Are Red Flag Laws a green light to save lives?

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Abstract

Mass shootings have become a prominent topic of discussion in recent years, prompting policymakers in the United States to take action through state legislation aimed at reducing their occurrence. Red Flag Laws seek to implement gun control measures by allowing the removal of firearms from individuals who pose a danger to themselves or others. In this study, I examine the impact of Red Flag Laws on suicide rates and homicides, utilizing a two-way fixed effects difference-in-differences approach. The findings reveal that states with Red Flag Laws experience a decrease of just over 6% in suicide rates and 11% in homicide rates. These effects are primarily driven by states that permit both family members and law enforcement to petition a state court for the removal of firearms.

JEL Codes: K42; H11, I12
Keywords: Red Flag Law; suicide; gun violence

Introduction

The link between mental health and mass shootings has attracted growing public attention in recent years. Policymakers have responded by enacting extreme risk protective orders (ERPO), commonly known as Red Flag Laws. The first Red Flag Law was passed by Connecticut as a direct response to a mass shooting that occurred on March 6, 1998 at the Connecticut Lottery headquarters. Between 1999 and 2021, across all states who have passed and implemented Red Flag Laws, at least 18,383 petitions were filed [Research and Policy, 2023].

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A Red Flag Law is a form of gun control that allows law enforcement officers or family members to petition a civil court to temporarily remove firearms from an individual who they believe is a danger to themselves or others. The logic behind Red Flag Laws is that many shooters display warning signs before a shooting or tragic event takes place. Extreme risk protection orders bypass the criminal court system, giving family members or law enforcement officers a way to intervene before things escalate even further. If the civil court comes to the conclusion that an individual does indeed pose a serious threat to others or themselves, then that individual is temporarily barred from not only possessing a firearm but is also prevented from purchasing new firearms while the order is in place. It is important to note that the burden to prove that firearm removal is necessary is on the petitioner, meaning they must provide sufficient evidence that the individual in question does pose a danger to themselves or others. The individual in question does have the opportunity to refute the evidence presented as well as present their own evidence [Research and Policy, 2023]. The duration of the order varies among states; some can last up to 180 days, while others up to one year. Indiana, on the other hand, which implemented their Red Flag Law in 2005, has a duration that extends until it is terminated by the court.[1]

According to a study conducted by the Federal Bureau of Investigation (FBI) that examined pre-attack behaviors of active shooters in the United States between 2000 and 2013, it was found that, on average, each active shooter exhibited four to five observable concerning behaviors over time Silver et al. [2018]. These behaviors were noticeable to individuals in the shooter's vicinity. The study identified mental health issues, problematic interpersonal interactions, and leakage of violent intent as some of the most frequent concerning behaviors.

The study also investigated who noticed these concerning behaviors before the attacks took place. The results indicated that 87% of spouses or domestic partners, 68% of family members, and 25% of law enforcement personnel reported observing such behaviors prior to the attacks.To date, there has been no formal investigation conducted to assess the impact

[1]The supplemental appendix contains more details on who can initiate an extreme risk order and how long the orders can last.

of Red Flag Laws on mitigating these concerning behaviors and preventing acts of violence.

To address this question, I use a panel dataset and employ a two-way fixed effects (TWFE) difference-in-differences model looking at the staggered adoption of Red Flag Laws across the United States. I use homicide rate data from the FBI's Uniform Crime Reporting (UCR) and suicide rate data from the Center of Disease Control and Prevention (CDC) as dependent variables.

I find that for states that have enacted a Red Flag Law, the implementation corresponds to a 6.26% reduction in suicide rates and a 10.96% reduction in homicide rates. Furthermore, I find that states that allow both family members and law enforcement to petition a state court for a ERPO tend to be the driving force in the reduction of suicide rates as well as homicide rates when compared to states that only allow law enforcement to petition for a ERPO.

Literature Review

While Red Flag Laws have not been empirically explored in the economics literature, there are other fields that have explicitly examined them. For the most part, Red Flag Laws have been studied within the context of legal scholarship that debate their constitutionality and whether it infringes on the second amendment [Johnson, 2021], [Gay, 2020]. Another field that has explored Red Flag Laws is psychiatry.

Within the psychiatry field, the studies on Red Flag Laws focus on case studies to extrapolate the effects of the policy, they do not use any formal econometric models. They are not able to assess the external validity of the intervention policymaking across the country. For example, Swanson et al. [2019] evaluate Indiana's Red Flaw Law by examining 395 gun-removals in Marion County, Indiana, which includes Indianapolis. They extrapolate that one life was saved for every ten gun-removals. Swanson et al. [2017] investigates 762 gun-removal cases in Connecticut between October 1999, and June 2013. They found a reduction in firearm suicide rates among individuals subjected to firearm seizures. Kivisto and Phalen [2018] evaluate whether the Red Flag Laws in Connecticut and Indiana affect suicide rates. Overall, they find that risk-based firearm seizure laws corresponded with a reduction in population-level firearm suicide rates for both states examined. This present study is the first comprehensive empirical study on the effectiveness of Red Flag Laws on homicide and suicide rates.[2] To date, no one has empirically, with an eye towards causal inference, studied whether Red Flag Laws have had the intended impact on reducing violence.

Other gun laws have received attention and have been studied using various empirical approaches. There are three main themes within the gun law economics literature: Right-to-Carry (RTC) laws, mandatory waiting periods between the purchase of a firearm and its delivery to the final consumer, and Permit-to-Purchase (PTP) laws.

