Are Red Flag Laws a green light to save lives?

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Abstract

Mass shootings have become a hot topic of discussion in the United States in recent years. Policymakers have taken action through state legislation to develop a policy that would reduce the number of mass shootings. Red Flag Laws, also known Extreme Risk Protective Orders (ERPO), is a form of gun control policy designed to remove firearms from someone who presents a danger to themselves or others. I examine the effect that Red Flag Laws have on suicide rates and homicide rates in the states that have passed and implemented a Red Flag Law using a difference-in-differences approach. I find that suicide rates and homicide rates decrease by just over 6% and 10%, respectively, in the states that have a Red Flag Law. These effects are driven mainly by the states that also allow both family members and law enforcement to petition a state court for the removal of firearms.

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Introduction

Mental health and mass shootings have increasingly become relatively major topics in recent years, including a possible correlation between the two. One of the ways that policymakers have responded is through passing extreme risk protective orders (ERPO) also sometimes referred to as Red Flag Laws. Red Flag Laws have been around for a while, with Connecticut being the first state to pass a Red Flag Law. Following a mass shooting that took place on March 6, 1998 at Connecticut Lottery headquarters where the shooter killed four people before taking his own life, Connecticut passed the first Red Flag Law in 1999. Between 1999 and 2021, at least 18,383 extreme risk petitions were filed (Everytown Research & Policy).

Essentially, 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 takes place. Extreme risk protection orders gives family members or law enforcement officers a way to intervene before things escalate even further without having to go through the criminal court system. 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 a ERPO 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 (Everytown Research & Policy). 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]

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

According to a study conducted by the FBI that looked at pre-attack behaviors of active shooters in the United States between 2000 and 2013, "on average, each active shooter displayed four to five concerning behaviors over time that were observable to others around the shooter" (Silver et al. 2018). Some of the most frequent concerning behaviors included their "mental health, problematic interpersonal interactions, and leakage of violent intent". The study also examined who noticed concerning behaviors, for the spouse/domestic partner category 87%, family member 68%, and law enforcement 25%, reported noticing concerning behaviors prior to the attack. To date, there has not been a formal investigation into whether Red Flag Laws are impactful.

To address this question, I use a panel dataset using a two-way fixed effects (TWFE) difference-in-differences model looking at the staggering of policy implementation of Red Flag Laws across the United States. I use homicide rate data from the Federal Bureau of Investigation (FBI) Uniform Crime Reporting (UCR) and suicide rate data from the Center of Disease Control and Prevention (CDC) as dependent variables. For a falsification test I use property crime rate data from the FBI UCR. Control variables that are used in this project include data on population, gender, race, median household income, and unemployment rate.

I find that for states that have enacted a Red Flag Law, the implementation corresponds to just over a 6% reduction in suicide rates and a 10.4% reduction in homicide rates. These results are robust to the staggered policy implementation roll-out issue that has come about within the difference-in-differences identification strategy in recent years. 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 does include Indianapolis. They extrapolate that one life was saved for every ten gun-removals. Swanson et al. (2017) investigate 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 paper is the first comprehensive empirical study on the effectiveness of Red Flag Laws on homicide and suicide rates within the economics literature.[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.

[2]Rachel Dalafave (2021) 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.

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, Lott and Moody (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) examine how 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) examine 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) explore 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) examine 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 use panel data (state by year) collected from a variety of sources. These sources include the Federal Bureau of Investigation's (FBI) Uniform Crime Reporting (UCR) data, Center for Diseases Control and Prevention (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

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

CDC. It is available from 1999 to 2019. 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 used in this project 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.

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. Also, the District of Columbia implemented a Red Flag Law in 2019, but it is excluded from this project as Washington, DC is not a state but rather a district.

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	2019
Nevada	2020
Hawaii	2020
New Mexico	2020
Virginia	2020

There are potentially several reasons for this recent increase in passing a Red Flag Law. One of which could be the number of mass shootings that have occurred in recent years. Another reason could be that peoples mental health is more important than we once thought so policymakers are reacting to that change in priority of mental health.

Early adopters of Red Flag Laws such as Connecticut in 1999, and Indiana in 2005, came about as a reaction to a mass shooting or some type of gun violence conducted by someone with mental health problems. Although the states themselves self-select into this policy/treatment, the event(s) that led to them implementing a Red Flag Law were in fact exogenous. That is, the adoption of a Red Flag Law is unrelated with that state's level of homicide or suicide rates. Late adopters of a Red Flag Law are often the result of a mass shooting that took place in a neighboring state, which I argue is also exogenous. Red Flag Laws were implemented in response to high-profile mass shootings, not to increases in suicides or homicides. This allows me to treat the implementation of these policies as exogenous to my variables of interest, homicide and suicide rate.

