Today, intimate partner violence (IPV) continues to be a widespread issue in the US, with about 2 in 5 women experiencing some form of IPV at least once in their lifetime, according to the Centers for Disease Control and Prevention. Moreover, IPV has a layered relationship with pregnancy: while individual incidents of IPV, specifically rape, can lead to unplanned pregnancy, it is also possible for pregnancy to result in IPV. Not only is pregnancy a risk factor for violence generally, but pregnancy and parenting can increase financial, emotional, and physical stress on individuals as well as relationships. This increase in stress can result in or increase the frequency of IPV while also complicating one's ability to leave a relationship. The focus of this paper lies in this latter phenomenon, in which pregnancy affects IPV, and its implications for abortion regulations.

Because of the increased risk to IPV presented by pregnancy, access to abortion services can be critical to escape abuse. However, recent changes in US state-level abortion policies greatly impact abortion access and may have downstream effects on rates of IPV. Yet, there are few research studies thus far that analyze the effect of restrictive abortion laws on IPV. In this study, I examine the potential effect of state-level trigger abortion bans enacted soon after the June 2022 *Dobbs v. Jackson Women's Health Organization* Supreme Court decision on IPV incidents reported to law enforcement. I use data from the Federal Bureau of Investigation's National Incident-Based Reporting System from the 12 months preceding and following the *Dobbs* decision

to create a difference-in-differences regression, which compares the monthly rates of reported IPV cases in states with and without trigger bans. The results provide insufficient evidence to support the hypothesis that abortion restrictions have a causal relationship with IPV rates. However, continued research is needed to more accurately understand the relationship between abortion access and IPV rates as US abortion policies continue to evolve over time.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

INTRODUCTION

Intimate partner violence (IPV) typically occurs in an abusive relationship or former relationship in which one person uses a variety of tactics to exert power and coercive control over their partner. These tactics can take the form of physical, sexual, psychological, or other types of harm, with potentially long-lasting effects across the victims' lifespan (Domestic Abuse Intervention Programs, 2017). According to the US Centers for Disease Control and Prevention (CDC), 41 percent of women and 26 percent of men have experienced contact sexual violence, physical violence, or stalking by an intimate partner during their lifetime (2024). Globally, nearly 1 in 4 girls have experienced IPV by the time they turn 20 years old (Sardinha et al., 2024). Additionally, only about half of IPV cases in the US are reported to law enforcement, according to the Bureau of Justice Statistics' National Crime Victimization Survey (Morgan & Truman, 2020).

The present study focuses on IPV and its connection to reproductive choices, because becoming pregnant can increase women's vulnerability to IPV. This is partially because pregnancy itself is a risk factor for higher rates of violence both within and outside of abusive relationships. For example, pregnant people experience higher rates of IPV, homicide, and physical abuse (American College of Obstetricians & Gynecologists, 2012; Donofrio, 2024; Goodman, 2021; Wallace et al., 2021). Additionally, pregnancy may create more obstacles for a person to leave a relationship—even an abusive one. The anticipation of sharing a child often entails a lifelong link between the pregnant person and their partner. Pregnant people may further hesitate to leave a relationship since raising a child requires great financial and emotional support. Thus, pregnant people may be more susceptible to IPV since it is more difficult for them to escape violent relationships. For these reasons, the ability to terminate an unwanted pregnancy by accessing abortion services may be critical, not only to maintain control over reproductive health but also to ensure safety from potential intimate partner abuse.

However, state-level laws recently enacted to restrict abortion services in response to the 2022 *Dobbs v. Jackson Women's Health Organization* Supreme Court case may significantly hinder individuals' ability to undergo any desired abortion procedures. As a result, some experts fear that a decrease in abortion access may lead to higher risk of violence against women, because those who may seek abortion services for safety against future IPV would not be able to receive those services. Recent literature has found significantly higher rates of IPV in states with laws that reduced abortion access prior to 2020 (Keegan et al., 2024; Neff et al., 2024; Wallace et al., 2024). Regarding abortion restrictions after the *Dobbs* decision, early data regarding the frequency of reproductive coercion reports from the National Domestic Violence Hotline suggests that there could be downstream effects on IPV, though this has not yet been studied causally (Tobin-Tyler & Dickman, 2024).

Therefore, I hypothesize that the enactment of state-level abortion bans may be a determinant of IPV rates. This is because restrictive abortion policies directly affect access to abortion services for an individual in any given state (Grossman et al., 2014; Lindo et al., 2020). Abortion access subsequently contributes to IPV in two main ways, which can be understood as two sides of the same coin. First, the degree of abortion access affects the ability of victims to escape abusive relationships and thus escape future incidents of IPV, because terminating a pregnancy can be a significant step in severing ties with an abusive partner. Second, the degree of abortion access affects the ability of abusive partners to commit reproductive coercion, because abusive partners use denial of wanted abortions as a tool to control their partners' pregnancy outcomes. So, a lack of abortion access may increase abusers' ability to deny abortions, thus making it easier to commit reproductive coercion and increasing the frequency of IPV incidents that involve sexual violence. I describe these two phenomena as two sides of the same coin because they ought to be considered in relation to one another. Where the abusers' ability to commit reproductive coercion greatly exceeds the victims' ability to escape the abusive relationship, the incidence of ensuing IPV would theoretically be higher than in circumstances where the opposite is true. Given that only a few years have passed since the *Dobbs* case, few studies have yet explored the effect of the newest abortion restrictions on IPV.

In this paper, I explore the relationship between restricted abortion access and IPV, specifically by examining the potential effect of state-level trigger abortion bans on IPV rates. The term "trigger abortion bans" in this paper refers to state laws that restrict abortion access before fetal viability, which were intended to take effect once the federal right to abortion conferred by *Roe v. Wade* was overturned, as it was in the 2022 *Dobbs* Supreme Court ruling. I create a difference-in-differences regression using data on IPV incidents reported to law enforcement from the FBI's National Incident-Based Reporting System (NIBRS) during the 12 months preceding and following the *Dobbs* decision. The difference-in-differences analysis compares the monthly IPV rates in states that enacted trigger bans to states that did not, to determine whether changes in abortion policies caused IPV rates for one group of states to change at a different rate than the other group. My results find insufficient evidence to support the hypothesis that trigger abortion bans have a causal relationship with IPV rates. However, continued research is critical for policymakers to more accurately understand the relationship between abortion access and IPV, as evolving restrictive abortion policies could potentially have downstream effects on violence and safety concerns for women.

BACKGROUND

The landmark 2022 *Dobbs v. Jackson Women's Health Organization* Supreme Court decision eliminated the constitutional right to abortion prior to fetal viability, overturning the historic *Roe v. Wade* decision which first secured this right in 1973. To better understand the state-level differences in abortion policies today, it may be helpful to note the history of US abortion policies as early as the mid-nineteenth century. The American Medical Association campaigned to regulate abortion practices for the first time starting in 1857, arguing that life begins at conception. Subsequently, over 40 states passed anti-abortion laws between 1860 and 1880, and abortion was illegal across the US by 1900. General attitudes towards abortion continued to shift according to large-scale sociopolitical events. During the first half of the twentieth century, support for abortion rose in response to the Great Depression and World Wars, when it was more difficult to financially support a family. Support fell again with the resurgence of traditional family gender roles during the peace time after the wars. Abortion access then gained more support in the aftermath of rubella outbreaks in the early 1960s, due to the risk of birth defects from contracting rubella during pregnancy.

It was in this political climate that the US Supreme Court heard the 1973 *Roe v. Wade* case, ultimately deciding that women have a constitutional right to abortion. The justices ruled in a 7-2 majority that according to the right to privacy contained in the Due Process Clause of the Fourteenth Amendment, an individual may choose to have an abortion until the fetus reaches viability, or the ability to survive independently outside of the womb. This decision superseded state-level restrictive abortion laws passed prior, thus conferring a federal right to abortion up until the point of fetal viability.

Yet, opponents of abortion rights did not disappear after the *Roe* decision. Many advocated for state-level legislation that would further regulate abortion beyond the federal right conferred by *Roe*. To this day, state-level differences in abortion policies have far-reaching implications for the extent of abortion services and facilities available to individuals. From the late 1980s through the 2010s, several states enacted regulations for abortion clinics in the name of patient safety. In reality, many of these clinic regulations proved burdensome enough to cause clinics to close, thereby limiting abortion access. According to the Guttmacher Institute, 23 states have passed some form of these laws, termed Targeted Regulations of Abortion Providers (TRAP laws). For example, the 2013 Texas House Bill 2 resulted in the closure of nearly 20 facilities within six months and increased the average distance needed to travel to the nearest abortion clinic (Benson Gold & Hasstedt, 2016; Gerdts et al., 2022; Grossman et al., 2014; Lindo et al., 2020). In this way, some state abortion regulations significantly limited abortion access even after *Roe*.