The seminal paper on RTC laws starts with Lott and Mustard [1997] where they find that RTC laws reduced crimes rates in the United States, without an increase in accidental deaths. More recent, Moody and Lott [2022] investigated whether RTC laws still reduce crime. They conclude that states with a RTC law have a much lower murder rate than those states without a RTC law, while not increasing other crime such as violent or property crime. Another recent RTC law paper examines the impact of when a RTC law was banned in Brazil [Schneider, 2021]. Schneider finds that after the RTC law was banned, Brazil experienced a reduction in gun-related homicides by 12.2% as well as a reduction in gunshot wounds that were 'intended to kill' by 16.3% in the year after the ban was implemented. Others have contended the deterrence effect of concealed weapons [Aneja et al., 2014]. They find that RTC laws increase aggravated assault, rape, robbery, and murder.

Mandated delays between the purchase and delivery of a handgun, also referred to as a waiting period, have also been explored to measure if they have had any impact on outcomes such as suicides, homicides, along with other crimes. Edwards et al. [2018] examines how

[2] Dalafave [2020] uses a difference-in-differences approach to evaluate Red Flag Laws in 5 states (Connecticut, Indiana, California, Washington, and Oregon). She finds a statistically significant reduction in suicide rates, but not in homicide rates.

waiting period laws have an impact on firearm-related homicides and suicides. They find a reduction of 3% in firearm-related suicides, with no evidence of a substitution effect towards non-firearm related suicides. They also conclude that waiting periods do not appear to have any impact on homicide rates. Koenig and Schindler [2021] examines a six-month period post the 2012 Presidential election and Sandy Hook shooting to see if handgun purchase delays had any impact on homicide rates. They found that states with a handgun purchase delay experienced a 2% lower homicide rate during that six-month period compared to states without such a law. Luca et al. [2017] explores the impact of handgun waiting periods on gun deaths, specifically homicides and suicides. They find that waiting periods significantly reduce homicides by 17% and suicides by 7-11%.

Permit-to-purchase laws have also been studied within economics to measure the impact on outcomes such as homicide rates. Rudolph et al. [2015] examine Connecticut's 1995 PTP law and find that it reduced homicide rates. More specifically, they find a 40% reduction in firearm homicide rates during the first decade post-implementation. Looking at it from the opposite direction, Webster et al. [2014] examines Missouri's repeal of their PTP law in 2007. They find that Missouri's 2007 PTP law repeal was associated with an annual increase in homicide rates of 23%, when they use UCR data they find that murder rates increased 16%.

Other papers within the economics gun law literature include gun law changes in a single state or public access to a handgun carry permit database. A recent paper by Kahane and Sannicandro [2019] examine gun law changes in Massachusetts using a synthetic control approach. In 1998, Massachusetts enacted 23 gun laws, Kahane and Sannicandro find a statistically significant reduction in suicide rates but the effects abate by 2005. Acquisti and Tucker [2022] examine crime and handgun carry permit data for the city of Memphis to estimate the effect of publicly available handgun carry permit database on burglaries. Unsurprisingly, they find that burglaries increased in zip codes with fewer gun permits and decreased in zip codes with more gun permits, after the database became publicly available.

My contribution is to empirically test the effectiveness of Red Flag Laws by measuring if there has been a reduction in suicide rates as well as homicide rates in states that have implemented a Red Flag Law.

Data

Data Source

I construct a state by year panel with data collected from a variety of sources. These sources include the FBI's UCR database, CDC, Bureau of Economic Analysis (BEA), and Bureau of Labor Statistics (BLS). I collected homicide rates from the FBI's UCR database at the state level. Data are available from 1990 to 2020.[3] I collected suicide rate data from the CDC. That data is available from 1990 to 2020. Both variables are measured per 100,000 people.

For falsification purposes I collected data on total property crime at the state level from the FBI's UCR database. I was able to gather on property crime from 1990 to 2020. It is also measured per 100,000 people.

Other variables employed include population data, male and female data, as well as race/ethnicity data provided by the CDC for the years 1990 to 2020. The income data was extracted from the BEA for the years 1990-2020, more specifically the median annual income. Seasonally adjusted annual state-level unemployment rate data was collected from the BLS also for the years 1990 to 2020. I simply took the first month of each year for each state and used that unemployment rate for the entire year. For example, Alabama's monthly unemployment rate in January 1990, was 6.7% so I used that for Alabama's 1990, unemployment rate in my data-set.

[3]The FBI does not have homicide rate data on Mississippi from 1990-94.

Policy Implementation

Below is a table of the states that currently have a Red Flag Law implemented. The vast majority of states that have adopted a Red Flag Law have done so within the past few years. Despite the District of Columbia adopting a Red Flag Law in 2019, it is excluded from the analysis due to its unique status as a federal district, rather than a state.

States	Year Implemented
Connecticut	1999
Indiana	2005
California	2016
Washington	2016
Oregon	2018
Florida	2018
Vermont	2018
Maryland	2018
Rhode Island	2018
Delaware	2018
Massachusetts	2018
New Jersey	2019
Illinois	2019
New York	2019
Colorado	2020
Nevada	2020
Hawaii	2020
New Mexico	2020
Virginia	2020

There are potentially several reasons for the recent increase in Red Flag Laws. One significant factor is the rise in mass shootings that have occurred in recent years.

Early implementations of Red Flag Laws, such as those in Connecticut in 1999 and Indiana in 2005, were responses to mass shootings or other forms of gun violence committed by individuals with mental health issues. Although the states themselves voluntarily adopted these policies, the events leading to their implementation were random, meaning they were unrelated to the states' levels of homicide or suicide rates. Late adopters of Red Flag Laws often acted in response to mass shootings that occurred in neighboring states, which can be considered as random events.