For instance, Connecticut has cited a mass shooting that took place at Connecticut Lottery Corporation headquarters where an employee killed four of his bosses before committing suicide as a reason for the implementation of their Red Flag Law (Foley & Thompson 2018). Indiana, the second state to implement a Red Flag Law in 2005, cited the incident where four police officers had been wounded and another officer killed by a mentally ill man who had just killed his own mother and had stopped taking his prescribed medication for schizophrenia (Indiana Law Enforcement Memorial 2022). Indiana actually named their Red Flag Law after the police officer that had been killed (Indiana Jake Laird Law). California was the next state to implement a Red Flag Law in 2016. The event that they cite actually happened in 2014 near the campus of University of California, Santa Barbara where a mentally ill man killed six people and injured thirteen others before committing suicide (Foley & Thompson 2018).

In recent years mass shootings have increased or at the very least they are covered more in the news cycle than they have been in the past. Some recent notable mass shootings 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, Parkland, FL high school mass shooting in 2018, and El Paso, TX Wal-Mart shooting in 2019. Most of the states where these shootings have taken place went on to pass and implement a Red Flag Law in hopes of preventing the next mass shooting or at the very least reduce the chance that it happens. For other states, that neighbor a state where a mass shooting took place, some of them took the proactive instead of reactive approach in hopes of preventing something like that happening in their state. Consistently, state laws answer after high profile events. I argue these events are essentially random. More importantly, they are not driven by the state's underlying aggregate volume of homicides or suicides and, crucially, for identification, time trends in there 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	2.966	0.2	20.3
Suicide Rate	1,050	13.99	4.16	1.5	29.7
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.

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 and 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 results that Red Flag Laws have had on suicide rates. The variable of interest in Table 2 is the impact that Red Flag Laws had on suicide rates from 1999-2019, notated by the Red Flag Law variable. The first column includes control variables such as median income, race ratio (White), gender ratio (Male), Population, as well as Unemployment Rate. The second column drops all the control variables. It also important to note that since the suicide rate data only starts in 1999, Connecticut is considered "always treated" and states that did not implement a Red Flag Law until 2020, are in the control group.

Table 2: Suicide Rate Results

Dependent Variable:	Suicide Rate	
Years:	1999-2019	1999-2019
Model:	(A)	(B)
Variables		
Red Flag Law	-0.8868**	-1.307***
	(0.3315)	(0.3847)
Median Household Income	-3.12×10^{-5}	
	(4.16×10^{-5})	
White Ratio	64.00***	
	(15.42)	
Male Ratio	175.1***	
	(50.42)	
Population	-2.64×10^{-7}***	
	(8.39×10^{-8})	
Unemployment Rate	0.0568	
	(0.0689)	
Fixed-effects		
States	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	1,050	1,050
R^2	0.92852	0.91855

These are the DiD regression coefficients from equation 1 when the dependent variable is suicide rates. Suicide rate data is at the state level and runs from 1999-2019. All variable data is at the state level on an annual basis. Both models include both state and year fixed effects. Standard errors are clustered at the state level in parentheses. *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2 shows that there is statistical significance at the 5% level 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 9% in the suicide rate for states that have implemented a Red Flag Law. When all control variables are dropped the impact of Red Flag Laws grows even larger, going from -0.88 to -1.30, and there is statistical significance at the 1% level.

The standard errors are clustered at the state level as noted in Table 2. The reason for clustering at the state level is to account for the fact that I expect the errors to be related within group over time, which can make standard errors a little overconfident (i.e., too small) if not taken into account.[5] The R^2 of 92.8% in model (A) and 91.8% for model (B) shows that the models are a relatively good fit.

Table 3 provides the results of the impact of implementing a Red Flag Law on homicide rates. One important thing to note is for that the homicide rate models, I run two different time windows, one from 1999-2020 (like the suicide rate model shown previously) and the other on a longer window; 1990-2020. The larger window allows me to further explore the impact of Connecticut's Red Flag Law by having observations before it was implemented (1999) whereas, in the shorter time window, Connecticut is considered "always treated". It also allows for more observations for Indiana (2005), which was an early-adopter of a Red Flag Law. In addition to those two span of times (1999-2020 and 1990-2020) I also drop all controls for both time windows to assess the impact of omitted variable bias on my coefficient of interest. Another important part to point out is that, since I have homicide rate data for 2020, the estimates are able to include states that implemented a Red Flag Law in 2020: Nevada, Hawaii, New Mexico, and Virginia.