During President Donald Trump's first term in the White House, three new Supreme Court justices were appointed and confirmed by the Republican administration, contributing to a surge in the pro-life movement across the nation. On June 24, 2022, this Supreme Court ruled in the *Dobbs v. Jackson Women's Health Organization* case that abortion was not a fundamental right protected in the US Constitution, thus reversing the decision made in *Roe v. Wade*. The *Dobbs* decision made it possible for states to place legal bans on abortions for the first time in nearly 50 years. In the years leading up to and following *Dobbs,* several states responded to the court decision in a wide variety of ways. In anticipation of an anti-abortion Supreme Court ruling, 13 states passed "trigger bans" in advance of the decision as early as 2018, such that restrictions on abortions would go into immediate effect upon passage of any court ruling overturning *Roe v. Wade*. Other states enacted abortion bans after the *Dobbs* ruling went into effect, and still others passed laws which would explicitly protect an existing right to abortion in the state. Additionally, much of the legislation restricts abortion to different extents. For example, some states banned abortions at any point during pregnancy, while others banned abortions only after 24 weeks postfertilization. Some abortion bans include exceptions in cases of incest or rape while others do not. Nevertheless, many abortion regulations across the country now restrict abortion in some form or another, with the procedure now completely illegal in several states, and policies have continued to change in the years following the *Dobbs* ruling.

In this paper, I focus on the state-level trigger abortion bans which were passed prior to and became effective in the weeks soon after the *Dobbs* Supreme Court decision. Though the details of each state's regulations may differ, these trigger bans are all "total abortion bans" which make abortion procedures illegal regardless of how far along the pregnancy is. The 13 states which passed abortion bans in advance of the Supreme Court decision included Arkansas, Idaho, Kentucky, Louisiana, Mississippi, Missouri, North Dakota, Oklahoma, South Dakota, Tennessee, Texas, Utah, and Wyoming. Out of these 13 states, trigger bans went into immediate effect on June 24, 2022 for 6 states (Arkansas, Kentucky, Louisiana, Missouri, Oklahoma, and South Dakota). For another 4 states (Idaho, Mississippi, Tennessee, and Texas), trigger bans went into effect during the following weeks, so nearly all trigger bans were enforceable by August 25, 2022.

For the remaining 3 states (North Dakota, Utah, and Wyoming), court challenges blocked enforcement of their trigger bans significantly, such that these states did not truly have a total abortion ban during the first 12 months after *Dobbs*. In addition, there was one other state that did not pass a trigger ban prior to the *Dobbs* decision but did enact a total abortion ban on June 24, 2022, which was Alabama. Because of the timing of Alabama's abortion ban, this paper will consider Alabama within the same group as other states whose trigger bans took effect directly following *Dobbs*. Thus, by this count, there were 11 states that effectively enacted trigger abortion bans after *Dobbs*: Alabama, Arkansas, Idaho, Kentucky, Louisiana, Mississippi, Missouri, Oklahoma, South Dakota, Tennessee, and Texas. Figure 1 displays a map of US states which are colored based on the type of abortion bans they represent in this paper. A detailed summary of abortion bans in each state after *Dobbs* can be found in Appendix A, listed in order of the first date of enforcement.

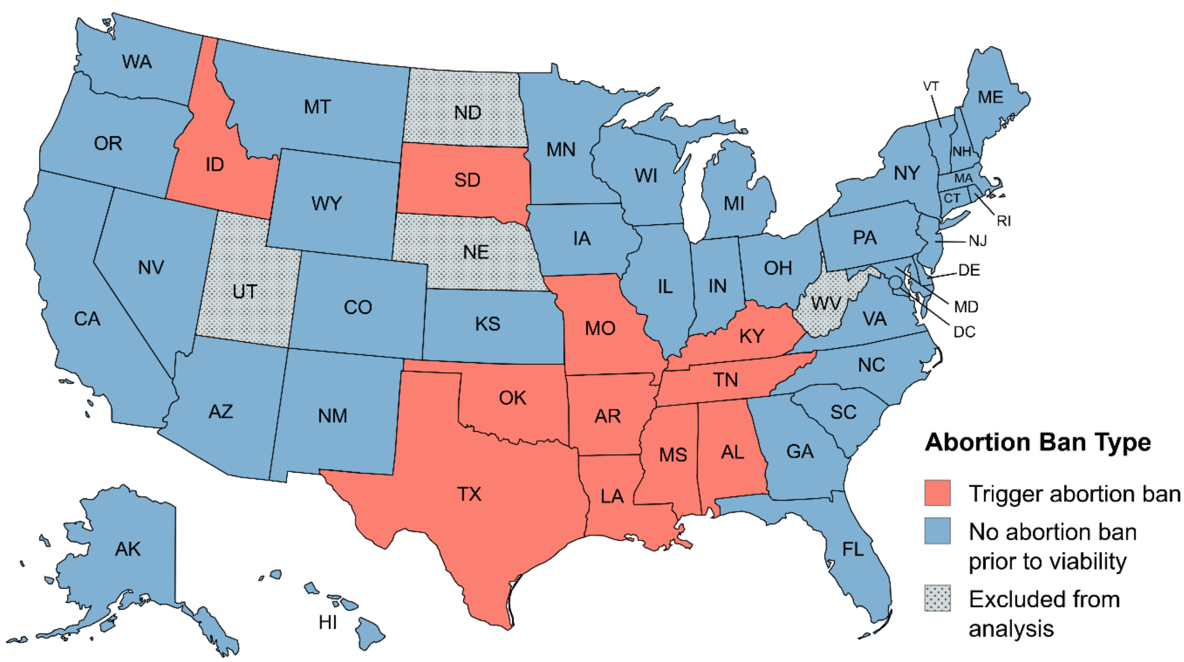

Figure 1. Map of US states by abortion ban type.

LITERATURE REVIEW

Scholarly research over the past couple of decades has confirmed that abortion-seeking behaviors can be related to avoiding IPV. Studies find that fear of violence from a partner is often cited as a primary motivation for women seeking abortion (Chibber et al., 2014; Williams &

Brackley, 2009). Access to abortion may also make it easier for a victim to leave an abusive partner and escape future acts of violence. Women who obtain an abortion are more likely to leave abusive relationships than women who seek but are unable to obtain an abortion, and they are less likely to experience physical violence from their co-conceiver in the following 2.5 years (Roberts et al., 2014). Across the literature, we find an emergent theme that the ability to obtain abortion services can be critical to avoiding abuse (Ely & Murshid, 2021).

Given that the level of access to abortion services may have a significant effect on a woman's ability to escape IPV relationships, it follows that state-level differences in abortion laws may lead to differences in IPV rates. Although there are many studies on IPV, sexual violence, reproductive health, unwanted pregnancy, and abortion seeking, there is limited research that specifically studies the potential impact of restricted abortion access on IPV experiences and incidence. The relevant existing studies that examine the effects of abortion restrictions on various types of IPV primarily focus on the effects of state-level Targeted Regulations of Abortion Providers (TRAP laws) up until 2020, or they examine measures of abortion access unrelated to specific policies, such as the number of abortion clinics available in a given geographical area. Few studies have yet been published about the potential impact of the 2022 *Dobbs v. Jackson Women's Health Organization* Supreme Court ruling or related abortion laws, presumably because of how recently the *Dobbs* decision occurred. Among the studies that analyze outcomes in the years after *Dobbs*, few focus on IPV as the outcome of interest and none thus far have sought to establish a causal relationship.

Restrictive Abortion Access and Violence

A significant body of research examines the downstream effects of TRAP laws and other state-level restrictive abortion policies passed over the last decade, from impacts on maternal and infant mortality to teen pregnancy and foster care admissions (Adkins et al., 2024; Declercq et al., 2022; Jones et al., 2024). However, only a few studies have begun to illuminate a causal relationship between abortion restrictions and increased rates of violence against women, and of these studies, the focus is often on experiences during pregnancy. Neff et al. (2024) finds that women living in 16 states with restrictive abortion policies were approximately 1.5 times more likely to experience IPV during pregnancy in 2020 than those in other states. In states with restrictive abortion policies from 2018 to 2020, Keegan et al. (2024) found that rates of homicide against peripartum people (pregnant or partum within one year) are significantly higher than in other states, and firearms are used in two-thirds of IPV-related homicides against peripartum people. Since most of the states with abortion bans do not require those convicted of domestic violence to relinquish firearms, the combination of firearm access and high rates of IPV-related homicide for peripartum people in abortion ban states may create a particularly dangerous environment for women experiencing IPV (Tobin-Tyler & Dickman, 2024). These studies begin to establish some relationship between abortion restrictions and IPV but are limited in scope to pregnant women.

Regarding the broader population of women, there are even fewer studies about the impact of abortion restrictions on IPV. One study found that enforcement of each additional TRAP law from 2014 to 2020 was associated with an increase in the rate of IPV-related homicide for reproductive-aged women by about 3 percent (Wallace et al., 2024). For incidents of violence against women more broadly, Muratori (2021) found a causal relationship between access to abortion, measured by travel distance to the nearest abortion clinic, and a small percentage increase in gender-based violence. Yet, gaps in the literature remain regarding the general impact of abortion access on the rates of IPV.