For example, Connecticut cited a mass shooting at the Connecticut Lottery Corporation headquarters, where an employee killed four bosses before taking his own life, as a reason for implementing their Red Flag Law [Foley and Thompson, 2018]. Indiana named their Red Flag Law after a police officer who was killed by a mentally ill man, who had also killed his own mother, after stopping his prescribed medication for schizophrenia (Indiana Law Enforcement Memorial 2022). California referenced a tragic event near the University of California, Santa Barbara, where a mentally ill man killed six people and injured thirteen others before committing suicide [Foley and Thompson, 2018]. The University of California, Santa Barbara incident was also mentioned as a reason for implementing the Red Flag Law in the state of Washington since one of the victims was a Washington native.

In recent years, mass shootings have either increased or gained more coverage in the news cycle. Notable examples include the Orlando nightclub shooting in 2016, the Las Vegas mass shooting in 2017, the Southern Baptist Church shooting in Sutherland Springs, TX in 2017, the Parkland, FL high school mass shooting in 2018, the Santa Fe, TX high school mass shooting in 2018, and the El Paso, TX Wal-Mart shooting in 2019.

A turning point in the number of states with Red Flag Laws occurred after the Parkland, FL high school mass shooting in 2018, as the number of states passing such laws more than doubled following that tragic event [Wing and Jeltsen, 2018, Livingston, 2018]. For example, Delaware, which had previously failed to pass a Red Flag Law in 2013, unanimously passed the law after the Parkland, FL shooting [Livingston, 2018]. Other states, like New York and Colorado, also cited specific incidents, such as the Dayton, OH shooting and the death of Deputy Zackari Parrish, respectively, as reasons for implementing their Red Flag Laws. Nevada referred to the Las Vegas strip mass shooting, Hawaii mentioned a 1999 shooting at Xerox Corp, and New Mexico cited the El Paso, TX Wal-Mart mass shooting as contributing factors for their respective Red Flag Laws [Arnold, 2019, Phillips, 2018, Apgar, 2019, Dayton, 2019, Boyd, 2020]. Virginia, on the other hand, referenced the Virginia Beach mass shooting as a contributing factor for their Red Flag Law [Duster, 2019].

Most of the states where these shootings occurred went on to pass and implement Red Flag Laws in an effort to prevent future incidents or at least reduce the likelihood of their occurrence. While Massachusetts did not specify a particular tragic event that led to the passing and implementation of their Red Flag Law, they cited the national increase in mass shootings as a contributing factor [Miller, 2018]. Other states, neighboring those where mass shootings took place, took a proactive approach in hopes of preventing similar incidents within their borders. State Red Flag Laws are therefore a response to high-profile events, which are essentially random. Importantly, they are not driven by the states' underlying aggregate levels of homicides or suicides, and they do not reflect time trends in those levels.

Table 1 below provides the summary statistics for this project. In addition to the variables mentioned above I for simplicity I created a population ratio of males to females labeled "Male Ratio" and a race ratio variable of whites to blacks labeled "White Ratio". The panel data-set covers all fifty states over a thirty-one year period from 1990 to 2020.

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
Homicide Rate	1,545	5.24	2.97	0.2	20.3
Suicide Rate	1,550	13.84	4.01	1.5	31.4
Property Crime	1,550	3,364.21	1,139.05	1,053.2	7,566.5
Population	1,550	5,861,491	6,497,797	453,690	39,512,223
Male Ratio	1,550	0.492	0.008	0.479	0.527
White Ratio	1,550	0.886	0.098	0.608	0.997
Median Household Income	1,550	35,331.58	12,467.3	13,356	78,609
Unemployment Rate	1,550	5.4	1.87	2	13.7

The male variable statistic indicates the ratio among males and females. The white variable statistic indicates a race ratio of whites to blacks. 2020 suicide rate data was not available at the time of this writing. The homicide and suicide rates are calculated by dividing the number of murders (suicides) by the total population then multiplying the result by 100,000 to give the figure as the number of murders (suicides) per 100,000 people. The FBI did not have homicide rate data on Mississippi from 1990-94.

Identification Strategy

I investigate empirically the impact that Red Flag Laws have had on homicide rates and suicide rates in the states that have a Red Flag Law on the books. I formalize this relationship with the following regression model:

$$Y_{st} = \alpha RedFlagLaw_{st} + \beta X_{st} + \sigma_s + \tau_t + \epsilon_{st}. \tag{1}$$

The variable Y_{st} represents an outcome for state s and year t. I will use both homicide rate and suicide rate as dependent variables. The model includes state fixed effects, notated by σ, year fixed effects, τ, and an error term, ϵ. I also include time-varying state level controls, which is notated by X. The coefficient of primary interest is α which is the difference-in-differences (DiD) estimate of the effect of Red Flag Laws on homicide rate or suicide rate in states that have passed a Red Flag Law. Difference-in-differences attempts to identify a causal effect by comparing the changes in outcomes over time between a group that has received the treatment/adopted a policy to a group that did not receive the treatment/adopt the policy.

Results & Discussion

Results

Table 2 below presents the main results for this paper, demonstrating the impact of Red Flag Laws on both homicide rates and suicide rates. The table includes models with and without control variables. The variable of interest in Table 2 is the effect of Red Flag Laws on suicide rates and homicide rates from 1990 to 2020, denoted by the Red Flag Law variable. Models (A) and (C) incorporates the full set of control variables. Models (B) and (D) exclude all control variables.