[4] The 6% comes from taking the coefficient of 0.8868 from the Red Flag Law variable in Model (A) to the suicide rate mean of 13.99, $(\frac{0.8868}{13.99}) = 0.0633$.

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

Table 3: Homicide Rate Results

Dependent Variable:	Homicide Rate			
Years:	1990-2020	1990-2020	1999-2020	1999-2020
Model:	(C)	(D)	(E)	(F)
Variables				
Red Flag Law	-0.5452***	-0.6871***	-0.5626***	-0.7755***
	(0.1904)	(0.2509)	(0.1690)	(0.1934)
Median Household Income	1.99×10^{-5}		-4.52×10^{-5}	
	(4.03×10^{-5})		(3.13×10^{-5})	
White Ratio	-3.554		2.967	
	(13.57)		(14.21)	
Male Ratio	64.46*		100.8***	
	(37.84)		(34.27)	
Population	-5.21×10^{-7}***		-2.1×10^{-7}***	
	(7.66×10^{-8})		(5.84×10^{-8})	
Unemployment Rate	-0.0382		-0.1353***	
	(0.0554)		(0.0494)	
Fixed-effects				
States	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,545	1,545	1,100	1,100
R^2	0.88223	0.85931	0.90830	0.89975

These are the DiD regression coefficients from equation 1 when the dependent variable is homicide rates. 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. Standard errors are clustered at the state level in parentheses. *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

From Table 3 across all models there is statistical significance on the Red Flag Law variable. Passage of a Red Flag Law corresponds to a decrease of homicide rates ranging from just under 10.5% to just shy of 15%. In all specifications standard errors are clustered at the state level for the same reason that they were clustered in Table 2 when the dependent variable was suicide rates. There is a reduction in the homicide rate across all models, similar to what I find on suicide rates. Model (C) shows the results for the full dataset from 1990-2020, and includes 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 10.4% in states that have adopted a Red Flag Law.[6] Model (D) uses the same window of time of model (C) but drops the control variables and I find an even greater reduction in homicide rates, which translates to a reduction in homicide rates by 13.11%.

When the window of time is shortened (1999-2020) to match the data availability range of suicide rates, I find an even stronger reduction in homicide rates compared to the larger window of time that reflects the full data-set (1990-2020). In model (E) I find a reduction in the homicide rate of 10.72%, which is marginally greater than the reduction I found in model (C). Model (F) is where I find the greatest reduction in homicide rates with a decrease in the magnitude of 14.79%. This is an even stronger finding compared to the reduction found in model (D) of 13.11%. Furthermore, it does appear that Red Flag Laws are working like policymakers would hope that they would in reducing mass shootings and deaths from firearms via a reduction in homicides and suicides.

Parallel Trends

The primary identifying assumption of the difference-in-differences methodology 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. 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 results are presented below, Figure 1 shows the event study for homicide rate and Figure 2 shows the event study for suicide rate.

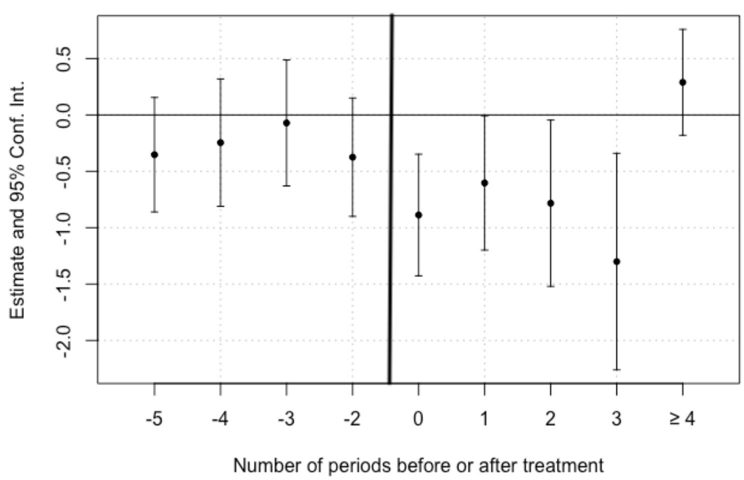
These estimates ask whether homicide rate patterns were changing in the time period leading up to or after a Red Flag Law adoption. It's important to note, that with the staggered adoption, the after treatment period is limited in the number of observations since

[6]The 10.4% comes from taking the coefficient of 0.5452 from the Red Flag Law variable in Model (C) to the homicide rate mean of 5.24, $(\frac{0.5452}{5.24}) = 0.1040$.