Implications of Abortion Restrictions after Dobbs

In addition, causal research studies thus far have focused on examining abortion access in the US socio-political climate prior to the 2022 *Dobbs* decision. However, now that the right to abortion is no longer guaranteed in all US states, the policy landscape regarding abortion and outcomes related to reproductive health may continue to change rapidly in many states. Very recent studies begin to discuss the effects of abortion restrictions in light of the *Dobbs* decision in several subject areas outside of IPV, including access to maternal healthcare, maternal and infant mortality rates, rates of unwanted pregnancy, poverty, and others (Coverdale et al., 2022; Donofrio, 2024; Gordon et al. 2022; Portney & Sweet, 2024; Singh & Gallo, 2024). If recent changes in state abortion policies have been consequential enough to significantly impact reproductive health and other life outcomes, it is possible that they may affect IPV as well.

While some literature has been published to discuss the mechanisms through which abortion restrictions may affect IPV, no causal research studies have been conducted yet. In particular, Donofrio (2024) argues that US case law has largely failed to consider the ramifications for IPV survivors when ruling about abortion access, such as in *Dobbs*. The author explains that “people who become pregnant as a result of reproductive coercion or while in an abusive relationship lose autonomy to determine whether to carry a pregnancy to term and whether to remain permanently tied to a perpetrator through a child” (Donofrio, 2024, p. 702). Moreover, researchers have pointed out a 98 percent increase in calls to the National Domestic Violence

Hotline regarding reproductive coercion in the year following *Dobbs*, which could be a potential indicator of the impact of *Dobbs* on IPV (Tobin-Tyler & Dickman, 2024). However, it is important to note that none of these studies have established any causal links.

Outside of the relevant literature reviewed above, to my knowledge, there are not yet any studies published that find a causal effect of restricted abortion access on IPV after the *Dobbs* ruling. The present study aims to fill these gaps in research by using a difference-in-differences regression model to explore the early effects of trigger abortion bans after *Dobbs* on IPV rates in the most current socio-political climate. A difference-in-differences analysis compares a metric of interest among two groups of subjects across two periods of time. Thus, my analysis compares the monthly IPV rates in states that enacted trigger bans to states that did not, to determine whether changes in abortion policies caused IPV rates for one group of states to change at a different rate than the other group.

CONCEPTUAL FRAMEWORK

I hypothesize that abortion restrictions affect the rate of IPV by decreasing victims' access to abortion as a tool to escape abusive relationships. My model uses state-level trigger abortion bans effective at the time of the *Dobbs* decision as a proxy for restricted abortion access. Additionally, my model will account for several demographic and sociological factors which moderate this relationship. These are diagrammed in Figure 2 and enumerated below.

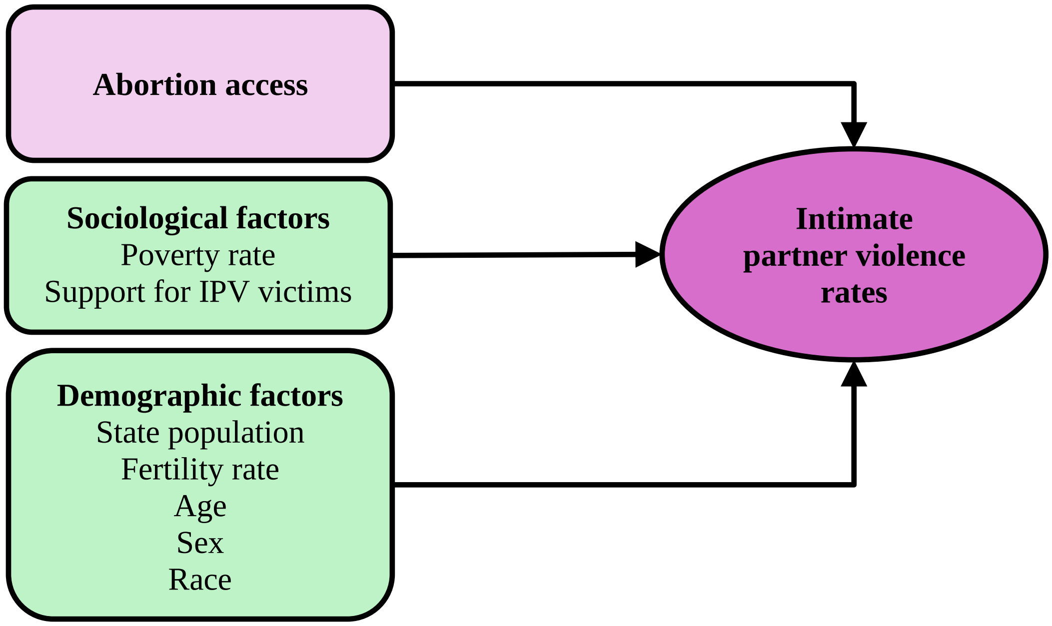

Figure 2. Conceptual framework illustrating the impact of state abortion bans and other factors on rates of IPV.

Sociological Factors

There are two main covariates incorporated into this model relating to sociological factors which may influence IPV rates in some way: the poverty rate and the resources available in a given state for victims in abusive relationships to seek help from future violence. First, I include the state-level poverty rate in my model, because poverty is related to a host of other sociological phenomena including rates of crime, IPV, and unwanted pregnancy. Because of these correlations, poverty rates may help to account for some of the variation in IPV rates across states.

The amount of support available for victims in IPV relationships may affect the relationship between restricted abortion access and IPV, because it influences the ability of victims to escape their abusive relationships and/or avoid future violence from their partners. While many resources focus on response to IPV incidents that have already occurred, interventions for people in active relationships with abusive partners can also help them escape ongoing and future acts of violence. For example, many IPV advocacy organizations provide counseling and trauma-informed practices for IPV victims, helping them assess their situation and make decisions about how to proceed with an abusive relationship (McNamara et al., 2008; Sullivan et al., 2018). Workers for a crisis hotline may advise victims on how they may safely flee unsafe circumstances (Wood et al., 2023). IPV shelters may provide housing for victims, simultaneously acting as a refuge for them to seek assistance and avoid violent assaults (Chanley et al., 2001; Robinson et al., 2020). Other resources are dedicated explicitly towards prevention efforts such as educational programs in schools (Whitaker et al., 2013). The availability of all these resources can vary greatly across states depending on the funding available for them. In my model, I account for these differences by including the amount of federal grant awards given to each state per fiscal year from the Office of Violence Against Women (OVW), divided by the state population. This variable is measured in US dollars per capita.

Demographic Factors

There are five main demographic factors that are accounted for in this model as covariates because they each may be linked to the average state-level rates of IPV: state population, fertility rate, and sex, age, and racial/ethnic distributions of the population. I include a measure of the annual state population since the size of each state may have some bearing on the amount of resources available as well as the rate of violent crimes including IPV. The annual fertility rate in each state is used to control for differences in overall rates of conception across states. Next, I control for age and race/ethnicity because rates of IPV victimization and perpetration differ across age groups as well as racial and ethnic groups (Cho, 2012; Johnson et al., 2015; Kivisto, 2022;

Lipsky et al., 2012). In order to account for differences in the distributions of age across states, I incorporate the percentages of the state female population who are aged 15-17 years and 18-24 years old. These specific age groups are used to capture the teenage and young adult years because global rates of IPV victimization are especially high for adolescent and young women, compared to older women (Sanz-Barbero et al., 2018; Sardinha et al., 2024; Stöckl et al., 2014). For race and ethnicity, I use the percentages of the population who identify as non-Hispanic White, non-Hispanic Black, and Hispanic in each state. Additionally, I incorporate two measures designed to capture any differences among states regarding the size of the population that is susceptible to IPV via reproductive coercion. I include the ratio of the female to male state population, as well as the percentage of the state population who are females of child-bearing age (15-44 years old), since this group is most likely to be affected by reproductive coercion.

Additional Considerations

When developing this model, I considered including the rates of violent crimes along with poverty rates, since some geographic locations may be generally more prone to violent crime incidents including IPV. Similar to poverty rates, I reasoned that the inclusion of state-level violent crime rates would help to account for variation in IPV rates across states. When I included violent crime rates in my analysis, I found that violent crime rates were very highly correlated with IPV rates, so these two variables were unlikely to be independent of one another. As a result, I have omitted violent crime rates from my regression model to avoid violating the assumption of independence. However, I included it in the descriptive statistics analysis to better understand the demographics of the states in the analysis.

DATA AND METHODS

To perform my analysis, I relied on data regarding individual crime incidents that occurred during the 12 months leading up to and following the *Dobbs* Supreme Court decision in all 50 US states plus the District of Columbia (DC), from the National Incident-Based Reporting System (NIBRS) within the Federal Bureau of Investigation's (FBI) Uniform Crime Reporting (UCR) program. The NIBRS dataset compiles crime reporting data submitted to the UCR program by city, county, state, and federal law enforcement agencies across the country. It includes standardized information about the offenses, property, victims, offenders, and arrestees associated with crime incidents known to the police that fall under 22 types of "Group A" offenses and 11 types of "Group B" offenses, including assault, sex offenses, and other crimes commonly experienced in the context of IPV.[1] For NIBRS, each incident is defined as "one or more offenses committed by the same offender, or group of offenders acting in concert, at the same time and place." Within one incident, all offenders are considered to have committed all of the offenses in the incident.