Table 2: TWFE DiD Results

Dependent Variable:	Suicide Rate		Homicide Rate	
Years:	1990-2020	1990-2020	1990-2020	1990-2020
Model:	(A)	(B)	(C)	(D)
Variables				
Red Flag Law	-0.8699**	-1.381***	-0.5744***	-0.7086**
	(0.3515)	(0.4328)	(0.1870)	(0.2680)
Median Household Income	0.2489		0.5259	
	(1.169)		(1.1163)	
White Ratio	57.47***		-3.680	
	(13.46)		(13.56)	
Male Ratio	84.41		64.21*	
	(83.12)		(37.90)	
Population	−0.08121***		−0.08915***	
	(0.01927)		(0.01315)	
Unemployment Rate	0.0190		-0.0395	
	(0.0556)		(0.0553)	
Fixed-effects				
States	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,550	1,550	1,545	1,545
R^2	0.91055	0.88976	0.88228	0.85930

These are the DiD regression coefficients from equation 1 when the dependent variable is suicide rates for columns (A) and (B) and when the dependent variable is homicide rates for columns (C) and (D). Suicide rate and homicide rate data is at the state level and runs from 1990-2020. All variable data is at the state level on an annual basis. All models include both state and year fixed effects. The coefficients and standard errors for Median Household Income and Population have been re-scaled to be in the thousands. Standard errors are clustered at the state level in parentheses. *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2 shows that there are varying levels of statistical significance for states that have implemented a Red Flag Law compared to states without such a law. The difference-in-differences estimator provides evidence that the treatment (implementing a Red Flag Law) did indeed correspond with a movement in the expected direction. There is a reduction in the number of suicides in the treated group that have a Red Flag Law when compared to states in the control group. For model (A) this is just over a 6% decrease in suicide rate.[4] For model (B), where no control variables are included I find a reduction of 10% in the suicide rate for states that have implemented a Red Flag Law.

The standard errors are clustered at the state level. The reason for clustering at the state level is to account for within state heterogeneity, which can potentially make the standard errors too small.[5] Since it is a state-level policy this is the appropriate clustering level [Abadie et al., 2023].

Models (C) and (D) in Table 2 provides the results of the impact of implementing a Red Flag Law on homicide rates. The variable of interest in Table 2 is the impact Red Flag Laws had on homicide rates from 1990-2020, notated by the Red Flag Law variable. Model (C) includes control variables such as median income, race ratio, gender ratio, Population, as well as Unemployment Rate. Model (D) drops all control variables.

Implementation of a Red Flag Law corresponds to a decrease of homicide rates ranging from just under 11% to just over 13.5%. In both homicide rate specifications, standard errors are clustered at the state level. There is a reduction in the homicide rate across both models, similar to what I find on suicide rates. Model (C) shows the results including all the control variables. The result of interest is the negative coefficient on the Red Flag Law, which translates to a reduction in homicide rates by 10.96% in states that have adopted a Red Flag Law.[6] Model (D) drops all control variables and I find an even greater reduction in homicide rates, which translates to a reduction in homicide rates by 13.52%. It appears that Red Flag Laws are working as policymakers intended: deaths from firearms via a reduction in homicides and suicides.

[4]The 6% comes from taking the coefficient of 0.8669 from the Red Flag Law variable in Model (A) to the suicide rate mean of 13.84, $(\frac{0.8669}{13.84}) = 0.06263$.

[5]Each model presented in this paper has the standard errors clustered at the state-level to account that the errors might be related within each state over time, which could lead to smaller standard errors.

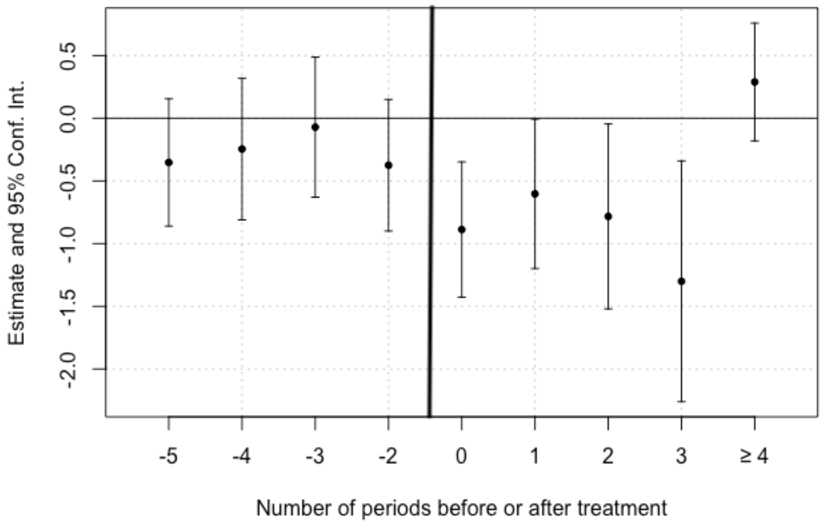
[6]The 10.96% comes from taking the coefficient of 0.5744 from the Red Flag Law variable in Model (C) to the homicide rate mean of 5.24, $(\frac{0.5744}{5.24}) = 0.1096$.