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.

Essentially, 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.

Figure 1: Homicide Rate Event Study

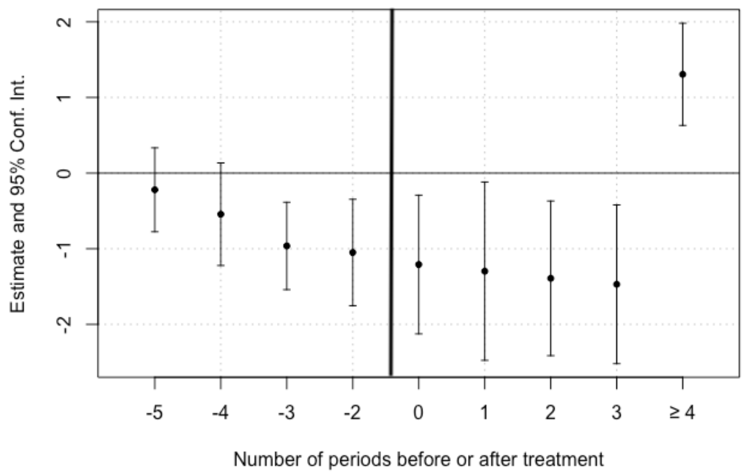


The specification above shows evidence of parallel trends for homicide rates, since the coefficients are statistically indistinguishable from zero in the pre-treatment period. I fail to detect a visible or statistically distinguishable pre-trend in homicide rates. A χ^2 test of joint significance and reveals a p-value of 0.12. Immediately after a Red Flag Law is implemented there is a reduction in homicide rates, which persists for years after its adoption.

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. It's also important to note that for suicide rates the data I have collected runs from 1999-2019. This means that I do not have any pre-treatment observations for Connecticut, which implemented their Red Flag Law in 1999.

Figure 2: Suicide Rate Event Study



The specification above shows less clear evidence of parallel trends for suicide rates. Although the coefficients for t=-5 and t=-4 periods are essentially zero once t=-3 period begins the coefficients from t=-3 to t=+3 are statistically different from zero. A χ^2 test on the joint significance and reveals a p-value of less than 0.01. This implies a violation of the parallel trends assumption in the difference-in-differences identification strategy. This implies that I am unable to make causal claims that the implementation of Red Flag Laws caused the reduction in 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 downward time trend.

Heterogeneous Causality Effects

Table 4 below presents the results of when the Red Flag Law variable is decomposed into Law Enforcement Only and Law Enforcement & Family. For the states that have implemented a Red Flag Law, they either allow law enforcement only to request or invoke the Red Flag Law, or in some states, family members can also request or invoke the Red Flag Law. Of the 19 states that currently have a Red Flag Law on the books, seven states only allow law enforcement entities to enact the Red Flag Law, the remaining 12 states allow both law enforcement entities as well as family or household members to enact the Red Flag Law. Table 10 in the supplemental appendix further breaks down which states fall into which categories.

Table 4: Results for Red Flag Law Decomposed

Dependent Variables:	Suicide Rate		Homicide Rate	
Years:	1999-2019		1990-2020	
Model:	(G)	(H)	(I)	(J)
Variables				
Law Enforcement Only	-0.4852	-0.6455	-0.4222	-0.3989*
	(0.3880)	(0.4949)	(0.2631)	(0.2135)
Law Enforcement and Family	-0.7089*	-1.223**	-0.6763**	-0.9624**
	(0.4144)	(0.4750)	(0.2973)	(0.3959)
Median Household Income	-3.33×10^{-5}		2.16×10^{-5}	
	(4.39×10^{-5})		(4.07×10^{-5})	
White Ratio	64.80***		-3.394	
	(15.65)		(13.75)	
Male Ratio	176.2***		62.96*	
	(50.16)		(37.12)	
Population	-2.69×10^{-7}***		-5.2×10^{-7}***	
	(8.7×10^{-8})		(7.66×10^{-8})	
Unemployment Rate	0.0641		-0.0391	
	(0.0707)		(0.0554)	
Fixed-effects				
States	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,050	1,050	1,545	1,545
R^2	0.92725	0.91697	0.88229	0.85961