In order to capture IPV incidents before and after *Dobbs*, I specifically focused on incidents in the NIBRS dataset that meet the following conditions:

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[1] Group A offense types include arson, assault offenses, bribery, burglary/breaking and entering, counterfeiting/forgery, destruction/damage/vandalism of property, drug/narcotic offenses, embezzlement, extortion/blackmail, fraud offenses, gambling offenses, homicide offenses, kidnapping/abduction, larceny/theft offenses, motor vehicle theft, pornography/obscene material, prostitution offenses, robbery, forcible sex offenses, nonforcible sex offenses, stolen property offenses, and weapon law violations. Group B offense types include bad checks, curfew/loitering/vagrancy violations, disorderly conduct, driving under the influence, drunkenness, nonviolent family offenses, liquor law violations, peeping Tom, runaway, trespass of real property, and all other offenses.

1. First, I subsetted the data to include only incidents that concern intimate partners. These are observations in the NIBRS dataset in which at least one of the relationships between a victim and perpetrator is coded as spouse, common law spouse, boyfriend/girlfriend, homosexual relationship, ex-spouse, or ex-relationship.
2. Next, I subsetted the data to include incidents whose offense types most closely align with the definition of IPV. In the NIBRS dataset, these offense types include murder/nonnegligent manslaughter, kidnapping/abduction, rape, sodomy, sexual assault with an object, fondling, aggravated assault, simple assault, intimidation, extortion/blackmail, statutory rape, human trafficking (commercial sex acts), and human trafficking (involuntary servitude).

According to the criteria used to define IPV above, there were a total of 2,775,970 reported IPV incidents across the years 2021 through 2023 within this dataset: 864,890 incidents occurred during 2021; 903,037 incidents during 2022; and 1,008,043 incidents during 2023. Once I narrowed down my data observations to IPV incidents, I aggregated incidents based on the date of the incident and the state where the incident occurred. I then obtained the total numbers of IPV incidents that occurred during each month in each state, allowing me to conduct my analysis on the state-month level.

Next, I paired these data with information regarding state-level trigger abortion bans which went into effect upon the *Dobbs* ruling. To do this, I created two indicator variables. One of the variables represents whether a state is among the group of those that enacted a trigger abortion ban, where the value of 1 applies to states that passed total abortion bans prior to fetal viability which became enforceable no later than 2 months after the *Dobbs* ruling and the value of 0 applies to all other states. The states which enacted trigger bans include Alabama, Arkansas, Idaho, Kentucky, Louisiana, Mississippi, Missouri, Oklahoma, South Dakota, Tennessee, and Texas. The second indicator variable is a time-related variable corresponding to the date of the *Dobbs* decision. I organized the observations into two groups based on 12-month time periods. The baseline time period prior to *Dobbs* is comprised of the 12 months from June 2021 through May 2022, while the time period after *Dobbs* is comprised of the 12 months from September 2022 to August 2023.[2] These two time periods form the basis for the time-based indicator variable, where the value of 1 applies to all months after the *Dobbs* ruling was issued and the value of 0 applies to the months prior. Finally, I created an interaction term between these two indicator variables. The interaction term equals 1 only for observations in trigger ban states after *Dobbs*, allowing me to isolate any special effect related to the enforcement of these bans. This interaction term serves as the key independent variable in my model.

I excluded four states from my analysis because their abortion policies did not fit well in this difference-in-differences analysis: Nebraska, North Dakota, West Virginia, and Utah. While Nebraska, North Dakota, and West Virginia did not enact trigger bans, they did enact abortion bans that went into effect within the first 12 months following the *Dobbs* decision. The abortion bans could have hypothetically impacted the IPV rates in these three states, but I dropped them from my model because they do not align with the time periods in the difference-in-differences analysis. In Utah, policymakers passed legislation that would have enacted a total trigger abortion ban, but its implementation was blocked by a court ruling. An existing 18-week abortion ban was

[2] There is currently little research on the effects of abortion policies on IPV, so it is not yet known whether any effect would be lagged. However, it is plausible that human behavior regarding abuse may not change right away because patterns of behavior in relationships could be more gradual to change over time. I tried multiple models which incorporated either no lag, a lag of 2 months, or a lag of 4 months, but I did not find that the lagged models provided significantly different results. Therefore, I focus on the non-lagged model in this paper for simplicity.

subsequently put into effect instead. Because this 18-week ban is considerably less restrictive than the total abortion bans common amongst all other trigger ban states, I dropped Utah from my analysis to avoid skewing the results. Accounting for these dropped observations, the total sample size of my data is equal to 1,128 observations, or one observation per state per month over 24 months (47 states including DC × 24 months).

As discussed in the previous section, my analysis incorporates a number of covariates as well, for which data has been gathered from additional sources:

- Data regarding the annual state populations, state-level distributions of age and sex, state-level distributions of race, and state poverty rates over time were obtained from the US Census Bureau's American Community Survey (ACS) 5-year series (2018-2022).
- Data regarding the state-level fertility rates over time were obtained from Natality data published by the Center for Disease Control's (CDC) Wide-ranging Online Data for Epidemiologic Research (WONDER).
- Data regarding the state-level violent crime rates over time were obtained from the FBI's Uniform Crime Reporting (UCR) program.
- Data regarding the amount of OVW grant funding awarded to each state per fiscal year were obtained from the OVW Awards by State and Program website.

More information about the data collection for these sources can be found in Appendix B. Table 1 summarizes the definitions for each of the variables included in this model.

Table 1. Definitions of variables.

Variable	Definition	Source
Dependent variable		
IPV rape	A continuous variable measuring the number of incidents of IPV-related rape, per 100,000 people, reported for each state and month.	FBI's NIBRS dataset, years 2018-2022.
Independent variable		
Abortion ban	A dichotomous variable indicating whether the state enacted a trigger abortion ban which was enforceable after the *Dobbs* decision.	LawAtlas State Abortion Bans dataset.
Post-Dobbs	A dichotomous variable indicating whether the date is before or after the *Dobbs* decision, equal to 1 for months starting in September 2022 and onwards.	Guttmacher Institute.
Trigger ban states × Post-Dobbs	A dichotomous variable derived by interacting the variables *Abortion ban* and *Post Dobbs*, equal to 1 for observations related to trigger ban states on or after September 2022.	Derived from *Abortion ban* and *Post Dobbs* variables.
Sociological factors		
Violent crime	A continuous variable measuring the state-level violent crime rate, per 100,000 people.	FBI's Uniform Crime Reporting program.
Poverty rate	A continuous variable measuring the percentage of the state population living with individual or family incomes below the federal poverty line.	US Census Bureau's Historical Poverty Tables.
OVW funding	A continuous variable measuring the amount of grant funding awarded by the OVW to organizations in the state during the fiscal year, in dollars per capita.	OVW's Awards by State and Program tables.
Demographic factors		
Population	A continuous variable measuring the annual state population, in thousands of people.	US Census Bureau's ACS 5-Year series.
Fertility rate	A continuous variable measuring the annual state-level fertility rate, equal to the number of births per 1,000 females.	CDC's WONDER database for Natality Information, 2016-2023 (Expanded) data.
Age and sex		
Sex ratio	A continuous variable measuring the ratio of the female to male population in the state.	US Census Bureau's ACS 5-Year series, Table S0101, "Age and Sex."
% Child-bearing	A continuous variable measuring the percentage of the state population who are a female of child-bearing age (15-44 years old).	US Census Bureau's ACS 5-Year series, Table S0101, "Age and Sex."
% Aged 15-17	A continuous variable measuring the percentage of the female state population aged 15 to 17 years old.	US Census Bureau's ACS 5-Year series, Table S0101, "Age and Sex."
% Aged 18-24	A continuous variable measuring the percentage of the female state population aged 18 to 24 years old.	US Census Bureau's ACS 5-Year series, Table S0101, "Age and Sex."

Table 1. (Cont.)

Variable	Definition	Source
Race and ethnicity		
% White	A continuous variable measuring the percentage of the state population identifying as non-Hispanic, White.	US Census Bureau's ACS 5-Year series, Table 03002, "Hispanic or Latino Origin by Race."
% Black	A continuous variable measuring the percentage of the state population identifying as non-Hispanic, Black.	US Census Bureau's ACS 5-Year series, Table 03002, "Hispanic or Latino Origin by Race."
% Hispanic	A continuous variable measuring the percentage of the state population identifying as Hispanic.	US Census Bureau's ACS 5-Year series, Table 03002, "Hispanic or Latino Origin by Race."