Parallel Trends

The primary identifying assumption of the difference-in-differences method is that of parallel trends in homicide rates and suicide rates. Causal identification requires that treated states follow time trends in homicides and suicides that run parallel to the time trends of the untreated states in pre-treatment periods. While I obviously cannot observe these rates for the treated states had they not been treated, I can assess the common trends prior to treatment. To test for differential trends, I conduct an event study and check for pre-existing trends in homicide rate and suicide rate. The t=-5 corresponds to Connecticut (who implemented their Red Flag Law in 1999) having implemented it in 1994 instead. For Indiana, the t=-5 corresponds to the year 2000. For California and Washington it would be 2011, and so on and so forth. It works in the same idea when the after treatment period begins. For the t=+2, states like Florida and Vermont (who both implemented their Red Flag Law in 2018) would correspond to 2020. Whereas for Connecticut, the t=+2 corresponds to 2001. The results are presented below, Figure 1 shows the event study for homicide rate and Figure 2 shows the event study for suicide rate.

These estimates ask whether homicide rate patterns were changing in the time period leading up to or after a Red Flag Law adoption. It's important to note, that with the staggered adoption, the post-treatment period is limited in the number of observations since most states have passed a Red Flag Law in recent years. For example, there are four states (Nevada, Hawaii, New Mexico, and Virginia) that implemented a Red Flag Law in 2020, meaning there are no after treatment observations in the data. Something similar can be said for the states that implemented a Red Flag Law in 2019 (New Jersey, Illinois, New York, and Colorado) there is only one observation for each state for the plus one (after treatment) period.

Figure 1: Homicide Rate Event Study

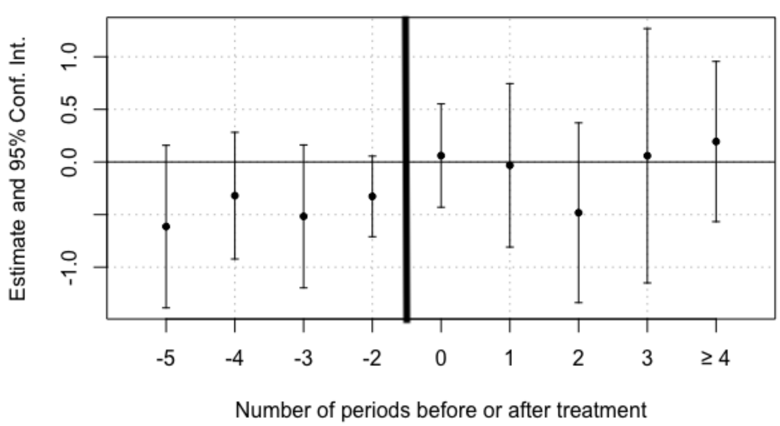


It is important to note the fact that zero is within every confidence interval for the entire pre-treatment period. In addition to conducting an event study on homicide rates, I also performed a χ^2 test to assess the joint significance, which resulted in a p-value of 0.2. This finding suggests that there is evidence to support making causal claims regarding the impact of Red Flag Laws implementation on the reduction of homicide rates.

One potential issue for the after treatment period is the ≥ 4 where homicide rates essentially return back to zero, but this could be a limitation of the number of data observations. With most states that having implemented a Red Flag Law, have done so in recent years. Therefore, not enough time has passed to have observations three or four plus years ex-post. For the vast majority of states I only have observations going up to and including when t=+2 (after treatment part of the figure). Thus, these are relatively few states with values of t≥ 4 hence, the effect can no longer be distinguished from zero. It is puzzling that point estimate, while close to zero, is positive. It is entirely possible that the effect of the policy has "worn off" so to speak. Similar to the idea of "out of sight, out of mind" where citizens forget that the policy exists if it falls out of the news media coverage and it is talked about as much as when it was first implemented. Additionally, a "backlog effect" could be causing the large reduction identified. That is, families who might have concern for years now have an avenue through which to take action. When the law is implemented these families take action. But years after the passage, this backlog is cleared and only new mental health concerns are acted upon. Only after more time has passed will researchers be able to understand the long-term effectiveness of these laws.

Figure 2 shows difference-in-differences event study results for suicide rates. These estimates ask whether suicide rate patterns were changing in the time period leading up to or after a Red Flag Law adoption. There are similar issues with the data observations for suicide rates as there were with homicide rates, more specifically during the after treatment period.

Figure 2: Suicide Rate Event Study



The specification above shows less clear evidence of parallel trends for suicide rates. A χ^2 test on the joint significance has a p-value of less than 0.01. This implies a violation of the parallel trends assumption in the difference-in-differences identification strategy. Consequently, it becomes challenging to establish causal claims regarding the impact of Red Flag Laws implementation on the reduction of suicide rates. Based on the event study presented in Figure 2, suicide rates were already declining prior to the implementation of a Red Flag Law. Therefore, while I expect the Red Flag Laws to have a causal effect on suicides, some of the estimated reductions can be coming from the pre-existing upward time trend.

Heterogeneous Effects

Table 3 below presents the results when the Red Flag Law variable is divided into two categories: Law Enforcement Only and Law Enforcement & Family. In states that have implemented a Red Flag Law, there are two variations: some states allow only law enforcement to request or invoke the Red Flag Law, while other states permit both law enforcement and family members to do so. Out of the 19 states that currently have a Red Flag Law, seven states exclusively authorize law enforcement to enact the law, while the remaining 12 states allow both law enforcement and family or household members to utilize it. For a detailed breakdown of which states fall into each category, please refer to Table 9 in the supplemental appendix.