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 (G) and (H); homicie rate is the dependent variable for models (I) and (J). 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 12 in the Supplemental Appendix. Standard errors are clustered at the state level in parentheses. *Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

From Table 4, the Red Flag Law variable is decomposed into two separate variables: Law Enforcement Only and Law Enforcement & Family states that allow either law enforcement or family and household members to request an extreme risk protection order have some level of statistical significance on both suicide rates and homicide rates. The impact of Red Flag Laws is muted when only law enforcement can apply the law. This seems entirely plausible for one glaring reason. When more people have the ability to do or say something when they see that something is wrong or off, the more success the law will have. Now, it is important to note that family or household members is limited to only people who are very close to the individual who is at risk of harming themselves or others. The results from Table 4 show statistical significance for both dependent variables, with covariates and without covariates, on the law enforcement & family variable. With most models show statistical significance at the 5% level, on the law enforcement & family variable.

Robustness Checks

One potential limitation to this model is the staggered treatment effect, in which there are early adopters of Red Flag Laws (Connecticut) and later adopters (Nevada, Hawaii, New Mexico, and Virginia). Using a TWFE difference-in-differences model, where there is a staggered policy adoption (like the case for this project), there could be bias in the presence of treatment effect heterogeneity (Goodman-Bacon 2021). Recent advances in econometric theory suggest that staggered difference-in-differences identification strategies might not provide sound estimates of the average treatment effect (ATE) or the average treatment effect on the treated (ATT).

To help mitigate this limitation, I run a Bacon decomposition which decomposes TWFE models into all two-by-two estimates and their corresponding weights following Goodman-Bacon (2021). The issue with the staggered treatment effect is which group is driving the coefficient of interest. For example, are the early adopters driving that negative coefficient, or is it the later adopters? Essentially, we want to avoid the early treated vs. later treated bias driving the coefficient of interest. Goodman-Bacon's decomposition allows applied work to identify which type fo group is actually driving the coefficient of interest.

In recent years, the differences-in-differences literature has been exposed for its potential bias when treatment, such as a policy adoption, is staggered due to heterogeneity treatment (Goodman-Bacon (2021) and Gardner (2021)). In light of this exposure, there have been some developments to diagnosis the extent of the bias and solutions for this bias. I take advantage of Andrew Goodman-Bacon's diagnostic tool of decomposing which type of category (early vs. later treated, always treated vs. later treated, treated vs. untreated, and later vs. early treated) is driving the coefficient as well as Jonathan Gardner's two-stage difference-in-differences to address this issue.

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 2019). 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. Since most states that have a Red Flag Law adopted it recently, meaning the later treated group is larger than the earlier treated group, it could potentially bias the coefficient of interest by changing the weighted average. The Bacon Decomposition is essentially a weighted average of all potential two-by-two DiD estimates where the weights are based on group sizes as well as variance in treatment.

Jonathan Gardner's two-stage difference-in-differences is an original alternative to TWFE and will identify the overall ATT, even under heterogeneity and staggered adoption. The first stage estimates group and period fixed effects using only the comparison units (states) for each group and period. This includes never-treated units as well as not-yet-treated units. Once the group and period fixed effects are estimated, they are subtracted from the outcome variable. The second stage estimates the overall ATT. It does so by taking the transformed outcome variable from the first stage and regressing it onto treatment status by comparing the average outcomes between treated and untreated groups. "The reason that this estimates the overall ATT is because the mean outcome, after netting out estimated group and period fixed effects, this "new error term" is no longer correlated with group and period fixed effects, as they will be gone from the regression altogether" (Cunningham, 2021).

Bacon Decomposition

Table 5 below shows the results for the Bacon decomposition for suicide rate. It is important to note that my suicide rate data starts in 1999, the same year that Connecticut implements their Red Flag Law, meaning that Connecticut is considered "always" treated. Something else to keep in mind is four states (Nevada, Hawaii, New Mexico, and Virginia) did not implement their Red Flag Law until 2020, and since my suicide rate data ends in 2019, they are considered untreated. The tables below (Tables 5 & 6) do not include any control variables in the specification such as median income, population, unemployment rate, race, or gender.[7]

Table 5: Suicide Rate

	1999-2019	
Type	Weight	Avg. Estimate
Earlier vs. Later Treated	0.10360	0.18440
Later vs. Always Treated	0.02439	-0.39038
Later vs. Earlier Treated	0.01850	0.16682
Treated vs. Untreated	0.85351	-1.19789

From Table 5 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 > 0.85). This is a good indication that the results in Table 2 from the TWFE difference-

[7] 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 5-7, meaning including or not including controls does not greatly influence which type is driving the coefficient.

in-differences model is driven by the states that implemented a Red Flag Law compared to states that do not. One minor concern is the 10% weight that is driven by the "Earlier vs. Later Treated", which is a potential issue that could cause bias when using TWFE DiD when there is staggered treatment.

