My name is Felisha Bull and I am representing Gun Owners of America. I am submitting Dr. John R. Lott's research on red flag laws and crime reduction in response to Designated Parties promoting policies that would facilitate easier removal of firearms from people who have not committed a crime. Please see the following research and data from Dr. John Lott.

Larger data tables can be found here: https://ssrn.com/abstract=3316573

Do Red Flag Laws Save Lives or Reduce Crime?

John R. Lott, Jr.
President
Crime Prevention Research Center

Carlisle E. Moody
College of William and Mary
and
Crime Prevention Research Center

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Abstract

Red flag laws had no significant effect on murder, suicide, the number of people killed in mass public shootings, robbery, aggravated assault, or burglary. There is some evidence that rape rates rise. These laws apparently do not save lives.

I. Introduction

By the end of 2018, thirteen states have passed Red Flag or Extreme Risk Protection Order (ERPO) laws which allow police or family members or those living in the same residence to file a petition for a court order temporarily seizing the firearms of persons accused to be a danger to themselves or others (Devos et al., 2018). Using the most recent data, we investigate the effect of Red Flag laws on murder, suicide, and deaths due to multiple victim public shootings. We use murder rather than firearm homicide and suicide rather than firearm suicide because there may be substitution and homicide includes justified homicides and homicides committed in the line of duty by police officers. Four of these states implemented this policy before the end of 2017: California (2016), Connecticut (1999), Indiana (2005), and Washington (2016). We will study these laws being in effect for a combined total of 36 years.

The basic idea is that some individuals who pose a danger to themselves and others and that danger is magnified by the presence of firearms. Therefore, any policy that can effectively remove the firearms, if only temporarily, from such individuals could save lives either through the reduction of homicide or by making the completion of a suicide attempt more difficult. However, it is possible that these laws could increase homicide or suicide. In the absence of a Red Flag law, a person contemplating homicide or suicide might speak to a family member and, as a result, be dissuaded from that course of action. If the same person is aware of the existence of a Red Flag law, then he or she may well not approach a family member or anyone else who might initiate an ERPO. The result could be that such individuals go on to kill themselves or others.

These laws are not specifically limited to people who are mentally ill, as there are already options to commit those posing a danger to themselves or others. No specific guidelines for identifying people are given, ERPO are meant to let people determine on their own whether someone is dangerous. Discussions before the Uniform State Law Commission indicate that those making these decisions rely on a variety of factors in predicting future behavior, such as a history of violent behavior, gender, and age. So while there are already laws that ban felons or those with some types of misdemeanors from owning guns, ERPOs allow people to take into account arrests that didn't result in a conviction or simply complaints.

While mass public shootings have served as the instigation for ERPO laws, this is the first panel analysis that looks at death rates from mass public shootings and suicides or changes in violent crime rates, including murder.

II. Results

The basic model is a fixed effects regression model for all 50 states and DC from 1970 to 2017 in which the natural log of the murder and suicide rates and the number of people killed in mass public shootings are the dependent variables (suicide is available only up to 2016, mass shootings are available from 1977). We use a standard difference-in-differences dummy variable model as well as a spline model and a combination dummy-spline "hybrid" model to determine the effects of the Red Flag law.

Following the specifications used in Moody and Marvell (2010), in addition to lagged endogenous variables, the initial specifications also included: Population density, Crack epidemic measure, Arrest rate for violent crime, Prison population per capita, lagged Executions, Truth in sentencing, Real income per capita, Poverty rate, Unemployment rate, Total employment, Military employment per capita, Construction employment per capita, and demographics (percent of the population that is black and age distribution by five year age intervals from 15 to 64 and those 65 and older). The gun control laws accounted for: Three strikes, Right to carry, Castle doctrine, Stand your ground, Use a gun go to jail, Waiting period, Background check, private sale Background check, Safe storage law, Juvenile gun ban, One gun per month, and Saturday night special bans.

We use a general-to-specific modeling approach (Moody and Marvell 2010), where we dropped all variables with t-ratios less than one in absolute value and then subjected them to an F-test for joint significance. In all cases, the tests we did were not significant at the .05 level, indicating that we were justified in our model reductions. The full estimates with all the variables produced even less significant results for the Red Flag laws. We report the results of the expanded models, all the estimated control variables, all the other specifications discussed below that are not reported in the tables, as well as provide the data in the robustness section of the online appendix (https://tinyurl.com/y6vnljwt).

The results with respect to the murder rate are presented in Table 1A. The coefficients, standard errors and t-ratios are conventional, but the p-values for the policy variables are generated by a placebo law exercise, the need for which is due to the small number of policy changes. Since there are only four states that have adopted Red Flag laws in our sample period, the standard errors are underestimated (Conley and Tabor 2011). In our placebo law exercise we replace the four "treated" states with randomly chosen states with imaginary placebo laws for the same years as the laws in the treated states. We then re-estimate the model. We repeat this 1000 times to generate distributions of outcomes centered on zero, the true value of the coefficients on the policy variables for those states that did not adopt a Red Flag law. From these distributions (for which we know that the null hypothesis of no effect is true) we can find the number of times the placebo laws generated t-ratios greater, in absolute value, than the t-ratios generated by the actual treated states. These are divided by 1000 to generate the p-values.