Table 3: Results for Red Flag Law Decomposed

Dependent Variables:	Suicide Rate		Homicide Rate	
Years:	1990-2020		1990-2020	
Model:	(E)	(F)	(G)	(H)
Variables				
Law Enforcement Only	-0.4801	-0.8250*	-0.4207	-0.3970*
	(0.3171)	(0.4364)	(0.2603)	(0.2118)
Law Enforcement and Family	-1.348***	-2.005***	-0.7630**	-1.059**
	(0.4814)	(0.5538)	(0.3135)	(0.4473)
Median Household Income	0.3756		0.5773	
	(1.1571)		(1.1214)	
White Ratio	57.90***		-3.509	
	(13.42)		(13.74)	
Male Ratio	79.08		62.08	
	(83.10)		(37.10)	
Population	−0.08083***		-0.08881***	
	(0.001839)		(0.01303)	
Unemployment Rate	0.0147		-0.0412	
	(0.0562)		(0.0552)	
Fixed-effects				
States	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,550	1,550	1,545	1,545
R^2	0.91090	0.89042	0.88238	0.85968

These are the DiD regression coefficients when the indicator variable "Red Flag Law" from equation 1 is decomposed into one of two variables: "Law Enforcement Only" or "Law Enforcement and Family." Suicide rate is the dependent variable for models (E) and (F); homicide rate is the dependent variable for models (G) and (H). Of the 19 states that have a Red Flag Law on the books, 7 states fall under the "Law Enforcement Only" variable with the remaining 12 falling under the "Law Enforcement and Family" variable. For which states fall under which of the two variables, see Table A.1 in the Supplemental Appendix. The coefficients and standard errors for Median Household Income and Population have been re-scaled to be in the thousands. Standard errors are clustered at the state level in parentheses. *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

In Table 3, the Red Flag Law variable is divided into two separate variables: Law Enforcement Only and Law Enforcement & Family. The states that allow either law enforcement or family and household members to request an ERPO demonstrate statistical significance concerning both suicide rates and homicide rates across all models. However, it appears the effectiveness of Red Flag Laws are less impactful when only law enforcement are allowed to implement the policy. This observation is sensible and highly plausible due to a compelling reason. When a greater number of individuals, including family members who often possess more knowledge, have the ability to take action or voice concerns upon noticing something unusual, the effectiveness of the law is likely to increase.

The results from Table 3 indicate statistical significance for both dependent variables, both with and without control variables, in regards to the Law Enforcement & Family variable. Models (E) and (F), where the dependent variable is suicide rate, the statistical significance is at the 1% level for the Law Enforcement & Family variable. Models (G) and (H), where the dependent variable is homicide rate, the statistical significance is observed at a 5% level for the Law Enforcement & Family variable.

The findings from Table 3 suggest that the involvement of family members in the implementation of Red Flag Laws has significant policy implications. When family and household members are included in the process of requesting or invoking Red Flag Laws, the impact on reducing suicide rates and homicide rates becomes more apparent. These results further corroborate the findings reported by the FBI regarding active shooters. The FBI's research indicated that in cases involving active shooters, family or household members often noticed four to five concerning behaviors. Spouses or domestic partners reported noticing 87% of these behaviors, while family members noticed 68% [Silver et al., 2018].

By allowing family members to participate, these laws enable those who are closest to individuals at risk of harming themselves or others to take proactive measures. More often than not, family members have personal knowledge of the individual's behavior, mental health, as well as potential warning signs. This makes them valuable sources of information for identifying and addressing potential risks before a tragic event takes place.

The statistical significance observed in the results highlights the effectiveness of including family members in the implementation of Red Flag Laws. This indicates that their involvement can contribute to more successful interventions and prevention efforts. With a broader network of individuals empowered to act when they observe concerning behaviors or indicators of potential harm, the likelihood of detecting and addressing risks increases.

From a policy perspective, these findings suggest that expanding the scope of Red Flag Laws to include family members as stakeholders is beneficial. Policymakers should give careful consideration to including family members and household members, who share a close relationship with individual who is suspected of being a danger to themselves or others, to play a role in the implementation and enforcement of these laws. One way this could be achieved is by providing training, resources, and support to help family members identify warning signs, communicate concerning behavior to authorities, and help them steer through the legal process.

Moreover, these results further highlight the importance of public engagement and partnership in addressing mental health along with public safety concerns. By recognizing the crucial role that family and household members can play, policymakers can strengthen the effectiveness of Red Flag Laws and improve overall outcomes in preventing suicides and homicides.

Moreover, these results emphasize the importance of community involvement and collaboration in addressing mental health and public safety concerns. By recognizing the valuable role that family members can play, policymakers can enhance the effectiveness of Red Flag Laws and improve overall outcomes in preventing suicides and homicides.[7]

[7] In addition to these decomposed Red Flag Law variable results, I also run event-studies for each type of Red Flag Law (Law Enforcement Only and Law Enforcement & Family) for each dependent variable (Homicide Rate and Suicide Rate). These event studies can be found in the Supplemental Appendix, Figures 4 and 5.

Robustness Checks

One potential limitation of this model is the staggered treatment effects, which occur when Red Flag Laws are implemented at different times across states. For example, some states like Connecticut adopted the policy early on, while others such as Nevada, Hawaii, New Mexico, and Virginia implemented it at a later stage. When using a TWFE DiD model to analyze this staggered policy adoption, there is a possibility of bias due to the heterogeneity of treatment effects. Recent advancements in econometric theory suggest that staggered difference-in-differences identification strategies might not yield accurate estimates of the Average Treatment Effect (ATE) or the Average Treatment Effect on the Treated (ATT).

To address this limitation, I employ Goodman-Bacon [2021] decomposition that breaks down TWFE models into all two-by-two estimates and their corresponding weights. The staggered treatment effect raises the question of which group is primarily influencing the coefficient of interest. For instance, is it the early adopters or the later adopters driving the negative coefficient? Goodman-Bacon's decomposition enables applied research to determine which specific group is truly responsible for driving the coefficient of interest.