Table 6 below shows the results for the Bacon decomposition for homicide rate. When examining the 1999-2020 (far-right) section of the table Connecticut is considered "always" treated but the four states (Nevada, Hawaii, New Mexico, and Virginia) that did not implement their Red Flag Law until 2020 are now considered treated since I have homicide rate data for 2020.

Table 6: Homicide Rate

	1990-2020		1999-2020	
Type	Weight	Avg. Estimate	Weight	Avg. Estimate
Earlier vs. Later Treated	0.18389	-0.05773	0.13615	-0.34922
Later vs. Always Treated	NA	NA	0.02623	-0.11683
Later vs. Earlier Treated	0.02816	-0.46999	0.02444	-0.84900
Treated vs. Untreated	0.78795	-0.85047	0.81318	-0.86597

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

From Table 6 the dominant type is the "Treated vs. Untreated" with a weight of 79% for the 1990-2020 section of the table and 81% for the 1999-2020 section of the table, similar to the 85% that was presented in Table 5 for the same type, which is a good sign that the results in Table 3 are not biased by the staggered implementation of the policy. Across the board there is a negative average estimate for each type, for both time periods (1990-2020 and 1999-2020). Once again there is a minor concern in regards to the 18% (1990-2020) and 14% (1999-2020) weight associated with the "Earlier vs. Later Treated" type. This makes a great deal of sense considering the number of states that adopt and implement this policy later.[8] Because of these minor concerns, I run a two-stage difference-in-differences below for a further robustness check on the staggered roll-out of the policy.

[8] I am including 2020 where four out of the total 19 states implement a Red Flag Law. Those four states account for 21% ($\frac{4}{19}$) of the total states treated.

Two-Stage Difference-in-Differences

Table's 7 and 8 below shows the results from Jonathan Gardner's two-stage difference-in-differences. The first stage estimates the group and period fixed effects by regressing out the fixed effects for the comparison states. The second stage estimates the overall average treatment on the treated (ATT) by taking the transformed outcome variable from the first stage and regressing it onto treatment status by comparing the average outcomes between treated and untreated groups. Essentially, the two-stage difference-in-differences isolates the ATT even under staggered roll-out/implementation and heterogeneity.

Table 7 below shows the results for suicide rates when using Gardner's two-stage difference-in-differences identification strategy. Table 7 is comparable to Table 2 in that Table 2 shows the results from my primary specification (TWFE DiD) on suicide rates, and Table 7 shows that my results are robust to using a different specification. Essentially, Table 7 replicates what is done and presented in Table 2 in terms of dependent variable and controls as well as time frame/window of sample, but using a recently developed DiD econometric method.

Table 7: Two Stage DiD Suicide Rate Results

Dependent Variables:	Suicide Rate	Suicide Rate
Years:	1999-2019	1999-2019
Model:	(K)	(L)
Variables		
Red Flag Law	-1.342***	-1.611***
	(0.2373)	(0.3264)
Fit statistics		
Observations	1,050	1,050
R^2	0.05324	0.07729

These are the two-stage DiD regression coefficients, where the dependent variable is suicide rates. Model (K) does not include any control variables, Model (L) includes all control variables involved with this project. Standard errors are clustered at the state level in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

Table 7 shows the results for suicide rate from 1999-2019. Model (K) does not include control variables, while model (L) does include control variables such as median household income, population, unemployment rate, race, and gender variables. These results are awfully similar to the coefficient that is presented in Table 2, model (B) where the coefficient is -1.307 and in Table 8, model (K) the coefficient is -1.342. This shows that my initial results are robust to a new econometric method that is an original alternative to the traditional TWFE DiD. The results from model (L) in Table 7 (-1.611) show an even stronger reduction in suicide rates when compared to model (A) in Table 2 (-0.8868), implying that it is possible that my primary specification (TWFE DiD) is actually underestimating the impact of Red Flag Laws on suicide rates. There is also an increase in the statistical significance when comparing a 5% statistical significance in model (A) in Table 2 to a 1% statistical significance in model (L) in Table 7.[9] This provides further evidence that Red Flag Laws are indeed corresponding to a significant reduction in suicide rates.