Perusal of Table 1 reveals that, despite the apparently significant t-statistics, the laws have had no significant effect on either murder at the .05 significance level based on the placebo law p-values. In fact, none of the policy variables are significant at the .10 level.[1] In addition, if

[1] The p-values for the policy variables are as follows: hybrid model, dummy .245, spline .212; dummy only .178; spline only .132.

individual state trends are excluded, the results are not statistically significant at even the traditional levels.

The corresponding results for suicide are presented in Table 1B. Again, the apparently significant policy variables turn out to be insignificant when using the placebo law p-values.[2] The coefficients are also economically very small. In the first specification, a Red Flag law initially increases the suicide rate by 0.02 percent, and that effect is reduced to zero by the fourth year that it is in effect.

The results with respect to deaths due to mass public shootings are shown in Table 2. We follow the traditional FBI definition that was used for 30 years until 2013 of four or more people killed in a public place that did not involve some other crime such as gang fights or robberies. Since the dependent variable is the number of people killed, we used the fixed effects negative binomial model. We followed the same general to specific modeling approach used in the first two tables. Since the policy variables are not significant in these results, we do not need to use placebo law p-values. The results are consistent with those of murder and suicide, the coefficients on the policy variables are not significantly different from zero. The coefficients imply a small initial increase in deaths from mass public shootings of between 0.1 and 0.2 per year.

Finally, Table 3 investigates the impact of ERPO laws on other crime rates using specifications that correspond to those shown in Table 1, and with the exception of one specification showing an increase in rape rates (specification 2), none of the coefficients are statistically significant at the .05 level. At the .10 level, the first specification also shows an increase in rape rates. In both cases, the results imply about a four percent increase in rape rates.

We conducted a number of robustness checks. Connecticut increased the number of gun seizures tenfold in 2007 from 10 to 100 in 2007 and over 700 by 2013 (Swanson et al. 2016, p.8). Consequently, we re-estimated the models using 2007 as the implementation date for Connecticut. The results were unchanged. We also estimated models for murder and suicide using pre- and post-law dummy variables, one for each two-year period. We found, for both murder and suicide, that none of the post-law dummies were significantly different from zero using placebo law p-values. Similarly, there was no significant difference between the means of the pre-law and post-law dummies.

III. Conclusion

Red flag laws had no significant effect on murder, suicide, the number of people killed in mass public shootings, robbery, aggravated assault, or burglary. There is some evidence that rape rates rise. These laws apparently do not save lives.

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[2] The p-values for the policy variables are: hybrid model dummy .188, spline .131; dummy only .457; spline only .212.

References

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Table 1: Examining the impact of Extreme Risk Protection Orders on Murder and Suicide

A) Natural Log of the Murder Rate (Including state and year fixed effects and individual state time trends)

Variable	Coefficient (1)	T-ratio	Coefficient (2)	T-ratio	Coefficient (3)	T-ratio
ERPO dummy variable	-5.983	2.47	-7.016	2.71		
ERPO spline variable	-0.669	2.43			-0.991	3.24
N	1,977		1,977		1,977	

B) Natural Log of the Suicide (Including state and year fixed effects and individual state time trends)

Variable	Coefficient (1)	T-ratio	Coefficient (2)	T-ratio	Coefficient (3)	T-ratio
ERPO dummy variable	0.017	2.32	0.012	1.25		
ERPO spline variable	-0.005	3.63			-0.004	2.92
N	1,734		1,734		1,734	

Notes: * $p<0.05$; ** $p<0.01$; the Red Flag law dummy and spline variables were not significant using placebo law values; regressions are weighted by state population; standard errors are clustered on states; coefficients on the individual state trends, state, and year dummies are suppressed to conserve space; complete results for other control variables are available here https://tinyurl.com/y6vnljwt.

Table 2: Examining the impact of Extreme Risk Protection Orders on the number deaths from Multiple Victim Public Shootings (Negative binomial regressions)

Variable	Coeff (1)	T-ratio	Coeff (2)	T-ratio	Coeff (3)	T-ratio
ERPO dummy variable	0.189	0.17	0.111	0.14		
ERPO spline variable	-0.020	0.09			0.006	0.04
N	1,476		1,476		1,476	

Note: * p<0.05; ** p<0.01; fixed effects negative binomial model; coefficients are incident rate ratios; p-values for policy variables are not adjusted using placebo law methods; complete results for other control variables are available here https://tinyurl.com/y6vnljwt.

Table 3: Examining the impact of Extreme Risk Protection Orders on the Natural Log of other Crime Rates that correspond to the estimates provided in Table 1 (Including state and year fixed effects and individual state time trends)

Variable	Rape	Robbery	Assault	Burglary
(1) Dummy and Spline Model				
ERPO dummy variable	4.419	-22.716	0.781	-0.313
	(3.45)	(1.78)	(0.71)	(0.25)
ERPO spline variable	-0.076	0.973	0.556	0.120
	(0.21)	(0.93)	(1.52)	(0.48)
(2) Dummy Only				
ERPO dummy variable	4.283	-20.971	1.781	-0.094
	(4.72)*	(1.66)	(1.13)	(0.10)
(3) Spline Only				
ERPO spline variable	0.142	-0.150	0.595	0.105
	(0.39)	(0.31)	(1.52)	(0.49)
N	1,928	1,928	1,928	1,928

Notes: T-ratios in parentheses;* p<0.05; ** p<0.01, using placebo law p-values; regressions include state and year dummies and individual state trends; regressions are weighted by state population; standard errors are clustered on states; complete results for other control variables are available here https://tinyurl.com/y6vnljwt.