Specification of Regression Model

My model uses a difference-in-differences approach by comparing the change in IPV rates for states before and after the enactment of a trigger abortion ban to the change in IPV rates for states that did not enact an abortion ban during the same time period. The specification for this model is represented by the following equation:

$$
\begin{aligned}
(IPV\ rate)_{it} = \beta_0 + \beta_1(Abortion\ ban)_i + \beta_2(Post\ Dobbs)_t \\
+ \beta_3[(Abortion\ ban) \times (Post\ Dobbs)]_{it} + \beta_4(Poverty\ rate)_{it} \\
+ \beta_5(OVW\ funding)_{it} + \beta_6(Population)_{it} + \beta_7(Fertility\ rate)_{it} \\
+ \beta_8(Sex\ ratio)_{it} + \beta_9(\%\ Child-bearing)_{it} + \beta_{10}(\%\ Aged\ 15-17)_{it} \\
+ \beta_{11}(\%\ Aged\ 18-24)_{it} + \beta_{12}(\%\ White)_{it} + \beta_{13}(\%\ Black)_{it} \\
+ \beta_{14}(\%\ Hispanic)_{it} + \alpha_i + t_t + \mu_{it}
\end{aligned}
$$

Where *i* represents the state, *t* represents the month and year time period, α_i represents state time-invariant characteristics, t_t represents state-invariant characteristics over time, and μ_{it} represents the error term. The coefficient β_0 represents the y-intercept for the model; the coefficients β_1, β_2, and β_3 correspond with the key independent variables; the coefficients β_4 and β_5 correspond with the covariates related to sociological factors; and the remaining coefficients correspond with the covariates related to demographic factors.

There are three coefficients for my main independent variables in this model. The β_1 coefficient for the *Abortion ban* variable estimates the difference in IPV rates related to residing in one of the states that enacted a trigger abortion ban compared to other states before *Dobbs*. The β_2 coefficient for the *Post-Dobbs* variable estimates the change over time in IPV rates for states without trigger abortion bans from the months before to the months after the *Dobbs* decision. Finally, the β_3 coefficient on the interaction term between the *Abortion ban* and *Post-Dobbs* variables estimates any additional effect on IPV rates after the *Dobbs* decision for only states that enacted a trigger ban, which thus isolates any potential difference-in-differences estimate. Therefore, a finding of a β_3 coefficient in my analysis that is statistically different from zero and positive would provide evidence to support my hypothesis that regulations limiting abortion access such as state-level trigger abortion bans enacted at the time of the *Dobbs* decision increase the rates of IPV.

DESCRIPTIVE STATISTICS

Table 2 presents descriptive statistics for the key dependent and independent variables in my analysis, as well as the demographic and sociological control variables, for all states represented in my model across the two 12-month periods in the analysis. The average number of IPV incidents reported per state per month during this period was about 26.9 per 100,000 people, though this number varied greatly by state, with Nevada, District of Columbia, and Tennessee most frequently reporting the highest monthly IPV rates. Likewise, both the violent crime rate and the poverty rate varied significantly across states: state-level violent crime rates ranged from 3.2 up to 120.1 monthly violent crimes per 100,000 people, and poverty rates ranged from 6.1% to 21.5% of the state population experiencing poverty. These and some of the other demographic variables which vary across states appear to reflect the diversity of US states and their populations.

Table 2. Summary statistics of state-level monthly IPV rates and other characteristics (N=1,128).

Variable	Mean	SD	Min	Max
Independent Variable: Enacted trigger abortion ban (proportion)	23.4%	-	-	-
Dependent Variable: Number of monthly reported IPV incidents (per 100,000 people)	26.9	11.8	0.9	80.5
Crime and Sociological Factors				
State-level violent crime rate (per 100,000)	22.9	12.6	3.2	120.1
State-level poverty rate (%)	11.0	3.1	6.1	21.5
OVW funding per fiscal year by state (dollars per capita)	3.3	4.2	0.6	24.1
Demographic Characteristics				
State population (in 100,000s)	68.8	75.0	5.8	394.6
State-level fertility rate (per 1,000)	55.4	5.0	42.1	68.58
Sex and age distributions of state population				
Ratio of female to male population	1.02	0.03	0.90	1.10
State population who are child-bearing females (aged 15-44 years) (%)	19.4	1.3	17.4	26.8
Female population aged 15-17 years (%)	3.7	0.3	2.2	4.4
Female population aged 18-24 years (%)	9.0	0.6	7.3	10.8
Racial/ethnic distribution of state population				
Non-Hispanic White (%)	65.0	15.8	21.0	92.0
Non-Hispanic Black (%)	11.5	10.4	0.5	43.9
Hispanic (%)	12.9	10.4	1.8	49.8

Table 3 provides the descriptive statistics of the same variables but differentiated across the specific groups in my difference-in-differences analysis. Out of the 47 states (including DC) in the analysis, 11 passed trigger abortion bans that became effective immediately or almost immediately after the *Dobbs* Supreme Court decision, no later than August 25, 2022: Alabama, Arkansas, Idaho, Kentucky, Louisiana, Mississippi, Missouri, Oklahoma, South Dakota, Tennessee, and Texas. These states make up the group referred to as "Trigger ban states" in Table 3, while all other states fall under the category "Non-trigger ban states."

Table 3. Average summary statistics by state trigger abortion ban status.

	Before *Dobbs* Decision		After *Dobbs* Decision	
Variable	**Non-trigger ban states**	**Trigger ban states**	**Non-trigger ban states**	**Trigger ban states**
N=1,128	432	132	432	132
Dependent Variable: Number of monthly reported IPV incidents (per 100,000 people)	25.0	33.2	25.6	31.6
Sociological Factors				
State-level violent crime rate (per 100,000)	21.4	27.7	22.1	25.8
State-level poverty rate (%)	10.4	13.9	10.1	13.2
OVW funding per fiscal year by state (dollars per capita)	3.1	2.3	4.0	2.4
Demographic Characteristics				
State population (in 100,000s)	70.5	62.6	70.7	63.2
State-level fertility rate (per 1,000)	54.6	61.0	53.1	59.9
Sex and age distributions of state population				
Ratio of female to male population	1.01	1.02	1.01	1.02
State population who are child-bearing females (aged 15-44 years) (%)	19.4	19.5	19.4	19.6
Female population aged 15-17 years (%)	3.6	3.9	3.7	4.0
Female population aged 18-24 years (%)	9.0	9.2	8.9	9.2
Racial/ethnic distribution of state population				
Non-Hispanic White (%)	64.6	68.0	63.8	67.2
Non-Hispanic Black (%)	10.4	15.2	10.3	15.0
Hispanic (%)	13.8	9.4	14.1	9.9

These two groups of states differ significantly from each other for almost every variable. Trigger ban states tend to have higher violent crime rates ($p<0.0001$), higher poverty rates ($p<0.0001$), and lower OVW grant funding awarded per capita ($p<0.0001$) compared to non-trigger ban states. The sex, age, and racial/ethnic distributions of the populations are different as well. Trigger ban states tend to have higher fertility rates ($p<0.0001$), a higher female to male ratio ($p=0.002$), and larger percentages of younger females in the 15-17 ($p<0.0001$) and 18-24 year age groups ($p<0.0001$). They tend to be more White ($p=0.0009$), more Black ($p<0.0001$), and less Hispanic ($p<0.0001$). The only two factors in which the two groups do not differ significantly are the state populations ($p=0.15$) and the percentage of the state population who are females of child-bearing age ($p=0.14$). Overall, these descriptive statistics demonstrate that trigger ban states and non-trigger ban states differ on many accounts, but controlling for these factors in the model would help to set up valid comparisons across these two groups.

In addition, the numbers of reported IPV do not appear to change significantly from before to after *Dobbs* for either group of states. Because of this, it is possible that the coefficients in my regression analysis will be relatively small in magnitude. Regarding IPV rates, trigger ban states have higher numbers of reported IPV incidents than other states both before *Dobbs* ($p<0.0001$) and after *Dobbs* ($p<0.0001$). Moreover, neither the trigger ban states nor the non-trigger ban states experienced significant changes in IPV rates over time ($p=0.17$ and $p=0.45$, respectively). Based on these descriptive statistics alone, there is not yet evidence for a significant relationship between trigger abortion bans and IPV rates during the 12-month periods before and after *Dobbs*.

RESULTS AND DISCUSSION

In this analysis, I explore whether there is a causal effect of the state-level trigger abortion bans enacted after the 2022 *Dobbs v. Jackson Women's Health Organization* Supreme Court decision on the monthly rates of IPV. I used a linear regression model with interaction terms to conduct a difference-in-differences analysis, with additional covariates related to selected sociological and demographic factors. Table 4 displays the results of the regression, split into three related models: (1) the model in the first column incorporates only the key independent variables for the difference-in-differences analysis; (2) the model in the second column adds on the covariates representing sociological factors; and (3) the model in the third column adds on the covariates representing both sociological and demographic factors. In Model 1, the variation in the key independent variables alone account for about 6 percent of the variation in IPV rates, as indicated by the adjusted r-squared value of 0.06. As sociological and demographic covariates are added to Models 2 and 3, the adjusted r-squared value increases to 0.12 and 0.35, respectively, so when all variables in this analysis are included, the model accounts for about 35 percent of the variation in IPV rates. Several of the covariates included in the analysis were statistically significant at the 5 percent level in the directions expected, indicating that these factors were fairly predictive of IPV rates. However, the overall regression results do not provide evidence of a causal effect on IPV rates as a result of enacting trigger abortion bans during this time period.