Table 8 below shows the results for homicide rates when using Gardner's two-stage difference-in-differences identification strategy. Table 8 is comparable to Table 3 in that Table 3 shows the results from my primary specification (TWFE DiD) on homicide rates and Table 8 shows that my results are robust to using a different specification. Essentially, Table 8 replicates what is done and presented in Table 3 in terms of dependent variable and controls as well as time frame/window of sample, but using an original alternative to the TWFE DiD.

Table 8: Two Stage DiD Homicide Rate Results

Dependent Variables:	Homicide Rate	Homicide Rate	Homicide Rate	Homicide Rate
Years:	1990-2020	1990-2020	1999-2020	1999-2020
Model:	(M)	(N)	(P)	(Q)
Variables				
Red Flag Law	-0.5834**	-0.6528***	-0.7726***	-0.5803***
	(0.2342)	(0.1730)	(0.1689)	(0.1461)
Fit statistics				
Observations	1,545	1,545	1,100	1,100
R^2	0.01275	0.01926	0.03867	0.02406

These are the two-stage DiD regression coefficients, where the dependent variable is homicide rates. Models (M) and (P) does not include any control variables. Models (N) and (Q) includes all control variables involved with this project. Standard errors are clustered at the state level in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.*

[9] The statistical significance for model (K) in Table 7 and model (B) in Table 2 are identical, at the 1% level.

Table 8 shows the results for homicide rate utilizing the full data-set (1990-2020) and the shorter time frame (1999-2020) to closely match the length of the suicide rate data. Models (M) and (P) do not include control variables whereas models (N) and (Q) do include the full set of control variables involved with this project. Across the board there is a statistically significant reduction in homicide rates, mostly at the 1% level.

When comparing the results from Table 8 to the results presented in Table 3, the reductions are extremely similar. In two cases, the results from Table 8 are marginally stronger than what is presented in Table 3. For example, when using the full data-set, with controls, model (N) in Table 8 presents a coefficient of -0.6528, compared to the result presented in model (C) in Table 3 that has a coefficient of -0.5452. Both models (N) and (C) show levels of statistical significance of 1%. The other case where the two-stage difference-in-differences finds a marginally stronger reduction in homicide rates is when the data-set is shortened to 1999 to 2020, with controls, comparing model (Q) in Table 8 to model (E) in Table 3. In this particular case, model (Q) in Table 8 presents a coefficient of -0.5803 and model (E) in Table 3 presents a coefficient of -0.5626. Both models (Q) and (E) show levels of statistical significance of 1%. The other comparisons (model (M) in Table 8 and model (D) in Table 3, and model (P) in Table 8 and model (F) in Table 3) are quite comparable.

This implies overall, my primary specification (TWFE DiD) results are robust when using a recently developed DiD method that is an original alternative to the TWFE DiD method. Furthermore, this study has demonstrated that even with the staggered adoption of Red Flag Laws, taken into account when using Goodman-Bacon's Bacon Decomposition and Gardner's two-stage difference-in-differences identification strategy, that Red Flag Laws are associated with a significant reduction in homicide rates as well as suicide rates.

Falsification Test

For a robustness check, I utilize property crime data as a falsification test on whether Red Flag Laws have had any effect on property crime. Implementing a Red Flag Law should not cause a substitution effect towards committing property crime. It stands to reason that a policy intended to reduce violence should not have an impact on a crime such as property crime in that someone who is considering committing suicide or killing someone else would suddenly change their mind and instead commit property crime. The purpose of a falsification test is to further validate my results by asking whether the Red Flag Laws did not cause something unrelated, like property crime, to be significantly impacted. If the adoption corresponds to drops in unrelated crimes then one can question my results.

Table 9 below presents the results from the falsification test where the dependent variable is property crime. I continue to employ the TWFE DiD model from equation (1), with a year fixed effect and state fixed effect. I run the falsification test using controls and for both time windows, from 1990-2020, as well as 1999-2020.