A basic DiD estimator is a weighted average of all two-by-two estimators in the data. Those weights come from the size of each subgroup (within the context of this project the number of states at a given time that are in the treatment group relative to the number of states in the control group) and the variance of treatment (when the treatment turns on in terms of how close to the beginning/end of the subsample). The estimates can change due to the weights changing, the two-by-two DiD terms changing, or in some cases it can be a combination of both [Goodman-Bacon, 2021]. The vast majority of states that have adopted a Red Flag Law have done so within the past few years, meaning there are several states that turned the treatment on near the end of the subsample. This could potentially bias the DiD estimator I get when I run my TWFE DiD model. The Bacon Decomposition separates the four two-by-two DiD estimates where the weights are based on group sizes as well as variance in treatment.

Bacon Decomposition

Table 4 below shows the results for the Bacon decomposition for suicide rate. The tables below (Tables 4 & 5) do not include any control variables in the specification such as median income, population, unemployment rate, race, or gender.[8] It is important to note that since my suicide rate data starts in 1990 and the first state to implement a Red Flag Law was in 1999, there is no "always treated" group.

Table 4: Suicide Rate

	1990-2020	
Type	Weight	Avg. Estimate
Earlier vs. Later Treated	0.16806	0.07662
Later vs. Earlier Treated	0.02563	-0.05828
Treated vs. Untreated	0.80631	-1.72635

From Table 4 the driving force for the negative coefficient that is presented in Table 2 for the Red Flag Law variable largely comes from the "Treated vs. Untreated" type (weight > 0.80). This is a good indication that the results in Table 2 from the TWFE DiD model is driven by the states that implemented a Red Flag Law compared to states that do not. It appears the source of bias is small, with the "Later vs. Earlier Treated" group contributing only 0.02563 of the weight towards the coefficient of interest.

Table 5 below shows the results for the Bacon decomposition for homicide rate.

Table 5: Homicide Rate

	1990-2020	
Type	Weight	Avg. Estimate
Earlier vs. Later Treated	0.17240	-0.05663
Later vs. Earlier Treated	0.02629	-0.50424
Treated vs. Untreated	0.80130	-0.86267

In order to balance the panel, which is required to run the Bacon decomposition, Mississippi had to be dropped since I am missing Mississippi's homicide rate data from 1990-1994

[8] I do run specifications that do include control variables and those tables can be found in the supplemental appendix. The results in those tables in the supplemental appendix reflect similarly to the results presented in Tables 4-5, meaning including or not including controls does not greatly influence which type is driving the coefficient.

Similar to Table 4, Table 5 shows the "Treated vs. Untreated" with a weight of 80% is the driving the coefficient of interest. This is a good indication that the results in Table 2 from the TWFE DiD model is driven by the states that implemented a Red Flag Law compared to states that never do. Again, it apepars the source of bias is minor, with the "Later vs. Earlier Treated" group contributing only 0.02629 of the weight towards the coefficient of interest. Another important point to highlight is that all the estimates in Table 5 are negative.

Callaway & Sant'Anna

To further assess the sensitivity of my results presented in Table 2 using a doubly-robust estimator. My goal is to estimate average treatment effects of Red Flag Laws on treated states. One estimator I use to do so is [Callaway and Sant'Anna, 2021]. This approach first estimates group/cohort and time specific average treatment effects on the treated (ATT), using two-period/two-group DiD estimators and then aggregates them, weighting them with respect by the size of the treatment group/cohort, to produce summary treatment effect estimates. The primary concept in Callaway and Sant'Anna [2021] is the group-time ATT. The group-time ATT is a different ATT for a cohort of treated units at the same point in time. For example, in this paper, California and Washington both implemented their Red Flag Law in 2016, then they are referred to as the 2016 group, or cohort. If seven more states implemented their Red Flag Law in 2018, then they would be referred to as the 2018 group. And so forth. For each cohort/group Callaway and Sant'Anna [2021] calculates a group's ATT. For instance, the 2016 group, this estimator allows me to see their group's ATT in 2017 and 2018. Essentially, as far out as the data-set goes I can see a group's ATT and in the context of this paper I can see each group's ATT through 2020. Upon calculating each group's ATT Callaway and Sant'Anna [2021] aggregate all of them into fewer simpler parameters.

Table 6 below presents the results for suicide rates and homicide rates when using Callaway and Sant'Anna's estimator.

Table 6: Callaway & Sant'Anna Results

Dependent Variable:	Suicide Rate	Homicide Rate
Years:	1990-2020	1990-2020
Model:	(I)	(J)
Variables		
Red Flag Law	-0.0763	-0.4741***
	(0.2496)	(0.1503)
Control Group		
Never Treated	X	X

These are the coefficients when using Callaway and Sant'Anna's estimator, where the dependent variable is suicide rate for column (I) and homicide rate for column (J). Standard errors are clustered at the state level in parentheses. The control group consists of units that never receive the treatment
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

In Table 6, the Red Flag Law variable represents the overall ATT. The overall ATT calculates the average treatment effect across all groups that received the treatment. It represents the average effect of the policy (Red Flag Laws) across all states that implemented this policy in any given year.

Columns (I) represents the results when the dependent variable is suicide rate. Despite the negative coefficient of interest (Red Flag Law), it is not statistically significant. This suggest the TWFE DiD results on suicide rates do not hold up when using a doubly robust estimator.

Columns (J) represents the results when the dependent variable is homicide rate. The coefficient of interest exhibits the expected sign and is statistically significant at the 1%-level. This further supports the initial TWFE DiD findings, indicating that the implementation of Red Flag Laws has a significant impact on reducing homicide rates in states that have passed and implemented such laws.