Table 4. Regression results of IPV rates on trigger abortion bans after *Dobbs* decision (N=1,128).

Dependent Variable: Number of monthly reported IPV incidents per 100,000 people			
Variable	**(1)** Difference-in-differences	**(2)** Sociological covariates	**(3)** Sociological & demographic covariates
Key independent variables			
Trigger ban states	8.2***	6.7***	6.1***
Post-*Dobbs*	0.6	0.3	0.3
Trigger ban states × Post-*Dobbs*	-2.2	-1.6	-1.9
Sociological factors			
State-level poverty rate (%)		0.5***	0.07
OVW funding per fiscal year by state (dollars per capita)		0.5***	-0.2
Demographic characteristics			
State population (in 100,000s)			-0.08***
State-level fertility rate (per 1,000)			0.2
Sex and age distributions of state population			
Ratio of female to male population			-7.0
State population who are child-bearing females (aged 15-44 years) (%)			4.7***
Female population aged 15-17 years (%)			4.4*
Female population aged 18-24 years (%)			-6.2***
Racial/ethnic distribution of state population			
Non-Hispanic White (%)			0.3***
Non-Hispanic Black (%)			0.2**
Hispanic (%)			0.6***
Adjusted r-squared	0.06	0.12	0.35
F-statistic (overall significance for model)	26.57***	30.40***	43.67***
Joint f-statistic for trigger ban states (significance of both the trigger ban states variable and interaction variable)	39.85***	23.03***	13.21***
Joint f-statistic for post-*Dobbs* (significance of both the post-*Dobbs* variable and interaction variable)	0.96	0.50	1.01
*Statistical significance denoted as follows: *** p<0.001, ** p<0.01, * p<0.05*			

The results suggest that the IPV rates for trigger ban states and non-trigger ban states are significantly different from one another; overall, the states that enacted a trigger ban are more likely to have higher levels of IPV. However, this does not necessarily represent a causal effect from the abortion bans themselves. Rather, this difference in IPV rates stems from the many sociological, demographic, and other differences between these two groups of states, as illuminated by the descriptive statistics presented previously in this paper. Some of the factors that are more strongly associated with trigger ban states, such as higher poverty rates and violent crime rates, tend to be correlated with higher rates of IPV in general (Cunradi et al., 2000).

Figure 3 helps to visualize the difference in IPV rates between the two groups, by presenting the predicted values of the monthly IPV rates both before and after the *Dobbs* decision, for both the trigger ban states and the non-trigger ban states. In the graph below, the trigger ban states are represented by the red line, while non-trigger ban states are represented by the blue line.

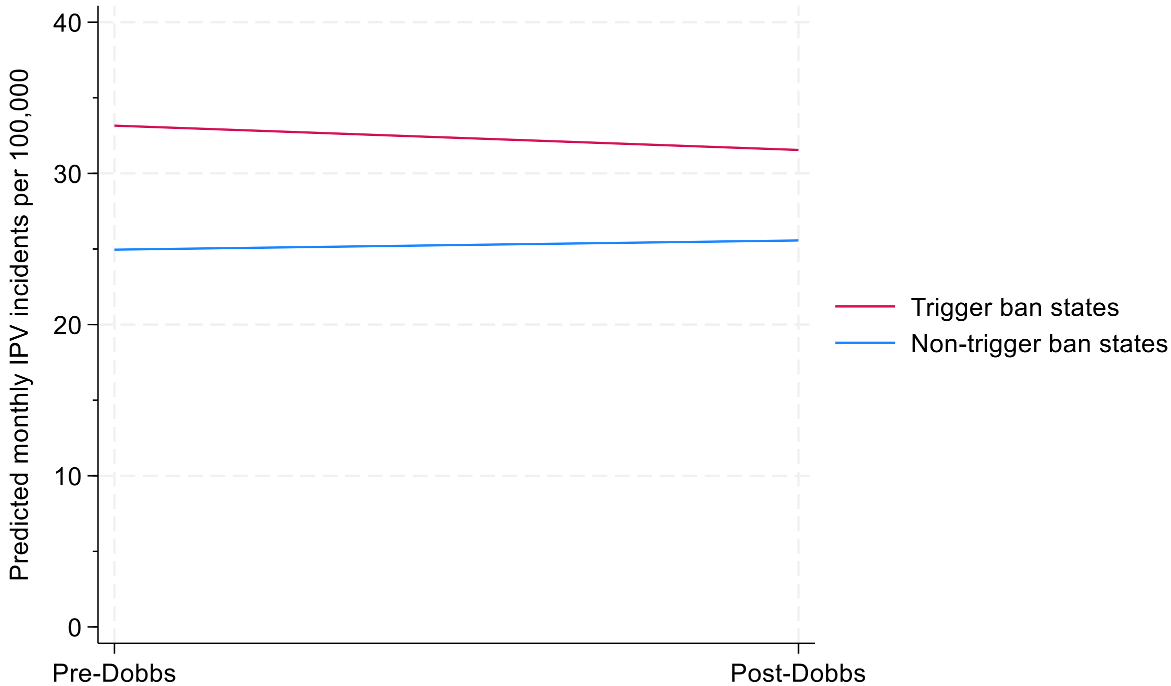

Figure 3. Predicted values of IPV rates during 12-month pre-*Dobbs* and post-*Dobbs* time periods for both trigger ban states and non-trigger ban states.

During the 12-month baseline period prior to the Dobbs decision, trigger ban states are predicted to have about 33.2 monthly IPV incidents per 100,000 people, significantly higher than non-trigger ban states which have about 25.0 monthly IPV incidents per 100,000 people ($p<0.0001$). If my hypothesis were true that restrictive state-level abortion policies like the trigger bans cause IPV rates to increase, we would expect the slope of the blue line to remain flat over time. This would indicate that there were no significant changes in IPV rates for non-trigger ban states, because there were no changes in abortion restrictions for this group of states during this time period. We would also expect the slope of the red line to be more positive compared to the blue line, as this would indicate that IPV rates increased over time as a result of the trigger bans enacted during this period.

In reality, neither group of states experienced a significant change in IPV rates between the pre-*Dobbs* and post-*Dobbs* periods, which was expected for non-trigger ban states but not for trigger ban states. The two lines are effectively parallel, meaning that IPV rates change at the same rate for trigger ban states as they do for non-trigger ban states, despite the enactment of trigger abortion bans during this period. Thus, this analysis does not provide evidence for a causal effect of state trigger bans on IPV rates.

These findings are reflected statistically in the regression output as well. In all three models shown in Table 4, the coefficient for whether states enacted a trigger ban is positive and significant at the 0.001 (0.1 percent) significance level. In Model 3, trigger ban states were associated with an average of about 6.1 more monthly IPV incidents per 100,000 people than non-trigger ban states at baseline, holding constant other variables in the model. This confirms that IPV rates are significantly different between the two groups of states overall. However, neither the coefficient for the post-*Dobbs* variable nor the coefficient for the interaction term are statistically significant throughout this analysis. A joint f-test which examines the significance for both variables confirms that these coefficients are not statistically significant at any conventional level in any of the three models. This suggests that IPV rates for non-trigger ban states did not change significantly between the pre- and post-*Dobbs* time periods. Neither did IPV rates for trigger ban states change significantly differently, compared to those of non-trigger ban states during this time period. Therefore, there is insufficient statistical evidence to prove a significant relationship between trigger abortion bans and IPV rates.

There are multiple potential explanations why we may not see a causal effect on IPV rates around the time of the *Dobbs* decision. Because the *Dobbs* decision went into effect shortly after the start of the COVID-19 pandemic, it is possible that lingering effects of the pandemic overshadow the potential effects of the trigger abortion bans during this period. In response to the pandemic, many communities implemented "lockdowns" and other public health policies to prevent the spread of disease by discouraging individuals from leaving their homes or gathering in large groups. For those who may be susceptible to IPV within their homes, such policies made it easier for abusers to perpetrate violence with less scrutiny from others outside the household (Bradbury-Jones & Isham, 2020). The lockdown policies also resulted in higher degrees of social isolation and unemployment, both of which are risk factors for IPV (Hwang et al., 2020; Kim, 2019; Schneider et al., 2016). Moreover, individuals with strong social support are less likely to be exposed to IPV (Howell et al., 2018; Nguyen et al., 2018); this protective factor was likewise weakened during the pandemic (Usher et al., 2020). In the social environment of the COVID-19 pandemic, the rates of IPV increased from pre-pandemic rates (McNeil et al., 2023; Peitzmeier et al., 2021). As public health policies reverted back to pre-pandemic norms in the following years, it is possible that the number of reported IPV cases began to fall again, consequently hiding any potential increases in IPV that occurred due to changes in abortion restrictions.