Table 9: Falsification Test

Dependent Variables:	Property Crime	
Years:	1990-2020	1999-2020
Model:	(R)	(S)
Variables		
Red Flag Law	-5.062	7.599
	(107.6)	(84.75)
Median Household Income	-0.0098	0.0024
	(0.0148)	(0.0125)
White Ratio	3,795.8	581.0
	(4,466.3)	(5,321.8)
Male Ratio	81,795.5***	74,841.4***
	(16,403.3)	(20,130.5)
Population	-0.0001**	-7.16×10^{-5}
	(6.18×10^{-5})	(5.14×10^{-5})
Unemployment Rate	35.21	37.01*
	(27.18)	(20.66)
Fixed-effects		
States	Yes	Yes
Year	Yes	Yes
Fit statistics		
Observations	1,550	1,100
R^2	0.92273	0.92561

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 reason for two models is to closely match data availability for homicide rate (data from 1990 to 2020) as well as suicide rate (data from 1999 to 2019). Both models include state and year fixed effects as well as include all control variables involved in this project. Standard errors are clustered at the state level in parentheses.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The results in Table 9 suggest that Red Flag Laws did not have an impact on property crime. The coefficients are not statistically significant from zero.

Conclusion

Overall, this study provides evidence that Red Flag Laws do have an effect on reducing homicide rates as well as suicide rates. TWFE difference-in-differences estimates suggest that Red Flag Laws are associated with a significant reduction in suicide rates ranging from a 6% decrease to a 9% reduction. When looking at homicide rates the reduction is even larger, ranging from 10.4% to 13.1% reduction. Recent developments in the difference-in-differences literature when the treatment has a staggered roll-out has been called into question for which group is actually driving the results. Testing via the Bacon decomposition shows that the overwhelming majority of my results are driven primarily by the treated vs. untreated groups. Furthermore, using a newly developed method such as Jonathan Gardner's Two-Stage Difference-in-Differences generates findings consistent with my original specification. Finally, I find the reductions are 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 that they believe is a danger to themselves or others. It stands to reason that when more people are able to take action this can increase the effectiveness of the policy and possibly save lives in the process. Overall, I believe this study provides positive evidence in favor of such a policy as a Red Flag Law.

Some potential issues or limitations with this project could be that not enough time has passed to truly test the effectiveness of this policy. Especially, considering that most states only recently implemented a Red Flag Law. As time progresses and more data becomes available it would be beneficial to re-run these models and see if the effect widens or narrows with more time. More data availability on Extreme Risk Protective Orders would also be able to further test just how effective Red Flag Laws truly are. It is also possible that some other form of gun control that was implemented during this sample could be contributing to the results presented in this paper. With the state of mental health appearing to be on the decline in the United States it is important to have policies in place in hopes of being able to protect someone from themselves and possibly protect others.

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Supplemental Appendix

Table 10: 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

Bacon Decomposition with Controls

Table 11: Suicide Rate 1999-2019

Type	Weight	Avg. Estimate
Both Treated	0.13622	0.24622
Later vs. Always Treated	0.02974	-0.27224
Treated vs. Untreated	0.83405	-1.04972

Table 12: Homicide Rate Rate 1999-2019

Type	Weight	Avg. Estimate
Both Treated	0.18031	-0.40658
Later vs. Always Treated	0.03455	-0.26443
Treated vs. Untreated	0.78514	-0.86544

Mass Shootings

- Connecticut Lottery Shooting on March 6, 1998
  - Lottery employee killed four supervisors before turning the gun on himself
- Columbine High School mass shooting on April 20, 1999
  - Two gunmen killed 12 students and one teacher, another 21 people were wounded, both gunmen committed suicide
- Police officer shot and killed on August 18, 2004 by a mentally disturbed man in Indiana
  - Indiana's Red Flag Law named after police officer (Timothy Jacob 'Jake' Laird)
- California mass shooting on May 23, 2014 near the campus of University of California, Santa Barbara
  - Man killed six people and injured thirteen more by gunshot, stabbing, and even vehicle ramming
- Orlando, FL nightclub mass shooting on June 12, 2016
  - 49 people were killed another 53 injured
- Las Vegas mass shooting on October 1, 2017
  - 58 people were killed including the gunman
- Southern Baptist Church shooting in Sutherland Springs, TX on November 5, 2017
  - 26 people were killed another 20 injured
- High School mass shooting in Parkland, FL on February 14, 2018
  - 17 people were killed another 17 injured
- Wal-Mart mass shooting in El Paso, TX on August 3, 2019
  - 23 people were killed another 23 injured