While Table 6 displays slightly smaller effects compared to Table 2, specifically in column (D) where no control variables are used and the dependent variable is the homicide rate, a reduction of 13.52% is observed. On the other hand, in column (J) of Table 6, applying the coefficient to the mean homicide rate results in a 9.05% reduction.

Falsification Test

For a robustness check, I conducted a falsification test using property crime data to determine if Red Flag Laws have had any effect on such crimes. The rationale behind this test is that the implementation of a Red Flag Law should not lead to a substitution effect where individuals, instead of engaging in violent acts, opt to commit property crimes. It is reasonable to assume that a policy aimed at reducing violence would not influence someone contemplating suicide or homicide to suddenly shift their actions towards property crime.

The purpose of conducting a falsification test is to further validate my findings by examining whether the implementation of Red Flag Laws has had a significant impact on unrelated crimes, such as property crime. If the adoption of Red Flag Laws coincides with notable declines in unrelated crimes, it raises concerns about the validity of my results.

Table 8 below displays the result of the falsification test conducted using property crime as the dependent variable. The TWFE DiD model from equation (1) is employed, incorporating both year fixed effects and state fixed effects. The falsification test is executed with control variables.

Table 7: Falsification Test

Dependent Variable:	Property Crime	
Years:	1990-2020	
Model:	(M)	(N)
Variables		
Red Flag Law	16.04	-156.5
	(114.4)	(148.6)
Median Household Income	-0.0102	
	(0.0146)	
White Ratio	3,836.2	
	(4,475.3)	
Male Ratio	81,962.4***	
	(16,411.3)	
Population	-0.01706**	
	(0.01055)	
Unemployment Rate	35.10	
	(27.10)	
Fixed-effects		
States	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	1,550	1,550
R^2	0.92273	0.88969

These are the DiD regression coefficients from equation 1 when the dependent variable is property crime. The purpose of these results is to show that Red Flag Laws did not impact something they were not targeted to have an impact on. The model includes state and year fixed effects as well as include all control variables involved in this project. The coefficients and standard errors for Median Household Income and Population have been re-scaled to be in the thousands. Standard errors are clustered at the state level in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The findings in Table 8 indicate that the implementation of Red Flag Laws did not have a significant impact on property crime. The coefficients obtained from the analysis are not statistically significant, indicating that there is no meaningful relationship between the enactment of Red Flag Laws and changes in property crime rates.

The lack of statistical significance suggests that the introduction of Red Flag Laws did not cause a substitution effect where individuals inclined towards violent acts shifted their behavior towards property crime instead. This reinforces the notion that the primary objective of Red Flag Laws, which is to reduce violence and prevent harm to oneself or others, did not inadvertently lead to an increase in property crimes. The results of the falsification test provide additional support for the validity of the findings regarding the impact of Red Flag Laws on suicide rates and homicide rates.

Conclusion

Overall, this study provides evidence supporting the effectiveness of Red Flag Laws in reducing both homicide and suicide rates. The difference-in-differences estimates suggest a significant reduction in suicide rates, ranging from a 6% decrease to a 10% reduction. Similarly, the study finds a larger reduction in homicide rates, ranging from 10.96% to 13.52%.

Recent advancements in the difference-in-differences literature have raised questions regarding which specific group is driving these results, particularly when the treatment is implemented over time. To address this concern, the Bacon decomposition method was employed, revealing that the vast majority of the results are primarily driven by the treated vs. untreated group. Furthermore, utilizing the estimation method developed by Callaway and Sant'Anna yields consistent findings with the original specification for homicide rates.

Importantly, the study highlights that the reductions in both suicide and homicide rates are primarily driven by states that allow family members, in addition to law enforcement, to petition a state court for the removal of firearms from a family member whom they perceive as a threat to themselves or others. This inclusion of more individuals in the process increases the efficacy of the policy, potentially leading to saving lives. In conclusion, this study provides compelling evidence in support of Red Flag Laws as an effective policy measure.

Some potential issues or limitations with this study include the limited time that has elapsed since the implementation of Red Flag Laws in most states. Given their relatively recent adoption, it may be necessary to reevaluate the effectiveness of these policies as more time passes and additional data becomes available. Furthermore, the availability of more data on Extreme Risk Protective Orders would allow for a more comprehensive examination of their true effectiveness.

Another potential limitation is the possibility that other forms of gun control measures implemented during the study period could have influenced the presented results. Considering the decline in mental health in the United States, it becomes crucial to have policies in place aimed at protecting individuals from themselves and potentially safeguarding others as well.

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Supplemental Appendix

Table A.1: Red Flag Law State Categories

State	Law Enforcement	Family Member	Duration of the Final Order
California	✓	✓	1 year
Colorado	✓	✓	6 months
Connecticut	✓		Up to 1 year
Delaware	✓	✓	Up to 1 year
Florida	✓		Up to 1 year
Hawaii	✓	✓	1 year
Illinois	✓	✓	6 months
Indiana	✓		Until terminated by the court
Maryland	✓	✓	Up to 1 year
Massachusetts	✓	✓	Up to 1 year
Nevada	✓	✓	Up to 1 year
New Jersey	✓	✓	Until terminated by the court
New Mexico	✓		Up to 1 year
New York	✓	✓	Up to 1 year
Oregon	✓	✓	1 year
Rhode Island	✓		1 year
Vermont	✓		Up to 6 months
Virginia	✓		Up to 180 days
Washington	✓	✓	1 year