In fact, the average reported IPV rates were trending upwards for a couple of years prior to and during the pandemic, before plateauing after 2021. Figure 4 displays the average monthly IPV rates per 100,000 people during each year from 2018 to 2023. IPV rates increased significantly for both groups of states from 2019 to 2020 ($p=0.0001$) and again from 2020 to 2021 ($p<0.0001$), then evened out from 2021 to 2023. These changing trends could potentially indicate that factors related to the COVID-19 pandemic or other unexplained factors affected the rates of IPV from 2021 to

2023 differently than they did from 2019 to 2021. However, if this were true, it would be difficult to isolate the effects of COVID-19, abortion policy changes, and any other factors that impacted IPV rates all at the same time.

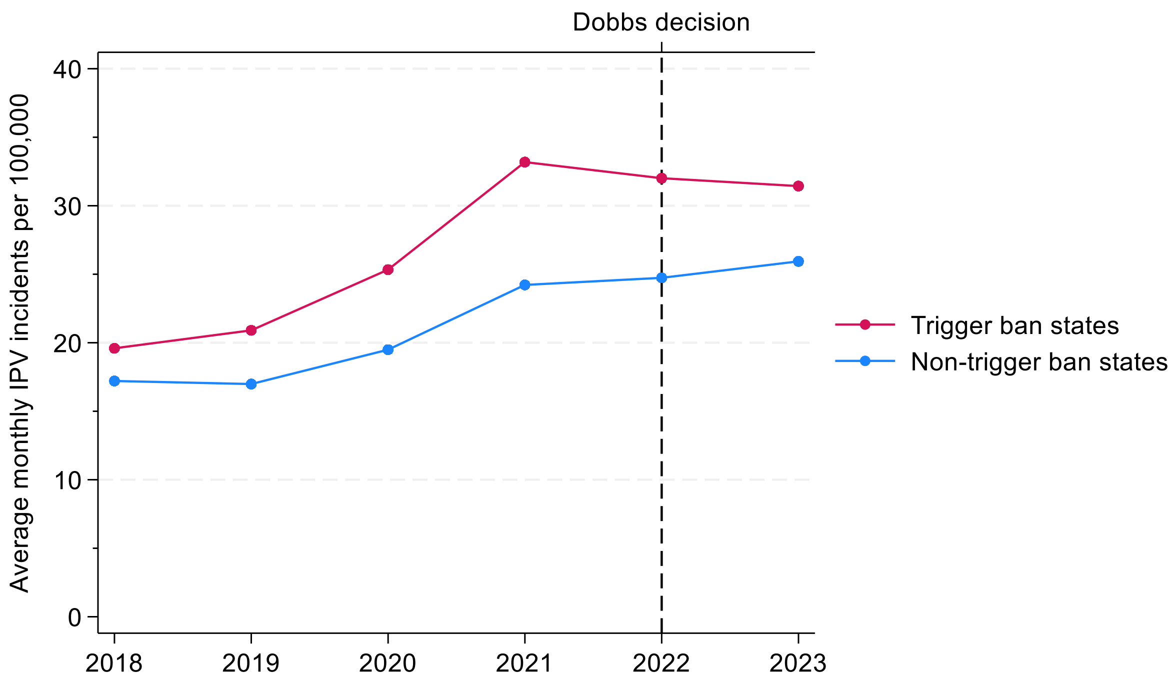

Figure 4. Average monthly IPV rates during years 2018 to 2023 for both trigger ban states and non-trigger ban states.

It is also possible that we do not see evidence of a relationship between trigger bans and IPV rates because the effect of the bans occurs much slower than expected. If changes in restrictive abortion policies were to impact human behavior over a longer time period, we would find that the effect of trigger bans on IPV rates is very lagged. Although I did run regression models that incorporated a 2-month lag and a 4-month lag and did not find differing results from the non-lagged model, it is possible that our dependent variable is lagged even further. Due to the crime reporting data that is currently available, I was only able to test models with a maximum of a 4-month lag in my analysis, but perhaps this could be an area of interest for future studies as more data becomes available.

Finally, it is hypothetically possible that IPV rates did in fact increase as a result of trigger abortion bans but the frequency of reporting IPV incidents simultaneously decreased, so that the rates of IPV observed by law enforcement agencies did not appear to increase at all. If a change in abortion policy did truly increase the rate of IPV by making it more difficult for women to avoid or prevent IPV, it may have also changed the way victims respond to IPV experiences. For example, women who may be made more vulnerable to IPV because of abortion restrictions may find it more difficult to report IPV incidents to law enforcement, due to their partner's potentially abusive or controlling behavior. Alternatively, women who may have experienced greater endangerment to IPV as direct a result of an abortion policy change could have experienced a decrease in trust for law enforcement as a whole, thereby making them more reluctant to report IPV. These are hypothetical explanations as to why a potential relationship between abortion restrictions and IPV rates may not be captured in the results of my analysis, though I am not currently aware of any literature or data which could confirm these to be true.

CONCLUSION

The results of my model fail to find a significant relationship between the US state-level trigger abortion bans enacted after the *Dobbs v. Jackson Women's Health Organization* Supreme Court decision and the rate of intimate partner violence (IPV). When comparing the group of states with trigger bans to the group without trigger bans, I find that trigger ban states had a higher average monthly IPV rate than non-trigger ban states during the 12-month period prior to the implementation of trigger bans. However, the IPV rates did not significantly change for either group after these policy changes went into effect. Thus, this analysis does not provide sufficient evidence to support the hypothesis that restricted abortion access, as represented by trigger abortion bans, results in increased IPV.

This overall finding differs from the conclusions drawn in recent studies that focus on the relationship between abortion access and IPV. For example, Neff et al. (2024) found that women were 1.5 times more likely to experience IPV during pregnancy when living in states with restrictive abortion policies during 2020, and Wallace et al. (2024) found that enforcement of each additional Targeted Regulation of Abortion Providers (TRAP law) between 2014 and 2020 was associated with a 3 percent increase in the rate of IPV-related homicide. While each of these previous studies address slightly different research questions, the overall consensus from this small body of literature is that abortion restrictions are associated with higher rates of IPV. However, the extent of the current scholarly research on this topic is limited, so further research is needed to reach firm conclusions regarding the implications of abortion restrictions on IPV.

One major consideration is that this study is among the first to examine trigger abortion bans as a proxy for abortion access. Previous studies have used more general metrics for abortion access, such as distance to the nearest abortion clinic, or they have focused on TRAP laws and other abortion restrictions prior to 2020. Because there were already many existing abortion restrictions prior to the introduction of abortion bans, it is possible that abortion access was already relatively low in the states that eventually enacted trigger bans. If so, the observed effect of the trigger bans may be muted since IPV rates would have already been elevated due to prior abortion restrictions. Out of the 11 trigger ban states studied in this paper, nearly all already had TRAP laws in place prior to the implementation of total abortion bans in 2022. For these states, IPV rates hypothetically would not change significantly in response to any trigger bans which were enacted on top of existing TRAP laws, and this reasoning could potentially explain why this study did not find evidence of a significant relationship between abortion access and IPV when previous studies have. Future research should thoughtfully consider how to capture subtle changes in the levels of abortion access as state-level abortion policies shift. For example, future studies may employ a quantitative metric to compare the levels of abortion access before and after the adoption of abortion bans, such as the distance to the nearest abortion provider, instead of using direct analyses of the abortion policies themselves. Changing the structure of the analysis in this way could potentially yield new insights.

In addition, my analysis is potentially limited by the crime data currently available regarding IPV, for multiple reasons. First, IPV is greatly underreported. According to a 2024 report by the Council on Criminal Justice, only approximately 70 percent of aggravated domestic violence incidents are reported to law enforcement (Piquero & Wheeler, 2024). This percentage is likely to be even lower for IPV incidents that involve sexual violence, as only about 1 in 3 incidents of all sexual assault are reported to law enforcement (Rape, Abuse & Incest National Network, n.d.). The data source for IPV rates in this study, the Federal Bureau of Investigation's (FBI) National Incident-Based Reporting System (NIBRS), only includes incidents of IPV that are known to law enforcement agencies. Thus, it is likely that a large portion of all IPV incidents are excluded from the analysis.

The incidents of IPV which are missing from my analysis could potentially bias the results if there is an omitted variable that causes IPV incidents to go unreported at a higher rate in trigger ban states than in non-trigger ban states, or vice versa. One conjecture is that if abortion bans did truly increase IPV, then IPV victims could be more reluctant to report IPV incidents to the police in trigger ban states, because they may perceive governing authorities to hold some responsibility in creating the conditions that caused them to experience IPV, thereby eroding their trust in law enforcement. If this were true, then the coefficients of the key independent variables in my model would be downwardly biased, such that any effect on IPV caused by trigger abortion bans would be understated compared to its actual value. However, it is currently impossible to confirm such a bias empirically, since we do not know the effect of trigger abortion bans on IPV victims' willingness to report IPV incidents.

Second, the NIBRS data may not accurately capture all IPV incidents because the offense types reported by law enforcement agencies do not completely align with all the possible forms that IPV can take. There are multiple categories of offenses in the NIBRS dataset that capture physical and sexual violence, such as simple assault, aggravated assault, and rape, while other types of IPV are not included. Most notably, there are no offense types which would capture incidents of psychological abuse. This limitation of the data introduces a type of measurement error into the analysis which would deflate the observed rates of IPV for all states. However, I do not have reason to believe that such an error would disproportionately impact trigger ban states or non-trigger ban states, assuming that the types of IPV that victims experience are independent of the state they live in.

Future studies may avoid the limitations of this study by choosing data sources that more accurately capture the true rates of IPV victimization, rather than those incidents reported to law enforcement. The Bureau of Justice Statistics, for instance, conducts the National Crime Victimization Survey (NCVS) which relies on a household survey in which individuals answer questions about their experiences, regardless of whether law enforcement was involved. The

NCVS could not be used for this study, however, because its data was not yet made available on the state-level at the time of this analysis.

Another potential data source is the National Domestic Violence Hotline (NDVH), which publishes data about the volume of calls it receives from victims of IPV, including the number of incidents described by callers in a year by state, as well as a variety of qualitative data about their experiences. Analyses based on NDVH reports are more likely to reflect actual rates of IPV compared to the NIBRS dataset, because victims may be more likely to contact anonymous hotlines for advice than to contact the police to file a report. Additionally, since the NDVH is specifically designed to support victims of IPV, the organization is better positioned to collect relevant information about each incident of abuse, regardless of whether it falls under a specific crime category, as in the NIBRS data. The NVDH state-level data for years 2020 and onwards have not yet been released at the time that this analysis was performed. Nevertheless, future research studies may consider using these data sources to potentially yield less bias in their results.

As more data becomes available over time, future studies may further explore the potential impact of restrictive abortion policies on IPV by performing analyses that incorporate longer lag times. It is possible that patterns of abusive behavior take time to develop after changes in abortion access, and if so, further research should be conducted to determine when an abortion policy change is likely to affect IPV.

Ultimately, this analysis is just one of the first studies exploring the potential impact of state abortion bans on IPV. There remain several gaps in the literature for future researchers to pursue, including multiple considerations regarding the types of abortion access metrics and IPV data sources to examine. My research does not provide substantial evidence that state-level trigger abortion bans significantly impacted the rates of IPV after the 2022 *Dobbs* Supreme Court decision. Yet, this finding may seem somewhat unusual compared to previous literature which did find evidence that restrictive abortion policies prior to 2020, including TRAP laws, were associated with increased rates of IPV. Further research should be conducted to better understand the nuances of the relationship between abortion access and IPV, especially as abortion policies continue to shift over time. The enactment of abortion bans in the wake of the *Dobbs* decision represents a unique moment in the modern history of US abortion policy, in which states were able to pass sweeping restrictions of abortion services for the first time in nearly 50 years. Now more than ever, it is critical for policymakers to learn more about the potential implications of abortion legislation on women's safety and wellbeing.

APPENDIX A: SUMMARY OF STATE ABORTION POLICIES

Table A.1. List of US states by type of abortion policy and date of enforcement after *Dobbs v. Jackson Women's Health Organization*.

State	Enacted a trigger ban?	Post-*Dobbs* abortion policy	First date of post-*Dobbs* abortion restrictions
Arkansas	Yes	Total abortion ban (trigger ban)	June 24, 2022
Kentucky	Yes	Total abortion ban (trigger ban)	June 24, 2022[3]
Louisiana	Yes	Total abortion ban (trigger ban)	June 24, 2022[4]
Missouri	Yes	Total abortion ban (trigger ban)	June 24, 2022[5]
Oklahoma	Yes	Total abortion ban (trigger ban)	June 24, 2022
South Dakota	Yes	Total abortion ban (trigger ban)	June 24, 2022
Alabama	No	Total abortion ban	June 24, 2022
Ohio	No	6-week abortion ban until November 7, 2023; 22-week abortion ban in effect[6]	June 24, 2022
Texas	Yes	Total abortion ban (trigger ban)[7]	July 1, 2022
Mississippi	Yes	Total abortion ban (trigger ban)	July 7, 2022
Utah	Yes	18-week abortion ban[8]	July 2022
Idaho	Yes	Total abortion ban (trigger ban)	August 25, 2022
Tennessee	Yes	Total abortion ban (trigger ban)	August 25, 2022
West Virginia	No	Total abortion ban	September 16, 2022
North Dakota	Yes	Total abortion ban[9]	April 26, 2023
Nebraska	No	12-week abortion ban	May 22, 2023
North Carolina	No	12-week abortion ban	July 1, 2023
Indiana	No	Total abortion ban	August 21, 2023
South Carolina	No	6-week abortion ban	August 23, 2023
Florida	No	6-week abortion ban	May 1, 2024
Iowa	No	6-week abortion ban	July 29, 2024
Georgia	No	6-week abortion ban	October 7, 2024

[3] Kentucky: Temporarily blocked by courts from June 30 to August 1, 2022.
[4] Louisiana: Temporarily blocked by courts from June 27 to July 8 and then again from July 12 to July 29, 2022.
[5] Missouri: Temporarily blocked by courts starting in December 2024 until present.
[6] Ohio: 6-week abortion ban was permanently blocked by a state constitutional amendment starting November 7, 2023. A separate 22-week abortion ban is currently in effect.
[7] Texas: Passed a trigger ban prior to *Dobbs* and began enforcement of a total abortion ban on August 25, 2022. Prior to enforcement of the trigger ban, a pre-Roe ban went into effect on July 1, 2022.
[8] Utah: Passed a trigger ban prior to *Dobbs* but enforcement was blocked by courts starting in July 2022. A separate abortion ban prohibiting abortions after 18 weeks went in effect in July 2022.
[9] North Dakota: Passed a trigger ban prior to *Dobbs* but enforcement was blocked by courts. A separate total abortion ban was enacted on April 26, 2023.

Table A.1. (Cont.)

State	Enacted a trigger ban?	Post-*Dobbs* abortion policy	First date of post-*Dobbs* abortion restrictions
Arizona	No	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)	N/A
California	No	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)	N/A
Connecticut	No	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)	N/A
Delaware	No	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)	N/A
Hawaii	No	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)	N/A
Illinois	No	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)	N/A
Kansas	No	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)	N/A
Maine	No	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)	N/A
Massachusetts	No	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)	N/A
Montana	No	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)	N/A
Nevada	No	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)	N/A
New Hampshire	No	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)	N/A
New York	No	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)	N/A
Pennsylvania	No	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)	N/A
Rhode Island	No	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)	N/A
Virginia	No	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)	N/A
Washington	No	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)	N/A
Wisconsin	No	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)	N/A
Wyoming	Yes	Abortion banned after or near fetal viability (policy is no more restrictive after *Dobbs*)[10]	N/A
Alaska	No	No abortion ban	N/A
Colorado	No	No abortion ban	N/A

[10] Passed a trigger ban prior to Dobbs but enforcement has been blocked by courts indefinitely. Abortions currently prohibited after fetal viability.

Table A.1. (Cont.)

State	Enacted a trigger ban?	Post-*Dobbs* abortion policy	First date of post-*Dobbs* abortion restrictions
District of Columbia	No	No abortion ban	N/A
Maryland	No	No abortion ban	N/A
Michigan	No	No abortion ban	N/A
Minnesota	No	No abortion ban	N/A
New Jersey	No	No abortion ban	N/A
New Mexico	No	No abortion ban	N/A
Oregon	No	No abortion ban	N/A
Vermont	No	No abortion ban	N/A

APPENDIX B: DATA COLLECTION DETAILS FOR COVARIATES

Additional details are included below regarding the data sources for the covariates included in this analysis.

US Census Bureau's American Community Survey

The American Community Survey (ACS) is a survey conducted by the US Census Bureau on a yearly basis about a variety of topics. The ACS is mailed to a sample of about 3.5 million residential addresses per year, with each address having a 1-in-480 chance of selection. Households then respond online, by mail, or with a field representative. In this paper, information about the age, sex, and racial/ethnic distributions of each state population were obtained from two of the publicly available online data tables: Table S0101, "Age and Sex" and Table 03002, "Hispanic or Latino Origin by Race."

Center for Disease Control and Prevention's Wide-Ranging Online Data for Epidemiologic Research

The Center for Disease Control and Prevention's (CDC) Wide-Ranging Online Data for Epidemiologic Research (WONDER) is an online database containing public health data made available to the public. One of the datasets available on WONDER is the Natality data which is provided by the US Department of Health and Human Services, the CDC, and the National Center for Health Statistics. The data is derived from the US records of birth to form a county-level national data collection, with several attached demographic data, including state, county of mother's residence, child's gender and weight, gestation period, maternal race, maternal age, maternal education, selected medical risk factors, tobacco use, prenatal care, and birth plurality.

Birth rates and fertility rates can be calculated, including those for each state, which are used in this analysis.

Office on Violence Against Women Grant Funding Awards

The Office on Violence Against Women (OVW) awards grant funding annually to programs across all 50 states and the District of Columbia. The amounts and recipients of these grant awards are publicly available online. The total amounts of grant funding awarded to each state during the years of my analysis are incorporated into the regression model.

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